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Local Markets in the Energy Sector Based on Distributed Ledger Technologies

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Abstract

Achieving the global energy goal of limiting global warming to 1.5° C and the massive expansion of renewables needed to get there would require integration of more renewable energy resources from not just large scale producers but also small and medium scale electricity producers. This has resulted in distributed energy resources, where end consumers within the power grid are becoming active prosumers thereby being able to produce or consume electricity at will to or from the grid, respectively. However, these distributed energy resources added high level of complexity to the reliability and stability of the power grid making it difficult to be managed by the traditional top-down approach because of the complexity and variable nature of renewable energy resources. There is also a need for coordination to manage the huge spatiotemporal fluctuations that would occur in such an energy system. Local energy markets as a solution to these daunting challenges propose the use of bottom-up market approach to manage electricity trading in the power grid. This dissertation presents different comprehensive analysis, evaluations, models, and bidding strategies for local energy markets based on distributed ledger technologies, to guide policy makers and interested companies willing to apply it as a puzzle piece for a successful transformation of the energy system towards carbon neutrality.

The dissertation starts with a survey analysis to determine the quantifying factors for participating in local energy markets based on distributed ledger technologies. The survey which received 261 responses showed that the major factors for participating in a local energy market based on distributed ledger technologies are security of supply, interest or willingness to support renewable energy integration, transparency, and trust. Additionally, a simulation-based analysis was conducted to determine the necessary conditions for most beneficial local energy markets. The results from the simulations show that the market is most beneficial for the consumers and prosumers within the community for a small or medium community with prosumer to consumer ratio between 0.3 to 0.5. Also, using accurate bidding and offering strategies creates more benefits for the local community compared to increasing the share of renewables within the community.

An advanced clustering algorithm was developed for clustering consumers and prosumers in local energy markets based on their bidding or offering preferences to ensure that energy is exchanged efficiently between consumers and prosumers within the local community. In a market where prosumers and consumers may desire a certain quality of energy or wish to exchange energy with a certain group, a decentralized market platform was developed. The model provides prosumers with the flexibility of choice of energy and trading group. Also, different reinforcement learning intelligent bidding and offering strategies were developed and evaluated. The results show that the most beneficial local markets are obtained when the intelligent agents make their bidding or offering towards a common goal.

Finally, two approaches which are the proof-of-concept and hybrid blockchain-based local energy market frameworks were developed. The challenges of the proof-of-concept blockchain-based local energy market framework which includes scalability, high operation cost and transparency were solved by the hybrid blockchain-based local energy market framework. The hybrid blockchain-based local energy market framework combines the on-chain features of blockchain and side-chain features of trusted execution environment to form an economically feasible market platform. The hybrid blockchain-based local energy market framework also provides integrity, high security, and low operation cost which makes it suitable for local energy market operation.

Zusammenfassung

Auch im Energiesektor muss das Ziel, die globale Erwärmung auf 1,5 °C zu begrenzen, erreicht werden. Um den hierfür erforderlichen massiven Ausbau der erneuerbaren Energien voranzutreiben, muss mehr Energie aus erneuerbaren Quellen nicht nur von großen, sondern auch von kleinen und mittleren Stromerzeugern in das Energiesystem integriert werden. Aus diesem Erfordernis sind dezentrale Energieressourcen entstanden, mit deren Hilfe Endverbraucher zu aktiven Prosumern innerhalb des Stromnetzes werden, indem sie nach Belieben Strom in das Netz einspeisen bzw. aus dem Netz verbrauchen. Jedoch wird es aufgrund der Variabilität dezentraler, erneuerbarer Energiequellen deutlich komplexer das Stromnetz zuverlässig und stabil zu halten. Dies kann nicht durch den traditionellen Top-down-Ansatz bewältigt werden. Auch die enormen räumlichen und zeitlichen Schwankungen, die in einem solchen Energiesystem auftreten, müssen koordiniert werden. Mit lokalen Energiemärkten und der Anwendung eines Bottom-up-Marktansatzes zur Steuerung des Stromhandels im Netz wird eine Lösung für diese gewaltigen Herausforderungen vorgeschlagen. Diese Dissertation stellt auf der Grundlage von Distributed-Ledger-Technologien (DLT) verschiedene umfassende Analysen, Bewertungen, Modelle und Strategien für lokale Energiemärkte vor. Damit werden politischen Entscheidungsträgern und interessierten Unternehmen Puzzleteile für eine erfolgreiche Transformation zu einem klimaneutralen Energiesystems zur Verfügung gestellt.

Die Dissertation beginnt mit einer Umfrageanalyse, in der die quantifizierenden Faktoren für die Teilnahme an DLT-basierten, lokalen Energiemärkten bestimmt werden. Die Umfrage, die 261 Antworten erhielt, zeigt, dass die Hauptfaktoren für die Teilnahme an einem DLT-basierten, lokalen Energiemarkt Versorgungssicherheit, Interesse oder Bereitschaft zur Unterstützung der Integration erneuerbarer Energien, Transparenz und Vertrauen sind. Darüber hinaus wurde eine simulationsbasierte Analyse durchgeführt, um die notwendigen Bedingungen für einen funktionierenden lokalen Energiemarkt zu ermitteln. Die Ergebnisse der Simulationen zeigen, dass der Markt für die Verbraucher und Prosumer innerhalb der Gemeinschaft für eine kleine oder mittlere Gemeinschaft mit einem Verhältnis von Prosumern zu Verbrauchern zwischen 0,3 und 0,5 am vorteilhaftesten reagiert. Darüber hinaus schafft die Verwendung genauer Gebots- oder Angebotsstrategien mehr Vorteile für die lokale Gemeinschaft als die Erhöhung des Anteils erneuerbarer Energien innerhalb der Gemeinschaft.

Um sicherzustellen, dass Energie effizient zwischen den Teilnehmern der lokalen Gemeinschaft ausgetauscht wird, wurde ein fortschrittlicher Clustering-Algorithmus entwickelt, der die Verbraucher und Prosumer des lokalen Energiemarktes auf der Grundlage ihrer Gebots- oder Angebotspräferenzen clustert. Für eine Marktsituation, in der Prosumer und Verbraucher eine bestimmte Energiequalität wünschen oder Energie mit einer bestimmten Gruppe austauschen möchten, wurde eine dezentrale Marktplattform entwickelt. Das Modell ermöglicht Prosumern Flexibilität bei der Wahl der Energie- und Handelsgruppe. Außerdem wurden verschiedene intelligente Gebots- und Angebotsstrategien für Reinforcement Learning entwickelt und evaluiert. Die Ergebnisse zeigen, dass sich der lokale Markt am vorteilhaftesten entwickelt, wenn die intelligenten Agenten mit ihren Geboten oder Angeboten auf ein gemeinsames Ziel ausgerichtet sind.

Schließlich wurden zwei Ansätze umgesetzt, zum einen ein Proof-of-Concept und zum anderen ein hybrides Blockchain-basiertes Gerüst für lokale Energiemärkte. Die Herausforderungen des Proof-of-Concept sowie durch die Blockchain im lokalen Energiemarkt, welche Skalierbarkeit, hohe Betriebskosten und Transparenz umfassen, wurden durch das hybride Blockchain-basierte lokale Energiemarkt-Framework gelöst. Diese Lösung kombiniert die On-Chain-Funktionen der Blockchain und die Side-Chain-Funktionen einer vertrauenswürdigen Ausführungsumgebung, um die Marktplattform wirtschaftlich zu gestalten. Das hybride Blockchain-basierte lokale Energiemarkt-Framework bietet Integrität, hohe Sicherheit und niedrige Betriebskosten, wodurch es sich für den Betrieb eines lokalen Energiemarktes als geeignet erweist.

Preface

This PhD dissertation was prepared at the School of Engineering and Design, Technical University of Munich, in partial fulfillment of the requirements for acquiring the degree of Doctor of Engineering.

The dissertation presents the work carried out by M.Sc. Godwin C. Okwuibe during his PhD degree. It started on 20^{th} January, 2020 and was completed on 20^{th} April 2023. From October 2019 until September 2022, the author was hired by OLI Systems GmbH as a Doktorand. During his time at OLI as a Doktorand, he worked mainly on two research projects namely Blockchainbasiertes dezentrales Energiemarktdesign und Managementstrukturen (BEST) and the SINTEG project C/sells within the context of his PhD. This dissertation is beckon on his contributions to the projects which are published as scientific papers.

The dissertation is presented as a cumulative dissertation with five chapters and appended with nine (six journal and three conference papers) scientific papers. Eight (five journal and three conference papers) of the papers have been peer-reviewed and published. The last journal paper is currently at the second stage of the review process.

Just to remind you that “Nobody owns life, but anyone who can pick up a frying pan owns death”, by William S. Burroughs. This page is for my late father, Late Mr. Ogbani Okwuibe, died 11.02.2000.

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This dissertation would not have been successful without the support of numerous people who have been part of my journey throughout my PhD.

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Contents

List of Publications

Appended publications

This dissertation is based on the following appended publications listed as follows:

1. **G. C. Okwuibe**, T. Brenner, P. Tzscheutschler and T. Hamacher. Survey and analysis of local energy markets based on distributed ledger technologies. IEEE Access, 11: 23771-23791 , 2023. doi: 10.1109/ACCESS.2023.3254508 .

2. **G. C. Okwuibe**, M. Wadhwa, T. Brenner, P. Tzscheutschler and T. Hamacher. Analysis of key performance indicators for local electricity markets' design. IEEE Canadian Journal of Electrical and Computer Engineering, 44(4):411-422, Fall 2021. doi: 10.1109/ICJECE.2021.3091718 .

3. **G. C. Okwuibe**, A. S. Gazafroudi, S. Hambridge, C. Dietrich, A. Trbovich, M. Shafie-khah, P. Tzscheutschler and T. Hamacher. Evaluation of hierarchical, multi-agent, community-based, local energy markets based on key performance indicators. Energies, 15(10): 3575, 2022. URL:https://doi.org/10.3390/en15103575 .

4. **G. C. Okwuibe**, A. S. Gazafroudi, E. Mengelkamp, S. Hambridge, P. Tzscheutschler and T. Hamacher. Advanced clustering approach for peer-to-peer local energy markets considering prosumer's preference vectors. IEEE Access, 11: 33607-33627, 2023. doi: 10.1109/ACCESS.2023.3264233 .

5. **G. C. Okwuibe**, K. Vinogradova, S. Klingner and Z. Han. Pooling platform: A Decentralized Local Energy Market Platform Based on Clustered Prosumer's Preferences. In 2023 International Conference on Future Energy Solutions (FES), Vaasa, Finland, 2023, pp. 1-6, doi: 10.1109/FES57669.2023.10182867.

6. **G. C. Okwuibe**, M. Wadhwa, T. Brenner, P. Tzscheutschler and T. Hamacher. Intelligent bidding strategies in local electricity markets: A simulation-based analysis. In 2020 IEEE Electric Power and Energy Conference (EPEC), pages 1-7. IEEE, 2020. doi: 10.1109/EPEC48502.2020.9320067.

7. **G. C. Okwuibe**, J. Bhalodia, A. S. Gazafroudi, T. Brenner, P. Tzscheutschler and T. Hamacher. Intelligent bidding strategies for prosumers in local energy markets based on reinforcement learning. IEEE Access, 10: 113275-113293, 2022. doi: 10.1109/ACCESS.2022.3217497 .

8. **G. C. Okwuibe**, M. Zade, P. Tzscheutschler, T. Hamacher and U. Wagner. A blockchain-based double-sided auction peer-to-peer electricity market framework. In 2020 IEEE Electric Power and Energy Conference (EPEC), pages 1-8. IEEE 2020. doi: 10.1109/EPEC48502.2020.9320030.

9. **G. C. Okwuibe**, T. Brenner, M. Yahya, P. Tzscheutschler and T. Hamacher. Design and Evaluation of Architectural Framework for a Secured Local Energy Market Model Based on Distributed Ledger Technologies. Submitted to IET Energy Systems Integration, (under review), 2023.

Other relevant publications

Other relevant publications contributed by the author which are not part of the dissertation but serve as preliminary studies to the dissertation are listed as follows:

1. **G. C. Okwuibe**, Z. Li, T. Brenner, and O. Langniss. A blockchain based electric vehicle smart charging system with flexibility. IFAC-PapersOnLine, 53(2):13557-13561, 2020. The 21st World Congress of the international Federation of Automatic Control (IFAC-V 2020), Berlin, 2020. URL:https://www.sciencedirect.com/science /article/pii/S2405896320311241.

2. M. Wadhwa, **G. C. Okwuibe**, T. Brenner, P. Tzscheutschler and T. Hamacher. Key performance indicator based design guidelines for local electricity markets. In 2020 IEEE Electric Power and Energy Conference (EPEC), pages 1-6. IEEE 2020. doi: 10.1109/EPEC48502.2020.9320047.

3. A. S. Gazafroudi, **G. C. Okwuibe**, S. Hambridge, C. Dietrich, A. Trbovich, P. Tzscheutschler, T. Hamacher and M. Shafie-khah. Mathematical model for agent-based local energy exchange engine (D3A). In 2021 International Conference on Smart Energy Systems and Technologies (SEST), pages 1-6. IEEE 2021. doi: 10.1109/SEST50973.2021.9543262.

4. Andreas Zeiselmair, Miguel Guse, Muhammad Yahya, Felix Förster, **Godwin Okwuibe**, and Birgit Haller. Decentralizing smart energy markets - tamper-proof documentation of flexibility market processes. In Blockchain Autumn School, Mittweida, 2020.

Acronyms

CHP	Combined Heat and Power.
DERs	Distributed Energy Resources.
DLT	Distributed Ledger Technologies.
EEG	Renewable Energy Sources Act.
EU	European.
EV	Electric Vehicle.
G2V	Grid to Vehicle.
GDPR	General Data Protection Regulation.
LEM	Local Energy Market.
MDP	Markov Decision Process.
P2P	Peer-to-peer.
PoA	Proof-of-authority.
PoB	Proof-of-burn.
PoC	Proof-of-capacity.
PoS	Proof-of-stake.
PoW	Proof-of-work.
PV	Photovoltaic.
RES	Renewable Energy Sources.
SARSA	State Action Reward State Action.
SGAM	Smart Grid Architecture Model.
TEE	Trusted Execution Environment.
TUM	Technical University of Munich.
V2G	Vehicle to Grid.
V2V	Vehicle to Vehicle.
VAT	Value-Added-Tax.
VRES	Variable Renewable Energy Sources.

1 Introduction

1.1 Motivation & Background

Favourable policies, social acceptance, and dropping of the cost of Photovoltaic (PV) per kWh installed in orders of magnitudes in the last decades have led to increasing share of electricity generated from Renewable Energy Sources (RES) in developed countries such as Germany [1, 2, 3, 4, 5, 6]. These policies intend to align with the renewable expansion within the electric power sector to limit global warming to 1.5° C [3, 2]. Consequently, the total share of renewable generation in Germany has increased from about 8% in 2002 to 44% in 2022 (Fig.1.1) [4]. The German government has also planned to achieve at least 65% (this target was changed to 80% by the Bundestag and Bundesrat in July, 2022) share of its electricity generated from RES by the year 2030 and further ensure that the whole power sector become carbon-neutral before 2050 [3, 2]. To achieve this, the country is extending its total Variable Renewable Energy Sources (VRES) capacity to 330 GW by 2030 (560 GW by 2040) [3, 2]. VRES such as wind and solar are not usually available all the time and in most times, they produce more energy than consumers demand and/or the grid capacity could transport at a time which results in grid congestion. VRES's are usually forecasted but not fully controlled like thermal power plants [1]. Hence, reserves are operated to offset the difference between the actual VRES generation and the forecast which could lead to congestion [7, 8, 9].

This administrative process that is used by network operators to manage network congestion that arise from VRES in order to ensure a stable and reliable grid is known as congestion management [14, 15, 16, 17]. Congestion management is cost intensive and increases with an increase in share of VRES in the electricity network as shown in Fig. 1.1. In Germany, the cost of congestion management in 2017 was 1.5 billion euro which is 6.2% of the total grid cost [10]. The major reason for congestion in Germany is the "north-south/ east-west" gap in Germany. This means that the major VRES sources are primarily in the north and east and the demand is mostly in the west and south and transmission capacity of high power lines is not sufficient for transporting the electricity at excess production time. Another factor is the monetary incentive structure for providing flexibility, there is no cheaper incentives available in the current framework than redispatch. The congestion management cost is passed to the end consumers through grid charges [18]. Table 1.1 displays the sample calculation of increase in grid fees in congestion situation according to [10]. Fig. 1.2 shows the composition of average electricity price in ct./kWh for a German household using up to 3,500 kWh per year from 2006 to 2022 [18]. From Fig. 1.2, the average electricity price has increased steadily from 2006 when the price was 19.46 ct/kW to 32.16 ct./kWh in 2021. This increase is reflected mainly with the renewable surcharge, the grid fee and Value-Added-Tax (VAT).

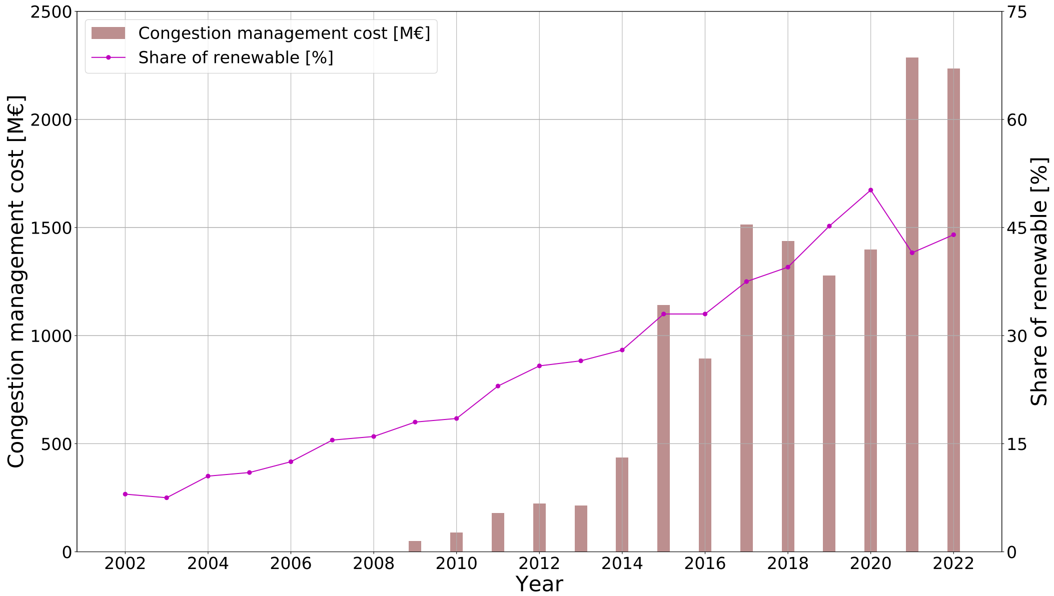

Figure 1.1: Congestion management cost and renewable share of public electricity generation in Germany [10, 11, 12, 1, 4, 13]. Note: The congestion management data available for year 2022 is for the first and second quarter only.

The renewable surcharge was used to offset the difference between the wholesale electricity acquisition/sales price and fixed feed-in tariff price guaranteed by law to renewable power producers in order to encourage feeding of more renewable to the grid [18]. The renewable surcharge increased from 0.88 ct./kWh in 2006 to 6.5 ct./kWh in 2021 while the grid fee increased from 6.93 ct./kWh in 2006 to 8.08 ct./kWh in 2022. This shows that the resultant effect of increase in share of VRES that created additional congestion management cost (Fig.1.1) is the increase in average electricity price of the consumer mainly reflected by increase in the grid fee and renewable surcharge (Fig. 1.2). Hence, with the Germany target of becoming carbon-neutral by 2050, there will be a consequential increase in congestion management cost which will result from managing the complex power grid due to too many VRES in the power grid. The resultant effect will be hike in the price of electricity if the above trend (Fig. 1.2) is maintained. Hence, the need to create a market platform to enable local consumers and small scale local electricity producers/consumers to trade energy within their locality and ensure that electricity is consumed closer to where it is produced and thereby avoiding the hike in congestion management cost.

In order to deliver the European (EU)'s Paris agreement which was set out to avoid the adverse effect of the climate change by limiting global warming to below 2°C and pursuing further efforts to limit it to 1.5°C [19, 20], in 2016, the EU clean energy package was introduced and adopted in 2019 by the EU commission [21]. The EU clean energy package enable consumers to participate actively in the electricity market through energy communities by generating electricity and then consuming, sharing or selling it among

Table 1.1: Sample calculation of increase in grid fees in congestion situations [10].

S/N	Quantity of electricity affected by grid congestion	Additional network fee in bottleneck situations	Increase in network charges in bottleneck situations
1	5 % (26 TWh)	5.55 ct./kWh	133 %
2	10 % (52 TWh)	2.89 ct./kWh	66 %
3	15 % (78TWh)	1.92 ct./kWh	44 %

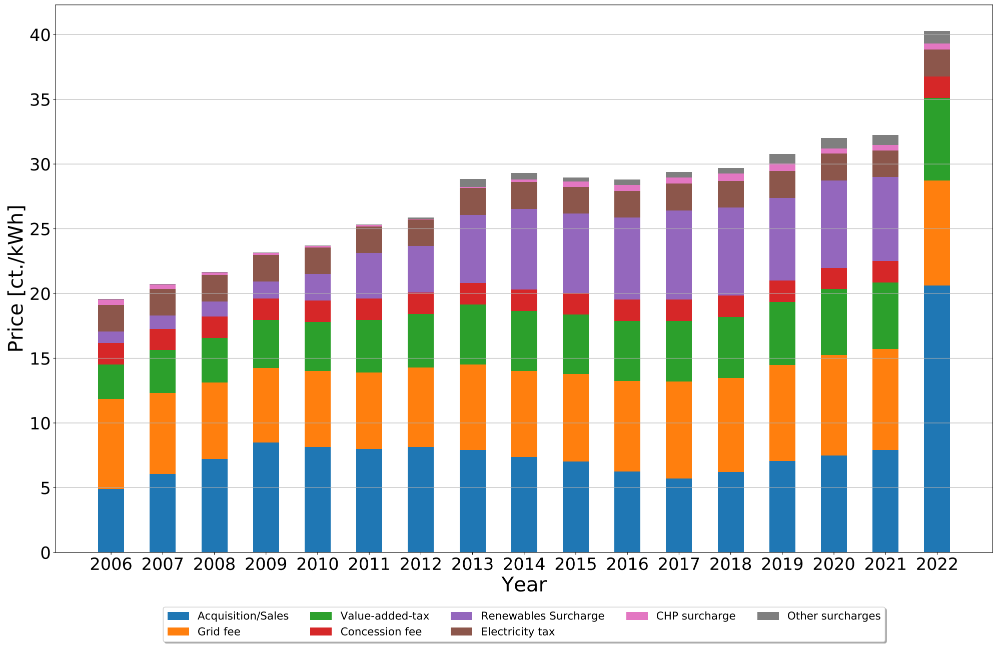

Figure 1.2: Composition of average power price in ct./kWh for a German household using 3,500 kWh per year, 2006 - 2022 [18].

themselves [22, 23, 24]. Thereby, enabling end consumers to be actively involved in the electricity market and have decision over their electricity production/consumption [25, 26]. Local Energy Market (LEM) provides an opportunity to enable local consumers and small scale electricity producer/consumers known as prosumers to be actively involved in local electricity trading and exchange energy with each other thereby making benefits from their electric devices [27, 28, 29, 30]. Thus, ensuring that energy is consumed closer to where it is produced and reducing congestion in the local grid thereby creating local energy balances between producers, prosumers and consumers at the distribution level [27, 28, 31, 32]. The security of supply of an LEM is ensured through connections of the local distribution grid to a superimposed electricity grid which is the upstream grid [27, 33, 34].

In 2022, because of the Russian-Ukraine war, the gas price increased in Germany resulting in doubling of the sales/acquisition cost of household electricity from 7.93

ct./kWh in 2021 to 20.64 ct./kWh in 2022 which results in increasing the electricity price from 32.16 ct./kWh to 40.07 ct./kWh, respectively [18, 35] (Fig. 1.2). The renewable surcharge was reduced to 0 ct./kWh by the second half of 2022 to cushion the effect of this hike in the electricity acquisition/sales price [18]. This shows the importance of investing in renewable energy resources and the need for LEM for proper coordination of energy flows between producers, prosumers and consumers in the local distribution grid. Furthermore, the growing importance of LEMs is due to the fact that the energy transition/carbon neutrality also requires a transition of the heating sector and mobility which will be incorporated into the electricity domain and were not previously (e.g oil/gas heaters being replaced by heat pumps and internal combustion engine cars being replaced by Electric Vehicle (EV)s) - and a lot of this occurs at the distribution grid level. The unit sale of electric vehicle in Germany has increased from 24.6 thousand in 2016 to 715.8 thousand in 2022 and is expected to reach 1629.7 thousand in 2027 [36, 37]. In the same way, the sale of heat pumps in Germany has increased from 57 thousand in 2015 to 154 thousand in 2021 [38]. Consequently, LEM is needed to properly coordinate the energy flow for these new devices and ensure that they do not result in higher grid congestion.

1.1.1 Definition and evolution of local energy markets

LEM is a community market platform for trading locally generated (renewable) energy among producers, prosumers, and consumers in the same or adjacent distribution network and within a geographic and social neighborhood [27, 39, 30]. According to Khorasany et al. [40] LEM is a micro-market concept which is based in a residential area that enables prosumers, consumers and producers within a community or neighbourhood to exchange energy among themselves. Siano et al. [41] defined LEM as a "*sub-market, where participants can be aggregated for flexibility purposes such as constraints management, portfolio optimization and system balancing in order to balance demand and supply*". The key factors identified in all these definitions are market platform, participants/prosumers/end consumers, and neighbourhood/community/locality. Thus most LEM definitions revolves around these three factors. The products that can be traded in an LEM include electricity (kWh), flexibility or heat [42, 43, 44, 45, 46]. Two products can be traded simultaneously such as flexibility and electricity [47, 48], or heat and electricity [49, 50].

The early mention of LEMs in literature and research works is dated to more than two decades ago [51, 52, 34, 53]. However, LEMs started gaining more attention of researchers from the 2000's [53, 54, 55, 56, 57, 34, 58, 59]. Most of the early research works in LEM are focused on the concept development and design of LEM [54, 55, 56, 59]. Research in LEM has extended this stage to discussion on market designs, bidding strategies, market mechanisms, business model development, risk analysis, security and privacy, and policy recommendations [60, 25, 29, 26, 61, 62, 63]. Notwithstanding the numerous attention already given to LEM by researchers, there is still no regulation for applying LEM in most countries. However, there are few LEM projects already implemented and ongoing in different countries such as Allgäu microgrid [64], LAMP [65], Brooklyn microgrid [66], etc [67].

1.1.2 Local energy markets components

Mengelkamp et al. [66] in their work derived seven market components for developing a microgrid energy market which includes microgrid setup, upstream grid connection, information system (e.g. market platform), market mechanism (market model), pricing mechanism (clearing mechanism), energy management trading system (e.g. bidding strategy), and regulation. Based on these previously developed components of microgrid energy markets and requirements of an LEM developed by [65] using the Smart Grid Architecture Model (SGAM) [68], this dissertation will focus on the basic components of an LEM which includes the market platform, market model, clearing mechanism and bidding/offering strategy. The market platform is the information system infrastructure that is responsible for running the market model. The market platform can be centralized, decentralized or distributed.

A centralized platform is a platform that is based on a trusted third party-agent which is responsible for running the market model in their platform [69]. A decentralized platform is a platform that is made of different sub-systems which interacts and communicates with each others. Moreover, a distributed platform is a platform that uses distributed ledger and is spread across multiple entities which are responsible for operating the platform and used to promote transparency [69]. Fig. 1.3 displays an example to differentiate centralized, decentralized and distributed market platform. In summary, an attack on a node of a market platform will result in total failure of the whole system for a centralized platform. However, for a decentralized platform, it will result in failure of some part of the system. But for a distributed platform, the system will not be affected by an attack on a single node.

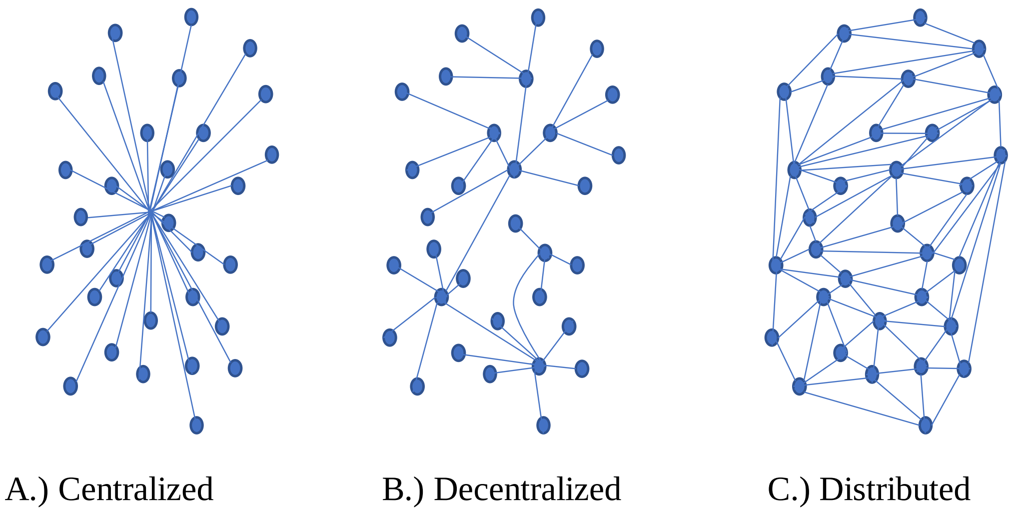

Figure 1.3: Centralized, decentralized and distributed market platforms [70, 71].

The market model is used to provide efficient bidding/offering format, payment/settlement rule, and allocation of traded energy by matching the bids and offers of the prosumers [50]. The market model is implemented on the market platform [66]. Hence, based on their implementation, market model can be classified as centralized, decentralized and distributed market models. Table 1.2 compares centralized, decentralized and distributed market models. The clearing mechanism is used to allocate the traded energy and the price for each allocated traded energy, which will be paid by the buyer or the price the seller will receive [66]. The bidding/offering strategy is an algorithm used by consumer/prosumer agents to determine the price (€ ct./kWh) the consumer/prosumer is willing to pay/receive for energy consumed/produced from/to the local community. Fig. 1.4 displays the schematic of an LEM.

Table 1.2: Comparison of centralized, decentralized and distributed market models [72, 73, 69, 74, 70].

S/N	Properties	Centralized	Decentralized	Distributed
1	Flexibility/scalability	Low	High	Very high
2	Transparency	Low	High	Very high
3	Reliability	Low	High	Very high
4	Customer centricity	Low	High	High
5	Maintenance cost	Low	High	Very high
6	Computational cost	High	Low	Relatively high
7	Resilience to attacks	Low	High	Very high
8	Transactions per second	Medium	High	Low
9	Security	Low	High	Very high
10	Privacy	Medium	Low	Very low

1.1.3 Evolution and definition of distributed ledger technologies

The concept of Distributed Ledger Technologies (DLT) is dated back to the early stage of the Roman Empire and Chinese Qing Dynasty where complex and sophisticated record keeping techniques, supplemented with heavy communication systems are used by banks to ensure accurate record keeping in the form of distributed ledger [75, 76, 77]. In 1991, the first document was published in this field by Stuart Haber and W. Scott Stornetta on “How to time-stamp a digital document” [78]. This became important as there was no clear history of origin in digital documents; one copy is just as good as the “original” and in principle indistinguishable. In 1997, Tim May proposed a digital money that uses ‘remailers’ system to forward messages while preserving anonymity between partners node [79]. Later in 2002, David Mazierers and Dennis Shaha in their work titled “Building secure file systems out of Byzantine storage” proposed a method to detect tampering attacks and stale data to build a trusted file system on an untrusted server [80].

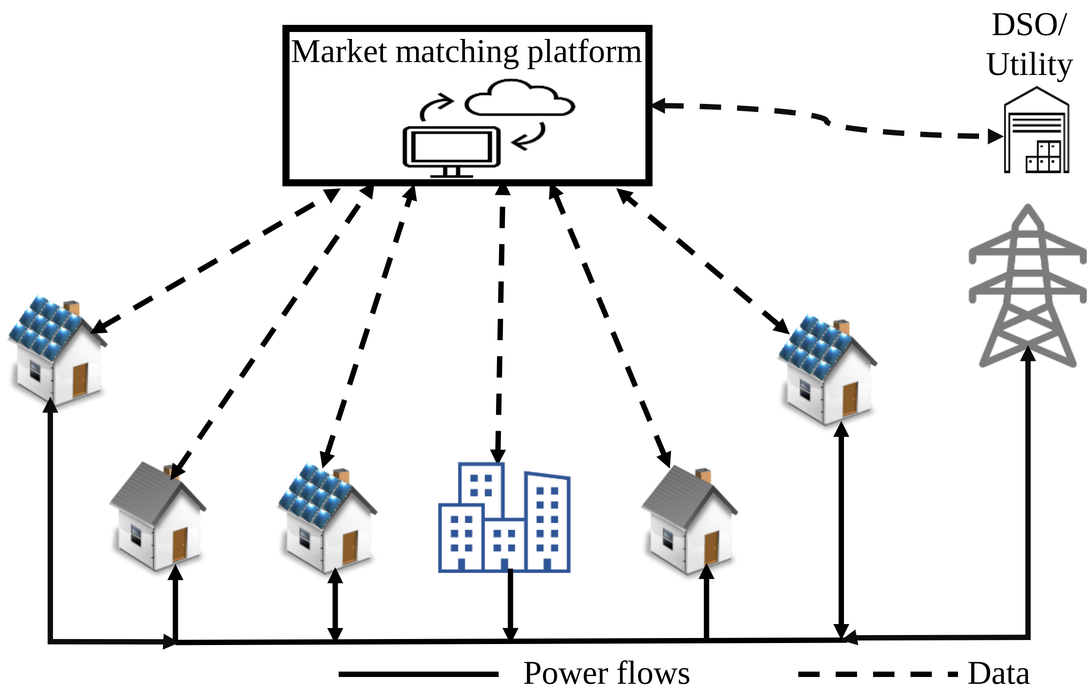

Figure 1.4: Schematic of local energy market components.

The major breakthrough was in 2005 when Nick Szabo proposed a new blockchain-based currency called BitGold which attempts to decentralize currency and shift control from a central entity to multiple entities [81]. This new currency was "*based on computing a string of bits from a string of challenge bits, using functions called variously "client puzzle function," "proof of work function," or "secure benchmark function"*" [81]. However, this proposed currency was unable to solve the double-spending problem of electronic transactions, which can result from digital currency users duplicating transactions and therefore spending the same digital currency more than once.

The most outstanding breakthrough was in 2008, when Satoshi Nakomoto published the Bitcoin whitepaper [82]. This work brought the concept Peer-to-peer (P2P) transactions using trustless network and Proof-of-work (PoW) consensus mechanism by the participating nodes to approve transactions before they are entered into the network. In 2014, Buterin introduced the concept of smart contract into blockchain by proposing Ethereum network [83]. Thus Ethereum has a turing completeness which Bitcoin did not, making it much more versatile than Bitcoin, opening up the avenue for other applications to run on it than value transfer. This eventually attracted researchers and many industries to the concept of blockchain and how to use smart contract features for their applications. Many other blockchain networks have been founded since then and more are still coming [84, 85, 86, 87, 88, 89, 90]. Also, other DLT concepts such as Tangle and hashgraph have been discussed and implemented since then [89, 91]. In the same way, other consensus mechanism such as Proof-of-authority (PoA), Proof-of-stake (PoS), Proof-of-burn (PoB), and Proof-of-capacity (PoC) are now being used [89, 90].

According to [89], DLT is a "spreadsheet that is used for recording transactions and transcribing accounting information such that the transactions are accessible and stored at each node of the network and has an intrinsic feature for enforcing consensus among its users before a transaction is written in the network". Thus, the basic concept concept of DLT is storage of data or transaction in a network where all members have access to the network and ensuring that all members in the network converge to the same state before a new data is entered in the network. DLT is a general protocol used for recording data in a distributed and secure manner while facilitating the maintenance of digital ledgers in the networks of untrusted parties [92, 93, 94]

1.2 Research objectives and research questions

The need to encourage more renewable energy sources integration into the electricity mix cannot be over emphasized as this will go a long way in reducing the global warming. However, due to the challenges accompanying this renewable generated electricity as a result of its temporal fluctuations and spatial inhomogeneity, hence, there lies the need to create a local market to ensure that electricity is consumed closer to where it is generated. Furthermore, the demand side is also becoming more volatile and flexible, and new assets are being added (primarily EVs and heat pumps) leading to sectoral coupling at the distribution grid level. Thereby, creating local balances of electricity at the distribution grid level.

Also, LEM provides opportunity for local traders such as consumers, prosumers and small scale producers to be involved in electricity trading, thereby making benefits from their electricity devices. This further helps to retain the local economy. The electricity from PV systems accounted for 9.9% of total generation in Germany and PV systems under the size of 10 kWp account for 64% of the total PV installations in Germany as of 2021 [95]. Fig. 1.5 displays the solar PV that will be out of the feed-in tariff from 2021 [96]. Small PV is important because it is installed close to the consuming assets, often even on the same (the lowest) grid level. This is why their participation in an LEM is key. Furthermore for post-EEG assets (and some other), LEMs can be very attractive from an economic point of view, especially in the current situation in Germany where feed-in tariff is only for a period of 20 years. Thus, LEM has the capacity of providing a market for trading electricity from small scale producers during the post-Renewable Energy Sources Act (EEG) time and ensuring that the percentage share of renewable energy sources in the electricity mix is not reduced.

In summary, the objective of this dissertation is to analyze the benefits of LEM and identify the most beneficial market model for this type of market while using the added values of blockchain technologies. By doing this, the following research questions will be answered.

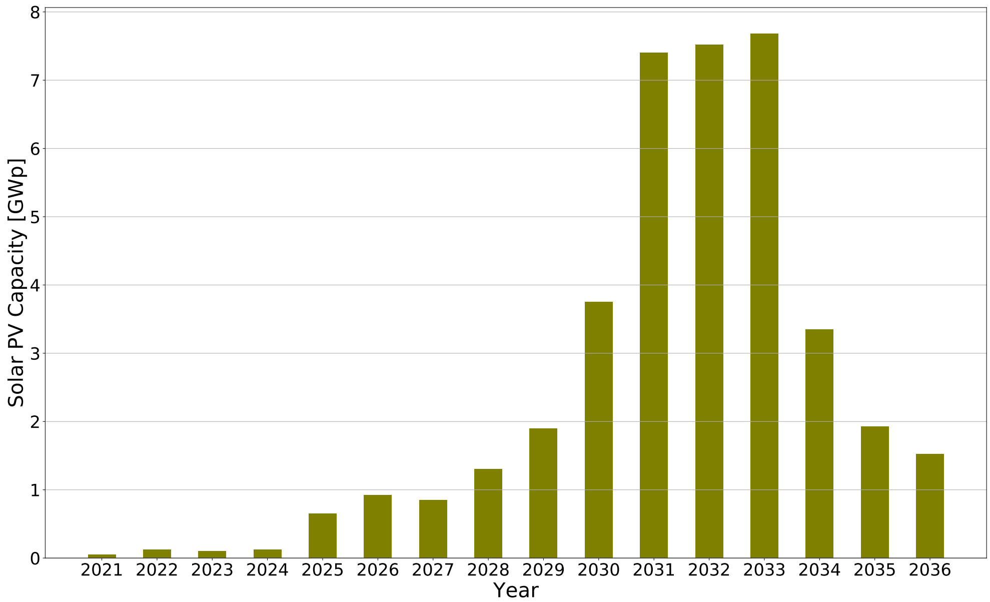

Figure 1.5: Solar PV capacity dropping out of German feed-in tariff scheme from 2021 onwards [96].

1. What are the quantifying factors for participation on local electricity markets based on distributed ledger technologies and the necessary conditions for the most beneficial LEM?
2. Which market models and clearing mechanisms are most suitable for local electricity markets?
3. Which trading strategies are most suitable for effective performance of local electricity markets?
4. Is it economically reasonable to use blockchain for local energy trading? If yes, what conditions must be fulfilled?

Fig. 1.6 displays the research questions and how they are connected in the stages of research. The analysis was performed first to identify the features that will be used for the model development. Then, the models were developed using the results from the analysis. Finally, the models were implemented in the platform and evaluated.

1.3 Dissertation and publication structure

This dissertation is structured as follows.

Chapter 2 presents an analysis of different LEMs. In section 2.1, a survey and community based analysis are presented to determine the quantifying factors for participation in a blockchain based LEM. Additional, a community based simulations analysis was

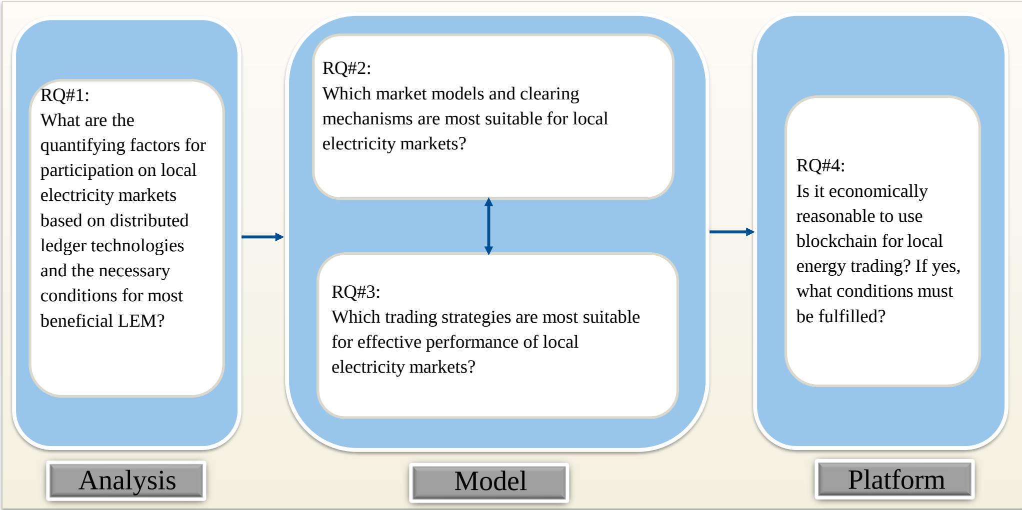

Figure 1.6: Research questions based on the developed models.

performed to determine the impact of different community sizes on the technical and economic benefits of consumers and prosumers in an LEM. In section 2.2, a simulation based analysis was conducted to determine the key performance indicators for participation in an LEM and the impact of bidding strategies in the performance of an LEM.

Chapter 3 presents the different developed market models and bidding strategies. In section 3.1, the market models are presented. Section 3.1.1 evaluates and discusses a multi layer LEM market model. Section 3.1.2 presents the advanced clustering LEM model based on prosumers preference vectors. The decentralized LEM model based on prosumer preferences is presented in section 3.1.3. In section 3.2, the bidding strategies are discussed and analyzed. Section 3.2.1 presents and discusses the developed Q-learning bidding strategy for LEM while section 3.2.2 presents a new Q-learning and State Action Reward State Action (SARSA) bidding strategies and a comparison between both.

Chapter 4 presents different distributed LEM models that were developed that run on a blockchain platform. In section 4.1, a fully distributed LEM model implemented on a blockchain platform is discussed. Section 4.2 presents a hybrid market platform that combines on-chain blockchain network and side-chain Trusted Execution Environment (TEE) features for implementing a transparent, secured and verifiable LEM model.

Chapter 5 answers the research questions already presented in section 1.2, concludes the dissertation with policy recommendations for implementing LEMs in Germany and presents recommendations for future research in the field.

Fig. 1.7 displays a schematic of the dissertation. The work presented in this dissertation is distributed across nine publications in total. Each publication is dedicated to answering a research question or a significant part of it as presented earlier in Section 1.2. Therefore, there are research questions answered in more than one publications. Fig.

1.8 displays the publications included in the dissertation. Fig. 1.8 uses the structure of Fig. 1.6 to show the research question answered by each publication.

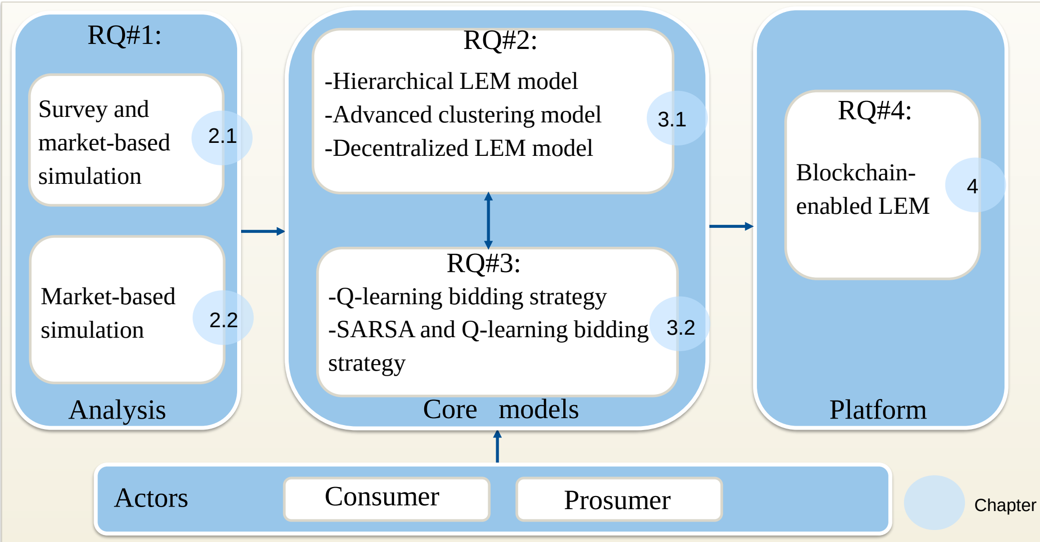

Figure 1.7: Schematic of dissertation. Light blue circles means the corresponding sections. Each section focuses on answering the research question on top.

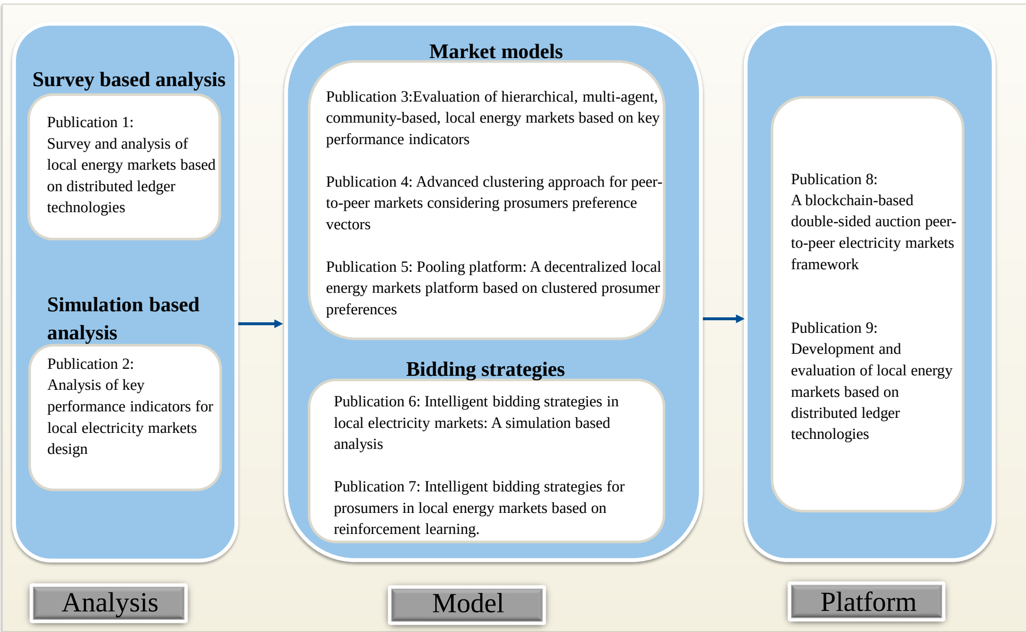

Figure 1.8: Publications included in the dissertation.

2 Analysis of local energy markets

Scientific context

The concept of LEM focuses on creating a market that brings together local consumers, prosumers and small scale producers together to exchange energy with each other on the same platform. Hence, the performance of such a market depends on the social behaviours of the consumers, prosumers and producers, the quantity of electricity produced/consumed within the community, the number of participants, the participants' bidding strategy and ratio of producers to consumers in the community. These factors and their effects on LEM performance are analyzed within this work.

The features of DLT, such as transparency, high security, consensus mechanism, immutability, distributed storage, and anonymity are widely discussed in literature [97, 98, 99, 100, 101, 89, 102, 103, 90] and many LEM models are already proposed in literature that utilize these features for LEM application [104, 105, 94, 66, 65, 69, 106, 46, 107, 108, 109, 41, 110, 73]. However, there is still no literature that considers the social behaviours of the local energy traders (consumers, prosumers and small-scale producers) to know which features of DLT is most important to them and to what level the stakeholders desire each features. In the same way, there is a wide variety of articles proposing different models for LEM application [44, 111, 60, 29, 112, 113, 114, 115, 48]. But only a few of these articles consider the social behaviours of the local energy traders in their model design [116, 44].

Efficient development of an LEM based on DLT requires an understanding of the features of DLT that are most important for a local energy trader and the factors that will make a consumer, prosumers and producers to participate in such kind of market. In addition, it is also important to know the community size and prosumers-to-consumers ratio that will result in optimum performance of such LEM since only but few lietratures have conducted a similar analysis [117]. The analysis in this chapter is developed in two scientific papers. The first paper [118] is a survey based analysis with community simulation and the second paper [119] is based on key performance indicator analysis.

2.1 Survey and community based analysis

Contribution

The paper of this section presents a survey and analysis of local energy markets based on distributed ledger technologies [118]. The analysis was conducted in two stages. The first stage is a survey of the quantifying factors for participation in an LEM based on DLT. For this, an online survey was developed and the link shared to consumers and prosumers through LinkedIn, Slack, E-Mails and Xing. The survey was online for over three months and received a total of 261 responses. The responses were filtered down to 232 due to incomplete responses. The responses were analyzed and visualized. The survey results illustrate that the major factor that can make local consumers/prosumers to participate in a blockchain based LEM is their willingness to support renewable energy integration, transparency and trust offered by a blockchain network.

In the second stage, a community based analysis was conducted to determine the necessary conditions for the most beneficial LEM. For this, a community based simulation set-up as shown in Fig. 2.1 was developed using Grid Singularity framework [120]. The simulation was verified using a combination of load and production profiles from German households [121], standard load profiles [122, 123], Renewables Ninja [124, 125] and LoadProfileGenerator [126, 127]. The market is a 15-minutes time step market where prosumers and consumers bid/offer energy every 15-minutes and the market is cleared afterwards. Energy not traded within the community is traded with the external grid which is the upstream grid. The simulation is varied by changing the community size from a total of 10 to 120 participants in 238 simulation scenarios. The different simulation scenarios are further obtained by varying the community production to consumption ratio and the number of consumers and prosumers in the community. By varying the number of prosumers and consumers, different community sizes such as small, medium and large communities are obtained. The results of the simulation showed that small and medium communities with prosumers-to-consumers ratio between 0.3 to 0.5 create more economic and technical benefits such as self sufficiency and self consumption for local consumers/prosumers compared to large communities.

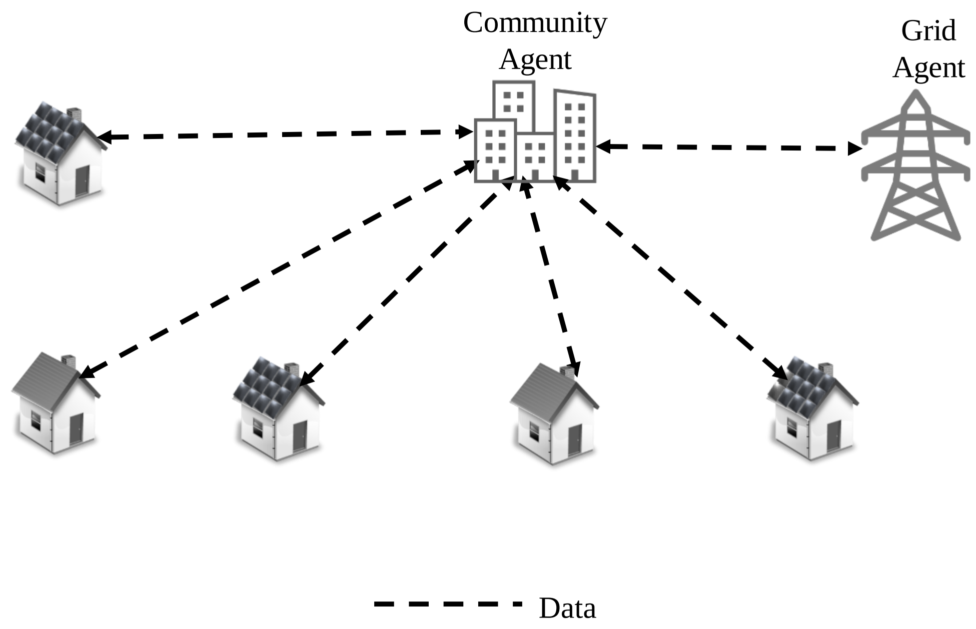

Figure 2.1: Schematic of community based LEM simulation set-up, after [118].

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Thomas Brenner	8%	Methodology, Validation, Writing - review and editing.
Peter Tzscheutschler	5%	Methodology, Validation, Writing - review and editing.
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SURVEY

Survey and Analysis of Local Energy Markets Based on Distributed Ledger Technologies

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ABSTRACT Local energy markets (LEMs) provide opportunity to handle the challenges arising from the lower grid level while using the traditional top-down approach to manage distributed generated renewable energy resources. Blockchain-based local energy markets (LEMs) have been introduced in recent years as a way to enable local consumers/prosumers to trade their energy locally in a distributed and highly secured manner in an LEM. However, there are still some challenges regarding the main factors that can drive local consumers/prosumers to participate in a blockchain-based LEM, optimal community size, and prosumer to consumer ratio for an efficient LEM. Also, there is still no information on how the quantifying factors for participation on a blockchain-based LEM can affect the performance of an LEM. This paper presents a survey and simulation based analysis of quantifying factors for participation in a blockchain-based LEM. The survey was distributed among local consumers/prosumers and a total of 261 responses were received from the responders. The results from the responders were analyzed using a Python code based statistical analysis model. The simulation based analysis was conducted using a community based LEM model and evaluated using data received from a combination of German household profiles and standard load profiles. The survey results showed that the major drive for local consumers/prosumers to participate on blockchain-based LEM is their willingness to support renewable energy integration, transparency, and trust offered by a blockchain network. On the other hand, the simulation based analysis showed that small and medium communities with prosumers to consumer ratios between 0.3 to 0.5 create more economic and technical benefits for local consumers/prosumers compared to large communities. The community based simulation results were modelled together with the survey results to determine how the individual quantifying factors for participating in a blockchain-based LEM can affect the performance of an LEM.

INDEX TERMS Blockchain, decentralized energy system, survey analysis, local energy market, multi agent system.

I. INTRODUCTION

A. MOTIVATION AND BACKGROUND

Local energy markets (LEMs) were introduced in the last few decades as a result of the challenges arising from increasing distributed renewable energy resources and to enable small-scale producers, prosumers, and consumers to become involved in the electricity market [1]. LEM has also achieved quite a loud interest in countries such as Germany where there is high support for renewable energy integration because of the ability of LEM to support local renewable energy integration and create more savings for distributed energy resources owners [2]. In recent times, distributed ledger technologies (DLTs) are reshaping the conventional ideas of business transactions and have caught the interest of researchers on how the different DLT features can be applied to the energy sector and LEMs in particular [3]. DLT is an information systems that use protocols to record, validate, update, and

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access record of transactions across a decentralized network of computers nodes and has intrinsic mechanisms of enforcing consensus among the nodes [4], [5]. The features of DLT that made it attractive in different industrial sectors including energy sector are decentralized database structure, consensus mechanism, immutability, transparency, anonymity, and high security [6], [7]. Recent research works has shown that DLT has the potentials to enable prosumers and consumers within a community to trade energy in a secure manner [8], [9]. Because of its data structure, consensus mechanism, and high data security, blockchain has achieved high popularity, applied in many use case, and usually discussed in most literature and research works compared to other DLT concepts such as Tangle and Hashgraph [4].

B. LITERATURE REVIEW

Among all the features of DLT, decentralized database structure is majorly utilized in the development of LEM platform [9], [10], [11]. Hence, most research works in the field of blockchain-based LEM are focused on decentralizing the data structure of the LEM platform. Reference [10] developed a full blockchain-based decentralized platform for peer-to-peer(P2P) energy trading in a day-ahead market. The concept of Merkle Patricia Tries is used in its real or modified form to develop an immutable blockchain platform for LEM [12]. Reference [13] proposed an immutable blockchain-based framework for negotiating an auction based P2P energy trading for a local community. The concept of consensus mechanism is widely discussed in literature and imminent in most DLT platforms, and blockchain-based LEM platforms [6]. The authors of [14] proposed a blockchain-based double sided auction LEM that enforces consensus among prosumers and consumers every time slot before the market is matched. Transparency is a blockchain feature that is usually discussed and implemented in LEM research works directly ensuring that all transaction data are visible to the participants. However, in real LEM projects, because of the regulations and data protection law, transparency is usually implemented in form of hashing [15]. Reference [16] proposed a blockchain-based solution to increase the transparency and integrity of P2P market platform. Immutability as a feature of blockchain is its ability to retain information without tampering with data in its platform. This feature always raise questions on the sustainability of blockchain for its application because of the large amount of gas required for complex calculations/transactions. The authors of [17] proposed a Cosmos sidechain network for trading energy in an LEM and showed that the platform is sustainable by applying it in a real case scenario of a small community in Switzerland. Notwithstanding the large knowledge already gained for blockchain application in LEM, researchers are still exploring the different blockchain features and the best way to apply them in LEM trading, hence, blockchain application for LEM is now growing beyound the maturity stage [18], [19].

On the other hand, the technical and economic analysis of LEM plays an important role on the deployment of LEM based on DLT. This is because, the knowledge of the economic and technical benefits that will arise from the market is required for a broad adoption in productive environments. For this reason, there are still few literature discussing and analyzing the technical and economic benefits of LEM. The authors of [20] analyzed the performance indicators for participation in LEMs and showed that bidding strategies have more effect on the performance of an LEM compared to adding more distributed energy resources into the local community. Reference [21] analyzed and discussed a decentralized P2P market and a centralized order book LEM with zero-intelligence and intelligent bidding strategies and showed that P2P markets with intelligent agents seem most advantageous compared to others. Reference [22] analyzed the effect of microgrid size and prosumer-consumer ratios to local self-consumption and self-sufficiency of a community. A multi and single layer LEM models were developed by [23] and evaluated using different LEM economic and technical performance indicators such as self-sufficiency, self consumption ratio and share of market savings to show the applicability of LEM. Reference [24] used data from system logs, surveys, and interviews to analyze interaction, acceptance, and participation of prosumers in a P2P LEM. The analysis of their results showed that P2P LEM has the capability to increase the salience of renewable energies and thus promote load-shifting activities. The outcome of the results from analysis, user behaviour and designs of LEM has stirred up different business models and pilot projects in the field of blockchain-based LEM [25], [26].

Notwithstanding different research works already published in the field of blockchain-based LEM and different pilot LEM projects, in overall, only a small fraction of all LEM projects have been developed with blockchain technologies. The few projects already developed in the field of blockchain-based LEM are the Brooklyn microgrid [27], the Landau project [28] and the Allgäu microgrid [29].

C. CONTRIBUTIONS AND ORGANISATION

The literature contains several studies proposing different structures and models for blockchain-based LEMs, however, there is still a gap in literature determining or analyzing the major factors that can make a prosumer or consumer participate in an LEM trading, the optimal community size, production-to-consumption ratio, and prosumer-to-consumer ratio for an efficient LEM. Furthermore, there still exist no literature discussing how the quantifying factors for participating in a blockchain-based LEM can affect the performance of an LEM. Hence, this work is aiming to determine the quantifying factors for participation on local electricity markets based on distributed ledger technologies and the necessary conditions for most beneficial LEM. We use two step methods of survey and community based simulation analysis. In the first step, a survey was distributed to prosumers/consumers and energy experts requesting answers from them on their willingness and their main driving factors to participate in an LEM and in an LEM based on blockchain technology. The survey received 261 responses and the results were evaluated using statistical analysis. In the second method, a single layer community based LEM model was developed and simulated for varying community sizes and prosumer to consumer ratios. The simulation model was evaluated using key performance indicators such as self-sufficiency, self-consumption ratio, share of market savings, share of consumer savings and share of prosumer savings. The prosumers and consumers also known as local electricity traders (LETs) are classified as household consumers, commercial consumers, household prosumers, and commercial prosumers. The main contributions of the paper can be summarized as follows:

- We develop and distribute a survey to investigate on quantifying factors to participate in LEM and blockchain-based LEM.
- The results from the survey were analyzed to determine the driving factors to participate on LEM and blockchain-based LEM.
- We conduct a simulation for a single layer LEM model with varying community sizes and prosumer to consumer ratios.
- We analyse the benefits of electricity trading in a single layer LEMs model with the use of key performance indicators such as self-sufficiency, self-consumption, and share of market savings.
- We modelled the quantifying factors for participanting in a blockchain-based LEM determined from survey together with the simulation results to determine how the different quantifying factors can affect the individual LEM performance indicators for a community based LEM.

The remaining sections of this work are structured as follows. The developed survey and analysis methods are described in Section II. The survey and simulation results are analyzed in Sections III-A and III-B, respectively. Finally, the paper is concluded in Section V.

II. ANALYSIS METHOD

In order to analyze the acceptability, willingness, interests, motivation, technical, and economic indicators that may enable prosumers to participate in a blockchain-based LEM, the analysis method is classified into survey and simulation based analysis.

A. SURVEY BASED ANALYSIS

For this method, a survey was conducted and shared among German households to illustrate their willingness, interest and social behaviour towards a blockchain-based LEM. Our approach is based on a similar work in this field by [2], however, we create an extensive study to analyze the different factors individually and their relation to LEM application with blockchain. Appendix A-A shows the survey questions.

TABLE 1. Age range of survey responders.

S/N	Age range (Years)	Number of responses
1	Under 30	34
2	30 - 50	82
3	Above 50	71

TABLE 2. Net income salary range of survey responders.

S/N	Salary range (Euro per annum)	Number of responses
1	Under 35,000	46
2	35,000 - 50,000	50
3	Above 50,000	88

The questions were developed and displayed online using SurveyMonkey and the web link to the questions distributed to responders. Fig. 13 displays a screen shoot of part of the survey questions on SurveyMonket website. The link to the questions was distributed using different online platforms such as LinkedIn, Slack channels, Xing and Emails. With Emails, it was sent directly to 400 customers of e-regio, a German electricity retail company using their contact Email. The survey takes approximately 12 minutes to complete it. The survey was opened online on SurveyMonkey website from 15th August until 20th December 2021 and it received a total of 261 responses. However, the responses were filtered down to 232 due to incomplete answers. Table 1 and 2 display the age and net income range of the responders, respectively. From the survey response response, 40.5% of the responders live in rented apartments/buildings, 57.8% live in their own house/apartments while 1.6% did not specify where they live.

B. SIMULATION BASED ANALYSIS

The simulation based analysis is based on the works of [20] and [23]. A single layer local electricity market as developed by [23] is simulated for varying community sizes, number of prosumers to total participants (nPP) ratio, and annual production-to-consumption ratio (PtC). Fig. 1 [23] displays the single layer local electricity market model where prosumers and consumers trade electricity within the local energy markets, electricity not traded within the LEM is traded with the upstream grid by the community agent.

Each household is represent by an agent which is responsible for making the bidding/offering of the household electricity every time slot, on behalf of the consumer or prosumer. At every market slot ($t-1$), the consumer agent (i) posts a bid containing the quantity of electricity ($q^b_{i,t}$) in kWh the consumer wants to buy and the maximum price ($p^b_{i,t}$) the consumer is willing to pay per kWh of electricity for the next time slot (t), as shown in Eq. (1), to the community market platform.

$$b_{i,t} = \{q^b_{i,t}, p^b_{i,t}\}, \forall t. \tag{1}$$

In the same way, at $t-1$, the prosumer agent (j) posts an offer containing the quantity of electricity ($q^s_{j,t}$) in kWh the prosumer wants to sell and the minimum price ($p^s_{j,t}$) the prosumer is willing to receive per kWh of electricity for the

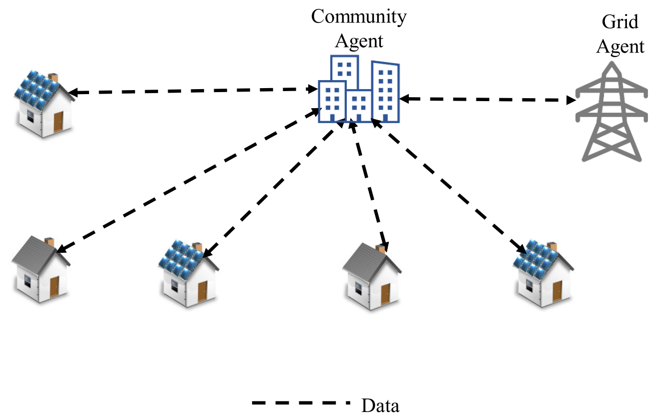


FIGURE 1. Single layer local energy market framework.

next time slot (t), as shown in Eq. (2), to the same community market platform.

$$s_{j,t} = \{q^s_{j,t}, p^s_{j,t}\}, \forall t. \tag{2}$$

Eqs. (3) and (4) represents all the bids and offers posted to the market platform at time $t-1$ for energy exchange that will happen at time t. $\mathcal{K}$ and $\mathcal{N}$ are the total number of bids and offers, respectively.

$$B_t = \{b_{1,t}, \ldots, b_{\mathcal{K},t}\}, \quad \forall t. \tag{3}$$
$$S_t = \{s_{1,t}, \ldots, s_{\mathcal{N},t}\}, \quad \forall t. \tag{4}$$

The market is matched at the end of the time slot $(t-1)$. The clearing mechanism is a two sided pay-as-bid market clearing mechanism with discriminative pricing. The community local grid fee (g) which is the fee the buyer pays for buying electricity from the LEM is first subtracted from the maximum price ($p^b_{i,t}$) the buyer is willing to pay to determine the bid price ($p^{b*}_{i,t}$) as shown in Eq. (5). The minimum price ($p^s_{j,t}$) the seller is willing to receive is the offer price.

$$p^{b*}_{i,t} = p^b_{i,t} - g, \quad \forall i, t. \tag{5}$$

The bids and offers are arranged in descending and ascending orders of bid and offer prices, respectively. Then, the bids and offers are matched one after the other until the intersection of the bidding and offering prices which after, the offer price is higher than the bidding price as shown in Fig. 2. The matched price ($p^m_{i,j,t}$) is the average of the bidding and offering prices. This is the price the seller j will receive for each kWh of its energy matched in the LEM with buyer i. This can also be referred to as the sold price. The matched price is represented in Eq. (6),

$$p^m_{i,j,t} = \frac{p^{b*}_{i,t} + p^s_{j,t}}{2}, \quad \forall i, j, t. \tag{6}$$

The bought price ($p^b_{i,j,t}$) is the price the buyer i pays per kWh of electricity bought from the LEM from seller j. This is the sum of the matched price and the grid fees (g) as presented in (7),

$$p^b_{i,j,t} = p^m_{i,j,t} + g, \quad \forall i, j, t. \tag{7}$$

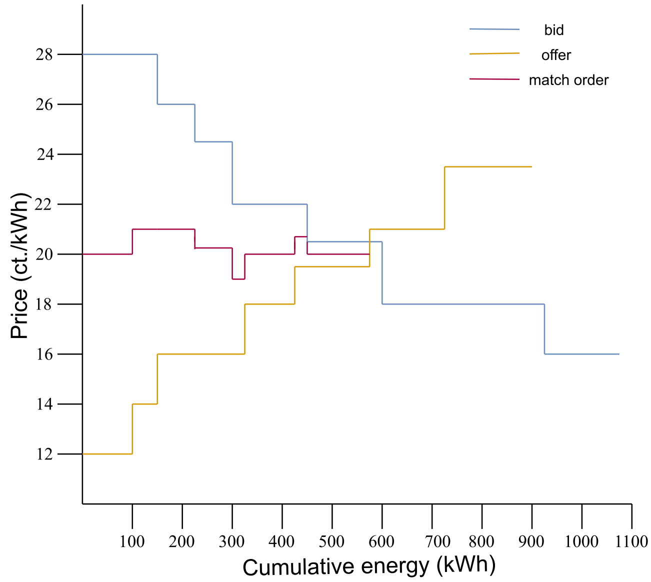


FIGURE 2. Two sided clearing mechanism with discriminative pricing.

At the end of the market clearing, electricity not traded within the LEM is bought/sold from/to the upstream grid using the grid price/feed-in tariff price. The trading strategy is a random trading strategy where the participants randomly select a bid/offer price within the range of the feed-in tariff price of 11.0 ct/kWh to the grid electricity price of 32.0 ct/kWh. The grid electricity price is capped at 32.0 ct/kWh because of the average cost of household electricity in Germany for the year 2021 [30]. The buyers' bid price include the metering and local grid fee of 0.33 ct/kWh and 4.0 ct/kWh, respectively. This sets the lowest price electricity can be exchanged between buyers and sellers within the LEM at a buying price of 15.33 ct/kWh.

The simulation is varied by changing the community size from a total of 10 to 120 participants in 238 simulation scenarios. The different simulation scenarios are further obtained by varying the PtC ratio of the LEM participants. Table 3 shows the various community types, the number of participants per community type, the community classification, and the number of simulation per community type. For the large communities, the simulation scenarios are obtained by varying the nPP ratio from 0.1 to 0.9 with a step of 0.1 and varying the PtC ratio from 0.2 to 1.4 with a step of 0.2. However, for the medium and small communities, the simulation scenarios are obtained by varying the nPP ratio from 0.3 to 0.6 with a step of 0.1 and varying the PtC ratio from 0.2 to 1.4 with a step of 0.2. From Table 3, the number of participants is the total number of consumers and prosumers within the community. Each prosumer or consumer within the community is referred to as local electricity trader (LET).

The simulation data are load profiles obtained from combination of profiles from [31], LoadProfileGenerator [32], [33], and standard load profiles [34], [35]. Table 4 displays how the different commercial and industrial participants such

TABLE 3. Simulation set-up for different community types.

S/N	Community type	No. of Participants	Community class	No. of scenarios
1	A	120	Large comm.	63
2	B	100	Large comm.	63
3	C	75	Medium comm	28
4	D	50	Medium comm	28
5	E	20	Small comm	28
6	F	10	Small comm	28

TABLE 4. Arrangement of industrial and commercial LETs in the different community types.

S/N	Community type	Small manufacturing firm with PV	Bakery	Office buildings with PV
1	A	6	6	15
2	B	6	6	10
3	C	4	4	5
4	D	4	4	5
5	E	2	2	3
6	F	-	1	1

as office building, bakery and small manufacturing firm are added to the different community types. The standard load profiles from Stromnetz Berlin for the year 2021 are used for commercial and industrial profiles [34]. The range of the annual consumption of the commercial profiles is between 25,000 kWh and 30,000 kWh, while for the industrial profiles, it is between 49,000 kWh and 54,500 kWh. To ensure that each LET is unique, a random error in the range of 5–20% was added to each time step of every commercial and industrial profile. The PV production profiles are profiles from Renewables Ninja [36], [37] using the Stuttgart region as the geographic location of the community. The losses of the PV systems were varied between 5% and 15% with a tilt angle of 35°. To ensure that all the seasons of the year are contained within the simulation, the simulation was done for the month of January, April, July and October.

III. RESULTS AND DISCUSSIONS

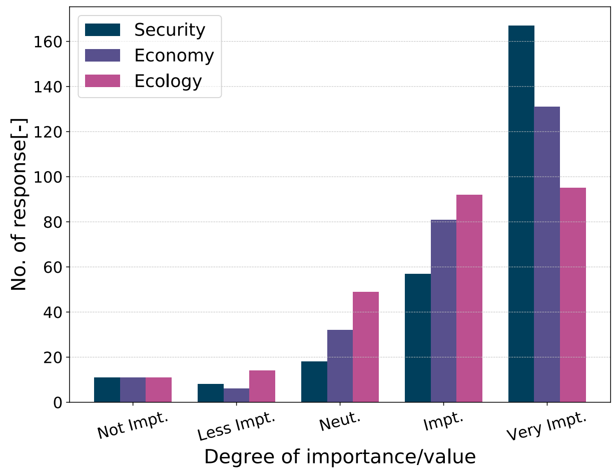
A. SURVEY ANALYSIS

In this section, the results from the survey described in Section II-A are presented and analyzed according to the environmental and energy policy, willingness and interest in LEM, affinity for and trust in new technology and importance of blockchain features.

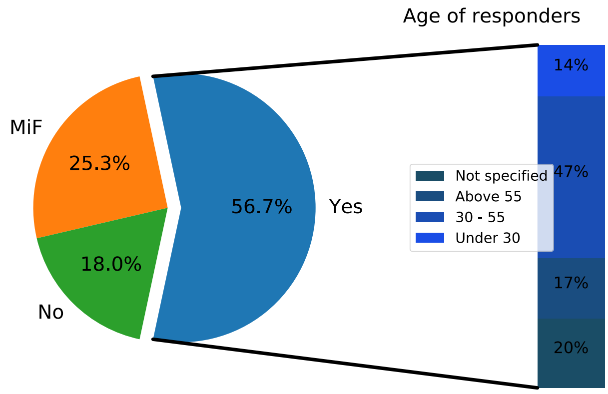
1) ENVIRONMENTAL PROTECTION AND ENERGY POLICY

Fig. 3 displays the level of willingness of the participants to support environmental protection, security of supply and economic value for energy sources. From Fig. 3a, the participants attributed high level of importance on the three elements of energy policy which are security of supply, economy and ecology. However, security of supply is of strong importance to the participants followed by economy before ecological advantage/value. This means that the future LEM participants are mostly interested in ensuring that the source of supply is secured and thereby having energy available at all times. After this is provided, then, making financial benefits from their LEM is of importance to them before supporting their environment.

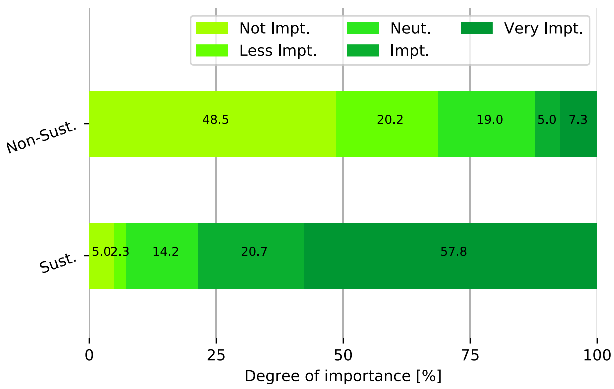
Fig. 3b displays the level of willingness of the participants to pay more for their renewable energy resources. From the diagram, 56.0% of the participants are interested in paying more for their renewable, 18.0% are not interested and 25.3% are interested in paying more may be in the future (MiF). This is evidence that majority of the participants whom are



(a) Importance of ecology, economy and security of supply

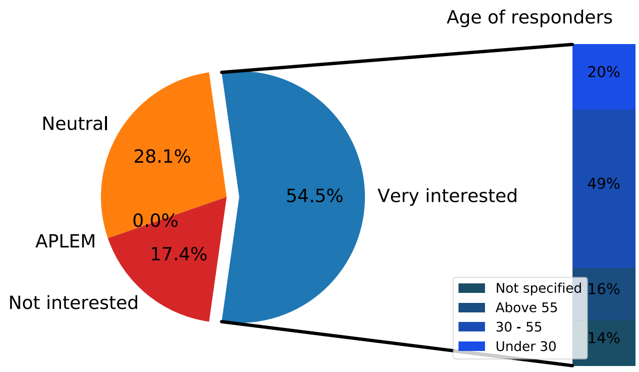


(b) Willingness to pay more for renewable energy

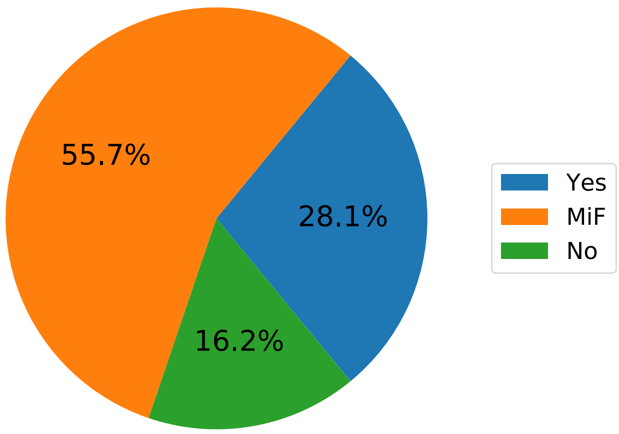


(c) Preferable source of energy

FIGURE 3. Level of willingness to support environmental protection, security of supply and economic value for energy sources.



(a) Level of interest in LEM



(b) Willingness to join LEM pilot project

FIGURE 4. Interest in LEM and willingness to join LEM pilot projects.

mostly within the age of 30 to 55 years are willing to pay more money to ensure that they have more renewable source of energy. Fig. 3c displays the preferable energy sources of the participants. From the diagram, it is evidence that majority of the participants which are more than 70.0% prefer renewable energy as their source of energy.

2) WILLINGNESS AND INTEREST IN LEM

Fig. 4 displays the level of willingness and interest of the participants to join LEM and LEM pilot projects. The diagram in Fig. 4a shows that 54.6% of the participants are very interested in joining LEM, 28.1% are neutral to joining LEM and 17.4% are not interested in joining LEM. On the other hand, no one (0.0%) is already part of LEM (APLEM). This means that majority of the participants are interested in joining LEM. Fig. 4b shows the level of willingness of the participants to join an LEM pilot project. From the diagram, it can be seen 28.0% of the participants are interested in joining pilot projects, 16.2% are not interested in joining pilot projects while 55.7% are interested in joining pilot projects may be in the future (MiF). This is evidence that even though most participants are willing to join LEM, a majority is not yet ready to join.

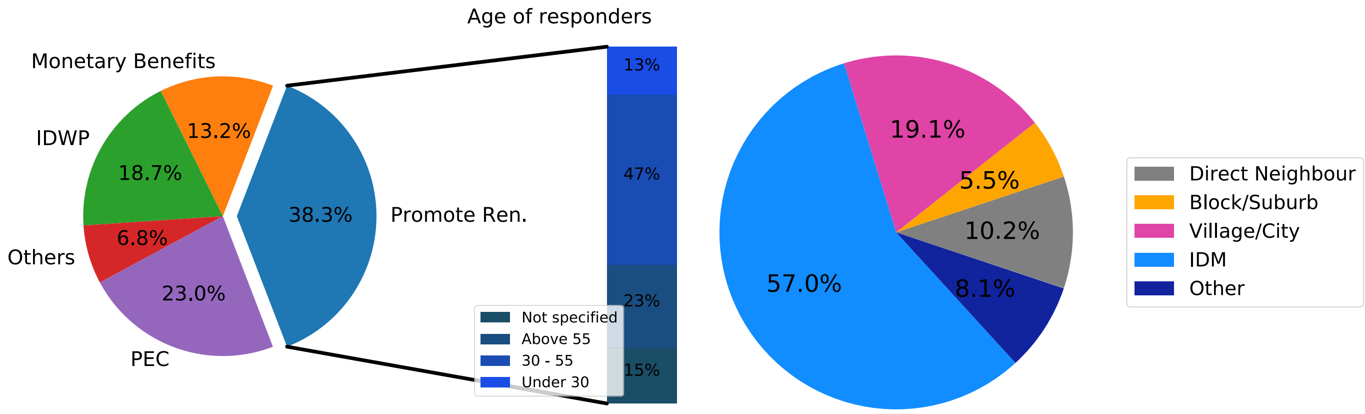
Fig. 5 displays the results of why the participants would like to join LEM and it also shows which trading partner they would prefer. From Fig. 5a, 38.3% would like to participate in an LEM in other to promote renewable (Promote Ren.) energy resources, 13.2% are willing to join for monetary benefits, 23.0% are willing to join because they want to be part of energy community (PEC), 18.7% do not want to participate (IDWP) in LEM and 6.8% have their personal reasons of wanting to join LEM. From the diagram, it is evidence that the major drive for prosumers and consumers to join LEM is to promote renewable energy trading and to be part of energy community. Only a few percentage of the participants wish to join LEM because of the monetary benefits. Fig. 5b displays the preferable trading partners of the participants. From 5b, 10.2% of the participants are willing to trade with their direct neighbour, 5.5% are willing to trade with people living within their block, 19.1% are willing to trade with people living within their village/city and 57.0% does not mind (IDM) who their trading partner is. 8.1% of the participants have different choice of trading partners such as friends and family members. The diagram shows that majority of the participants do not care who their trading partners are or should be but only care about the type of energy they consume.

3) AFFINITY FOR AND TRUST IN NEW TECHNOLOGY

The blockchain solution for LEM comes with new technology such as energy software applications, smart metering devices, and intelligent batteries. Hence, there is a need to access the participants willingness, interest, and trust for new technology that will follow the deployment of a blockchain-based LEM. Fig. 6a displays the level of importance of new technology (INT) to the participants. From the diagram, while 40.5% of the participants show that new technology is important to them, only 21.4% ranked new technology to be extremely important to them. This shows that new technology is not very important to the participants. Fig. 6b displays the level of trust on new technology (TINT) in an LEM by the participants. From the diagram, majority of the participants are neutral to new technology and only shows a low level of trust to new technology. This shows that before the deployment of blockchain-based LEM model, there is a need to engage the participants in order to let them know the importance of new technology and to increase their level of trust for new technology.

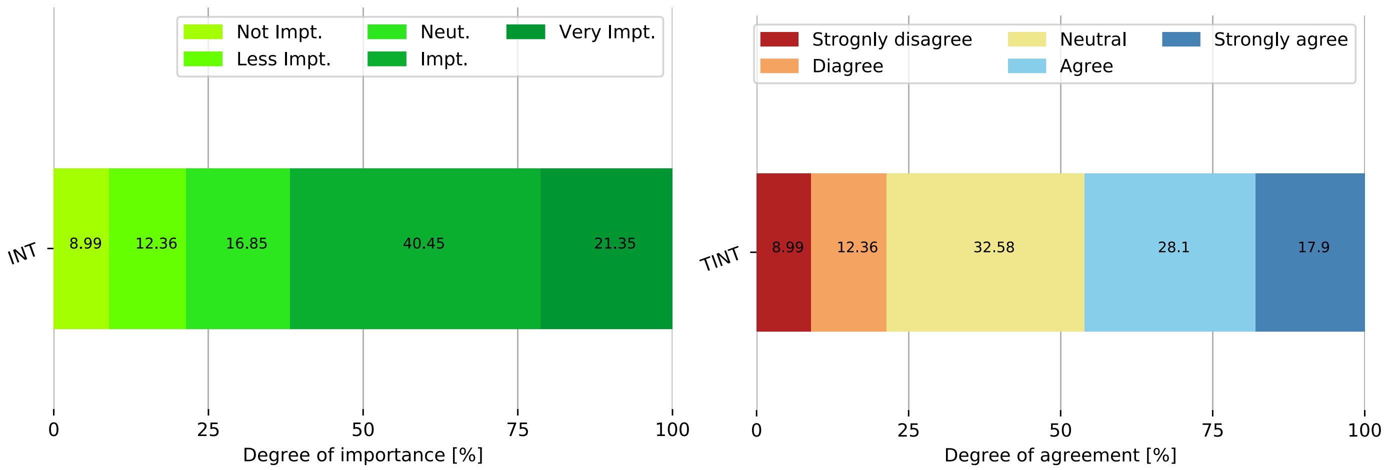
4) IMPORTANCE OF BLOCKCHAIN FEATURES

Blockchain comes along with new features such as alternative method of payment (cryptocurrency), immutability (Immu.), anonymity (Anon.), transparency (Trans.), decentralization (Decen.) and trust. The section evaluates the importance of these blockchain features to LEM participants. Fig. 7a displays the results of the participants' willingness to use an alternative payment method for trading their energy.The participants are open to blockchain technology in a similar way as they are open to new technologies in general as obtained in Fig. 6. Thus, it is evidence that majority of the participants are neutral towards using alternative mode of payments. This



(a) Major reason to participate in LEM (b) Preferable trading partner in LEM

FIGURE 5. **Reason to join LEM and preferable trading partner.**



(a) Level of importance/interest in new technology (b) Level of trust for new technology

FIGURE 6. **Level of interest and trust for new technology in LEM.**

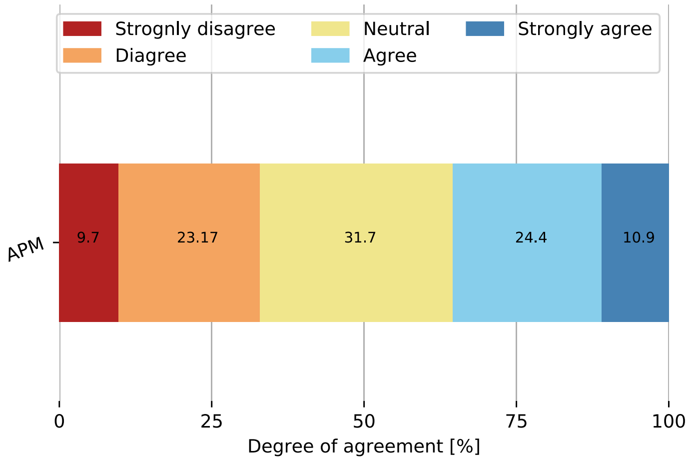
also means that to deploy blockchain-based LEM to the participants, there is a need to inform them and create awareness for them about the importance and benefits of alternative means of payments. Fig. 7b displays the level of importance attributed to the features of blockchain by the participants. The diagram shows that the participants attribute more importance to blockchain features such as trust, transparency and immutability than to anonymity and decentralization. Hence, in the design of LEM, it will be important to focus on utilizing these major features that form the bedrock of the willingness to participate in LEM trading based on blockchain technology.

B. COMMUNITY BASED SIMULATION ANALYSIS

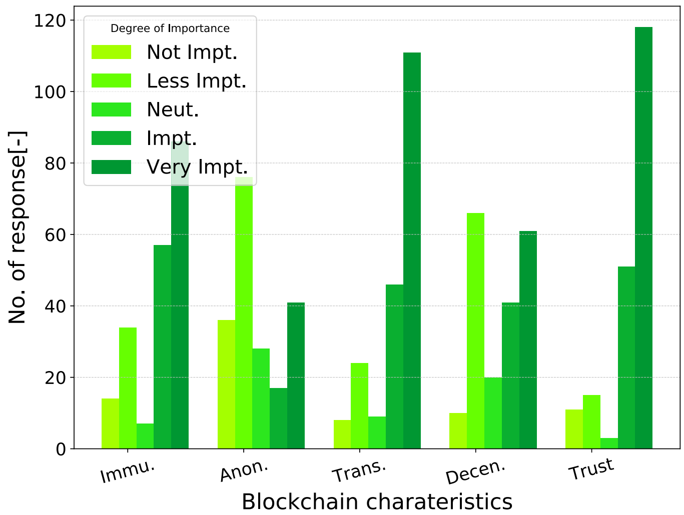
In this section, the community based simulation results of Section II-B are presented and analyzed. First, the technical and economic performance indicators of the large communities are presented and discussed. Afterwards, the indicators are compared with the different community sizes. Finally, the energy exchange within and outside the communities is compared and analyzed.

1) ANALYSIS OF TECHNICAL PERFORMANCE INDICATORS OF LARGE COMMUNITIES

Fig. 8 displays the self sufficiency (SS) and self consumption (SC) ratios of the large communities for varying PtC and nPP ratios. From Figs. 8a and 8c, it can be seen that the SS of communities A and B show similar characteristics for varying nPP and PtC ratio. The SS of community A ranges from 20.3% at nPP and PtC ratios of 0.1 and 0.2, respectively to 48.3% where the nPP and PtC ratios are 0.9 and 1.4, respectively. In the same way, SS of community B ranges from 19.7% at nPP and PtC ratios of 0.3 and 0.2, respectively to 47.6% where the nPP and PtC ratios are 0.3 and 1.4, respectively. Therefore, on average, community A shows better SS compared to community B. This is because the higher number of LETs in community A creates opportunity for trading more energy within the local community instead of buying from the upstream grid. Also, for communities A and B, increasing the PtC ratio increases the SS for community A and B. This is because increasing PtC ration means adding more renewable generated energy within the community which in turn helps to increase local consumption and



(a) Willingness to use alternative payment method



(b) Level of importance of blockchain features

FIGURE 7. **Importance of blockchain features for LEM.**

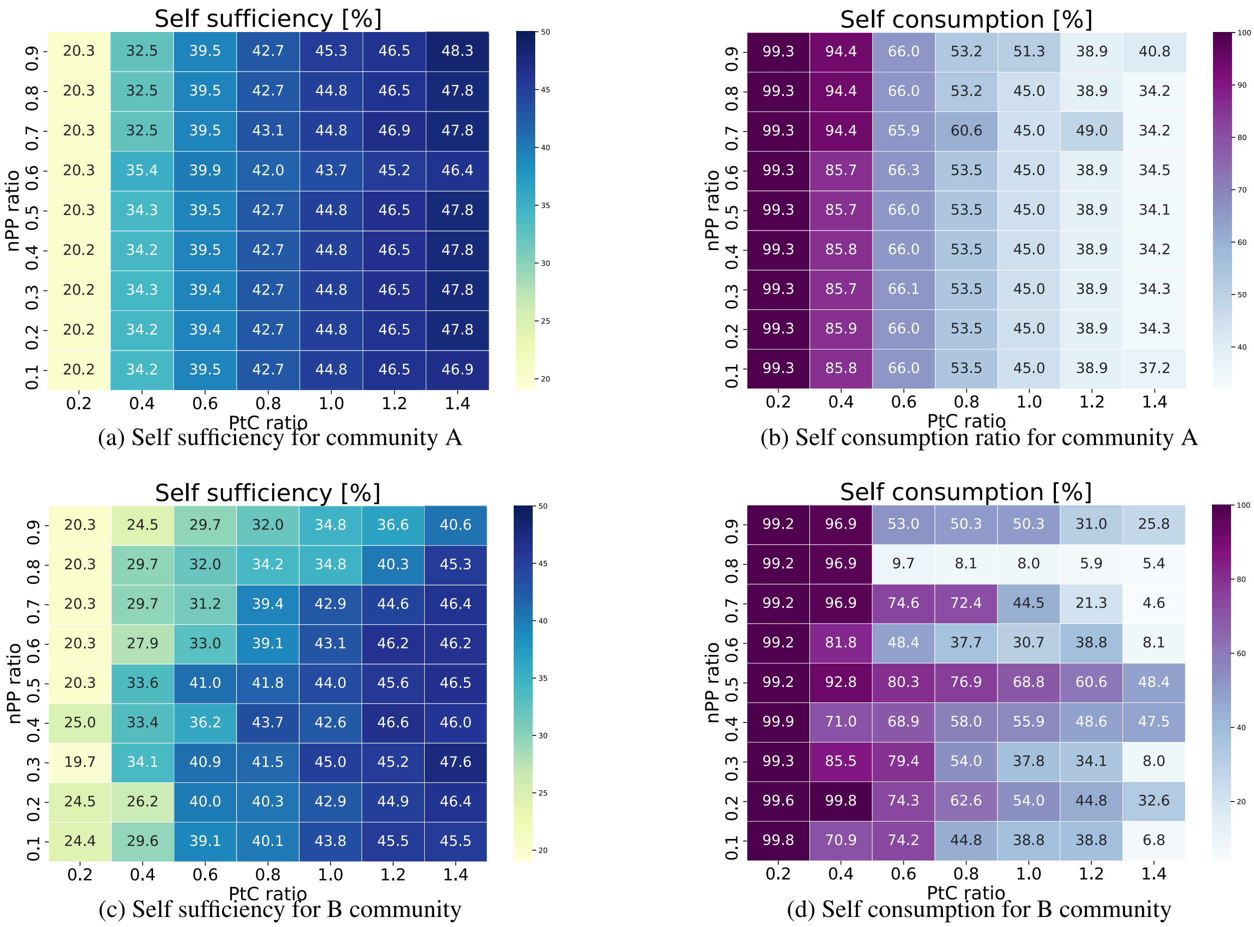
thereby increasing the community SS. On the other hand, the nPP has little impact on the communities which can be noticed in community B. From community B (Fig. 8c), nPP ratio within the range of 0.3 to 0.6 offers higher SS to the local community compared to others. This is illustrated in Fig. 8c, the SS increase from [19.7, 25.0] % at PtC ratio equal to 0.2 to [46.0, 47.6] % at PtC ratio equal to 1.4. Hence, the SS becomes higher as the nPP ratio moves close to 0.4. This is evidence that the nPP ratio has an impact on the performance of LEM.

Figs. 8b and 8d display the SC of communities A and B, respectively. Similar to SS, the SC of communities A and B show similar characteristics for varying nPP and PtC ratio. The SC of community A ranges from 34.1% at nPP and PtC ratios of 0.5 and 1.4, respectively, to 99.3% where the PtC ratio is 0.2. Similarly, the SC of community B ranges from 5.4% at nPP and PtC ratios of 1.4 and 0.8, respectively, to 99.9% where the nPP and PtC ratios are 0.4 and 0.2, respectively. Hence, increasing the PtC ratio decreases the community SC ratio for communities A and B. This is because, increasing the PtC ratio means adding more renewable to the local community, therefore, there is a higher likelihood that at high PtC ratio, all the energy generated within the local community will not be consumed thereby decreasing the SC ratio of the local community compared to when a lower renewable energy is generated. Therefore, the self SC rate increases with decreasing availability of renewable energy within the community. The nPP ratio has little impact on community A. This is because, the higher number of LETs in community A reduce the effect of varying the nPP ratio. As it can be seen in community B (Fig. 8d), nPP ratio within the range of 0.3 to 0.6 leads to a higher SC ratio of the community. This is evidence that reducing the community size reveals the impact of the nPP ratio to the LEM.

2) ANALYSIS OF ECONOMIC PERFORMANCE INDICATORS FOR LARGE COMMUNITY

Fig. 9 displays the share of market savings (SMS) of communities A and B and the share of individual savings (SIS) of household consumer 1 (C1) and household prosumer 1 (P1) for participating in communities A and B. The community SMS is the share of savings made by the LETs for trading within the LEM compared to when there is no LEM [23]. On the other hand, the share of individual savings is the percentage savings made by the individual LET for trading within the LEM compared to when there is no LEM [23]. Figs. 9a and 9b display the SMS of the communities A and B, respectively. From the diagrams, the SMS of the two communities show similar behaviours for varying PtC and nPP ratios. The SMS of community A ranges from 8.9% at nPP and PtC ratios of 0.1 and 0.2, respectively, to 59.9% where the nPP and PtC ratios are 0.2 and 1.4, respectively. Similarly, the SMS of community B ranges from 9.0% at nPP and PtC ratios of 0.2 and 0.2, respectively, to 58.9% where the nPP and PtC ratios are 0.3 and 1.4, respectively. Hence, increasing the PtC ratio of a community increases the SMS of the community. Increasing the PtC ratio of a community means adding additional renewable resources to the community. Adding more renewable generated resources to the community creates more financial benefits to the local community. On the other hand, varying the nPP ratio only has little impact on the local communities. In community A, for PtC equals 0.2, varying nPP from 0.1 to 0.9 only changed the SMS from 8.9% to 12.1%. Similarly, for community B, for PtC equals 0.2, varying nPP from 0.1 to 0.9 only changed the SMS from 9.0% to 12.2%. For both communities (Figs. 9a and 9b) a higher SMS is witnessed at high PtC ratio with nPP ratio between 0.2 to 0.6.

Figs. 9c and 9d display the SIS of C1 in communities A and B, respectively for varying PtC and nPP ratios. The

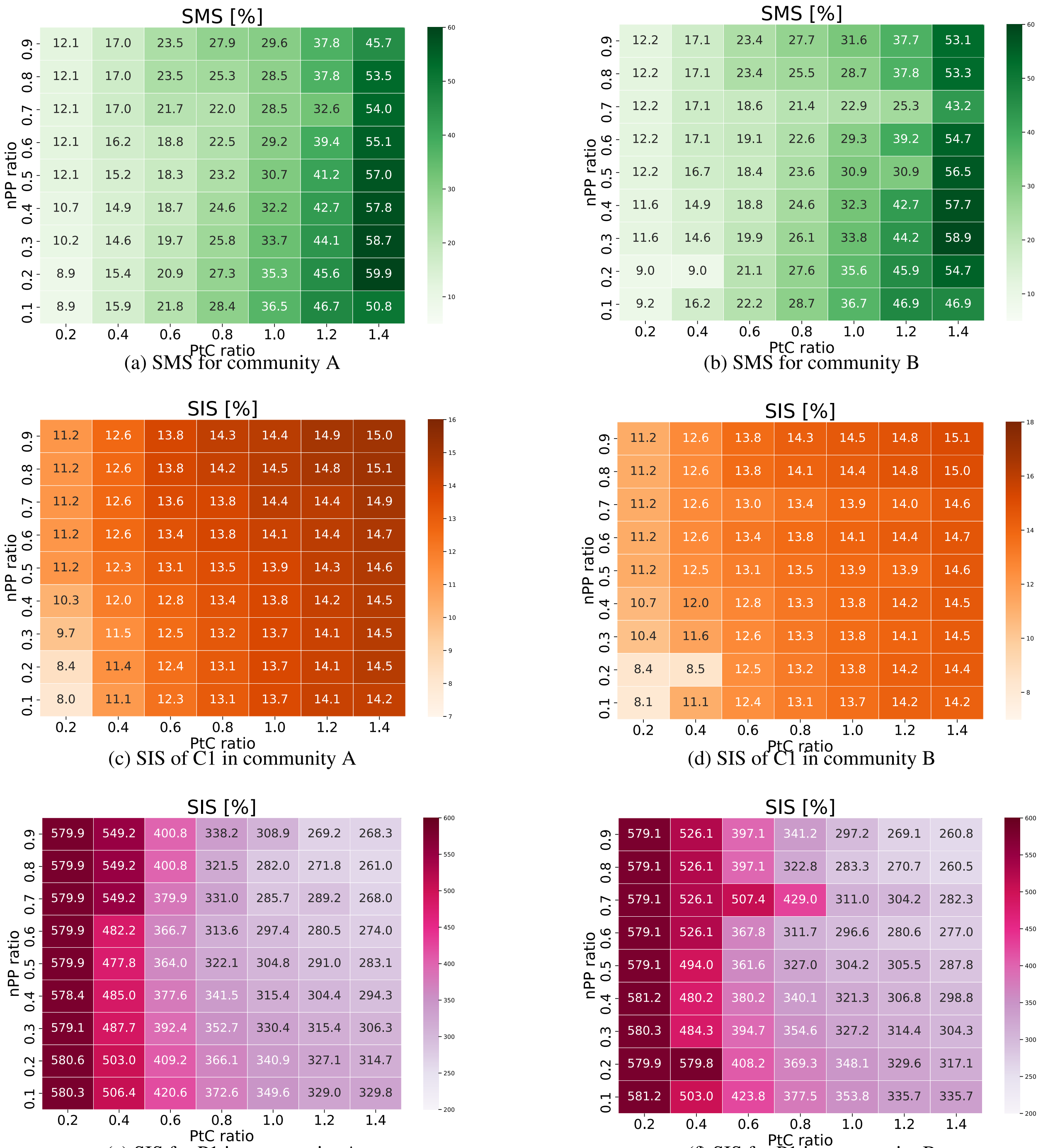


(a) Self sufficiency for community A
(b) Self consumption ratio for community A
(c) Self sufficiency for B community
(d) Self consumption for B community

FIGURE 8. Community self sufficiency and self consumption ratio for varying PtC and nPP ratio.

two communities show the same trends for SIS of C1 with varying PtC and nPP ratios. However, in community A, the average SIS of C1 is 13.2% which is a bit higher than the average SIS of C1 in community B which is at 13.0%. This is because the LETs in community A is higher than community B thereby creating additional opportunities for C1 to buy their energy. For both diagrams, increasing the PtC ratio increases the SIS of C1. This is because C1 is a consumer, thereby increasing PtC ratio creates opportunity for the consumer to buy more renewable from the community thereby increasing his/her share of savings. In the same way, increasing the nPP ratio increases the SIS of C1. Increasing nPP means adding more prosumers to the community. Since C1 is a consumer, adding more prosumers to the community even at constant PtC ratio creates more opportunities for the C1 to have variable options on whom to buy energy from thereby increasing their financial benefits from the LEM.

Figs. 9e and 9f display the SIS of P1 in communities A and B, respectively, for varying PtC and nPP ratios. Similar to SIS of C1, the two communities show similar features for varying PtC and nPP ratios. However, unlike C1, in community A, the average SIS of P1 is 388.2% which is lower than the average SIS of P1 in community B which is at 394.5%. This can be because of the higher number of prosumers in community A which make the community A LEM more compaetitive for P1 compared to community B where there are less prosumers and thus provides opportunity for P1 to trade most of their produced energy. Also, the range SIS of P1 (Figs. 9e and 9f) which is [260.5, 580.6] % is higher than the range of SIS of C1 (Figs. 9c and 9d) which is [8.0, 15.1] % because of the investment made by the prosumer by purchasing PV for trading in the LEM. Figs. 9e and 9f show a decrease in SIS of P1 for increasing PtC and nPP ratios. For example, at constant nPP of 0.2, for community A, increasing the PtC ratio from 0.2 to 1.4 decreases the SIS of P1 from 580.6% to 314.7%. Similarly, for community B, increasing the PtC ratio from 0.2 to 1.4 decreases the SIS of P1 from 579.9% to 317.1%. Increasing the PtC ratio decreases the SIS of P1 because, increasing PtC ratio means increasing the PV production of the community without increasing the PV generation of P1. This eventually creates competition for P1 as most other LETs within the community will produce electricity thereby potentially reducing trading opportunities of P1 and in overall the financial benefits of P1 from the LEM. In the same way, increasing the nPP ratio means adding more prosumers to the community without increasing the number of consumers. This eventually will create more competition for P1 thereby reducing its benefits from the markets.



(a) SMS for community A
(b) SMS for community B
(c) SIS of C1 in community A
(d) SIS of C1 in community B
(e) SIS for P1 in community A
(f) SIS for P1 in community B

FIGURE 9. Economic indicators for varying PtC and nPP ratio.

Fig. 14 in Appendix C displays the SIS of a commercial consumer (C4) and commercial prosumer (P5). Overall, the SIS of both LETs show similar trends to the household consumer and prosumer. However, on an average, the SIS of the commercial consumer (C4) is higher compared to the household consumer(C1) while the SIS of the household prosumer(P1) is higher compared to the commercial prosumer (P5) for the same PtC and nPP ratios. This is because, an LEM creates opportunity for a commercial consumer to buy electricity at a cheaper price within their neighbourhood thereby reducing his/her electricity cost. Since the energy consumption of a commercial consumer is higher than that of a household consumer, the commercial consumer will benefits more from the market since he/she would buy more energy from the LEM. However, for a commercial prosumer participating in the same LEM with a household prosumer, the probability that the household will sell their energy production is higher compared to a commercial consumer who has more energy to sell. Hence, the household prosumer will have higher SIS compared to a commercial prosumers who need to sell a lot of energy to equate their investment before he/she can make an equal SIS. This notwithstanding, the savings of the commercial consumer may be higher than the household consumer.

3) COMPARISON OF TECHNICAL INDICATORS BASED ON COMMUNITY SIZES

To further understand the effect of community size on the LEM performance indicators, the experiments were repeated for varying PtC ratio from 0.2 to 1.4 and nPP ratio from 0.3 to 0.6 for communities A to F as described in Tables 3 and 4. Fig. 10 displays the SS of the different communities for varying PtC and nPP ratios. The graphs of Fig. 10 display similar characteristics for increasing PtC ratio. Thus the SS of all communities at the different nPP rations increase from 19.0% at PtC ratio equal to 0.2 to about 50.0% at PtC equal to 1.4. Thus, at low PtC ratio, there is low renewable production within the communities thereby making the LETs to depend on upstream grid for their energy demand and thus having low SS. From Figs. 10a and 10b, the community SS increases swiftly with increasing PtC ratio. Also, small and medium communities show better SS compared to large communities. Thus at PtC equals to 0.2, the SS of the small/medium community is about 25% where as the SS of the large community is at about 20%. At all PtC ratios, the SS of small and medium communities are usually higher than that of the large community even until the maximum PtC where the SS of the small community is about 50%. At the same time, the SS of the large community is about 46%. Thus, for a small or medium community, with the nPP equals to 0.3 or 0.4, it is easy for the LETs to exchange energy at optimal level ensuring that all energy produced within the community is consumed within the community. This is compared to a large community where the exchange may be difficult to manage resulting in exchanging energy with the upstream grid. For Figs. 10c and 10d, the community SS of all communities show similar behaviours to Figs. 10a and 10b and within the same range of between 19 to 50 %.

Fig. 15 in Appendix C displays the community Self consumption (SC) ratio for varying community sizes, PtC and nPP ratios. Similar to the SS, the SC ratio graphs of Fig. 15 show similar variation for varying PtC ratio. The SC with nPP equal 0.3, 0.4 and 0.5 varies from 100% at low PtC ratios to about 34% at high PtC ratios. For nPP equals to 0.6, the SC varies from 100% at low PtC ratios to about 8.4% at high PtC ratios. Hence, increasing the PtC ratio decrease the community SC ratio. This is because, at lower PtC ratio, the energy production within the local community is low and therefore, there is higher tendency that majority of the energy will be consumed within the community thereby not selling to external grid. Increasing the PtC ratio increases the locally produced energy and thereby reducing the probability that all the energy will be traded within the community and hence, reducing the SC ratio of the community by selling the energy produced within the community to the upstream grid. For varying nPP ratios, the graphs with nPP equal to 0.5 and 0.6 show better performance of the community SC ratio with community D showing the best performance at nPP equals 0.6. Community D is a medium community, therefore, organizing trade within such community where the LETs are not too much and where there is sufficient energy to be traded by the participants can result in higher community performance of the SC.

4) COMPARISON OF ECONOMIC INDICATORS BASED ON COMMUNITY SIZES

Figure 11 displays the community SMS for varying community sizes, PtC and nPP ratios. For all nPP ratios, the community SMS of the different communities increases with increase in PtC ratio. For all nPP ratios, the SMS of the small and medium communities varies within the range of 18 to 80 % for varying PtC ratios of from 0.2 to 1.4. On the other hand, the SMS of large communities varies within the range of 13 to 60 % for varying PtC ratios of from 0.2 to 1.4. Hence, for all nPP ratios, the medium and small communities show better performance for SMS compared to the large communities. This is evidence that the medium and small communities provide more economic benefits to the LETs because of the efficient organization of trade at this community size which resulted in more economic benefits compared to large communities. At nPP equals 0.4, all the medium and small communities have their best SMS performance apart from community E which has its best performance at nPP equal 0.5. For example, the SMS of community E at nPP equals to 0.4 varies from 20 % at PtC equals to 0.2 to 80% when the PtC ratio is 1.4. However, with nPP equals to.5, the SMS varies from 27% when the PtC ratio is 0.2 and reached the maximum SMS which is 80% when the PtC is 1.2.

Fig. 16 in Appendix C displays the SIS of C1 for varying community sizes, PtC and nPP ratios. The SIS of C1 show similar behaviour for all the communities and for all nPP ratios. The SIS show close range of values for increasing PtC ratios in the different communities. The range of SIS of C1 is from 8.5 % at a PtC ratio of 0.2 to 14.8 % at a PtC ratio of 1.4. The SIS of C1 achieves its optimum in community E when the nPP ratio is 0.5 with SIS varying from 12.5 % at a PtC of 0.2 to 14.8 % at a PtC of 1.4. Figs. 17, 18 and 19 of Appendix C display the graph of the SIS for P1, C4 and P5, respectively for varying community sizes, PtC and nPP ratios.

5) COMPARISON OF ENERGY EXCHANGE

Fig. 12 displays the energy exchange within and outside the local community for varying community sizes and nPP ratios. Because of the advantages of medium and small communities in the previous simulations, this section analyses the energy exchange of the medium and small communities for nPP ratio equals 0.3, 0.4 and 0.5. The internal traded energy is the energy traded between the LETs for the whole simulation time within the LEM. The energy import/export is the energy imported/exported from/to the upstream grid. From Figs. 12b and 12c, it is evidence that the external energy exchange

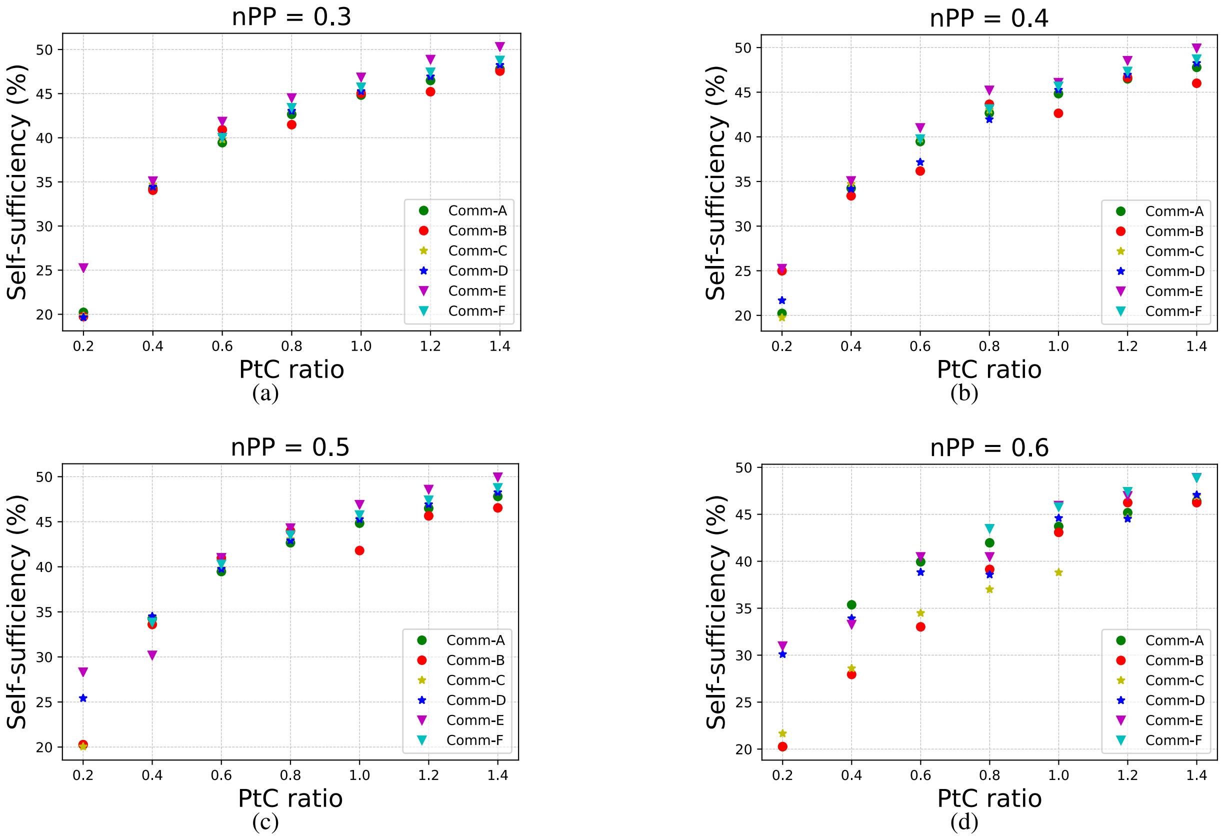


FIGURE 10. **Community self-sufficiency for varying PtC and nPP ratio, and community sizes.**

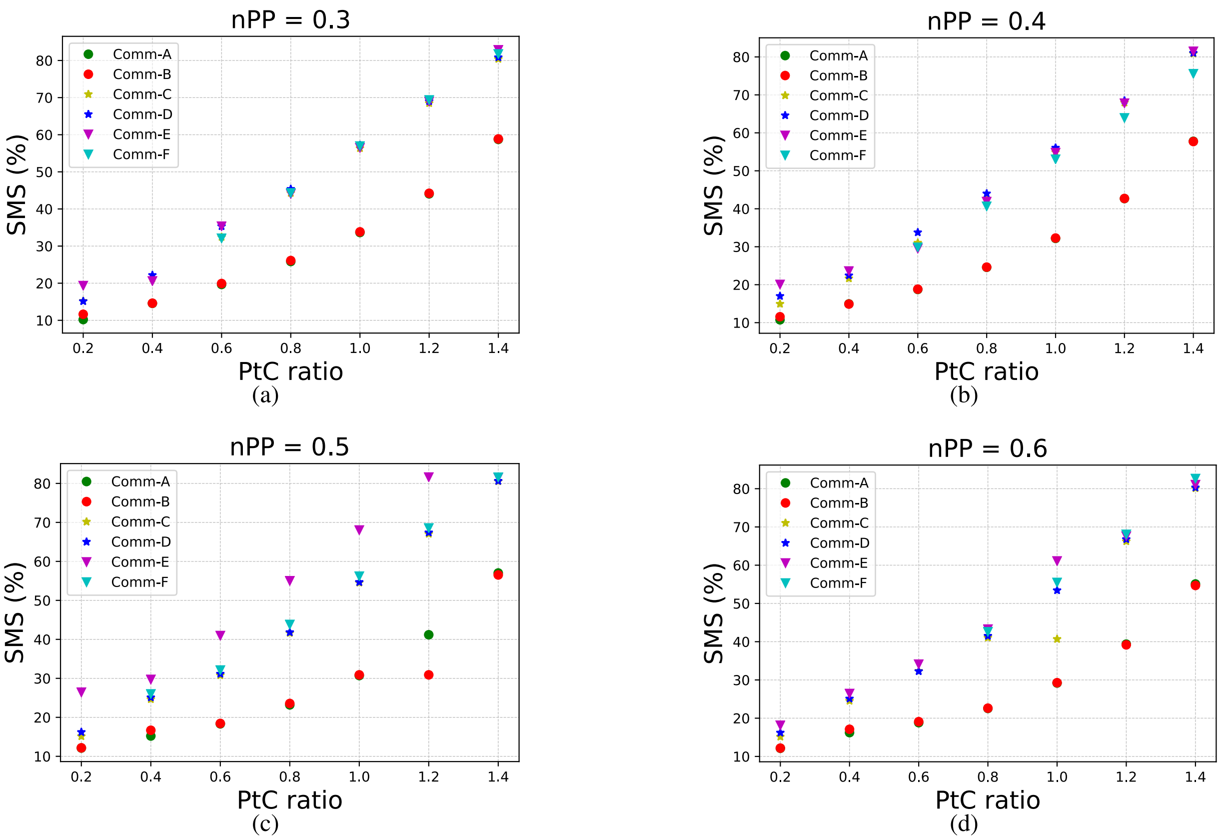
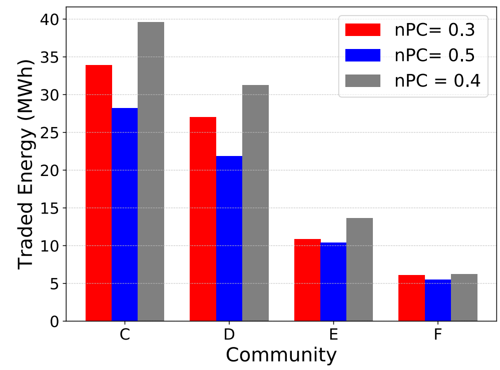
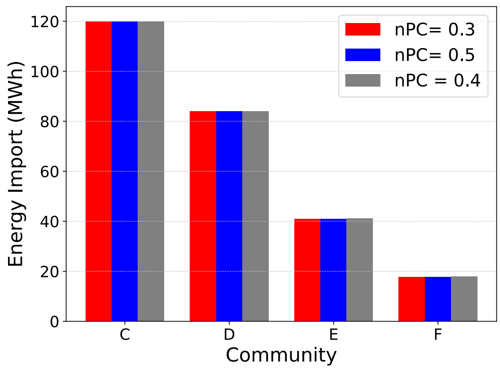


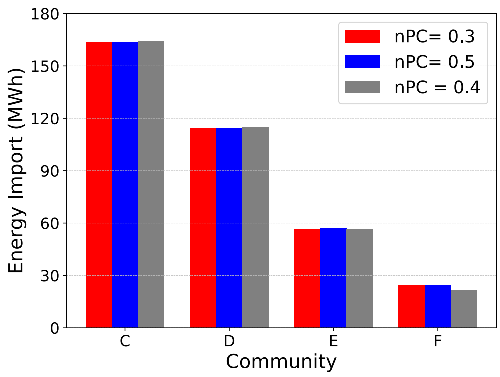
FIGURE 11. **Community SMS for varying PtC and nPP ratio, and community sizes.**



(a) Internal traded energy



(b) Energy import



(c) Energy export

FIGURE 12. Energy exchange within and outside the local community for varying nPP ratios.

with the upstream grid is relatively unaffected by the nPP ratio. Hence, the energy import is about 120 MWh, 85MWh, 40MWh and 17MWh for C, D, E, and F communities respectively. The nPP ratio affects mainly the internal energy exchange between the LETs as shown in Fig. 12a. From Fig. 12a, for all community types, nPP equals to 0.4 shows the maximum internal traded energy with an internal traded energy of about 40MWh in community C.

IV. EFFECTS OF LEM QUANTIFYING FACTORS ON PERFORMANCE INDICATORS

In this section, the quantifying factors for participation in an LEM based on DLT determined from the survey analysis are used to evaluate how they can affect the performance indicators of an LEM based on the simulation analysis. The quantifying factors are analyzed on how they can affect the performance indicators of LEM are the willingness to pay more for renewable energy, interest in LEM and willingness to join an LEM pilot project, willingness to join LEM based on full DLT, and willingness to join LEM based on Hybrid DLT.

A. WILLINGNESS TO PAY MORE FOR RENEWABLE ENERGY

The willingness to pay more for renewable energy (WPMR) is the consumers'/prosumers' willingness to pay a certain premium to buy renewable energy generated by producers/prosumers within their community. The survey results show that up to 56.7% of the participants are willing to pay a premium to have their energy sourced from renewable energy production. Reference [38] showed that by considering consumers/prosumers WPMR in a check and curtail combined with highest-to-lowest and periodic double auction clearing mechanism (CC-H2L-PDA), the traded energy of an LEM will be increased by 36.4% compared to a standard periodic market clearing mechanism. In a check and curtail LEM clearing, the market checks unsatisfied bids and curtails them before initiating another market clearing [38]. Furthermore, considering WPMR in a CC-H2L-PDA increases the trade price of the LEM by 12.0%. This paper will assume that these results are suitable to be used in our model since it was studied in a German case scenario and this data will be used to formulate the effect of willingness to pay a premium on the different performance indicators of the simulation analysis.

1) SELF-SUFFICIENCY AND SELF-CONSUMPTION RATIO

The market self-sufficiency (SS) and self-consumption (SC) ratios have similar characteristics at constant PtC ratio and will have similar effect on increasing the energy traded. In a community where 56.7% of the LEM participants are willing to pay a premium to buy renewable generated energy as received from the survey, and considering the result of the effect (36.4% increase) of WPMR on the traded energy quantity already established in literature [38], the overall increase in SS and SC due to WPMR will be around 20% at constant PtC ratio.

2) SHARE OF MARKET SAVINGS

The share of market savings (SMS) is already established as the resultant savings of the market participants in an LEM compared to when there is no LEM. In a market where consumers are willing to pay more for the same amount of electricity if it is coming from renewables, the resultant effect will not change the SMS of the LEM. This is because, the premium that is paid by the consumers is received by the prosumers without changing the market savings. Hence, WPMR has no effect on the SMS of the LEM at a constant PtC ratio.

3) SHARE OF INDIVIDUAL SAVINGS - CONSUMERS

An increase in the average trade price of LEM at constant PtC ratio decreases the average consumer savings. The consumer's share of individual savings (SIS) is proportional to the average consumer savings, increasing the LEM average trade price decreases the consumers SIS. By considering the effect of WPMR on the LEM trade price, we derive the equations shown in Appendix B to show the effect of WPMR on the consumers SIS. Hence, by considering the consumers WPMR, the consumers' SIS reduces according to Eq. (10).

4) SHARE OF INDIVIDUAL SAVINGS - PROSUMERS

An increase in the average trade price of LEM at a constant PtC ratio increases the average prosumer savings. The prosumer's share of individual savings (SIS) is proportional to the average prosumer savings, increasing the LEM average trade price increase the prosumers SIS. The equations derived in Appendix B show the effect of WPMR on the prosumers SIS. Hence, by considering the consumers WPMR, the prosumers SIS increases according to Eq. (12).

B. INTEREST IN LEM AND WILLINGNESS TO JOIN LEM PILOT PROJECT

The survey results show that only 28.1% of the participants are interested to join an LEM pilot project. This shows that in the current maturity of LEM added with limited awareness to local consumers, it is difficult to form an LEM of large community at the start of an LEM pilot project. Therefore, it is difficult to start a medium or large LEM community at the current stage of LEM. With a high percentage of responders willing to join in the future, the optimal values of an LEM performance indicators obtained from the simulation results can only be witnessed after some years from now. In summary, all the simulation performance indicators are affected equally by the willingness to join LEM pilot project. However, while values of performance indicators are zero at the start of pilot projects for the medium and large communities, it is expected that after some years from now, the full results obtained from the simulations can be achieved for all the community types.

C. WILLINGNESS TO JOIN LEM BASED ON FULL DLT

Developing LEM based on a full DLT features require development of a platform for trading local energy that has the capability to offer all the features of DLT including using cryptocurrency for the payment of traded energy. LEM participants are required to be completely involved in such market to make it a viable one because they need to be able to manage their cryptocurrency by themselves. From the results of the survey (Figs. 6 and 7), while 31 % of the participants are neutral to utilizing LEM with full DLT features, 33 % will not like to participate in such a market. If applied to the community simulation, it means that not all members of the community will be willing to participate in such a market thereby reducing the performance of such a market. Hence, with the current survey results, we conclude it that with the current maturity stage of DLT, if a fully DLT based LEM is implemented, that all LEM performance indicators will reduce by at least 42 % compared to the expected results from the community simulation.

D. WILLINGNESS TO JOIN LEM BASED ON HYBRID DLT

LEM based on hybrid DLT is an LEM that combines selected DLT features to implement a trading platform for consumers and prosumers. The survey results of Fig. 7b shows that most participants are interested in having selected features of DLT such as trust and transparency in their LEM platform. Hence, this will affect the level of participation in such market if implemented and finally, increase the performance indicator of such a market compared to an LEM based on a full DLT features. The expected out come of Fig. 7b is that an LEM based on hybrid DLT features will only reduce the expected value of all the LEM performance indicators by 17%.

E. COMBINED QUANTIFYING FACTORS

The identified quantifying factors are combined in two different ways to evaluate the resultant effect on the LEM performance indicators. The first scenario is the start of a pilot project of an LEM based on full DLT where prosumers and consumers are willing to pay premium for renewable energy (SPP+LEMDLT+WPMR). The second scenario is 5 years after the start of a pilot project of an LEM based on hybrid DLT where prosumers and consumers are willing to pay premium for renewable energy (FASPP+LEMHDLTT+WPMR). The effect of the combined quantifying factors on the performance indicators is the resultant effect based on the combined factors.

Table 5 displays the summary of the effects of the quantifying factors on the performance indicators for selected communities (Comm.) of the simulation results, PtC and nPP ratios equal to 0.8 and 0.4, respectively. In Table 5, value means the original results determined from the simulation for the performance indicator. Other columns show the value of the performance indicator when the prosumers are willing to pay more for renewable energy (WPMR), at the start of a pilot project (SPP), five years after start of a pilot project (FASPP), for LEM fully based on DLT (LEMDLT), for LEM based on hybrid DLT (LEMHDLT), SPP+LEMDLT+WPMR scenario (Comb.1) and FASPP+LEMHDLTT+WPMR scenario (Comb.2). The complete results and input data are explained in details and made open source which is accessible from [39]. The best performance for all indicators is witnessed at the Comb.2 scenario. The maximum SS for data shown in Table 5 is 44.7% witnessed in community E. In the same way, the maximum SC and SMS are 66.9% and 36.1% resulting from communities B and D, respectively.

V. CONCLUSION

This paper presents an analysis of the quantifying factors for participation in a blockchain-based LEM. The methods used

TABLE 5. SS, SC and SMS for different LEM quantifying factors and varying community sizes with PtC ratio = 0.8 and nPP ratio = 0.4.

S/N	Comm.	Value [%]	WPMR [%]	SPP [%]	FASPP [%]	LEMDLT [%]	LEMHDLT[%]	Comb.1 [%]	Comb.2 [%]
SS									
1	A	42.7	51.5	–	42.7	24.7	35.4	–	42.2
2	B	43.7	52.6	–	43.6	25.3	36.2	–	43.2
3	C	43.0	51.2	–	43.0	35.7	35.4	–	42.5
4	D	42.0	50.6	41.8	41.7	24.3	34.8	32.7	41.5
5	E	45.2	54.5	45.2	45.2	26.2	37.5	35.3	44.7
6	F	43.1	52.0	43.1	43.1	25.0	35.7	33.6	42.7
SC									
1	A	53.4	63.3	–	53.4	31.0	44.3	–	51.9
2	B	68.9	81.6	–	68.9	39.9	57.1	–	66.9
3	C	54.2	64.3	–	54.2	31.4	45.1	–	52.7
4	D	45.5	53.9	45.5	45.5	26.3	37.7	35.5	44.2
5	E	64.5	76.5	64.5	64.5	37.4	53.5	50.3	62.7
6	F	61.1	72.4	61.1	61.1	35.4	50.7	47.7	59.4
SMS									
1	A	24.5	24.5	–	24.5	14.2	20.3	–	20.1
2	B	24.6	24.6	–	24.6	14.2	20.4	–	20.1
3	C	42.6	42.6	–	42.6	24.7	35.4	–	34.9
4	D	44.0	44.0	44.0	44.0	25.5	36.5	34.3	36.1
5	E	41.9	41.9	41.9	41.9	24.3	34.7	32.6	34.3
6	F	40.6	40.6	40.6	40.6	23.5	33.7	31.7	33.3

in this work were a survey analysis which was distributed online among household consumers and prosumers, and a community-based simulation of single layer LEM model with varying community sizes and prosumers to consumers ratios. The survey received a total of 261 responses and the results analysis show that consumers and prosumers are more interested in security of their supply, followed by economic value that may arise from their consumption/supply before ecological benefits. Also, the major reason for most consumers and prosumers to participate in an LEM is to promote renewable energy and the consumers/prosumers are willing to pay more for renewable energy supply. While majority of prosumers/consumers are willing to join LEM, most of them are only willing to join pilot projects in the future. This shows that most prosumers/consumers still do not trust new technology. Also, the major blockchain features that can drive local electricity traders (LETs) into LEM are trust and transparency. The community-based simulation analysis showed that varying the annual production to consumption ratio has more effect on the economic and technical benefits of LEM compared to varying number of prosumers to total participants (nPP) ratios. Also, medium and small communities with nPP ratio between 0.3 to 0.5 create more economic and technical benefits to LETs compared to large communities.

Finally, modelling the quantifying factors for participating in a blockchain-based LEM with the community-based simulation results show that an optimal LEM based on DLT can be achieved in the future in a community scenario where the participants are willing to pay more to consume local renewable generated electricity and with a hybrid blockchain-based LEM. In future work, a hybrid blockchain-based local energy market framework will be developed based on the identified blockchain features that attract consumers and prosumers to trade in a blokchain based LEM such as transparency and trust. Our model will be further extended to use intelligent agents to determine the behaviours of the LEM performance indicators outside the simulation range based on the input and the results of the simulation.

APPENDIX A
SURVEY QUESTIONS AND SCREEN SHOOT
A. SURVEY QUESTIONS
1) ENVIRONMENTAL PROTECTION/ ENERGY

1. Where do you see yourself in this triangle? Please evaluate the answers with a scale from 1-5 from the less important to the most important aspect?

a. Security
b. Economy
c. Ecology
Remark:
1-not important,
2-less important
3-neutral
4-important
5-very important

2. Will you pay more for your electricity consumption only to increase the usage of RES?

a. Yes
b. Maybe in the future
c. No 3. Please evaluate the answers with a scale from 1-5 from the less important to the most important aspect? Would you prefer that the energy you consume is generated by:

a. Sustainable
b. Non-sustainable
c. Not-interested
Remark:
1-not important
2-less important
3-neutral

4-important
5-very important

2) LOCAL ENERGY MARKET

*Video explanation of LEM (LO3 Energy Presents Allgäu Microgrid at AÜW (Deutsch) - YouTube) https://www.youtube.com/watch?v = dPhfKGQEdxY

1. During the time that your PV system is producing surplus, would you sign up to participate by trading the surplus energy in a local energy market?
a. I am part of LEM
b. Yes, very interested
c. Neutral
d. Not interested

2. Where do you/ would you prefer to share or trade your energy?
a. Direct neighbors
b. Block/suburb
c. Village/city
d. It doesn't matter
e. Other

3. Would you participate in LEM if you could:
a. Promote renewable energy systems
b. Part of Energy share Community
c. monetary winning from energy trading
d. I don't want to participate
e. Other reasons

4. Would you be interested in joining a pilot community project?
a. Yes
b. No c. Maybe in the future

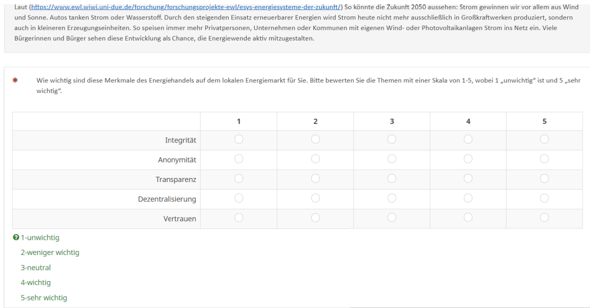
3) ROLE OF TECHNOLOGY IN ENERGY SECTOR

1. How important is it for you to know in real time your load consumption and/or production?
a. Very important
b. Important
c. Neutral
d. Less important
e. Not important

2. I trust the energy-apps, smart meter and intelligent batteries?
a. Strongly disagree
b. Disagree
c. Neutral
d. Agree
e. Strongly agree

4) FUTURE ENERGY

According to (https://www.ewl.wiwi.uni-due.de/forschung /forschungsprojekte-ewl/esys-energiesysteme-der-zukunft/) This is what the future could look like in 2050: Generating electricity primarily from wind and sun. Cars fill up with electricity or hydrogen. Due to the increasing use of renewable energies, electricity is no longer produced in large power plants, but also in smaller generation units. Private individuals



Laut (https://www.ewl.wiwi.uni-due.de/forschung/forschungsprojekte-ewl/esys-energiesysteme-der-zukunft/) So könnte die Zukunft 2050 aussehen: Strom gewinnen wir vor allem aus Wind und Sonne. Autos tanken Strom oder Wasserstoff. Durch den steigenden Einsatz erneuerbarer Energien wird Strom heute nicht mehr ausschließlich in Großkraftwerken produziert, sondern auch in kleineren Erzeugungseinheiten. So speisen immer mehr Privatpersonen, Unternehmen oder Kommunen mit eigenen Wind- oder Photovoltaikanlagen Strom ins Netz ein. Viele Bürgerinnen und Bürger sehen diese Entwicklung als Chance, die Energiewende aktiv mitzugestalten.

* Wie wichtig sind diese Merkmale des Energiehandels auf dem lokalen Energiemarkt für Sie. Bitte bewerten Sie die Themen mit einer Skala von 1-5, wobei 1 „unwichtig" ist und 5 „sehr wichtig".

	1	2	3	4	5
Integrität					
Anonymität					
Transparenz					
Dezentralisierung					
Vertrauen					

1-unwichtig
2-weniger wichtig
3-neutral
4-wichtig
5-sehr wichtig

FIGURE 13. A Part of survey question displayed on SurveyMonkey website.

and companies feed electricity into the grid with their own systems. The citizens see the development as an opportunity to actively help the energy transition.

1. Are you willing to use an alternative way of paying or to be paid for energy trading?
a. Strongly agree
b. Agree
c. Neutral
d. Disagree
e. Strongly disagree

Alternative- Coupons, Vouchers. For a better understanding check this video: How It Works | GrassrootsEconomics

2. How important are these features of energy trading in local energy market for you:
1-not important
2-less important
3-neutral
4-important
5-very important
immutability 1 2 3 4 5
anonymity 1 2 3 4 5
transparency 1 2 3 4 5
decentralization 1 2 3 4 5
trust 1 2 3 4 5

5) GENERAL QUESTIONS

1. What's your age?
a. Below 30
b. 30- 55
c. Above 55

2. The yearly net incomes:
a. Below 35.000 €
b. 35.000-50.000 €
c. Above 50.000 €

3. Where do you live?:
a. Rented house/ apartment
b. Own house
c. Other

4. Are you aware of your monthly consumption?

5. Which operator or energy trader would you prefer to get your energy from?
a. Local council
b. Local community energy group
c. Energy supplier/ retailer

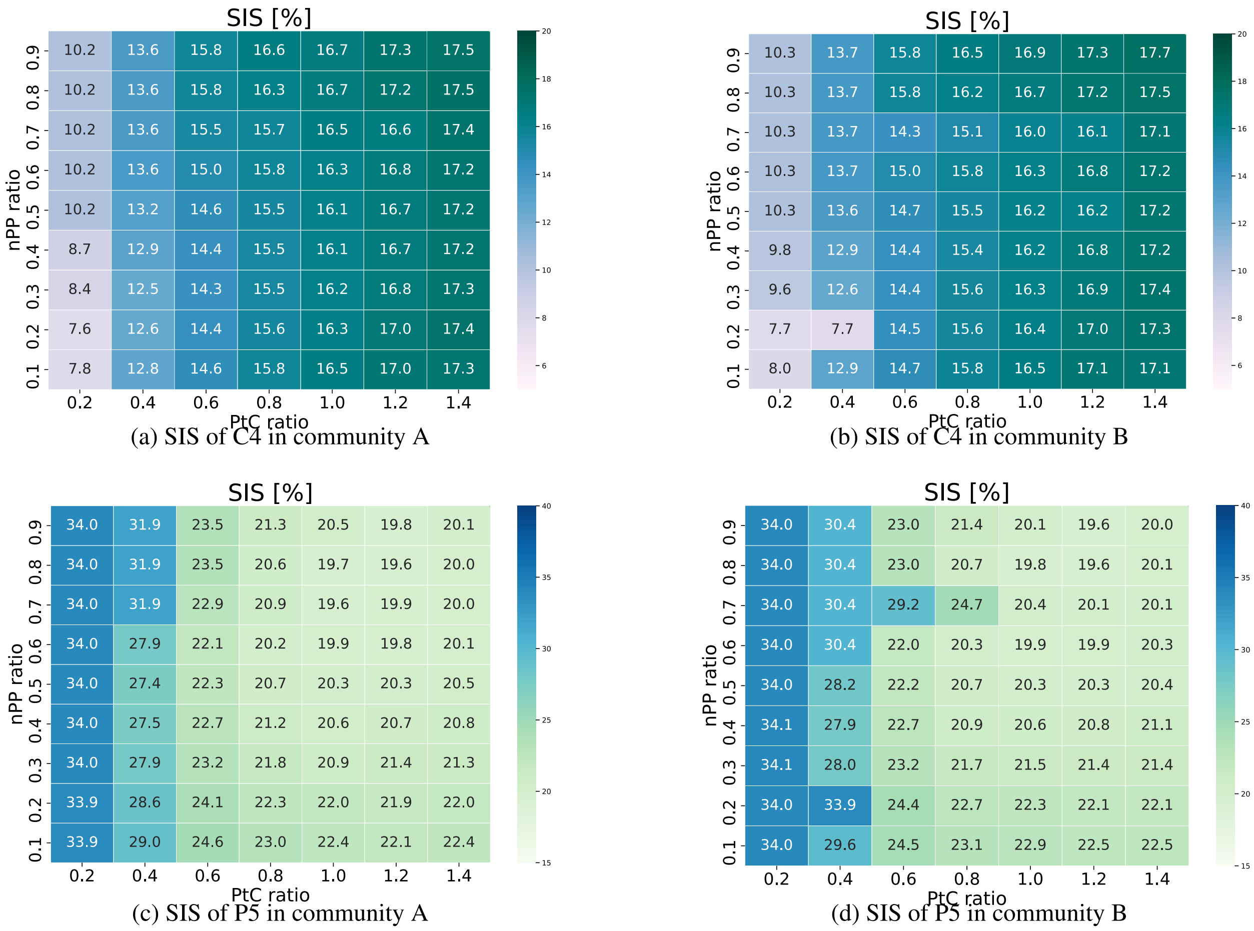


FIGURE 14. Economic indicators for varying PtC and nPP ratio in large communities.

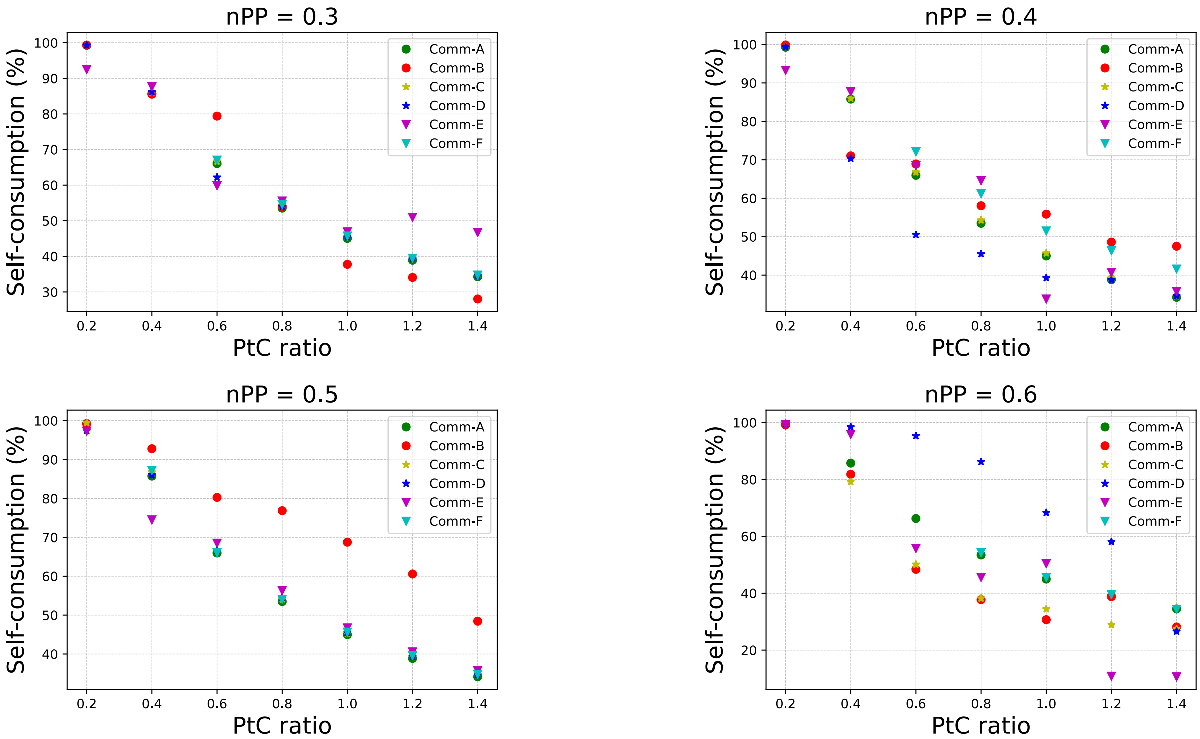


FIGURE 15. Community self-consumption ratio for varying PtC and nPP ratio, and community sizes.

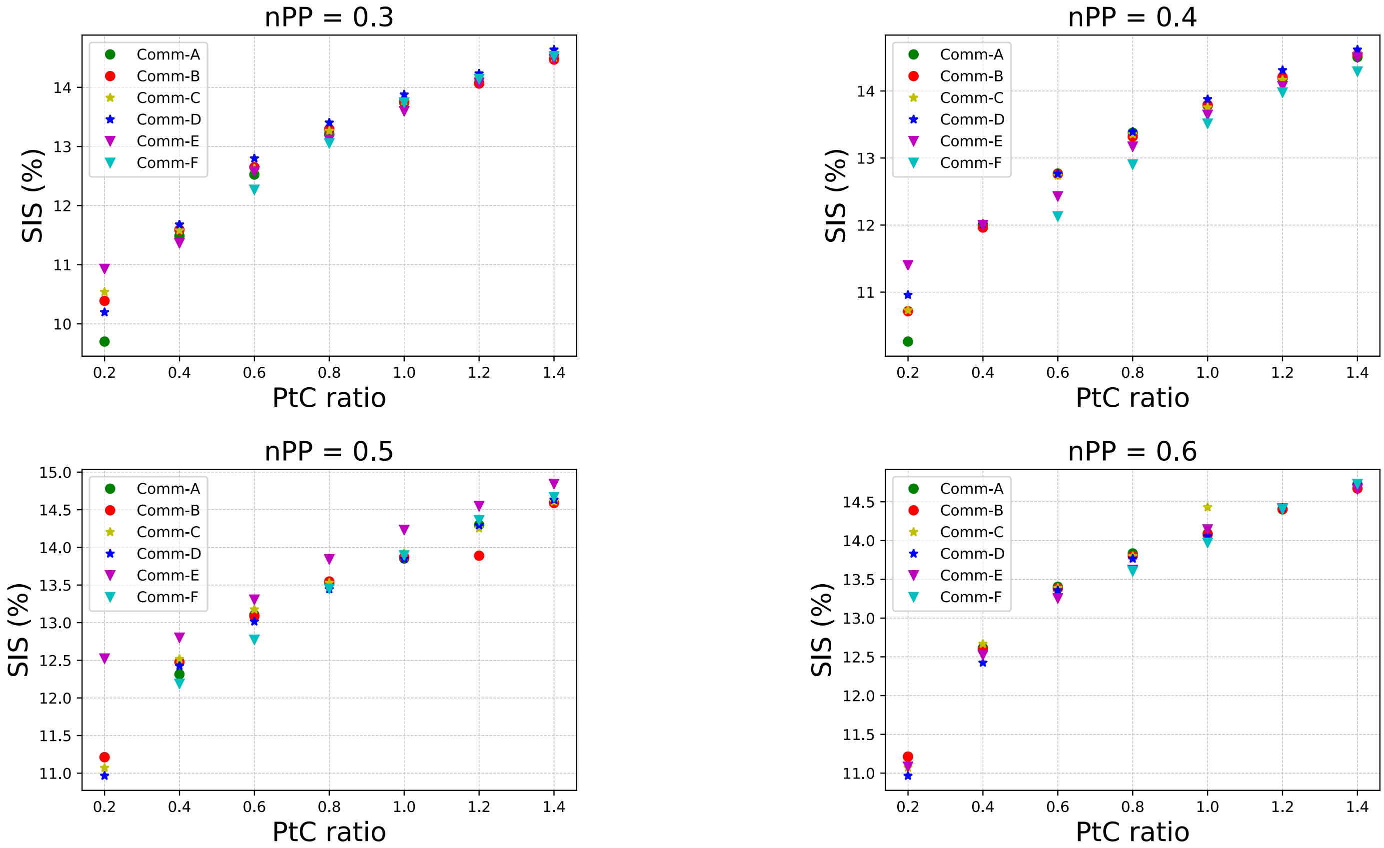


FIGURE 16. C1 SIS for varying PtC and nPP ratio, and community sizes.

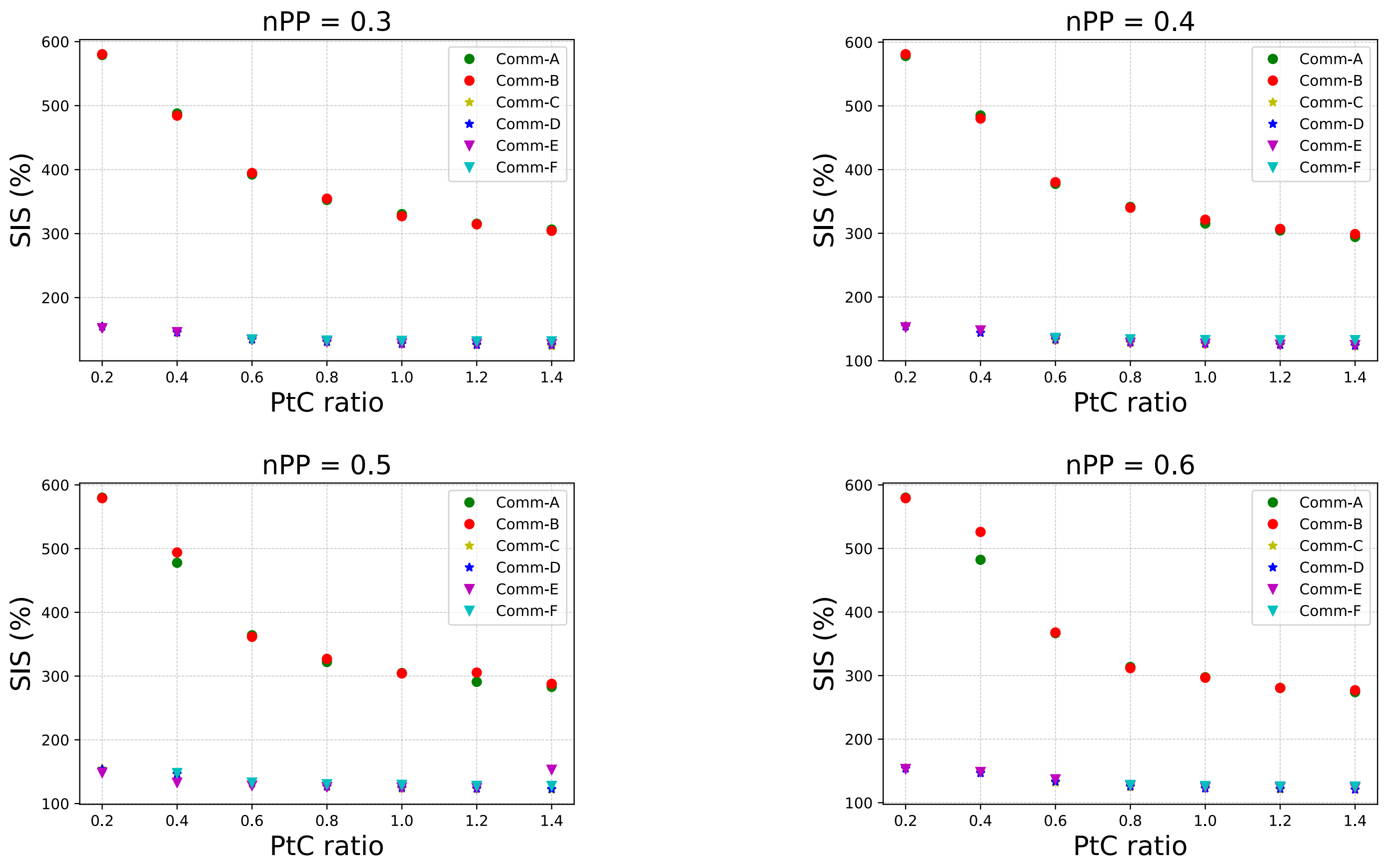


FIGURE 17. P1 SIS for varying PtC and nPP ratio, and community sizes.

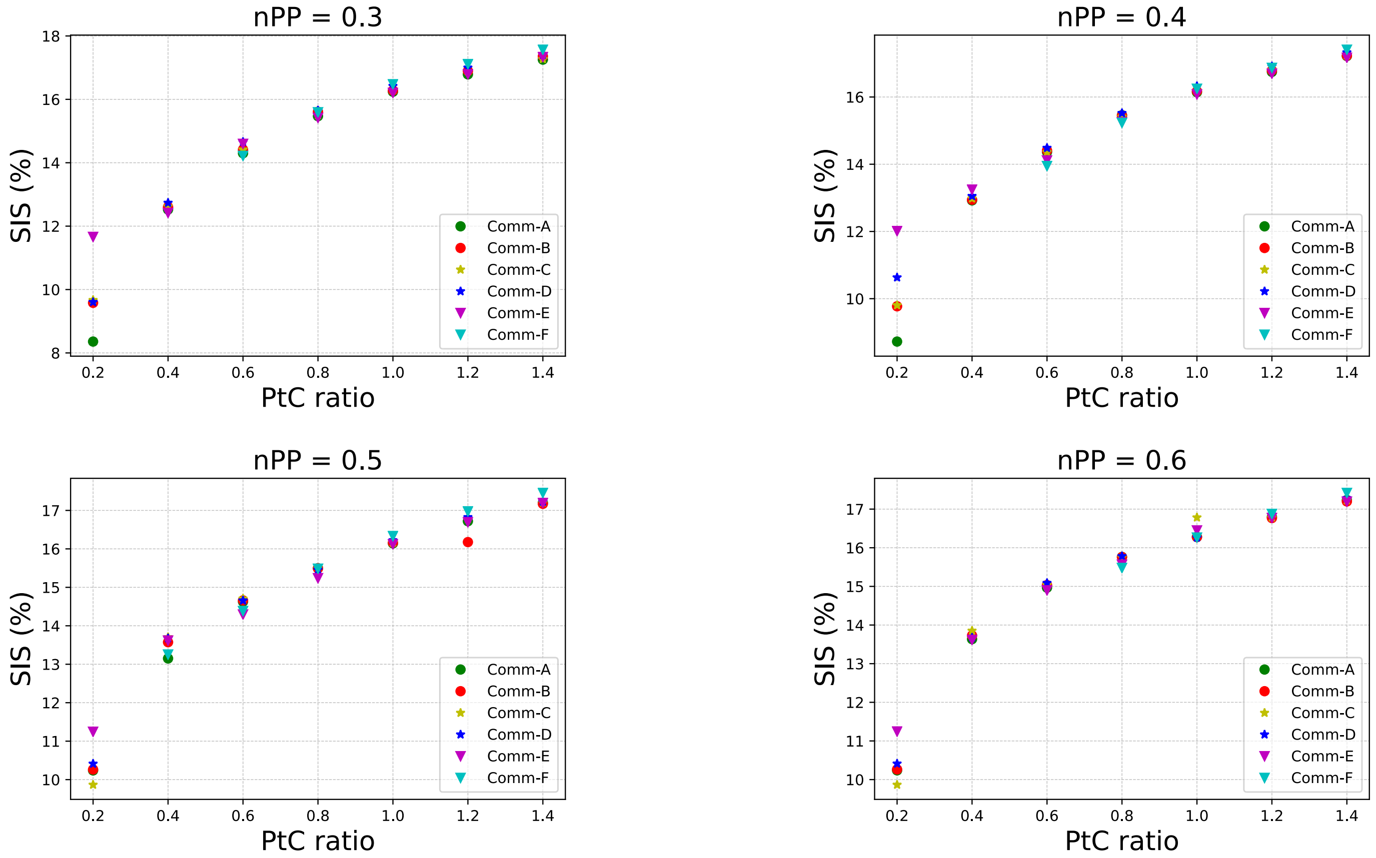


FIGURE 18. C4 SIS for varying PtC and nPP ratio, and community sizes.

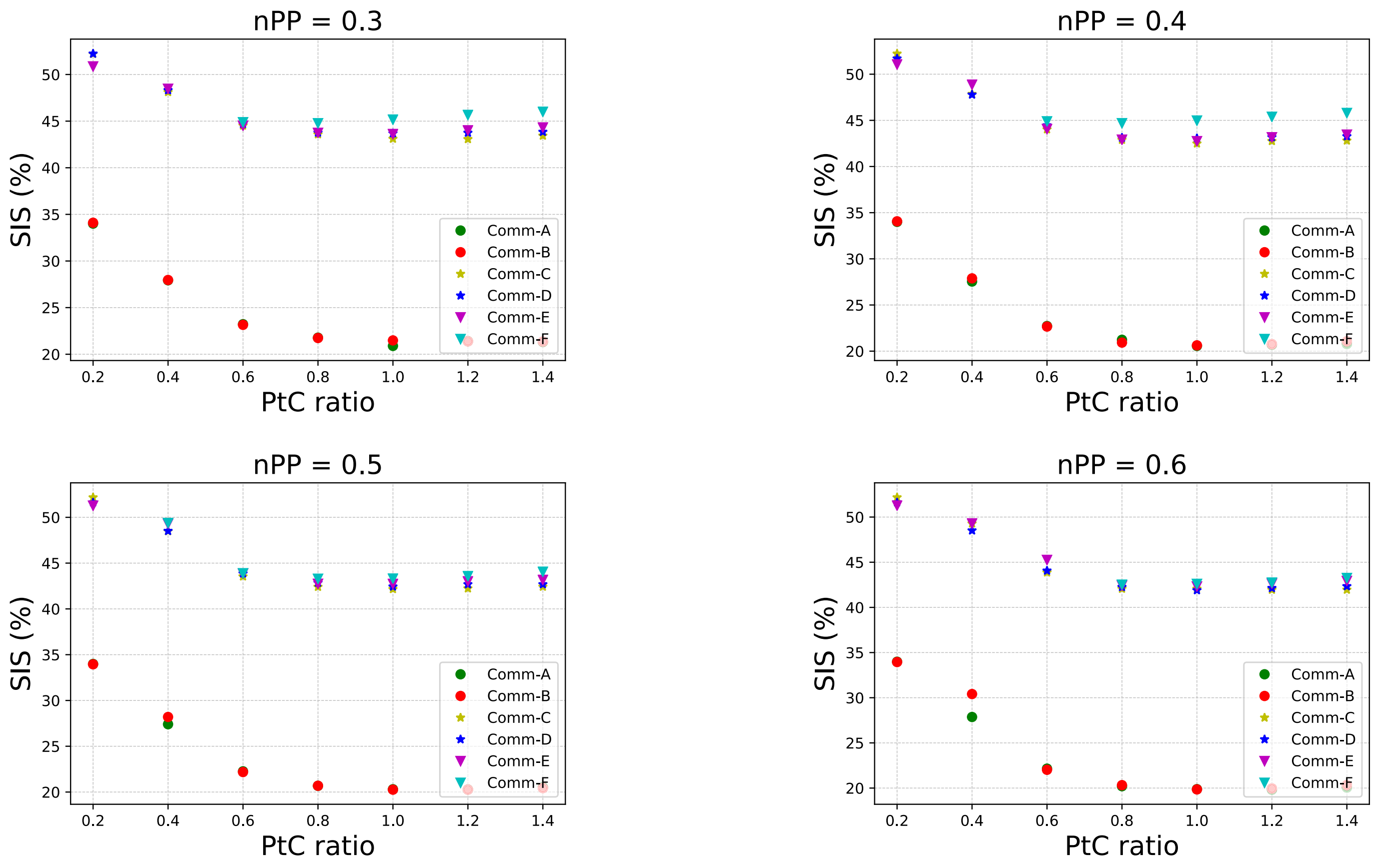


FIGURE 19. P5 SIS for varying PtC and nPP ratio, and community sizes.

B. SCREEN SHOOT OF PART OF SURVEY QUESTION DISPLAYED ONLINE

Fig. 13.

APPENDIX B
DERIVED EQUATIONS FOR DETERMINING THE SIS

$$\gamma = \frac{r_{wpmr} - r_{pda}}{r_{pda}} \tag{8}$$

$$SIS_{b,pda} \approx \frac{p_g - r_{wpmr}}{p_g} \tag{9}$$

$$SIS_{b,wpmr} \approx \frac{r_{wpmr}}{r_{pda}} SIS_{s,pda} - \gamma \times \beta \tag{10}$$

$$SIS_{s,pda} \approx \frac{r_{wpmr} - p_{fit}}{p_{fit}} \tag{11}$$

$$SIS_{s,wpmr} \approx \frac{r_{wpmr}}{r_{pda}} SIS_{s,pda} + \gamma \times \beta \tag{12}$$

NOMENCLATURE

β	Percentage of LEM participants from the survey willing to pay premium to buy more renewable energy.
γ	Weighted average ratio of increase in trade price for a market with WPMR compared to standard PDA.
p_{fit}	Electricity sell price to grid in kWh.
p_g	Electricity buy price from grid in kWh.
r_{pda}	Average trade price for a standard PDA market.
r_{wpmr}	Average trade price for WPMR market.
$SIS_{b,pda}$	Consumers SIS in a standard PDA market.
$SIS_{b,wpmr}$	Consumers SIS in a market that permits WPMR.
$SIS_{s,pda}$	Prosumers SIS in a standard PDA market.
$SIS_{s,wpmr}$	Prosumers SIS in a market that permits WPMR.

APPENDIX C
FURTHER SIMULATION BASED ANALYSIS RESULTS

See Figures 14, 15, 16, 17, 18, and 19.

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2.2 Key performance indicator simulation based analysis

Contribution

The paper of this section presents a key performance indicator analysis of various local energy market designs [119]. The analysis was conducted to determine the effect of the quantity of electricity produced/consumed within the community, the participants bidding strategy and pricing scenario on the performance of the LEM. The pricing scenarios are defined as "EEG" and "post-EEG" scenarios. The research started with a preliminary work which was published at the 2020 IEEE Electric Power and Energy Conference (EPEC) [128] and further extended to a journal paper [119]. In this paper, a community based simulation set-up was developed using Grid Singularity framework [120]. Within the framework, prosumers and consumers are enabled to trade energy with each other in a 15-minutes time step. The market cleared after every 15-minutes and energy not traded within the community is traded with the external grid which is the upstream grid. The simulation is varied by changing the annual production to consumption ratio within the community. Also, "residential households only" community was simulated and compared with a community with a combination of residential, commercial and industrial buildings. The evaluation was conducted for standard load profiles [126, 127, 122, 123] and real household profiles in different simulation scenarios. The real household profiles are load and PV profiles received from households and commercial buildings in Southern Germany for the month of August 2020. The major findings among other results revealed that the bidding strategy has more effect on the performance of an LEM compared to production-to-consumption ratio. Also, changing from the EEG to the post-EEG scenario creates additional market welfare to the consumers and prosumers within the LEM.

Publication #2: Analysis of Key Performance Indicators for Local Electricity Markets' Design

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Mukund Wadhwa	15%	Conceptualization, Data curation, Formal analysis, Methodology, Validation, Writing - review and editing.
Thomas Brenner	5%	Methodology, Validation, Writing - review and editing.
Peter Tzscheutschler	5%	Methodology, Validation, Writing - review and editing.
Thomas Hamacher	5%	Supervision, Writing - review and editing.

Analysis of Key Performance Indicators for Local Electricity Markets' Design
Analyse des indicateurs clés de performance pour la conception des marchés locaux de l'électricité

Godwin C. Okwuibe, *Member, IEEE*, Mukund Wadhwa, Thomas Brenner, Peter Tzscheutschler, and Thomas Hamacher

***Abstract*—Local electricity markets (LEMs) are investigated as a solution to provide consumers and prosumers the opportunity to have control over their electricity-related choices and make savings on their energy bills. This work analyzes market design factors, such as the number of update intervals per trading slot, the production-to-consumption (PtC) ratio, and pricing scenarios that influence the performance of an LEM. The decentralized autonomous area agent (D3A) has been used for running LEM simulations under the German regulatory framework. The results of the simulations compared using self-sufficiency, the share of market savings, and the average buying rate revealed that the performance of an LEM is highly dependent on the market design factors. Also, bidding strategy affects the performance of an LEM compared to the share of the local generation. The results imply that LEM can provide better incentives for both prosumers and consumers by providing them with the opportunity to trade their excess generation at prices higher than the feed-in tariff and lower their regular electricity tariff, respectively. With only a 20% reduction in average buying rate, it is also evident that LEMs provide a great opportunity for keeping smaller PV systems active after their 20 years of fixed remuneration under a state-sponsored incentive scheme in Germany.**

***Résumé*—Les marchés locaux d'électricité (LEMs) sont étudiés comme une solution pour offrir aux consommateurs et aux prosommateurs la possibilité de contrôler leurs choix en matière d'électricité et de réaliser des économies sur leurs factures d'énergie. Ce travail analyse les facteurs de conception du marché, tels que le nombre d'intervalles de mise à jour par créneau d'échange, le ratio production-consommation (PtC) et les scénarios de tarification qui influencent la performance d'un LEM. L'agent de zone autonome décentralisé (D3A) a été utilisé pour exécuter des simulations de LEM dans le cadre réglementaire allemand. Les résultats des simulations comparées en utilisant l'autosuffisance, la part des économies de marché, et le taux d'achat moyen ont révélé que la performance d'un LEM dépend fortement des facteurs de conception du marché. En outre, la stratégie d'appel d'offres affecte la performance d'un LEM par rapport à la part de la production locale. Les résultats impliquent qu'un LEM peut fournir de meilleures incitations à la fois pour les prosommateurs et les consommateurs en leur donnant respectivement l'opportunité d'échanger leur production excédentaire à des prix supérieurs au tarif de rachat et inférieurs à leur tarif d'électricité ordinaire. Avec une réduction de seulement 20 % du tarif d'achat moyen, il est également évident que les LEMs offrent une excellente opportunité de maintenir les petits systèmes PV actifs après leurs 20 ans de rémunération fixe dans le cadre d'un programme d'incitation parrainé par l'État en Allemagne.**

***Index Terms*—Bid, energy trading, trading price, trading agent, trading strategy.**

I. Introduction

OVER the last two decades, Germany has been setting an example on how a country can move from fossil fuel-based energy sources to low greenhouse gas emission sources. Energy transition (German: Energiewende) was initially supported by providing financial incentives in form of feed-in tariffs and preferential grid access to renewable energy (RE) sources under the Renewable Energy Source Act [German: Erneuerbare-Energien-Gesetz (EEG)] [1]. This financial support resulted in the growth of the share of RE in the electricity mix from 8.6% in 2002 to 50.5% in 2020 [2]. However, the significant increase in RE in the electricity mix has created some problems on its own. The power generation from variable RE (VRE) sources, such as wind and solar, accounts for the majority share of RE in the electricity mix. High shares of VREs require measures to be taken by the grid operators for stabilizing the grid [3]. The cost of stabilizing the grid and feed-in tariff payments to RE plant operators is passed on to the end consumer in form of network charge and EEG surcharge. In addition, other surcharges and levies are also added in order to ensure that the RE plant operation

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remains profitable. With the growth of VREs, the total cost of electricity paid by the end customer has been rising compared to neighboring countries, such as France [5], which has similar household energy consumption, but did not heavily invest in RE, such as Germany.

Consequently, the average price of electricity for a residential household has increased from 13.94 EUR ct./kWh in 2000 to 31.71 EUR ct./kWh in 2020, with only 23.4% as the retail price [6]. The EEG support scheme for a low-capacity ($\leq$100 kWp) RE power plant is valid for a period of 20 years. As a result, the first RE power plants installed under the scheme in 2000 will drop out of the financial support scheme in 2021. At the time of writing this work, no state-supported alternatives are available for the RE power plants that will stop receiving financial support via fixed feed-in tariff [7]. Therefore, continuing the operation of the smaller installations might not be a viable option. In addition, investment in energy assets, such as rooftop PV installations, heat pumps, and E-vehicles, requires high capital costs. These options are only available for consumers with significant disposable income. The current alternative to support the energy transition is by opting for a regular ecological energy tariff from the retailer. Also, with the plans of phasing out nuclear and coal-fired power plants by 2022 and 2038, respectively [9], there is an even greater need to increase the power generation from the RE sources (RESs). Part of the solution is increasing the localized generation and ensuring that the consumption happens close to the generation by using a local electricity market (LEM).

The LEM approach is gaining attention and support from researchers and businesses as a potential solution to increase the end customer participation in the electricity value chain. It provides an alternative approach to the traditional top-down hierarchy of power generation where large power plants generate electricity and transport it to the end customers via long-distance transmission and distribution infrastructures. LEMs also provide local electricity traders (LETs) with the opportunity to select their electricity sources or buyers, trade their small electricity volume, and decide the price that they are willing to pay or receive per unit (kWh). Recent research works in the area of LEM concentrate on the analysis of the participatory factors, regulation requirements, market design factors, and economic benefits of LEMs [10]–[12].

However, there is still no consensus on the market model to best utilize the benefits of LEM. To this end, we try to answer the following research questions.

1) What are the necessary conditions for the best and most beneficial LEM?
2) What are the policy recommendations for using PV power plants during the post-EEG time?

To answer these questions, we propose a framework for local electricity trading among households in a community. The effectiveness of the proposed model was evaluated using standard and real household profiles simulated over a year and one month, respectively. The markets were organized in different simulation scenarios to show the effects of the design factors. Technical and economic performances of the different simulated markets were compared using indicators, such as self-sufficiency (SS), the share of market savings (SMS), the share of individual savings (SIS), and the average buying rate. This work is an extension of the research done in [13].

The remaining parts of this work are structured as follows. Section II discusses the previous works and literature in the area of LEM. Section III describes the design approach and defines the evaluation parameters. The simulation model and data used are described in Section IV. Section V discusses the simulation results in detail, while Section VI concludes this article, giving information on how to further explore the topic.

II. Related Work

The initial mention of LEMs in research was over two decades ago [14], [15]. However, research on LEMs increased significantly in the last decade with studies in the area of the concept, methodology, trading design, trading agent, transactional object, and participants [16]. However, most research work in LEM focuses on case study analysis, whereas the in-depth understanding of LEMs is only explored recently [16]. Long *et al.* [17] in their work proposed three peer-to-peer (P2P) energy trading mechanisms, namely, bill sharing, mid-market ratio, and auction-based pricing strategy, in a community microgrid with a common grid contact point. The simulation results showed that, with moderate PV generation, P2P energy trading can result in the reduction of the community energy bill by 30%. In their further work [18], the authors implemented a battery-controlled optimized model using an energy sharing coordinator for coordinating energy trading in a common point grid-connected community microgrid. Comparing the model with conventional grid trading results in a 30% reduction of cost for community local energy traders, 20% increase in community SS, 10%–30% increase in community self-consumption, reduction in customers electricity bills, and increase in annual income of the prosumers. This eventually shows that LEM has the ability to yield economic benefits for end electricity consumers. However, Mengelkamp *et al.* [11] in their survey work show that valuation of green products, technology affinity, and community identity are the most important factors for participation in LEM. The research further concludes that community members are willing to pay more to use RESs.

The role of trading design in a market is to provide efficient allocation of the goods being traded between the participants [19]. In the case of LEMs, the possibilities for trading mechanisms vary significantly based on product traded (retail electricity, flexibility, balancing energy, and so on) and the goals of the different actors involved [16]. Mengelkamp *et al.* [16] in their review of existing literature on LEMs found several designs, such as trading via an aggregator, auction mechanism, direct trading mechanism between agents, real-time pricing mechanism, traditional electricity market design adopted for local market context, and intermarket/microgrid trading. In their review, they found the auction mechanism and direct trading mechanism between agents as the most commonly used methods.

According to [20], market designs for community LEM can be classified into full P2P, community-based, and hybrid P2P markets. In full P2P markets, the community traders are allowed to choose their electricity trading partner. However, in a community-based LEM, a defined market clearing mechanism is used to match bids (buy orders) and asks (sell orders) of buyers and sellers, respectively. A hybrid P2P market is a combination of full P2P and community-based markets. Hybrid P2P trading shows better performance and is more scalable [20]. Furthermore, the optimal economic and technical benefits of LEM require intelligent bidding strategies in a P2P LEM market clearing mechanism [21]–[23]. Several social, institutional, and economic issues faced in the traditional top-down power systems approach can be addressed by using a P2P federated power plant model. This can be done by coordinating distributed energy resources (DERs) in a community to act as virtual power plants [24]. The behavior of end costumers can be affected using game theory bidding strategy in a P2P trading model (ELECBAY) for grid-connected low-voltage (LV) distribution network [25]. Zhou *et al.* [26] use the economic and technical performance index to evaluate three market clearing mechanisms, namely, supply–demand ratio, bill sharing, and mid-market ratio from [17] and [27]. The simulation results show that P2P trading has the ability to add economic and technical values for residential electricity traders in Great Britain. Also, the supply–demand ratio clearing mechanism shows a better performance indicator compared to the other three clearing mechanisms. Further discussions on LEM design can be found on [28]–[31], while most recent research on market design is focusing on using machine learning models to coordinate LEM [32], [33].

Furthermore, LEM is gradually moving from laboratory experimental research to proof-of-concept projects [34]. The advent of blockchain attracted more research works [35]–[37] and projects in LEM as its believed that blockchain technologies can unlock most benefits of LEM [38], [39]. In this work, key performance indicators (KPIs) for evaluating an LEM are used to analyze the market factors for designing an LEM.

III. Local Electricity Market

Within this section, the market architecture, event sequence, clearing mechanism, energy trading, and evaluation parameters are described. Only the function layer of an LEM as described under the smart grid architecture model (SGAM) to evaluate the market trading infrastructure is used for the LEM design [40].

A. Market Architecture

Fig. 1 illustrates the actors, software components, hardware components, and information flow of the proposed LEM framework. The physical actors of the LEM are LETs (consumers and prosumers), aggregators, retailers, and distribution systems' operators (DSOs). The virtual actors are LET's trading agents and exchange engine. The hardware components are the smart meter gateway (SMGW) and the household energy management system (HEMS). LETs are end consumers and prosumers in the electricity network living together in a locality that wishes to trade electricity among themselves. For a prosumer or consumer to participate in local electricity trading, they need to make a contractual agreement with the

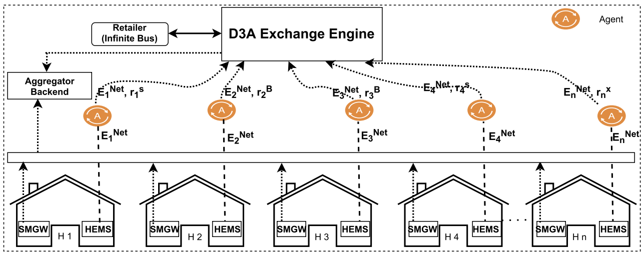

Fig. 1. Local energy market framework.

aggregator to show their willingness to join the energy trading community. If not already installed, the prosumer or consumer household/building needs to be equipped with SMGW and HEMS. The SMGW is used to measure and communicate the real-time production/consumption of the prosumer or consumer. HEMS is used to predict the future (next 15 min) energy requirements of the prosumer/consumer household. The LET trading agent is a Python-based program that decides the trading price for the LET and is responsible for posting the ask or bid to the exchange engine. Exchange engine is an open-source back-end code-base decentralized autonomous area agent (D3A) developed by grid singularity [41]. The exchange engine is used to match bids and asks in real time using an agreed market clearing mechanism. Retailers are responsible for providing/consuming the deficit/excess energy requirements of their customers. Retailers have an agreement with DSO to provide the net requirements of their customers. Furthermore, DSO is responsible for maintaining the grid. The aggregator is a separate entity responsible for connecting the prosumers and consumers to the LEM and providing them with their trading agent. They are also responsible for the settlement and transfer of funds from one actor to the other.

B. Event Sequence and Clearing Mechanism

1) Event Sequence: Fig. 2 shows the event sequence of the proposed LEM for a period of 30 min. LET agents post their bids and asks the LEM within the 15-min interval before the start of the 15-min energy exchange interval. The LEM trading interval is known as the slot length. Section III-B2 describes the clearing mechanism. Orders not matched until the end of the slot length are matched to the retailer selected by the LET. Exchange of the traded energy among the LETs happens during the 15-min interval (16th–30th minutes) from the end of the bidding and clearing period. At the end of the energy exchange interval, funds are transferred from the account of the electricity consumers (LETs) to the producers (LETs or retailers). Grid fee applicable on the traded energy is transferred from the buyer's account, i.e., consumer account to the DSO.

2) Clearing Mechanism: In an LEM, the double-sided pay-as-bid clearing mechanism offers more advantages compared to the order book market clearing mechanism [21]. The advantages are higher self-consumption, a higher percentage of traded electricity, and lower overall trade price [21]. These advantages of double-sided pay-as-bid over merit order clearing mechanism with gate closure form the bedrock for choosing a continuous double-sided pay-as-bid for the

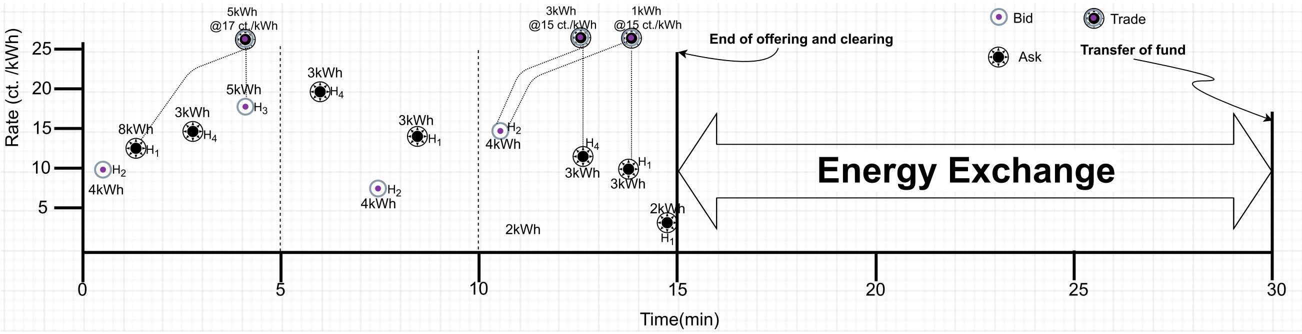

Fig. 2. LEM event sequence.

proposed model. The first 15-min time of Fig. 2 illustrates a double-sided pay-as-bid clearing mechanism. Since the mechanism is a continuous clearing, bids and asks are matched immediately, and a bid price is higher than an ask price. The price paid by the consumer after matching is the consumer's bid price. During the trading period, LET's agents can also update their bid/ask price if unmatched or partially matched. The update interval is the time after which an LET can update their bids/asks if unmatched or partially matched. The number of intervals is defined as the number of times an LET can update its bid/ask if unmatched or partially matched within the slot length. For a market with slot length, L_s (min), and update interval, L_i (min), the number of intervals, N_i, is defined as

$$N_i = \frac{L_s}{L_i}. \tag{1}$$

Fig. 2 shows a market with 5-min update intervals; therefore, the total number of intervals is 3. This means that the house agents (e.g., H1, H2, H3, and H4) can only update their bids/asks three times within a trading period. Within the first update interval (0–5 min), since H1 ask arrived before H4, H3 was matched to H1 to trade 5 kWh of electricity at H3's bid price (17ct./kWh). Since H3 was fully matched at the first interval, the H3 agent did not update their bid for the second and third intervals. However, H1's ask was partially matched. The unmatched bids of H2 and H4 were updated by their agents and sent to the clearing platform. For the second update interval, the updated price of the remaining bids is less than all the ask prices, and therefore, no matching can take place. The orders were updated by the agents again for the last update interval. Within the last update interval, all the bid prices are higher than the asks prices. However, H4 ask arrived before H1, and therefore, H2 is matched to trade 3 kWh with H4 at 15 ct./kWh. Afterward, H2 is matched to trade its remaining 1 kWh at 15 ct./kWh with H1. Since this is the last update interval, the remaining 2 kWh of H1 is traded with the retailer at the end of the update interval. Trading with the retailers is always less beneficial compared to the LET's trading among each other. Retailers' buy and sell prices form the lower and upper boundary of the trading price and usually the last option for the LETs. The retailers' buy price is the feed-in tariff.

C. Energy Trading in a Local Grid

To determine the energy and monetary balance of a household, we consider a local community consisting of N LETs in the local grid further referred to as agents. The constraints of the power lines are not considered. The feed-in of RE into the grid is assumed to be reimbursed by the retailer. For an LET i who owns a PV in their household, at time step t, the load and the generation in their PV system happening in time step $t+1$ are represented as $E^{L}_{i,t}$ [kWh] and $E^{PV}_{i,t}$ [kWh], respectively. Energy inflow and outflow are taken as positive and negative, respectively. The net energy to be traded by the LET i at time step t is defined as

$$E^{Net}_{i,t}[\text{kWh}] = E^{L}_{i,t} + E^{PV}_{i,t}. \tag{2}$$

A negative value of $E^{Net}_{i,t}$ [kWh] means that the LET i is producing energy at time step t, while a positive value of $E^{Net}_{i,t}$[kWh] means that the LET i is consuming energy at time step t. Therefore, a prosumer with a roof-top PV in their household can act as a consumer and a producer depending on their net energy at time step t.

1) Status Quo: Within this scenario, the local agent i can only fulfill their net energy requirements $E^{Net}_{i,t}$ [kWh] by trading with the retailer. The energy traded between the agent i and the retailer u is assumed to be at a constant selling and buying rate of $r^{S}_{i,u}$ and $r^{B}_{i,u}$ [ct./kWh], respectively, for all the time steps t. $r^{S}_{i,u}$ is taken as the fixed feed-in tariff of r^{f}_{i} received for supplying energy into the public grid, while $r^{B}_{i,u}$ combines retailer's opportunity cost of r^{opp}_{u}, value-added-tax (VAT) of x^{vat}%, and other applicable taxes, surcharges, and levies of r^{tax}. The equations for $r^{S}_{i,u}$ and $r^{B}_{i,u}$ can be defined as

$$r^{S}_{i,u}[ct./\text{kWh}] = r^{f}_{i} \tag{3}$$

$$r^{B}_{i,u}[ct./\text{kWh}] = \left(r^{opp,B}_{u} + r^{tax}\right)\left(1 + x^{vat}/100\right). \tag{4}$$

Consequently, the energy and monetary balance under the status quo for agent i is represented as

$$E^{Net}_{i,t}[\text{kWh}] = E^{ext}_{i,t} = E^{ext,in}_{i,t} + E^{ext,out}_{i,t} \tag{5}$$

$$\Pi^{S}_{i,t}[ct.] = E^{ext,in}_{i,t} r^{B}_{u} + E^{ext,out}_{i,t} r^{S}_{u}. \tag{6}$$

Here, $E^{ext}_{i,t}$ [kWh] and $\Pi^{S}_{i,t}$ [ct.] are the sum of externally traded energy (i.e., outside the established LEM boundary) and the monetary balance, respectively, at the end of trading slot t. Under status quo, the established boundary is an agent's point of connection to the external grid. For an LET i, $E^{ext,in}_{i,t}$ [kWh] and $E^{ext,out}_{i,t}$ [kWh] represent the external inflows and outflows of energy at time step t.

2) With LEM: For this scenario, a virtual layer of LEM is added to the local community. The external boundary is considered to be the single connection point of LEM with the rest of the local grid. After determining their net energy requirements $E_{i,t}^{Net}$ [kWh], the LETs post their asks or bids to the LEM platform for the next time step $t+1$. The ask contains the excess energy production $E_{i,t}^{Net}$ [kWh], and the price r_i^S [ct./kWh] that highlight the opportunity cost of $r_i^{opp,S}$ LET i is willing to accept. This bid contains the energy demand $E_{i,t}^{Net}$ [kWh], and the price r_i^B [ct./kWh] the LET i is willing to pay per kWh of electricity. Similar to status quo, r_i^B is calculated as a combination of opportunity cost LET i is willing to pay $r_i^{opp,B}$, VAT of x^{vat}%, and other applicable taxes, surcharges, and levies of r^{tax}. The equations for r_i^S and r_i^B can be defined as

$$r_i^S[ct./kWh] = r_i^{opp,S} \tag{7}$$
$$r_i^B[ct./kWh] = \left(r_i^{opp,B} + r^{tax}\right)\left(1 + x^{vat}/100\right). \tag{8}$$

The market is assumed to match viable bids and asks while taking the additional taxes and levies into account. The viable bids and asks are matched within the platform using the pay-as-bid mechanism. Assume a match between LET i and LET j to trade $E_{i,j,t}^{trade}$ [kWh] at the rate of $r_{i,j,t}^{trade}$ [ct./kWh] since the trade rate in a pay-as-bid mechanism is the buyer's bid, which includes the taxes and levies that are applicable on the trade. Therefore, the trade rates for buyers and sellers would be different and can be defined as buyer's trade rate $r_{i,j,t}^{trade,B}$ [ct./kWh] and seller's trade rate $r_{i,j,t}^{trade,S}$ [ct./kWh]. The equations for $r_{i,j,t}^{trade,B}$ and $r_{i,j,t}^{trade,S}$ can be defined as

$$r_{i,j,t}^{trade,B}[ct./kWh] = r_{i,j,t}^{trade} \tag{9}$$
$$r_{i,j,t}^{trade,S}[ct./kWh] = \frac{r_{j,i,t}^{trade}}{1 + x^{vat}/100} - r^{tax}. \tag{10}$$

Consequently, $E_{i,j,t}^{trade}$ can be further divided into buying trade, i.e., $E_{i,j,t}^{trade,B}$ [kWh] and selling trade, i.e., $E_{i,j,t}^{trade,S}$ [kWh] between LETs i and j. The residual generation $E_{i,t}^{ext,out}$ [kWh] and load $E_{i,t}^{ext,in}$ [kWh] not traded within the LEM are fulfilled by the retailer at a selling and buying rate of $r_{i,u}^S$ and $r_{i,u}^B$ [ct./kWh], respectively. As a result, the energy $E_{i,t}^{Net}$[kWh] and the monetary balance $\Pi_{i,t}^{LEM}$[ct.] of the LET i at time step t are shown in (11) and (12), respectively

$$E_{i,t}^{Net} = \Sigma_j^N\left(E_{i,j,t}^{trade,B} + E_{i,j,t}^{trade,S}\right) + E_{i,t}^{ext,in} + E_{i,t}^{ext,out} \tag{11}$$
$$\Pi_{i,t}^{LEM} = \Sigma_j^N\left(E_{i,j,t}^{trade,B} r_{i,j,t}^{trade,B} + E_{i,j,t}^{trade,S} r_{i,j,t}^{trade,S}\right) + E_{i,t}^{ext,in} r_u^B + E_{i,t}^{ext,out} r_u^S. \tag{12}$$

D. Parameters for Evaluating an LEM

The KPIs provide the opportunity to evaluate the effect or the importance of the factors used in the design of an LEM. The KPIs used in this work are the percentage of SS, SIS, average buying rate, and SMS. The model described in Section III-C is used to derive the mathematical formulations for the KPIs of an LEM that operates for a period of T.

1) Self-Sufficiency: SS of an LEM is the percentage of the local generation that is used to fulfill the energy requirements of the LEM without using any external sources [42]. Mathematically, it is the ratio of the sum of internal traded energy within the LEM and self-consumption of the individual households to the total load demand of the LEM. Mathematically, it is represented as

$$SS = \frac{\sum^N \sum^T \left(E_{i,j,t}^{trade} + |E_{i,t}^L - E_{i,t}^{ext,in}|\right)}{\sum^N \sum^T E_{i,t}^L} \times 100. \tag{13}$$

2) Share of Individual Savings: SIS is the share of the revenue made by individual LETs for trading within the LEM to trading without an LEM [22]. Mathematically, it is represented as

$$SIS = \frac{\sum_t^T \left(\Pi_{i,t}^S - \Pi_{i,t}^{LEM}\right)}{\sum_t^T \Pi_{i,t}^S} \times 100. \tag{14}$$

3) Share of Market Savings: SMS is the sum of the total revenue made by all LETs for trading within the LEM compared to the status quo. Mathematically, it is represented as

$$SMS = \frac{\sum_t^T \sum_i^N \left(\Pi_{i,t}^S - \Pi_{i,t}^{LEM}\right)}{\sum_t^T \sum_i^N \Pi_{i,t}^S} \times 100. \tag{15}$$

4) Average Buying Rate: The average buying rate is the average price of the total electricity traded among LETs N over a period T, in an LEM. ABR gives the local traders an indication of the extent the market is favoring buyers or sellers. Mathematically, it is represented as

$$ABR[ct./kWh] = \frac{\sum_t^T \sum_i^N \left(E_{i,j,t}^{trade} r_{i,j,t}^{trade}\right)}{\sum_t^T \sum_i^N E_{i,j,t}^{trade}}. \tag{16}$$

IV. Simulations

In order to analyze the effect of different LEM design factors, simulations of the designs were conducted using the back-end code base of the D3A framework. Retailers act as a backup to the LEMs to provide the residual energy requirements not fulfilled within the LEM. Furthermore, flexible, storage devices, and physical restrictions (electrical and thermal) of the local grid were not considered. An intraday market in a continuous double-sided auction pay-as-bid market clearing mechanism, where LETs can post their orders 15 min before delivery time, was used. Since the consumption and production profiles are provided to the platform as input data, settlement or balancing market is not required after market clearing. Each LET uses a zero intelligent bidding strategy where a random price is selected within a price range to bid for electricity within the local market platform.

Table I displays the components of the electricity pricing structure for households and commercial (with yearly consumption lower than 100 MWh) customers in Germany for the year 2020 [6]. As shown in table, electricity price is a combination of opportunity cost, network charges, various taxes, levies, and surcharges. Currently, there is no regulation available for establishing the pricing structure of an LEM in Germany. However, a regulatory niche under Energy Industry Act [German: Energiewirtschaftsgesetz (EnWG)] known as

TABLE I
COMPONENTS OF ELECTRICITY PRICE IN GERMANY FOR 2020

Components of electricity price	Residential consumers	Commercial consumers
Generation and opportunity cost	7.43	7.23
Network charges	7.75	7.12
Concession levy	1.66	1.66
Offshore-Liability levy	0.416	0.416
CHP levy (KWKG)	0.226	0.226
Levy for Interruptible loads	0.007	0.007
§19 StromNEV surcharge	0.358	0.358
EEG surcharge	6.756	6.756
Electricity tax	2.05	2.05
Value-added tax (VAT)	5.06	–
Total (EUR ct./kWh)	31.71	25.82

TABLE II
EEG MINIMUM AND MAXIMUM TRADING PRICES FOR LEM

Components	H-H/G-H	H-G	G-G
Opportunity cost	12/18	12/18	11/18
Metering fee	0.32	0.32	0.32
EEG surcharge	6.756	6.756	6.756
Value-added-tax (VAT)	3.62/4.76	-	-
Total (Euro ct./kWh)	22.70/29.83	19.08/25.07	18.07/25.07

TABLE III
POST-EEG MINIMUM AND MAXIMUM TRADING PRICES FOR LEM

Components	H-H/G-H	H-G	G-G
Opportunity cost	0/18	0/18	0/18
Metering fee	0.32	0.32	0.32
EEG surcharge	6.756	6.756	6.756
Value-added-tax (VAT)	1.34/4.76	-	-
Total (Euro ct./kWh)	8.42/29.83	7.07/25.07	7.07/25.07

"Customer Systems" (German: Kundenanlage) can be used to formulate the pricing structure for trading electricity among participants in an LEM under current regulations [43]. As an LEM can be legally defined as a Customer System, all levies and certain taxes applicable to household electricity prices are avoided. If an LEM is considered to be established in a physical microgrid setting, the fees that can be avoided are grid fees and electricity tax. Network charges are not applicable as small VRE generators do not legally qualify as an energy supplier and, therefore, cannot raise the grid-usage fee. As all the levies applicable to the price of electricity arise due to grid-related issues, they are also not applicable. According to 12b of Electricity Tax Act [German: Stromsteuer-Durchführungsverordnung (StromStV)], the electricity tax is only applicable to electricity produced by generators with a nominal power of over 2 MW [44]. As the generators in the LEM are all considerably smaller than the limit, electricity taxes are also avoided.

Tables II and III show the detailed cost of electricity in an LEM and minimum and maximum trading prices for different seller–buyer pairs for EEG and post-EEG time, respectively. The price components of trading electricity within an LEM consist of the opportunity cost of the electricity seller, metering fee, EEG surcharge, and 19% VAT. Within the EEG scenarios, the minimum opportunity cost for sellers is based on the fixed feed-in tariff received by the residential (H) and commercial (G) prosumers.

The different simulation scenarios were obtained by varying the number of intervals (N_i), the production-to-consumption (PtC) ratio, and the electricity pricing type. N_i was varied from 1 to 5 for the different PtC categories. Two pricing types, namely, "EEG scenarios" and "post-EEG scenarios" were investigated. EEG scenarios consider that LETs with rooftop PV on their household are eligible for the fixed feed-in tariff under EEG. However, this would require a change in the current regulation "Doppelvermarktungsverbot," which does not allow additional markets on top of the EEG scheme. Post-EEG scenarios assume that the PV owner has already received 20 years of remuneration under EEG and, consequently, has to shut down their PV systems if they are unable to sell their excess electricity within the LEM. Depending on the simulation data, the simulations were categorized into standard and real profile simulations. Standard profile simulations are simulations performed using household and commercial load and PV profiles from standard load and PV profiles. Real profile simulations are simulations performed using household and commercial load and PV profiles received from household and commercial buildings installed with SMGW and IR sensor-based reader combined with digital meters for measuring and communicating the metering data to the back-end database, respectively.

A. Standard Profile

The LEMs for this category were simulated for a year with 306 LETs made of 252 households, 18 office buildings, and 36 small manufacturing facilities, in 36 scenarios created by changing the combination of participants and the PtC ratio. The LETs for this category were classified into two simulation classes, namely, Class-1 and Class-2. Class-1 includes scenarios with residential households made of four prosumers and six consumers in different PtC ratios. Class-2 includes scenarios with four residential households, a bakery, an office building with PV, and a small manufacturing facility with PV in different PtC ratios. The PtC ratios are categorized into low (class-1 [0.2, 0.4] and class-2 [0.4, 0.6]), medium (class-1 (0.4, 0.6] and class-2 (0.6, 0.8]), and high (class-1 (0.6, 0.8] and class-2 (0.8, 1.0]). The household load consumption profile used for the simulation was generated using LoadProfileGenerator [45], [46] and standard load profile for the year 2019 from VDEW [47], [48]. The factors considered while generating the profiles were the number of people living in the household, their working schedule, types of household appliances used, and weather conditions for the Stuttgart region. The standard G1, G3, and G5 load profiles from StromNetz Berlin for the year 2019 [47] were used for the commercial load profiles. Consumption time series for all participants were scaled to 10 MWh/year for comparison. The annual consumption for the residential households was chosen to stay between 1600 to 5500 kWh while, for the office buildings and manufacturing facilities, between 27 000 and 52 000 kWh, respectively. In order to use unique consumption profiles for every household and commercial building, the standard load profiles were modified by adding an error

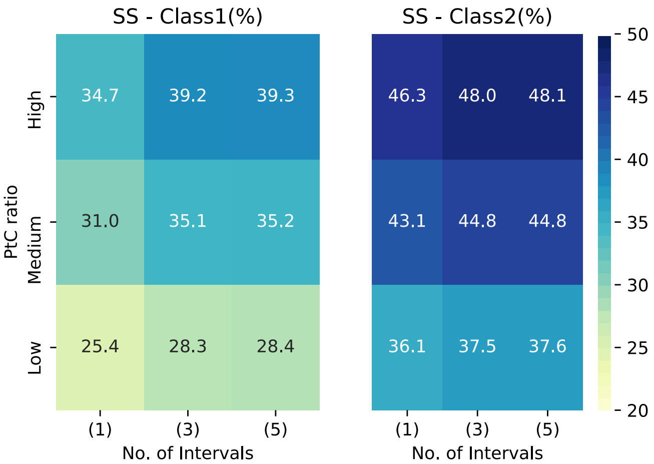

Fig. 3. SS for EEG scenarios with standard profiles.

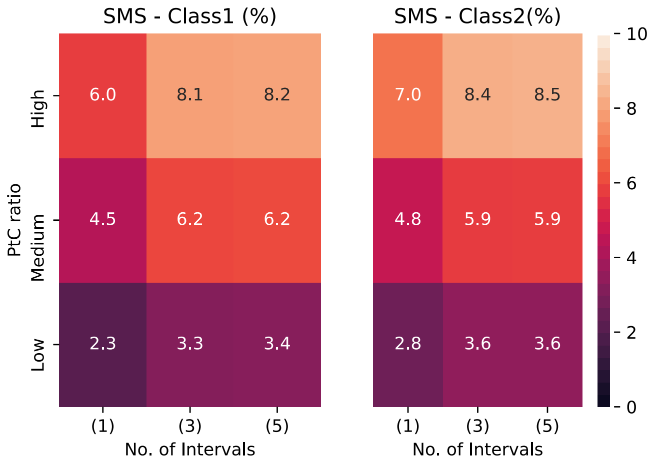

Fig. 4. SMS for EEG scenarios with standard profiles.

of 5%–30% randomly for each time step of every profile. The PV generation profiles were generated based on analysis from [49] using Renewables Ninja [50] for the region of Stuttgart. The PV systems' losses were varied between 5% and 15%, the tilt of all the PV systems were taken as 35°, and the profiles are scaled to fit the different PtC categories.

B. Real Household and Commercial Profiles

For this simulation category, 414 LETs made of 150 households and 264 commercial buildings were combined in 30 scenarios created by changing the combination of participants and the PtC ratio. The PtC were classified into very low [0.4, 0.5), low [0.5, 0.6), medium [0.6, 0.8], high (0.8, 1.0], and very high (1.0, 1.4). The load and PV profiles were collected from households and commercial buildings in Southern Germany for the month of August 2020. Standard load profiles were added to the profiles to fit the different PtC categories. In addition, the data from one of the large PV farms were scaled down by 1000, 300, 150, and 96 to achieve the low, medium, high, and very high (High**) PtC ratios, respectively. The very low (**Low) PtC category scenarios are where the large PV farm generation is zero.

V. Results and Discussion

Within this section, the results of the simulations introduced in Section IV are discussed and visualized.

A. Standard Profiles

1) Number of Intervals and Ratio of Production to Consumption:

a) Self-sufficiency: Fig. 3 displays the changes in SS as N_i increases from 1 to 5 and the PtC ratio from low to high for class-1 and class-2. For low PtC ratio, as N_i increases from 1 to 5, SS for class-1 and class-2 increases from 25.4% to 28.4% and 36.1% to 37.6%, respectively. However, the increase in SS as N_i increases from 1 to 3 is higher than from 3 to 5. Increasing N_i of the LETs provides the opportunity for more bids and asks to match and, thereby, increase the volume of energy traded and, consequently, increases the SS of the LEM. However, the effect reduces with the change of N_i from 3 to 5. This is because the LETs are already able to utilize the majority of the energy generated in the LEM, and the market is approaching its limit of SS without smart appliances or storage options.

Furthermore, for N_i equals five, as PtC increases from low to high, SS for class-1 and class-2 increases from 28.4% to 39.3% and 37.6% to 48.1%, respectively. For the same number of LETs, higher PtC leads to higher SS. Consequently, a higher volume of energy generation in the LEM leads to a bigger share of LEM's consumption being satisfied within the market. Hence, this brings about a large share of energy being traded in the market and, as a result, increases in SS. However, as the PtC increases, the SS of the LEM peaks and levels off. This is due to the misalignment of generation and consumption patterns. As the generation from rooftop PV is dependent on solar irradiation, it cannot supply during the night. Therefore, increasing the size of the PV generation cannot cover all the energy demands of the market.

b) Share of market savings: Fig. 4 shows the variation in SMS as N_i increases from 1 to 5 and the PtC ratio from low to high for class-1 and class-2. For low PtC ratio, increasing N_i from 1 to 5 increases the SMS for class-1 and class-2 from 2.3% to 3.4% and 2.8% to 3.6%, respectively. Similar to SS, the increase in SMS as N_i increases from 1 to 3 is higher than from 3 to 5. This is also due to the fact that LETs have already bought the majority of the energy generated in the LEM, and the market is approaching its maximum limit of SMS without flexibility options. For N_i equals five, as PtC increases from low to high, SMS for class-1 and class-2 increases from 3.4% to 8.2% and 3.6% to 8.5%, respectively. Also, for the same number of LETs, higher PtC leads to higher SMS. Hence, it is also evident that higher PtC results in a bigger share of LEM's consumption being satisfied within the market. This brings about a large share of energy being traded in the market and consequently, an increase in SMS. The reverse is the case for a low PtC.

2) EEG and Post-EEG Scenarios:

a) Self-sufficiency: The SS for EEG and post-EEG pricing scenarios with class-1 and class-2 LETs under different PtC categories was calculated and analyzed. Changing from EEG to post-EEG pricing scenario brings about a slight

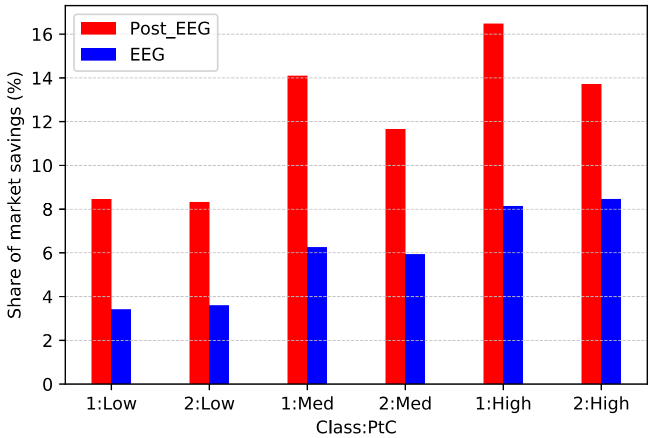

Fig. 5. SMS for EEG and post-EEG scenarios with standard profiles.

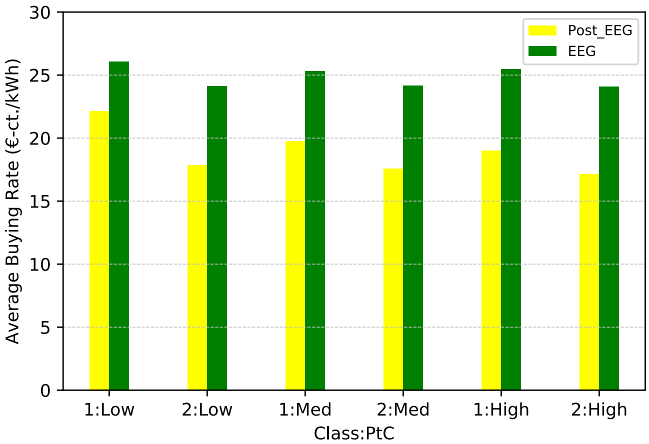

Fig. 6. Average buying rate for EEG and post-EEG scenarios with standard profiles.

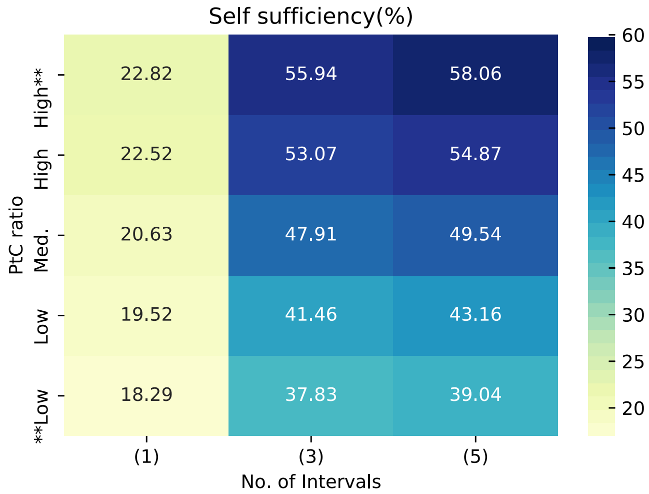

Fig. 7. SS for EEG scenarios with real household and commercial profiles.

average increase in about 0.17% on the SS of the LEM. This change is insignificant because there is no new generation added to the LEM and the trading strategy of all the participants did not change.

b) Share of market savings: The SMS for EEG and post-EEG pricing scenarios with class-1 and class-2 LETs under different PtC categories is shown in Fig. 5. Changing the pricing scenario from EEG to post-EEG increases the SMS. The average increase in the SMS is about 6.3%.

c) Average buying rate: Fig. 6 shows the average buying rates for EEG and post-EEG pricing scenarios with class-1 and class-2 LETs under different PtC categories. Varying the price from EEG to post-EEG scenario decreases the average buying rate by 5 EUR ct./kWh. This reduction is 20% of the average buying rate for the EEG scenario.

Removal of the fixed feed-in tariff in the post-EEG scenario provides the prosumers with no other option than to sell their excess generation in the LEM at any available cost. Therefore, it increases the probability of the buyers having a successful bid at a lower price. The lower cost of electricity leads to higher savings for consumers in the post-EEG scenario, which, in turn, results in an overall increase in SMS. Prosumers are still able to get compensated for their excess generation, which would ultimately save them money enough to compensate for their opportunity cost compared to the status quo where they are not able to sell their excess generation.

B. Real Household and Commercial Profiles

1) Number of Intervals and Ratio of Production to Consumption:

a) Self-sufficiency: Shown in Fig. 7 is the variation in SS as N_i changes from 1 to 5 and the PtC ratio from very low to very high for real household and commercial profiles. For a very low PtC ratio, as N_i varies from 1 to 5, SS increases from 18.3% to 39.0%. Similar to the standard load profile, there is a higher increase in SS for changing N_i from 1 to 3 compared to increasing N_i from 3 to 5. Increasing N_i means using a more accurate bidding strategy and, hence, an increase in traded volume results in an increase in SS. Furthermore, for the same number of LETs, increasing the PtC ratio results in an increase in the volume of energy to be traded and, consequently, an increase in SS. Changing the bid strategy to a more accurate strategy results in a higher increase in SS compared to increasing the PtC ratio. This is because a more accurate strategy results in matching most bids and asks within the LEM, while higher PtC ratio results in providing more energy to be traded within the LEM, which, if the strategy is not accurate, will not be traded. The SS of the real household and commercial profiles is higher compared to the standard profile of the same simulation setup and bid strategy. This is because the PV production of the month of August is higher compared to the average annual PV production. However, varying the PtC ratio and bid strategies results in a similar change in SS for both standard and real profiles.

b) Share of market savings: Fig. 8 shows the variation in the SMS by varying N_i from 1 to 5 and the PtC ratio from very low to very high for real household and commercial profiles. For a very low PtC ratio, increasing N_i from 1 to 5 results in an increase in the SMS from 3.1% to 10.6%. Also, similar to standard profiles, increasing N_i from 1 to 3 results in higher SMS compared to increasing it from 3 to 5. This is also because the LETs have already bought most of the available generated energy within the LEM using an accurate strategy and, therefore, approaching the maximum SMS at

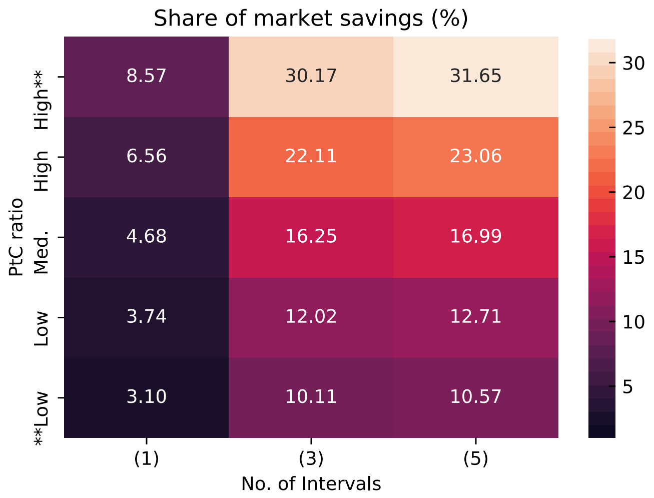

Fig. 8. SMS for EEG scenarios with real household and commercial profiles.

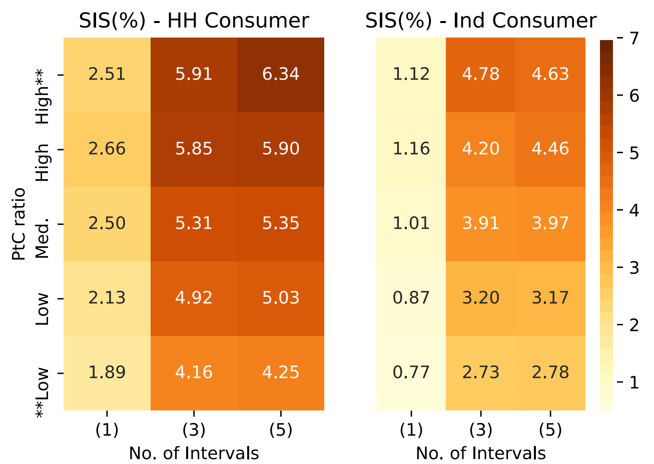

Fig. 9. SIS for household and commercial consumers.

which flexibility and storage options are required to increase the SMS. Also, increasing the PtC ratio results in an increase in the SMS of the local community. Furthermore, the SMS of the real households and commercial profiles is higher compared to the standard profile of the same simulation setup and bid strategy. This is also due to the fact that the PV production of the month of August is higher compared to the average annual PV production. However, varying the PtC ratio and bid strategies results in a similar variation of SMS for both standard and real profiles.

c) Share of individual savings—consumers: Fig. 9 shows the variation in the SIS by varying N_i from 1 to 5 and the PtC ratio from very low to very high for real household and commercial consumer profiles. Similar to SS and SMS, increasing the PtC ratio and N_i increases the SIS of both household and commercial consumers. Also, increasing N_i results in a higher increase in SIS compared to increasing PtC ratio. For each bidding strategy and PtC ratio, household consumers show a higher SIS compared to commercial consumers. This is because the bidding range of the household consumers is higher compared to the commercial consumers for each trading strategy. Also, since the retail price of electricity, as shown in Table I, is lower for commercial consumers compared to household consumers, it is more profitable for household consumers to trade on an LEM compared to commercial consumers and, hence, the higher SIS of the household consumers.

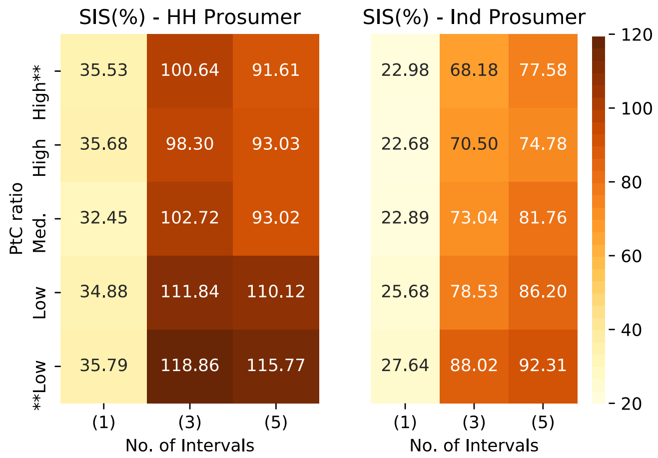

Fig. 10. SIS for household and commercial prosumers.

d) Share of individual savings—prosumers: Fig. 10 shows the variation in the SIS by varying N_i from 1 to 5 and the PtC ratio from very low to very high for real household and commercial prosumer profiles. In overall, increasing N_i results in an increase in SIS for both prosumers; however, increasing the PtC ratio results in a decrease in the SIS for both prosumers. Increasing N_i results in an increase in the bidding accuracy and, hence, creates the opportunity for the prosumers to sell their energy at a higher price, which, in turn, results in higher SIS. On the other hand, increasing the PtC ratio decreases the SIS of the prosumers because the individual excess energy of the prosumer did not increase; however, the opportunity for the consumers to trade with other producers increases. Hence, increasing the PtC ratio decreases the trading opportunity of the prosumers and, hence, leads to a reduction in the SIS of the individual prosumers. Similar to the SIS of the consumers, for each bidding strategy and PtC ratio, household prosumers show a higher SIS compared to commercial prosumers. This is as a result of the higher opportunity cost and bidding range of the household prosumers compared to commercial prosumers, as shown in Tables I and II, respectively.

2) EEG and Post-EEG Scenarios:

a) Self-sufficiency: Fig. 11 shows the SS for EEG and post-EEG pricing scenarios with real profiles. Changing the pricing scenarios from EEG to post-EEG results in an average increase in the SS of about 1.1%. This change is because of the increase in the bidding range of the post-EEG scenarios. However, similar to the standard profiles, the change in SS is small because there is no new generation added to the LEMs and the trading strategy is constant.

b) Share of market savings: The SMS for EEG and post-EEG pricing scenarios under different PtC ratios with real household and commercial profiles using N_i equals 5 is shown in Fig. 12. Similar to the standard profile, changing from EEG to post-EEG pricing scenario increases the SMS by an average of about 6.5%. This change is also a result of the increase in the bidding range in the post-EEG scenario.

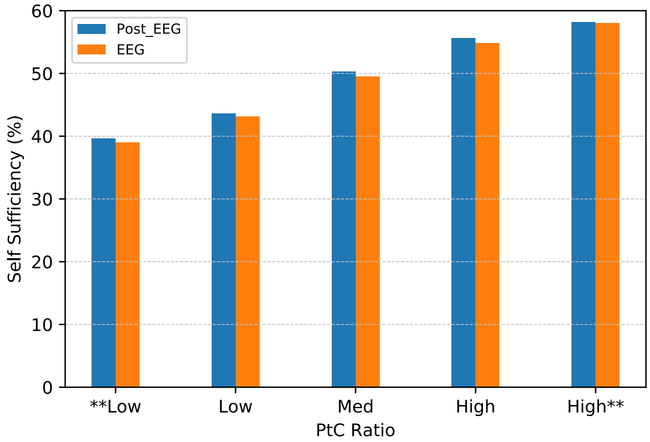

Fig. 11. SS for EEG and post-EEG scenarios with real household and consumption profiles.

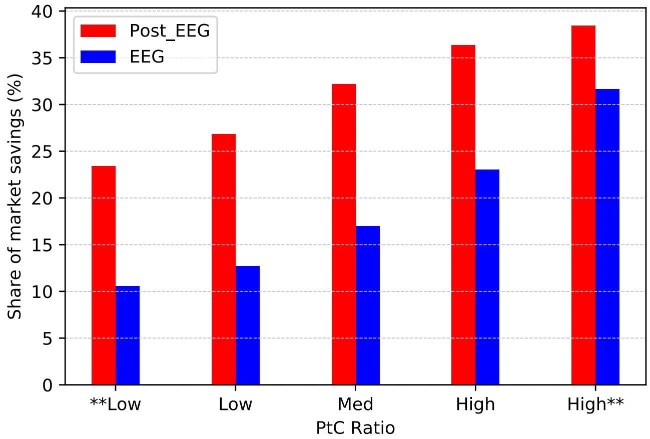

Fig. 12. SMS for EEG and post-EEG scenarios.

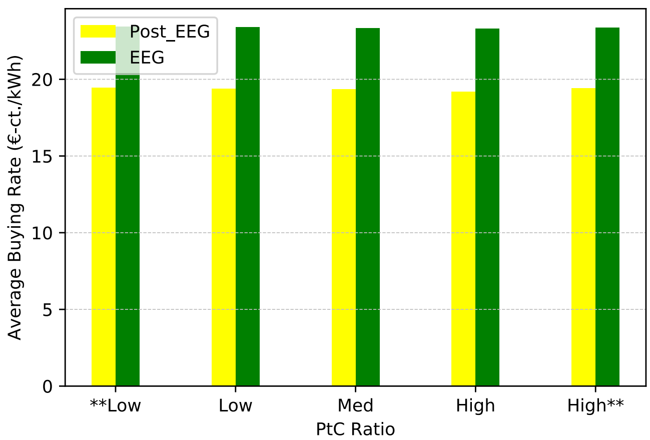

Fig. 13. Average buying rate for EEG and post-EEG scenarios.

Increasing the bidding range results in a more accurate bidding strategy, which, in turn, results in higher SMS.

c) Average buying rate: Fig. 13 shows the average buying rates for EEG and post-EEG pricing scenarios with N_i equals 5, under different PtC categories of real household and commercial profiles. Changing from EEG to post-EEG scenario decreases the average buying rate by 4.2 EUR ct./kWh. This reduction is 18% of the average buying rate for the EEG scenario and close to the 20% obtained for the standard profiles.

During the post-EEG scenario, prosumers sell their excess energy at available cost providing an opportunity for the consumers to buy energy at a lower cost compared to EEG scenarios for both standard and real household profiles. This higher bidding range results in an overall increase in SMS, a slight increase in SS, and a reduced average buying rate. The increase in SMS and SS witnessed with the real household profile compared to the standard profile is because the month of August has higher PV production compared to the average annual PV production in Southern Germany.

VI. Conclusion and Outlook

Apart from increasing the community SS, LEMs offer more financial benefits to the LETs compared to trading with the retailers. This work verified the usability and effectiveness of an LEM by conducting an analysis of LEMs under the current regulatory framework and incentive schemes in Germany. Multiple microgrid configurations were simulated using a continuous double-sided pay-as-bid market auction in the D3A simulation framework with a multiround zero intelligent bidding strategy. The followings form the key findings of the research.

1) Positive (increasing number of update intervals) variation of the number of update intervals per trading slot results in an increased bidding accuracy, which further brings about an increase in SS and SMS of the LEM.
2) Increasing the share of the local generation (i.e., High PtC) in the LEM creates high liquidity in the market. Thus, the traded volumes increase, while a decrease in the average buying rate is observed.
3) Increasing the share of generation of an LEM also leads to an increase in the SMS.
4) Changing from EEG to post-EEG regulations creates additional market welfare to the LETs.
5) The greater effect of the number of update intervals compared to the share of local generation shows that bidding strategy has more effect on the performance of an LEM compared to the share of local generation within the LEM.
6) Increasing the number of update intervals in a multiround auction LEM beyond three advances the SS only a little. This is because the LEM is approaching its maximum SS at which it requires flexibility or storage device in the form of power-to-heat, electric vehicles, or stationary storage devices to further increase the SS.

LEM has the ability to create valuable financial support for prosumers after the fixed feed-in tariff under EEG expires and, hence, can enable them to retain their electricity production and, consequently, maintain the share of RE within the grid. Furthermore, LEMs provide better financial incentives for the end customer to invest in energy assets compared to the existing state-sponsored incentive schemes. Therefore, LEMs can be a bigger driving force to increase small-scale RE generation and other energy assets. In addition, LEMs can provide the disfranchised energy end customer a better way to contribute to the energy transition. This, in turn, contributes in reaching the decarbonization goal within the electricity sector and further reduces the dependency on feed-in tariff. For efficient and effective running of LEM without putting charges on end consumers who do not participate in LEM, there should be a regulatory framework responsible for sharing of taxes and levies among LEM participants only. In addition, the German regulatory system needs to extend its framework to include pathways for the creation of LEMs and define the roles and responsibilities of the different actors required for its efficient working.

To further extend this work, future research will focus on simulating LEM scenarios with grid constraints being considered. In addition, the research will also focus on determining the optimal scenario for participation in markets based on LEM. The KPIs also need to be further extended to incorporate factors, such as market power. Furthermore, hardware-in-the-loop laboratory environment testing will be conducted before the final stage, which will be validating the results in a field test.

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3 Local energy market models and bidding strategies

3.1 Local energy market models

Scientific context

LEM market model is used to provide the market bidding/offering format, algorithm for allocation of traded energy between prosumers and consumers, payment/settlement rule, market cycle and event sequence of the LEM [50, 66]. Developing an efficient LEM requires an efficient market model design. The literature contains several studies that propose different market models for LEM design [111, 60, 29, 112, 113, 114, 115, 48, 45, 129]. Notwithstanding several studies and market models proposed in the literature, LEM is yet to be adopted in practice by many countries.

In this section, three papers are presented. The first paper presents a hierarchical model for the organisation of agent-based local energy markets [130]. The model was implemented and evaluated using the framework developed by Grid Singularity [120] and the LEM key performance indicators already developed in [119], respectively. In the second paper [131], an advanced clustering approach was developed for P2P energy trading of electricity between consumers and prosumers in an LEM. The first two papers are examples of centralized market models and show similar advantages. The third paper[132] presents a decentralized LEM platform for trading energy in an LEM based on the prosumers' and consumers' preferences.

3.1.1 Hierarchical local energy market models

Contribution

The paper of this section presents a mathematical model and an evaluation of hierarchical multi-agent local energy market model developed using Grid Singularity exchange [120]. The research started with a preliminary study [133], conducted and published as a conference paper at the 2021 International Conference on Smart Energy Systems and Technologies (SEST) before the final study which was published as a journal paper. Fig. 3.1 displays the schematic of the hierarchical model proposed in the paper. In this model, consumers and prosumers form sub-communities and trade energy with each other within the sub-communities. Energy not traded within a sub-community is forwarded to a higher community in the hierarchy by the sub-community agents. In this way, energy is traded from one hierarchy to another until the last hierarchy which is the up stream grid. Hence, energy not traded within the large community is traded with the upstream grid. The model was evaluated by comparing a single- and multi-layer hierarchical models.

The single and multi-layer LEM models were verified using combination of load and production profiles from German households [121], standard load profiles [122, 123], Renewables Ninja [124, 125] and LoadProfileGenerator [126, 127] in a 15-minutes time step market. The results from the simulations showed that the multi-layer hierarchical model creates additional economic and technical benefits for household prosumers as compared to trading within the single-layer hierarchical LEM. However, the single-layer LEM model appears to be more beneficial for industrial prosumers.

Figure 3.1: Schematic of hierarchical multi-agent model developed using Grid Singularity exchange [120]. Figure adopted from [130].

Publication #3: Evaluation of Hierarchical, Multi-Agent, Community-Based, Local Energy Markets Based on Key Performance Indicators

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Sarah Hambridge	7%	Conceptualization, Software, Writing—review and editing.
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Article

Evaluation of Hierarchical, Multi-Agent, Community-Based, Local Energy Markets Based on Key Performance Indicators †

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Abstract: In recent years, local energy markets (LEMs) have been introduced to empower end-customers within energy communities at the distribution level of the power system, in order to be able to trade their energy locally in a competitive and fair environment. However, there is still some challenge with regard to the most efficient approach in organising the LEMs for the electricity exchange between consumers and prosumers while ensuring that they are responsible for their electricity-related choices, and concerning which LEM model is suitable for which prosumer or consumer type. This paper presents a hierarchical model for the organisation of agent-based local energy markets. According to the proposed model, prosumers and consumers are enabled to transact electricity within the local energy community and with the grid in a coordinated manner to ensure technical and economic benefits for the LEM's agents. The model is implemented in a software tool called *Grid Singularity Exchange (GSyE)*, and it is verified in a real German energy community case study. The simulation results demonstrate that trading electricity within the LEM offers economic and technical benefits compared to transacting with the up-stream grid. This can further lead to the decarbonization of the power system sector. Furthermore, we propose two models for LEMs consisting of multi-layer and single-layer hierarchical agent-based structures. According to our study, the multi-layer hierarchical model is more profitable for household prosumers as compared to trading within the single-layer hierarchical LEM. However, the single-layer LEM is more be beneficial for industrial prosumers.

Keywords: bidding strategy; decentralized energy system; grid singularity exchange; local energy market; multi agent system; peer-to-peer

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1. Introduction

1.1. Motivation and Literature Review

Electricity markets aim to manage the increasingly complex power system and ensure that all the electricity generated within the electricity grid is accounted and paid for by the consumers. In recent years, the fast growth of distributed energy resources (DER), while supporting the energy transition, also added a high level of complexity in maintaining the power grid's reliability and stability. This daunting challenge cannot be resolved by the conventional top-down, centralized energy management approach due to the system complexity and variable nature of renewable generation [1]. As a solution, local energy markets (LEMs) have been introduced as new trading structures for the exchange of energy between prosumers and consumers at the distribution level of the power system, thus keeping the system cost and customer electricity prices relatively feasible and ensuring that electricity is consumed close to where it is produced. Authors in [2] defined LEMs as platforms for trading among prosumers and consumers within a geographic and social neighbourhood, in which the security of supply is ensured by superimposing the LEM into the up-stream grid. In addition, LEMs provide an enabling platform for energy participants to trade their services such as electricity, flexibility, and heat at the distribution level in a competitive and economically efficient way [3]. In the literature, several structures have been proposed for energy trading and sharing in LEMs, such as the peer-to-peer (P2P), community-based or pool market, and hybrid frameworks [4–7], which are explained in the following.

In the P2P framework, a prosumer has the opportunity to choose the energy product by assigning attributes of the actors whom they are willing to sell their energy production to or buy their demand from. In a situation where prosumers are unable to provide the attributes of their proposed trading partners, they are randomly matched [8]. Additionally, the concept of federated power plants based on self-organised P2P incentives for organising the DER through a bottom-up grid approach was proposed by [9]. The proposed concept promised to reduce the economic, social, and institutional challenges facing the traditional top-down power system approach. Authors of [10] proposed a multi-agent architecture for P2P electricity trading within micro-grids (MGs) that is based on blockchain technology. In [11], the authors proposed a P2P energy market platform based on a multi-class energy management system for coordinating energy trading between prosumers, distribution grid and in the wholesale market. The multi-class model added financial, social, philanthropic, and environmental values by accounting for the individual prosumer's preferences for their generated electricity. The P2P electricity trading platform for matching producer and consumer agents based on a two-sided market matching theory was proposed by [12]. The proposed platform was profitable and most suitable for aggregators managing prosumers with different degrees of willingness to buy or sell electricity. The authors of [13] proposed an agent-based simulation framework and evaluation index to compare the performance of P2P sharing market mechanisms.

On the other hand, a community-based local trading framework is generally defined as a centralized platform responsible for matching energy producers and consumers in the LEM with the use of an agreed market matching mechanism [5]. Optimization models (such as linear programming, mixed-integer linear programming, nonlinear programming, and mixed-integer nonlinear programming), mathematical methods (such as simplex method, branch-and-bound technique, quadratic programming, interior-point method, game theory, point estimate method, and fuzzy logic), and heuristic methods (e.g., particle swarm optimization algorithm and genetic algorithm) are used in the literature to organise trades in a community-based LEM [14–17]. The authors of [18] proposed an iterative algorithm for energy transactions between distribution network operators and the LEM's participants in order to provide additional profit to all participants. The authors of [19] implemented the uniform pricing, pay-as-bid, generalized second-price, and Vickrey–Clark–Groves clearing methods and evaluated the benefits and the efficiencies of the mechanisms. In [20], the authors suggested that the bidding strategy of the LEM participants have more impact on the performance of community-based LEMs as compared to increasing the production-to-consumption ratio of the local community. In [21], the authors proposed the advantages of a hierarchical approach for energy and flexibility trading in the LEM considering distribution network constraints and the offering/bidding strategies of prosumers.

According to [7], a hybrid LEM is a type of market that combines the attributes of both P2P and community-based trading frameworks. In their work, the authors of [5] derived the mathematical formulation of a hybrid market framework as a combination of the P2P and community-based market frameworks. A hybrid market framework based on a decentralized blockchain was proposed by [22] for exchanging energy among local electricity traders within a distribution grid. Decentralized energy management offers a wide range of options for prosumers to exchange their electricity product/demand and can also provide a higher level of transparency. Apart from the proposed LEM models found in the literature, there are also software tools supporting the operation and implementation of LEMs. Most of these tools are still in the research and development stage but are approaching market readiness [4,5,23].

1.2. Contributions and Organisation

Whilst there are several studies proposing different structures and models for LEMs, there is still a gap in the literature concerning the organisation of community-based LEMs by prosumers and consumers. This includes questions on which LEM models are suitable for different consumer and prosumer types and an analysis of the models' behaviour using varied market-clearing mechanisms. Consequently, in this paper, we focus on the following research question: which market structure and clearing mechanisms are most suitable for local electricity markets? In order to answer this, we propose mathematical models for the multi-layer and single-layer hierarchical organisation of agent-based local energy markets implemented on an interface and open-source code base of the Grid Singularity Exchange (GSyE, previously termed D3A) in order to model, simulate, and optimize energy trading in local communities. Furthermore, we evaluate the model using key performance indicators such as self-sufficiency, self-consumption ratio, share of market savings, and share of individual savings to analyse the model that is suitable for different types of consumers and prosumers. The prosumers and consumers are classified as household consumers, industrial consumers, commercial consumers, household prosumers, commercial prosumers, and industrial prosumers. Notably, this paper is an extended version of [24], where authors compared different market clearing mechanisms such as the one-sided pay-as-offer, the two-sided pay-as-bid, and the two-sided pay-as-clear market clearing mechanisms, and then showed the advantages of each clearing mechanism in a single-layer local electricity market. All in all, the main contributions of the paper can be summarized as follows:

- We propose a mathematical model for the hierarchical organisation of agent-based local energy markets.
- We implement the proposed hierarchical model in the Grid Singularity Exchange as an open-source code base software tool and show how it can be used for local electricity exchange.
- We analyse the benefits of electricity trading in hierarchical local energy markets with the use of key performance indicators for different market structures, market-clearing mechanisms, and different consumer and prosumer types.

The remaining sections of this work are structured as follows. The proposed LEM architecture, exchange agent, and bidding strategies are described in Section 2. The LEM data, community setup, and price components are discussed in Section 3. Section 4 presents the results of our case studies and discusses the findings in details. Finally, the paper is concluded in Section 5.

2. Proposed Hierarchical, Community-Based Local Energy Market Structure

In this section, the proposed community-based LEM structure, its actors, the mathematical model as well as the offering/bidding and matching strategies are explained. In our proposed model, the smart grid architecture's function layer is used to evaluate the market trading infrastructure of the proposed LEM design based on [25]. Furthermore, the distribution grid constraints are not considered in our proposed LEM structure because of the lack of real data for the studied local energy community.

2.1. Agents

The agents of the proposed LEM design can be classified into physical and virtual agents. The physical agents can be the distribution system operator (DSO) and the LEM's participants consisting of consumers, prosumers, and producers. The virtual agents include the exchange agent. Moreover, the LEM consists of external agents, the so-called retailer and grid agent, to enable transactions between the local community and the up-stream grid in case the LEM participants cannot transact electricity with the local community. The functions of the LEM's agents are explained in the following:

- **The Local Market Operator (LMO)** determines the market clearing (one-sided pay-as-offer, two-sided pay-as-bid, and two sided pay-as-clear) mechanism of the LEM and provides access to the LEM's individual participants. The LMO is responsible for maintaining the LEM exchange agent. The LMO is also in charge of providing market clearing results and market statistics to the DSO, retailer, and the LEM participants.
- **LEM participants,** also known as local electricity traders (LETs), are local agents who own loads, distributed energy resources, and energy storage systems that are empowered to transact in the LEM.
- **The DSO** is in charge of maintaining the distribution grid and ensuring grid stability. Moreover, the DSO expresses the state of the distribution grid (e.g., grid-connected and islanded modes based on the interaction between the distribution network and the up-stream grid) as well as assigns static and dynamic grid charges per kWh for electricity traded between LEM participants. Moreover, the grid charges are the cost of maintaining the distribution grid, which is paid per kWh of electricity transacted within the local community; this is incorporated in the process of clearing bids and offers.
- **Retailers** have a contract with LETs to provide them with continuous energy if they are unable to trade electricity with the LEM.
- **The grid agent** or the up-stream grid agent acts as an external agent of the LEM, and the local community is able to trade electricity with that in the case of extra local production or consumption. Moreover, the grid agent is modelled as an infinite bus on the distribution grid.
- **The exchange agent** is an open-source code based on Python and other programming tools; it was developed by Grid Singularity and is called the Grid Singularity Exchange [26]. The exchange agent is responsible for receiving bids and offers, matching the orders, and sending the matched results to LETs, retailers, and the DSO. In the exchange agent, physical agents are defined as those who serve as digital twins for electricity assets such as PVs, electrical loads, and energy storage systems. In addition to electricity asset agents, there are grid and virtual organisation-based agents, including the household, block, sub-community, and community agents in the hierarchy. Thus, the virtual community agents are responsible for energy transactions and forwarding unmatched bids and offers from a lower level to a higher level in the hierarchy. Finally, the grid agent provides the LEM with the external retail electricity price for allowing energy transaction with the up-stream grid.

2.2. Hierarchical Structure for Electricity Trading in the LEM

Figure 1 shows a simple hierarchical structure of agents within the multi-agent framework. To describe the mathematical model for the physical and virtual agents, we consider load, PV, and storage devices in a local community k that participate in local electricity trading. The load, PV, and storage agents can be represented by ($\mathcal{L}_k$), ($\mathcal{P}_k$), and ($\mathcal{E}_k$), respectively. If $\mathcal{H}_k$ represents the agent of the community k, then we have the following:

$$\{\mathcal{P}_k \cup \mathcal{L}_k \cup \mathcal{E}_k\} \subset \mathcal{H}_k. \tag{1}$$

If community k is a sub-community of community i with a set of other sub-communities, and the total number of sub-communities of community i is N, then we have:

$$\{\mathcal{H}_1 \cup \mathcal{H}_2 \cup \cdots \cup \mathcal{H}_N\} \subset \mathcal{A}_i, \tag{2}$$

where $\mathcal{A}_i$ represents the agent of community i, and $\mathcal{H}_1, \mathcal{H}_2, \ldots, \mathcal{H}_N$ represent the agents of sub-communities 1 to N, respectively. Furthermore, if community i is a sub-community of community j, and there exist other sub-communities within community j and an energy storage device belonging to community j, the total number of sub-communities belonging to community j is M, and the ESS agent of the community j storage system is represented by ($\mathcal{E}_j$). Then, we have the following:

$$\{\mathcal{E}_j \cup \mathcal{A}_1 \cup \mathcal{A}_2 \cup \cdots \cup \mathcal{A}_M\} \subset \mathcal{R}_j, \tag{3}$$

where $\mathcal{R}_j$ is the agent of community i. Finally, from (3), a community agent is defined as a virtual agent that can consist of other agents of communities or sub-communities, and agents representing physical assets within the community. This way, the community agent creates a hierarchical organisation of agents belonging to its own local area. Section 2.3 describes the setup of the hierarchical model, and how bids and offers are forwarded by the community agents.

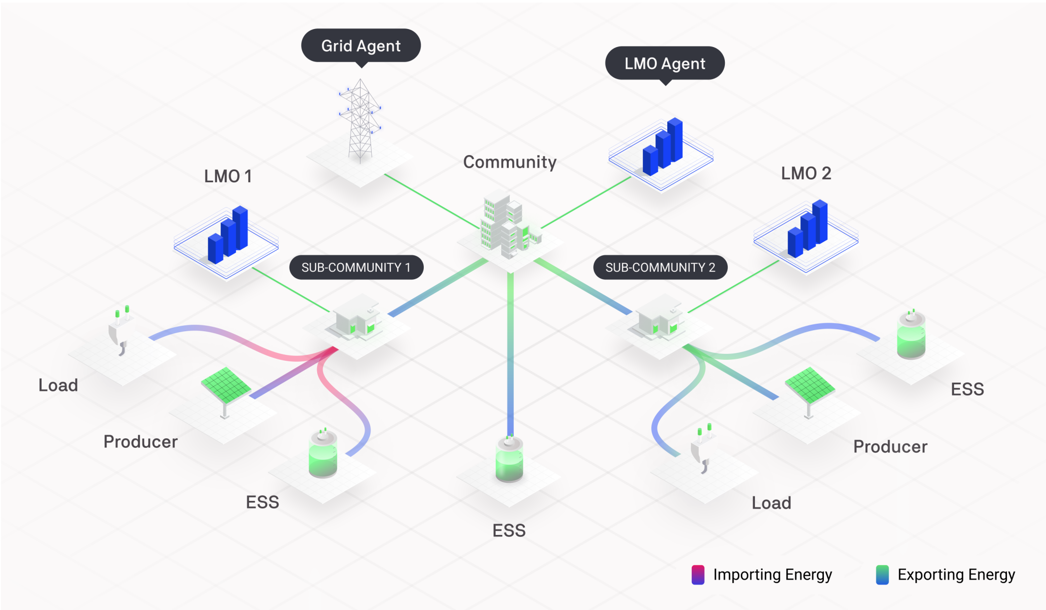


Figure 1. Multi-agent framework and hierarchical structure of LEMs based on the GSyE.

2.3. Hierarchical Bids and Offers Forwarding

In this paper, the analysed market clearing mechanisms in the exchange agent are the two-sided pay-as-bid (TPB) and the two-sided pay-as-clear (TPC) mechanisms. The LEM serving as a case study is a real-time market, set to 15 min time slots. Agents submit their bids and offers within the 15 min interval before the energy exchange time. Each time slot, T^{slot}, is divided into 15 s tick lengths, T^{tick}, as represented by (4):

$$N^{tick} = \frac{T^{slot}}{T^{tick}}, \tag{4}$$

where N^{tick} is the number of ticks per time slot. Depending on the type of market clearing mechanism, the tick length is the time before market clearing is triggered within the platform. According to the proposed LEM design, physical agents first submit their bids and offers directly to a local community in the first hierarchy. The first local community hierarchy level of the studied model is a block, the next level is a zone, and the final level is a community called the higher community. Assuming that the area of the first local community hierarchy is i, the set of bids in the community i from different physical agents at tick t is represented by $B_{i,t}$, and the set of offers of physical agents from the same community at tick t is represented by $S_{i,t}$. As the market has N^{tick} number of ticks, physical agents are able to submit their bids and offers at any tick. The set of bids submitted to community i at tick t is represented by the following:

$$B_{i,t} = \{b_{i,1,t}, b_{i,2,t}, \ldots, b_{i,n,t}\}, \forall t < N^{tick}, \tag{5}$$

where n is the total number of bids (physical agents) in community i at tick t. In other words, physical agent n is allowed to submit only one bid to the local community at tick t. $b_{i,n,t}$ is bid n of the bids in community i at tick t. Each bid ($b_{i,n,t}$) contains the quantity of energy ($q^b_{i,n,t}$) that the agent wishes to buy and the maximum price ($p^b_{i,n,t}$) per kWh of electricity that the agent is willing to pay for, as shown in (6):

$$b_{i,n,t} = (q^b_{i,n,t}, p^b_{i,n,t}), \forall t < N^{tick}, \tag{6}$$

In the same way, the set of offers submitted to community i at tick t is represented by the following:

$$S_{i,t} = \{s_{i,1,t}, s_{i,2,t}, \ldots, s_{i,m,t}\}, \forall t < N^{tick}, \tag{7}$$

where m is the total number of offers (physical agents) in community i at tick t. Physical agent m is allowed to submit only one offer to the local community at tick t. $s_{i,m,t}$ is the offer m in community i at tick t. Each offer contains the quantity of energy ($q^s_{i,m,t}$) that the agent wishes to sell and the minimum price ($p^s_{i,m,t}$) per kWh of electricity that the agent is willing to receive, as represented by (8):

$$s_{i,m,t} = (q^s_{i,m,t}, p^s_{i,m,t}), \forall t < N^{tick}. \tag{8}$$

The set of all bids and offers submitted to community i at tick t is the union of the set of bids and offers from (5) and (7), respectively. This is presented by the following equation:

$$\begin{aligned}\{B_{i,t} \cup S_{i,t}\} = \{&(q^b_{i,1,t}, p^b_{i,1,t}), (q^s_{i,1,t}, p^s_{i,1,t}), (q^b_{i,2,t}, p^b_{i,2,t}), (q^s_{i,2,t}, p^s_{i,2,t}), \ldots, \\ &(q^b_{i,n,t}, p^b_{i,n,t}), (q^s_{i,m,t}, p^s_{i,m,t})\}\end{aligned} \tag{9}$$

Thus, Equation (9) can be simplified into (10).

$$\{B_{i,t} \cup S_{i,t}\} = \{O_{i,1,t}, O_{i,2,t}, \ldots, O_{i,(m+n),t}\}, \tag{10}$$

where $O_{i,(m+n),t}$ is defined as the $(m+n)$th order submitted to community i at tick t. This order can be a bid or an offer to buy or sell a defined quantity of energy at a maximum/minimum price limit in ct/kWh. The LEM is cleared at the end of every tick. Hence, the matched bids and offers at the end of tick t is represented in the following equation:

$$\{B_{i,t} \Pi S_{i,t}\} = \{\underline{O}_{i,1,t}, \underline{O}_{i,2,t}, \ldots, \underline{O}_{i,y,t}\}, y \leq n, m, \tag{11}$$

where $\underline{O}_{i,y,t}$ is the yth match order at tick t containing the match quantity ($\underline{q}_{i,y,t}$), price ($\underline{p}_{i,y,t}$), identity of buyer (I^b), and identity of seller (I^s), as represented by (12):

$$\underline{O}_{i,y,t} = (\underline{q}_{i,y,t}, \underline{p}_{i,y,t}, I^b, I^s), y \leq n, m. \tag{12}$$

At same time, the unmatched bids and offers are represented by the set containing the difference between all submitted orders and the matched orders, as expressed in (13):

$$\{\overline{B}_{i,t} \cup \overline{S}_{i,t}\} = \{(B_{i,t} \cup S_{i,t}) - (B_{i,t} \Pi S_{i,t})\} \tag{13}$$

Equation (14) expresses the unmatched orders for d number of orders.

$$\{\overline{B}_{i,t} \cup \overline{S}_{i,t}\} = \{\overline{O}_{i,1,t}, \overline{O}_{i,2,t}, \ldots, \overline{O}_{i,d,t}\}, d \leq (n+m) - y. \tag{14}$$

Similar to Equation (9), for an f number of unmatched bids and an h number of unmatched offers, Equation (14) can be re-expressed in terms of bid and offer quantities and prices, as presented in (15):

$$\begin{aligned}\{\overline{B}_{i,t} \cup \overline{S}_{i,t}\} = \{&(\overline{q}^b_{i,1,t}, \overline{p}^b_{i,1,t}), (\overline{q}^s_{i,1,t}, \overline{p}^s_{i,1,t}), (\overline{q}^b_{i,2,t}, \overline{p}^b_{i,2,t}), (\overline{q}^s_{i,2,t}, \overline{p}^s_{i,2,t}), \ldots, \\ &(\overline{q}^b_{i,f,t}, \overline{p}^b_{i,f,t}), (\overline{q}^s_{i,h,t}, \overline{p}^s_{i,h,t})\}, d = f + h.\end{aligned} \tag{15}$$

Suppose community i is a sub-community of community j. The market is modelled such that the agent of community i ($\mathcal{A}_i$) will forward the unmatched bids and offers of community i to community j after two ticks. Similar to (9), the bids and offers of community j for n and m numbers of bids and offers, respectively, at the $(t+2)$th tick is given by the following equation:

$$\begin{aligned}\{B_{j,(t+2)} \cup S_{j,(t+2)}\} = \{&(q^b_{j,1,(t+2)}, p^b_{j,1,(t+2)}), (q^s_{j,1,(t+2)}, p^s_{j,1,(t+2)}), (q^b_{j,2,(t+2)}, p^b_{j,2,(t+2)}), \\ &(q^s_{j,2,(t+2)}, p^s_{j,2,(t+2)}), \ldots, (q^b_{j,n,(t+2)}, p^b_{j,n,(t+2)}), (q^s_{j,m,(t+2)}, p^s_{j,m,(t+2)})\}, \forall (t+2) < N^{tick}.\end{aligned} \tag{16}$$

Since community j is a large community with many other sub-communities, (16) can be expressed in terms of the orders from different sub-communities. If there are w sub-communities in community j, (16) can be expressed as follows:

$$\{B_{j,(t+2)} \cup S_{j,(t+2)}\} = \{(B_{1,(t+2)} \cup S_{1,(t+2)}), (B_{2,(t+2)} \cup S_{2,(t+2)}), \ldots, (B_{w,(t+2)} \cup S_{w,(t+2)})\} \tag{17}$$

where $(B_{w,(t+2)} \cup S_{w,(t+2)})$ is a set containing the bids and offers submitted to community j by the agent of community w, $\mathcal{A}_w$ at tick $(t+2)$. Since i is a sub-community within community j, we have the following equation:

$$\{B_{i,(t+2)} \cup S_{i,(t+2)}\} \subset \{(B_{1,(t+2)} \cup S_{1,(t+2)}), (B_{2,(t+2)} \cup S_{2,(t+2)}), \ldots, (B_{w,(t+2)} \cup S_{w,(t+2)})\}. \tag{18}$$

Hence, the orders submitted to community j by virtual agent ($\mathcal{A}_i$), which represent the sub-community i that exists in community j at the $(t+2)$th tick is as follows:

$$\begin{aligned}\{B_{i,(t+2)} \cup S_{i,(t+2)}\} = \{&(\overline{q}^b_{i,1,t}, \overline{p}^b_{i,1,t} - G_j), (\overline{q}^s_{i,1,t}, \overline{p}^s_{i,1,t}), (\overline{q}^b_{i,2,t}, \overline{p}^b_{i,2,t} - G_j), (\overline{q}^s_{i,2,t}, \overline{p}^s_{i,2,t}), \ldots, \\ &(\overline{q}^b_{i,f,t}, \overline{p}^b_{i,f,t} - G_j), (\overline{q}^s_{i,h,t}, \overline{p}^s_{i,h,t})\},\end{aligned} \tag{19}$$

where G_j is the grid fee for local community j at the simulation time slot. Comparing Equations (15), (16), and (19), we obtain the following:

$$\{\overline{B}_{i,t} \cup \overline{S}_{i,t}\} \subset \{B_{j,(t+2)} \cup S_{j,(t+2)}\}, \forall Li \subset Lj. \tag{20}$$

In this way, bids and offers are forwarded from a lower community or area hierarchy to a higher one. This forwarding of bids from lower to higher hierarchies happens as far as $t < N^{tick}$ and for all lower communities whose local area (L_i) is contained in the local area of the higher community (L_j). At $t = N^{tick}$, the remaining electricity quantity is traded with the up-stream grid at the grid price. Hence, for our case study, where we have three community hierarchies (blocks, zones, and higher communities), the reason for the 15 s tick length is to ensure that even the bids/offers submitted at the last minute of the 15 min market slot is forwarded in order to reach the up-stream grid agent if not traded within the LEM.

2.4. Trading Strategies for Physical Agents

The update interval is defined as how often an agent updates its bid and offer prices using the interval trading strategy. In the exchange agent, an interval-based trading strategy is defined for each physical agent, which is described in the following section.

2.4.1. EL Agents

The consumer defines the minimum and maximum rate at which they are willing to buy electricity. Equation (21) defines the algorithm for the load interval bidding strategy.

$$\Delta r^b = \frac{(r^{b,f} - r^{b,i})}{(T^s - T^i)} \times T^i, \tag{21}$$

The final and initial buying rate are $r^{s,f}$ and $r^{s,i}$, respectively. T^s and T^i represent the slot length and the update interval. The EL agent tries to buy electricity first at the lowest rate defined by the consumer. After a defined simulation update interval, the buying rate is increased by Δr^b if the trade is unsuccessful or partially successful. As represented in (21), the buy price is increased continuously after every update interval until all the electricity demands are provided, or until the defined maximum rate is reached, as shown in Figure 2a.

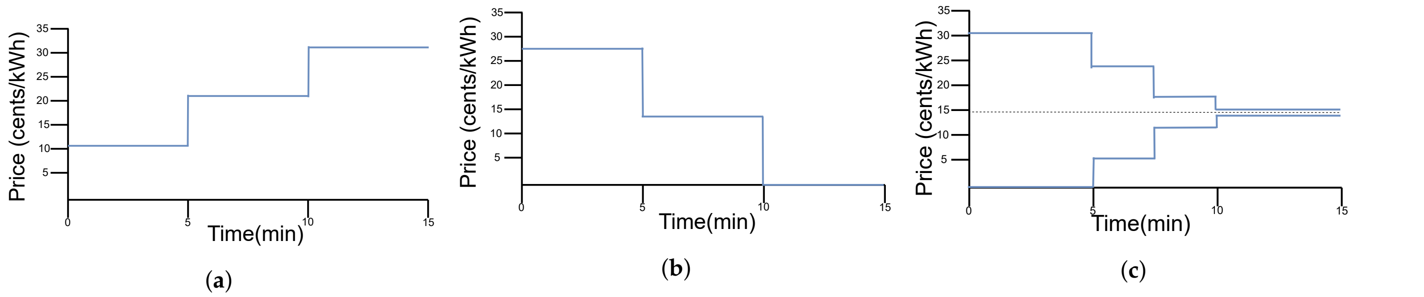


Figure 2. Trading strategy for (**a**) Load, (**b**) PV, and (**c**) battery agent.

2.4.2. EP Agents

Just as the EL agent, the initial and final trade rates are defined for the EP agents. However, the EP agents first try to sell their electricity at the maximum rate. This maximum rate is known as the initial selling rate. After every update interval, the selling rate is reduced by Δr^s based on Equation (22) if the energy quantity produced by the EP is not matched or just partially matched.

$$\Delta r^s = \frac{(r^{s,i} - r^{s,f})}{(T^s - T^i)} \times T^i, \tag{22}$$

where $r^{s,i}$ and $r^{s,f}$ represent the initial and final selling rates of the EP, respectively. The reduction in the EP's selling rate continues until all the EP electricity generation is sold or the defined minimum rate is reached, as shown in Figure 2b.

2.4.3. ESS Agents

The ESS agent trading strategy is a combination of the EL and EP trading strategies, with a defined boundary for the entire range of electricity rates, as shown in Figure 2c. Hence, the ESS agent trading rate is split into the upper and lower price ranges. The upper and lower price ranges are the selling and buying price ranges, respectively. ESS agents submit two orders to the exchange at each market slot that contain a bid and an offer. The bid price is determined using the lower price range and the load bidding strategy after each update interval. Simultaneously, the offer price is determined using the upper price range. This simple strategy is used by the ESS to buy energy at a cheaper rate and sell to the community at a higher one. However, in the local community, the cost of buying electricity from the ESS is always cheaper compared to buying it from the up-stream grid.

2.5. Performance Indicators

LEM performance indicators are parameters used to access the performance of an LEM. The LEM key performance indicators we used to evaluate our model are the share of individual savings, community self-sufficiency, and the self-consumption ratio. An additional performance indicator, known as the P2P closeness index, was also used to analyse our model. The performance indicators are defined as follows:

Share of individual savings: The share of individual savings (SIS) is the percentage of savings made by an individual prosumer or consumer for trading in the LEM as compared to trading without the LEM [20]. SIS is presented in (23), where $\Pi_{j,t}$ and $\Pi^*_{j,t}$ are the net costs for trading electricity without and with the LEM, respectively, for agent j at time t.

$$SIS_j = \frac{\sum_t (\Pi_{j,t} - \Pi^*_{j,t})}{\sum_t \Pi_{j,t}} \times 100, \tag{23}$$

Community self-sufficiency: Community self-sufficiency (SS) is the percentage of electricity demanded by the local community agents that is produced within the community, as defined in [27]. The community SS is expressed by (24), where $E_{j,i,t}$ is the amount of energy traded between EP agent j and EL agent i at time t.

$$SS = \frac{\sum_{j(j \neq i),i,t} (E_{j,i,t} + |L_{jt} - P^{ep}_{jt}|)}{\sum_{j,t} L_{jt}} \times 100 \tag{24}$$

Community share of market savings: Community share of market savings (SMS) is the sum of the shares of individual savings made by each local agent for trading within the LEM as compared to trading without the LEM [27]. The community SMS is represented in (25).

$$SMS = \frac{\sum_{j,t} (\Pi_{j,t} - \Pi^*_{j,t})}{\sum_{j,t} \Pi_{j,t}} \times 100, \tag{25}$$

P2P closeness index: The P2P closeness index is defined for the first time in this paper and provides information on how the total electricity exchanged within a community is geographically close, from the source of production to the point of consumption. It gives information on how close the electricity consumer is to the producer within a community where both actors exchange electricity. Equation (26) represents the P2P closeness index (CI):

$$CI = \frac{\sum_{j(j \neq i),i,t} E_{j,i,t} \times R^f}{\sum_{j(j \neq i),i,t} E_{j,i,t}} \times 100, \tag{26}$$

where R^f is the trade index and is in the range of [0, 1] ($0 \leq R^f \leq 1$), depending on how far the prosumer is from the consumer. This means that the closer the prosumer is to the consumer, the higher the trade index. Table 1 displays the trade index for different combinations of the buyers and sellers' geographic location.

Table 1. Trade index for different prosumer–consumer combinations.

Location of Buyer and Seller	Trade Index
Same block	0.8
Different blocks but same zone	0.6
Different zones but same community	0.4
Different communities	0.2

3. Simulation Setup

In this paper, several simulation scenarios are considered through different market clearing mechanisms by varying the community production-to-consumption ratio (PtC) and the number of hierarchies per local electricity market setup. To assess the performance of the hierarchical market model, we analysed the impact of different market models on an LEM. In this way, single-layer and multi-layer, hierarchical, agent-based local energy markets are studied utilising market key performance indicators to determine the most beneficial model for the LEM. The data and price components of the different simulation scenarios are described in the following sections.

3.1. Data Description

The LEM was simulated during a period of one week, with 120 LETs consisting of 68 household consumers, 4 commercial consumers, 7 commercial prosumers, 6 industrial prosumers, and 35 household prosumers in 28 simulation scenarios created by changing the combination of market clearing mechanisms, the number of hierarchy levels, and the annual PtC ratio. The load profile was a combination of profiles from [28], LoadProfileGenerator [29,30], and standard load profiles [31,32]. The varying factors, while using the LoadProfileGenerator software, were the number of occupants in each apartment, the work schedule of the occupants, types of household appliances, and age group of the occupants. The Stuttgart region was used for all the profiles. The commercial and industrial profiles used are standard load profiles from StromNetz Berlin for the year 2019 [31]. The annual consumption of the commercial profiles was between 25,000 kWh and 30,000 kWh, while for the industrial profiles, it was between 49,000 kWh and 54,500 kWh. A random error in the range of 5–30% was added to each time step of every commercial and industrial profile to ensure the uniqueness of the data for each LET. The PV production profiles were based on Ref. [33] using Renewables Ninja [34] for the Stuttgart region. The losses of the PV systems were varied between 5% and 15%. All the profiles were generated with a tilt angle of 35° of the PV. In the setup file, 14 households and one commercial prosumer were equipped with battery storage, with capacities ranging between 7.5 kWh and 13.5 kWh and maximum absolute power between 3.5 kW and 5.25 kW. Additionally, two community storage systems with a capacity of 140 kWh and 120 kWh and a maximum power of 40 kW were included in the local community. All storage systems had a minimum allowed state of charge of 10%.

3.2. Price Components

Two community configurations, namely single and multi-layer, hierarchical, agent-based local communities, were evaluated using different market clearing mechanisms. For both community models, the large community (higher community) was classified into sub-communities called zones. The zones were further classified into blocks. Table 2 shows the hierarchical arrangement of the large community, sub-communities, zones, and blocks. The prosumer and consumer types consist of household (HH), commercial (CM), and industrial (IND) types. The HHS and CMS are household and commercial prosumers with storage systems, respectively. In addition, the households were randomly assigned to different blocks, and the blocks were randomly assigned to different zones. Moreover, blocks were considered as households in the same building, and none of the blocks had more than one commercial prosumer. Since industrial prosumers and consumers have higher capacities, they were also classified separately under the zones. Thus, none of the blocks had any industrial consumers/prosumers. As zones contain LETs that are close to each other, local grid fees for trades within a zone were half of the community local grid fee. Consequently, blocks contained LETs that belong to a building block (e.g., an apartment) and could trade electricity without using the external grid. For trades within a block (blk), consumers only paid for the metering fees and VAT in addition to the energy cost.

The price component for both LEM models is shown in Table 3. The price components for trading within the local community include the energy price of the electricity producer, metering fee, local grid fee, and a 19% value-added tax (VAT) [35]. The energy price is the amount of money (cents/kWh) that a producer will receive for feeding electricity into the LEM. The metering and the local grid fees are surcharges paid for maintaining the metering infrastructure and the local distribution grid, respectively. The value-added tax (VAT) is the 19% paid for buying electricity from the local community. This is usually 19% of the sum of the energy price, metering, local, and up-stream grid fees. An additional surcharge known as the up-stream fee is added if the electricity is traded with the up-stream grid.

Table 2. Hierarchical arrangement of local traders.

Community	No. of Pros [Type]	No. of Cons [Type]	Sub-Communities	Community Storage
Blk-1	3 [HH]	4 [HH]	-	-
Blk-2	2 [HH]	4 [HH]	-	-
Blk-3	4 [HH]	5 [HH]	-	-
Blk-4	-	4 [HH]	-	-
Blk-5	1 [HH], 1 [HHS]	3 [HH]	-	-
Blk-6	1 [HH], 1 [HHS], 1 [CMS]	4 [HH]	-	-
Blk-7	2 [HHS]	3 [HH]	-	-
Blk-8	1 [HH], 1[HHS]	4 [HH]	-	-
Blk-9	2 [HHS]	4 [HH]	-	-
Blk-10	2 [HH]	3 [HH]	-	-
Blk-11	2 [HH]	3 [HH]	-	-
Blk-12	2 [HH], 1 [CM]	4 [HH]	-	-
Blk-13	2 [HH]	4 [HH]	-	-
Blk-14	2 [HHS]	3 [HH]	-	-
Blk-15	2 [HHS]	3 [HH]	-	-
Blk-16	1 [HH], 2 [HHS]	4 [HH]	-	-
Blk-17	1 [HHS]	4 [HH]	-	-
Blk-18	-	4 [HH]	-	-
Zone-A	2 [CM]	1 [CM]	[Blk-1, Blk-4]	1
Zone-B	2 [CM]	-	[Blk-5, Blk-9]	1
Zone-C	1 [CM]	2 [CM]	[Blk-10, Blk-13]	-
Zone-D	2 [IND]	1 [CM]	[Blk-14, Blk-18]	-
Zone-E	4 [IND]	-	-	-
Community	-	-	[Zone-A, Zone-E]	-

Table 3. Price components for hierarchical community and with the up-stream grid.

Components	Block Trades	Zonal Trades	Community Trades	Up-Stream Grid Trades
Energy price (ct/kWh)	[0 24.50]	[0 23.50]	[0 22.50]	[0 17.75]
Metering fee (ct/kWh)	0.32	0.32	0.32	0.32
Local grid fee (ct/kWh)	-	1.61	3.33	3.33
Up-stream grid fee (ct/kWh)	-	-	-	4.75
Value-added-tax (VAT) (ct/kWh)	[0.06 4.72]	[0.37 4.83]	[0.85 4.96]	[1.60 5.35]
Total (ct/kWh)	[0.38 29.54]	[2.30 30.26]	[4.50 31.11]	[10.00 31.50]

The total energy price was capped at 31.5 cents/kWh, which was based on the average electricity cost in Germany [36]. For the single-layer community model, there were no sub-community agents, and therefore the local agents (device agents) were able to trade electricity directly in the local community based on the market clearing mechanism, as shown in Figure 3. The higher-community agent was responsible for coordinating this market, and the electricity not traded within the community was bought/sold from/to the external up-stream grid agent by the higher-community agent. However, for the multi-layer community model, each sub-community had its own sub-community agent responsible for coordinating the trade within the sub-community, as shown in Figure 4. Electricity not traded within the sub-community was forwarded to the higher hierarchy by the sub-community agent.

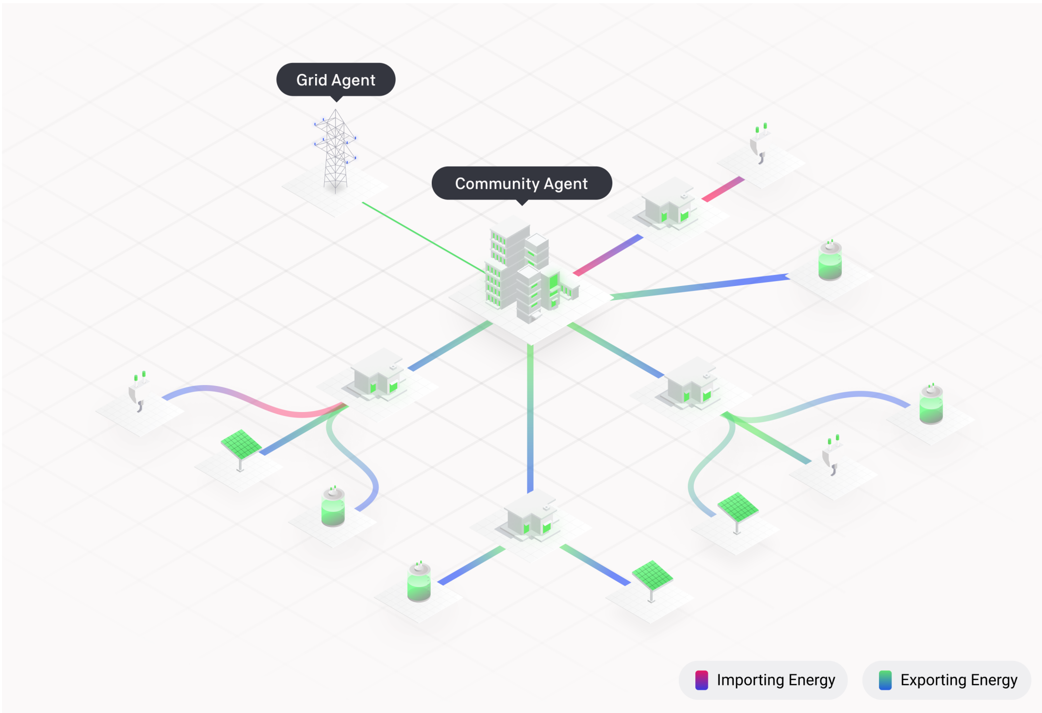


Figure 3. Single-layer, hierarchical, agent-based LEM.

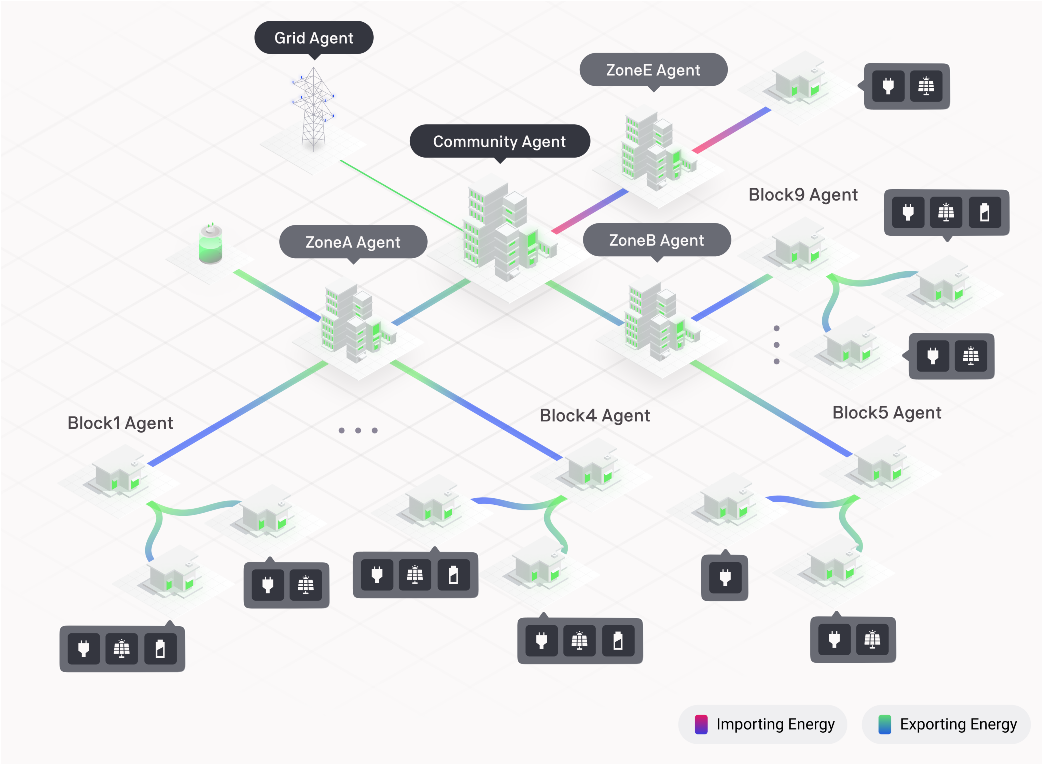


Figure 4. Hierarchical community as a multi-layer, hierarchical, agent-based LEM.

4. Results and Discussion

4.1. Energy Exchange per Community Block

In this section, the impact of different market models on local electricity trading is assessed. Figure 5a shows the energy exchange for selected community blocks with single-layer and multi-layer community setups using the two-sided, pay-as-bid market clearing mechanism. Internal trade is the energy traded between the device agents within a sub-community block. Total import is the total energy imported to a sub-community from the higher sub-communities, communities, and the up-stream grid. The sum of the energy exported to the higher sub-communities, communities, and up-stream grid from a sub-community is the total export of the sub-community. Comparing the higher and lower graphs of Figure 5a, it is evident that for all community blocks, internal trade is higher for the multi-layer as compared to the single-layer community. Furthermore, the total import and total export of the blocks are higher for the single-layer community as compared to the multi-layer community. Since the multi-layer community organises the market in a greater hierarchical form than the single-layer model, it ensures that local agents first trade electricity at the lowest sub-community level and forward only untraded energy to the higher communities. This results in higher levels of internal trade and in lower total import and total export for the multi-layer community as compared to the single-layer community.

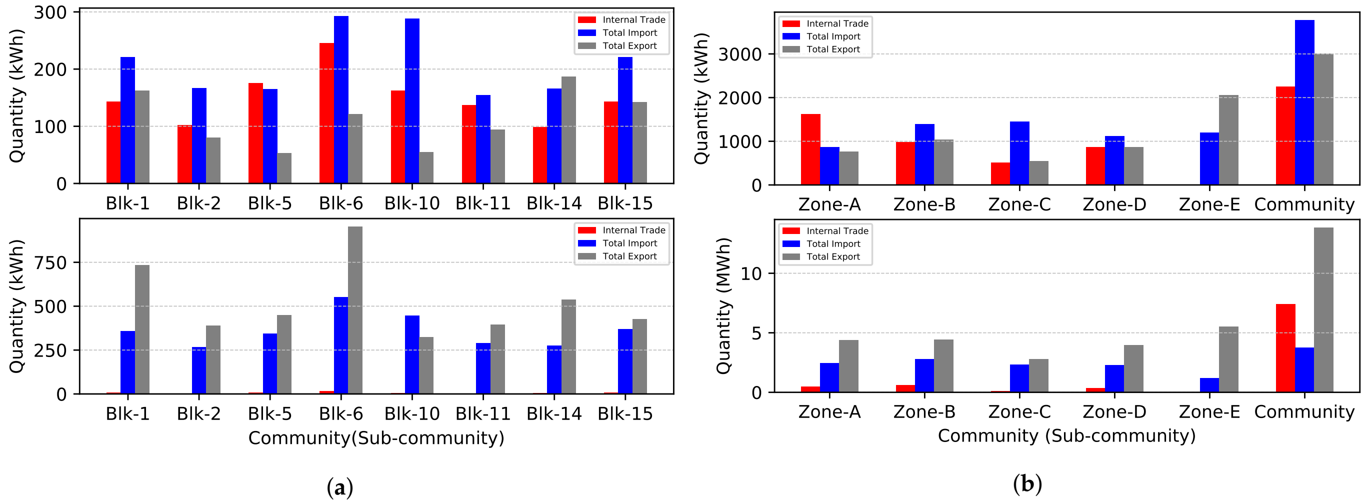


Figure 5. Energy exchange per (**a**) block, (**b**) zone, and higher community for the single-layer (**lower graph**) and multi-layer (**upper graph**) models.

4.2. Energy Exchange per Community Zone and Higher Community

Figure 5b displays the energy exchange of all the zones and higher communities with the single-layer and multi-layer community setups using the two-sided, pay-as-bid market clearing mechanism. The internal trade of a zone is the energy traded between the blocks and the device agents within a zone at the zonal level. In the same way, the internal trade of the higher community is the energy traded between the blocks, zones, and device agents within the higher community at the higher-community level. The total import of a zone is the total energy imported to the zone from the higher community and the up-stream grid. The total import of the higher community is the total energy imported to higher community from the up-stream grid. Moreover, the total export of a zone is the total energy exported to the higher community and the up-stream grid from the zone. The total export of the higher community is the total energy exported to the up-stream grid from the higher community. It is important to mention that all zones (from Zone-A to Zone-E) are sub-communities of the higher community.

The internal trade of all zones are higher for the multi-layer community compared to the single-layer community. Moreover, the total export and total import of each zone for the multi-layer community are lower compared to those of the single-layer community. Thus, it is evident that the multi-layer community coordinates the market trades better than the single-layer community. Furthermore, the total import of the higher community for the single-layer and the multi-layer communities is the same. This shows that both models only import energy that cannot be produced within the higher community from the up-stream grid. However, the internal trades of the higher community for the single-layer community is greater compared to the multi-layer community. Since the single-layer community is not coordinated, most of its trades take place at the higher-community level. This further results in higher internal trades and total export for the higher community within the single-layer community as compared to those of the multi-layer community.

Figure 6 shows further information on the electricity exchange for selected blocks and all the zones, including the higher community of the single-layer community. The external trades (external import and external export) of a community or sub-community are energy traded from the higher communities within the hierarchy and not from the up-stream grid. The external trades of the sub-community blocks and zones are higher compared to the internal trades. Hence, most of the trades for the single-layer community take place externally because the trades are not coordinated and thus happen randomly. The external trade of the higher community is zero because the higher community is the highest hierarchy of the LEM. Hence, any trade which is not made within the higher community is exchanged with the up-stream grid. Furthermore, the total import of the higher community is equal to its import from the grid (Imp4mGrid), and the total export of the higher community is equal to its export to the grid (Exp2grid).

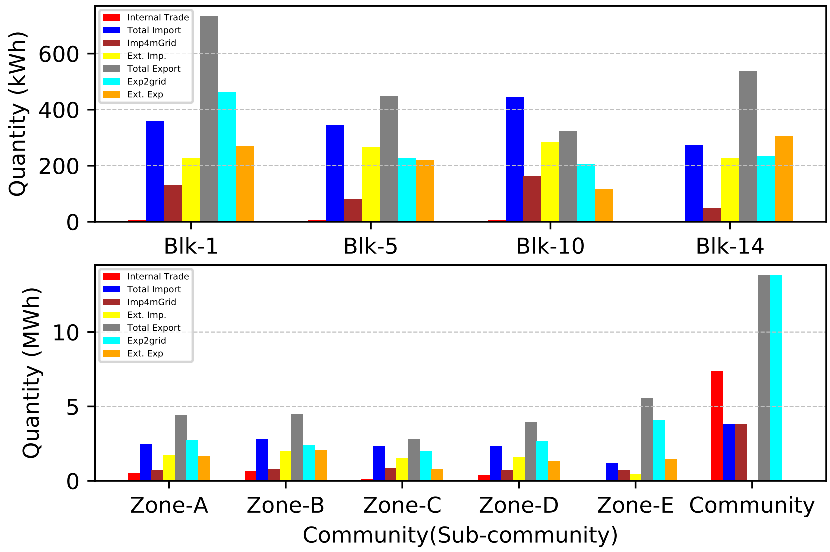


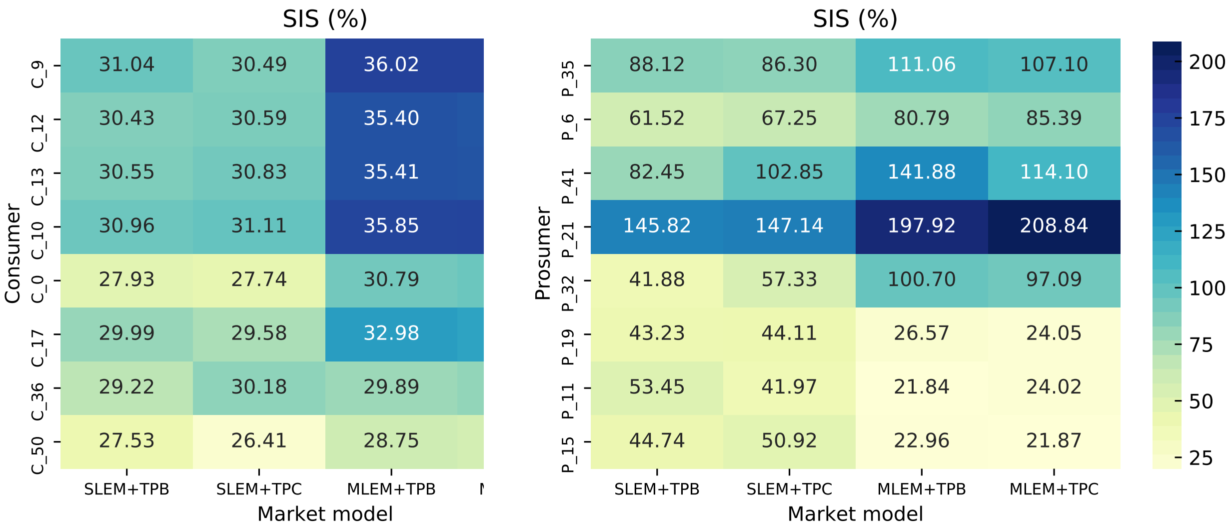
Figure 6. Energy exchange per block (**upper graph**) and zone (**lower graph**) for a single-layer community.

4.3. Comparison of Single-Layer and Multi-Layer, Hierarchical Local Energy Market Models

In this section, the market models for singe-layer and multi-layer hierarchical LEMs are compared in terms of the share of individual savings, share of market savings, community self-sufficiency, self-consumption ratio, and average trade rate with varying market clearing mechanisms.

4.3.1. Share of Individual Savings

Figure 7a shows the SIS for selected households (C_{50}, C_{36}, C_{17}, and C_0) and commercial (C_{10}, C_{13}, C_{12}, and C_9) consumers for different market models. The SLEM + TPB is defined as a market model with a single-layer hierarchical model for local energy trading based on the two-sided, pay-as-bid (TPB) market clearing mechanism. In the same way, the MLEM + TPC represents a market model with a multi-layer hierarchical structure of the local transaction based on the two-sided, pay-as-clear (TPC) market clearing mechanism. The single-layer and multi-layer market models are described in Section 3.2. From Figure 7a, it is evident that the multi-layer model creates more SIS for both household and commercial consumers of the TPC and TPB market clearing mechanisms as compared to the single-layer model. This is because the multi-layer community provides an opportunity for the consumers to buy their electricity from prosumers in their neighbourhood at a cheaper price and thus avoid a certain percentage of grid fees, which provides opportunity for the consumers to save more as compared to trading with prosumers outside their neighbourhood. However, the SIS of the commercial consumers is higher compared to that of the household consumers. Since the commercial consumers trade a higher amount of electricity as compared to household consumers, their SIS is higher than that of the household consumers.



(**a**) (**b**)

Figure 7. Share of individual savings for selected (**a**) consumers and (**b**) prosumers.

The SIS for selected industrial prosumers (P_{15}, P_{11}, and P_{19}), household prosumers (P_{32}, P_{21}, and P_{41}), and commercial prosumers (P_6 and P_{35}) is displayed in Figure 7b for different market models. As seen in Figure 7b, changing from the single to the multi-layer community model increases the SIS of commercial and household prosumers. Similar to the case of consumers, trading with the multi-layer community provides the opportunity for the household and commercial prosumers to sell their electricity at a more beneficial price, which in turn creates additional SIS for the prosumers. On the other hand, changing from the single-layer to the mutli-layer LEM model decrease the SIS of the industrial prosumers (P_{15}, P_{11}, and P_{19}), as shown in Figure 7b. This is because the industrial prosumers are not located within blocks, and most industrial prosumers are located in a separate zone due to their large capacity; hence, they are unable to take advantage of the multi-layer community. In other words, they are unable to benefit from selling their electricity at a rate that is better for consumers who are located in another zone. Furthermore, with a single-layer LEM model, all the local electricity traders compete directly with each other to trade electricity at the same hierarchical level. This provides the industrial prosumers with the opportunity to trade more of their electricity with consumers and prosumers who are not located within their zone at a more beneficial rate. This external electricity bought/sold from/to outside of the industrial prosumers' zone (Zone-E) but not from the upstream-grid is known as external import/export (Figure 6). Thus, unlike the household and industrial prosumers, a single-layer LEM model is more beneficial to industrial prosumers as compared to the multi-layer LEM model.

4.3.2. Community Self-Sufficiency

Figure 8a displays the community SS for increasing the production-to-consumption (PtC) ratio of the community under the four different market models. While the SS increases with an increasing PtC ratio, the market model types do not impact the community SS because the quantity of electricity imported from the up-stream grid is the same for the four models described, as seen in Figure 5b. This is because the cost of trading with the up-stream grid is higher for all the models. Hence, trading with the up-stream grid is the last option for the local agents since they have the same trading strategy.

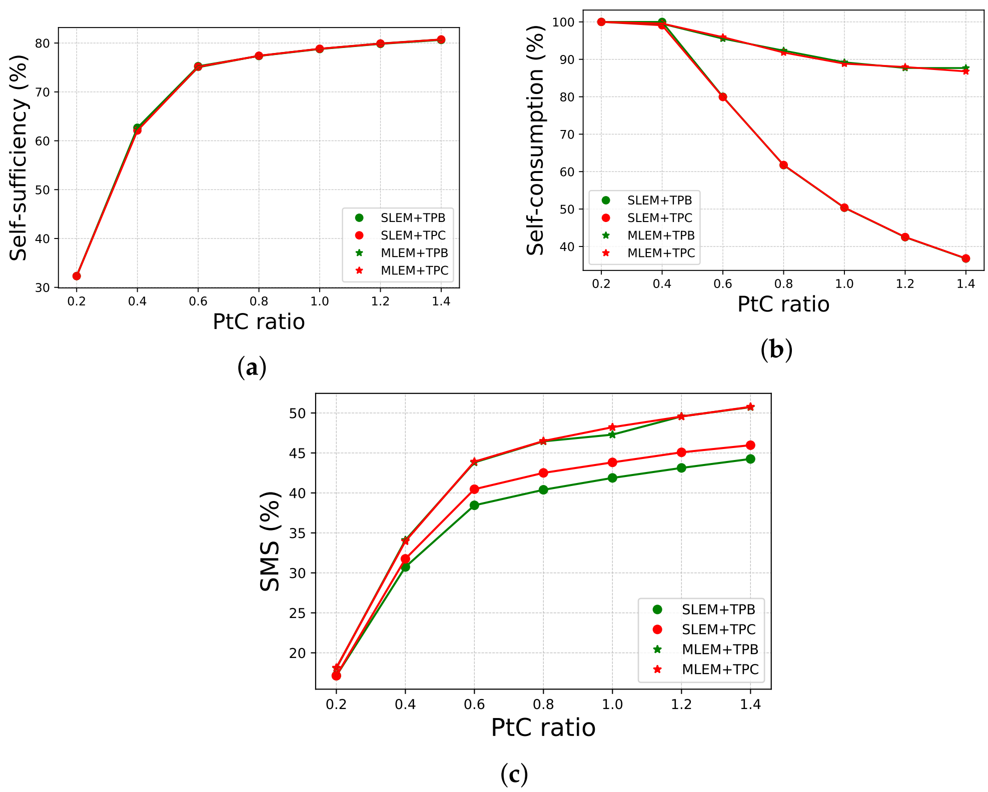


Figure 8. (**a**) Community self-sufficiency, (**b**) self-consumption, and (**c**) share of market savings for varying PtC ratios.

4.3.3. Community Self-Consumption

The variation in the self-consumption (SC) ratio of communities with varying PtC ratios is shown in Figure 8b. The SC is constant with the increase of the PtC ratio from 0.2 to 0.4 for all the models, as shown Figure 8b. However, increasing the PtC ratio results in a decrease in the SC of the community for all the models with a PtC ≥ 0.4. Furthermore, the reduction rate of the SC is higher for the single-layer market models (SLEM + TPB and SLEM + TPC) as compared to the multi-layer LEM models. In other words, increasing the PtC ratio means producing more electricity within the local grid. Since less (low PtC ratio) electricity is produced within the community with a PtC ratio less than 0.4, all the electricity produced within the community is consumed inside the community. This results in a constant 100% SC ratio, with PtC ratios from 0.2 to 0.4. Moreover, increasing the PtC ratio to higher than 0.4 causes some of the electricity produced within the local community to be exported to the up-stream grid. However, the export quantity is higher for the single-layer communities as compared to the multi-layer communities, as illustrated in Figure 5b. The increase in the export quantity to the up-stream grid resulting from uncoordinated single-layer communities is in line with the decrease in the SC ratio of single-layer communities compared to the increasing PtC ratio of multi-layer communities.

4.3.4. Community Share of Market Savings

Figure 8c displays the community SMS with varying PtC ratios for the different market models. Increasing the PtC ratio increases the community SMS for all the models. However, the multi-layer community model creates an additional SMS compared to single-layer communities with an increasing PtC ratio. This is due to the fact that using the multi-layer community model reduces the quantity of electricity exported to the up-stream grid as a result of the multi-layer community coordination strategy. This provides additional revenue to the local market players, which then increases the SMS of the community.

4.3.5. Community Average Trade Price

The average trade price of the TPB market clearing mechanism with the single and multi-layer LEM models of a community is shown in Figure 9. For both models, the average trade price is between 5.5 and 31.5 ct/kWh. During the day, the average trade price is from 15 to 5.5 ct/kWh, while the average trade price is between 23.5 and 31.5 ct/kWh during the night. The lower average electricity price during the day is because of the high trade volume that results from the renewable energy generated during the day within the community. Additionally, the average trade price of the multi-layer community during the day is higher than the average trade price of the single-layer community. Furthermore, there are more benefits for the local community when the absolute value of the difference between the average trade price and the median trade price is less. Hence, the higher average trade price of the multi-layer community during the day is an evidence that it is more beneficial to trade electricity with the multi-layer community compared to trading with the single-layer community.

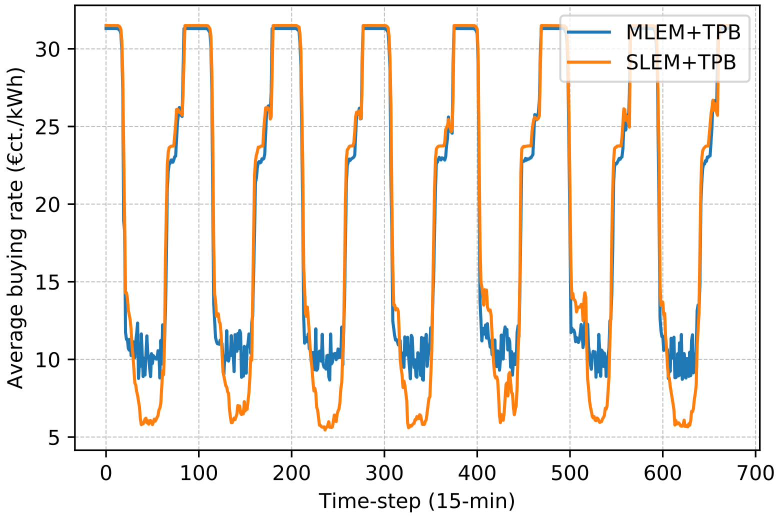


Figure 9. Community average trade price with the TPB clearing mechanism for one week.

4.3.6. P2P Closeness Index

Figure 10 illustrates the P2P closeness index for the four market models evaluated. It demonstrates how the P2P closeness is not affected by the LEM clearing mechanism. However, the market model has an impact on the closeness index of the LEM. The multi-layer community creates an additional closeness index as compared to the single-layer community because of its ability to coordinate the LEM; it also ensures that the energy generated within the LEM is consumed by consumers that are closer to the producers.

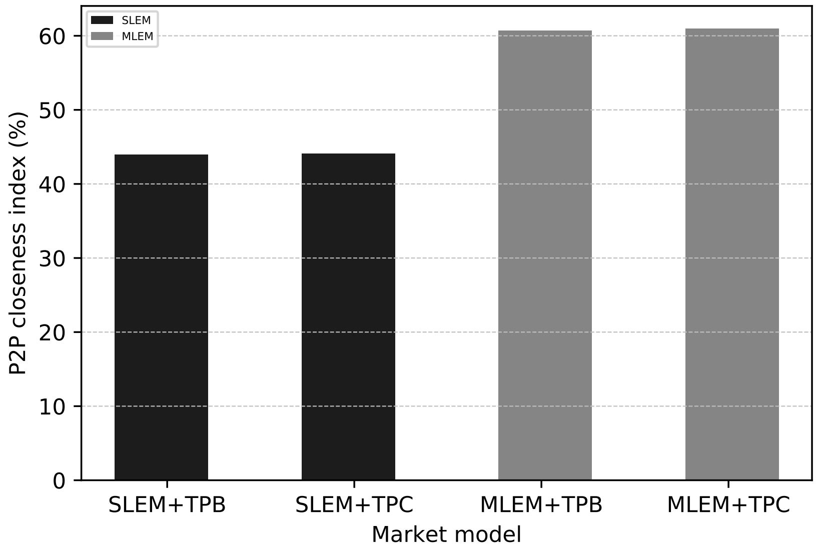


Figure 10. P2P closeness index for different market models.

4.4. Comparison of Sub-Community Average Trade Price

Figure 11 displays the average trade price for all the sub-communities and communities with the mutli-layer community model and the TPB clearing mechanism.

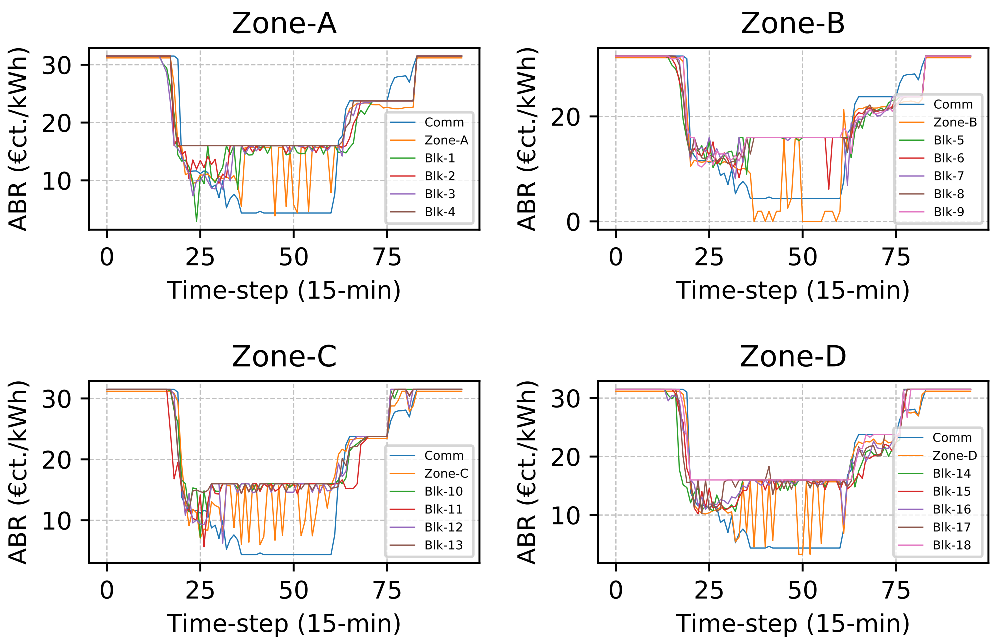


Figure 11. Community (sub-community) average trade price of Zone-A, Zone-B, Zone-C and Zone-D in multi-layer community model for a single day.

For all the communities (sub-communities), the average trade price of the lowest sub-communities (blocks) are closer to the average of the minimum and maximum trade prices. Furthermore, the average trade prices of the zones are between the average trade price of the blocks and that of the higher community. This shows that it is more beneficial to trade electricity at the lowest sub-community hierarchy within an LEM than trading within the higher community (sub-community) hierarchy. Hence, the higher the community hierarchical is from a device agent, the less beneficial it is for the agent to trade electricity within the community level. The average trade price of zone-B decreases to a level below the community trade price during the day time because of the large community and household storage systems in zone-B. Since there is no intelligent trading strategy for moving energy stored in the storage systems to when less electricity is generated in the LEM, this results in a drastic reduction of the average trade price for Zone-B.

4.5. Time Complexity

Table 4 shows the average computational time per market slot while running the simulation on a PC with 16.0 GB of RAM installed, an Intel (R) Core(TM) i7 2.90 GHz processor, and an Ubuntu operating system. Comparing the models reveals that the single-layer communities take about twice the time required by the multi-layer community to complete their computation for each market slot. Additionally, the TPB market clearing mechanism requires more time to complete their computation as compared to the TPC clearing mechanism. Hence, notwithstanding all other advantages of the multi-layer community over the single-layer community models, multi-layer community models still take less computational time per time slot as compared to single-layer community models. This technical benefit of multi-layer community models and other economic benefits they have over single-layer community models makes it advantageous to adopt a multi-layer community model for LEM implementation, especially for household and commercial consumers and prosumers.

Table 4. Average computational time per time slot for in different local market models.

Market Model	Average Computation Time per Slot (s)
SLEM + TPB	185.41
SLEM + TPC	181.55
MLEM + TPB	83.36
MLEM + TPC	81.55

4.6. Discussion

The proposed hierarchical, agent-based model framework organises bids and offers based on the location of the agents and considering local grid fees. The device agents compete with each other directly from the house level until the up-stream grid level, thereby ensuring a competitive and efficient market. Bids/offers which are not matched at sub-community levels are forwarded to higher sub-communities or communities that consider grid fees. This approach does not require a third part such as an aggregator to exchange its electricity with the up-stream grid as the local agents organise their electricity by themselves. In some of hierarchical models developed in the literature, there is only the presence of an aggregator responsible for aggregating the trade from different microgrids and buying/selling the deficit/excess from the up-stream grids [37,38]. However, in our proposed model, the device agents are responsible for making their bids/offers and even for interacting with the up-stream grid without a third party. This creates competitive markets among the local device agents as they are responsible for their bids/offers. Furthermore, the major advantage of our proposed model is to save more for the local electricity traders and give them more power to have control over their local generation and demands. However, the local participants also have to take up the risk or losses that may come up from such markets. The local market trader may incur some loss from the market if they do not use intelligent agents for the bidding/offering. Additionally, comparing our key findings in this paper with a previous work [20] that has similar data and bidding/offering strategy, our proposed model shows better performance indicators, especially with the SMS and the SS.

5. Conclusions

This paper presents a mathematical model for a hierarchical, agent-based local electricity market framework. The proposed model shows how bid/offers are forwarded from one community to others within a hierarchy considering grid fees. The model was implemented on the open-source Grid Singularity Exchange to show its applicability in local electricity exchange. The simulations were performed in a German case study, analysing multiple scenarios to compare different market-clearing mechanisms and market models for the LEM. The simulation results revealed that by comparing the multi-layer and single-layer hierarchical models for LEMs, the multi-layer model is able to coordinate trades within the LEM and ensure that electricity is consumed closer to where it is generated. Furthermore, the multi-layer LEM community model reduces the total energy export from the LEM to the up-stream grid, increases the internal energy exchange in the LEM, increases the individual savings of the households, and increases the self-consumption and market savings of the local community as compared to the single-layer LEM community model. Moreover, the multi-layer community models resulted in a closer P2P index, lower average trade rate, and decreased the computational time of the LEM. However, for an industrial prosumer wishing to participate in LEM trading for individual economic benefits, the single-layer community model is more profitable as compared to the multi-layer LEM models.

It is worth noting that the distribution network constraints and the administrative costs were not considered in this paper, which will be addressed in our future research. We will also explore the administrative cost in comparison with simpler systems, additional local market-clearing mechanisms based on user attributes, clustering algorithms, and intelligent bidding strategies for local electricity trading.

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3.1.2 Advanced clustering based on preference vectors

Contribution

The paper [131] in this section presents a clustering approach for P2P trading of energy in an LEM based on prosumers' and consumers' preference vectors. Fig. 3.2 displays the schematic of the proposed advanced clustering model presented in the paper. The model considers the heterogeneous characteristics of the prosumers' bidding and offering vectors. The heterogeneous characteristics are defined as the geographic location of the consumption device, location on the local community, bid/offer price and bid/offer quantity. The model combined k-means and hierarchical clustering to develop a clustering algorithm that depends on the weight of the vectors and not on the distance for developing the cluster metrics. In this way, the model is developed to ensure that prosumers with the same heterogeneous characteristics form clusters by themselves and trade energy with each other. The model was also verified with a combination of load and production profiles from German households [121], standard load profiles [122, 123], Renewables Ninja [124, 125] and LoadProfileGenerator [126, 127] in a 15-minutes time step market. The results from the simulations showed that the model was able to leverage the preference opportunity and ensure that electricity is consumed closer to where it is produced in a P2P trading manner.

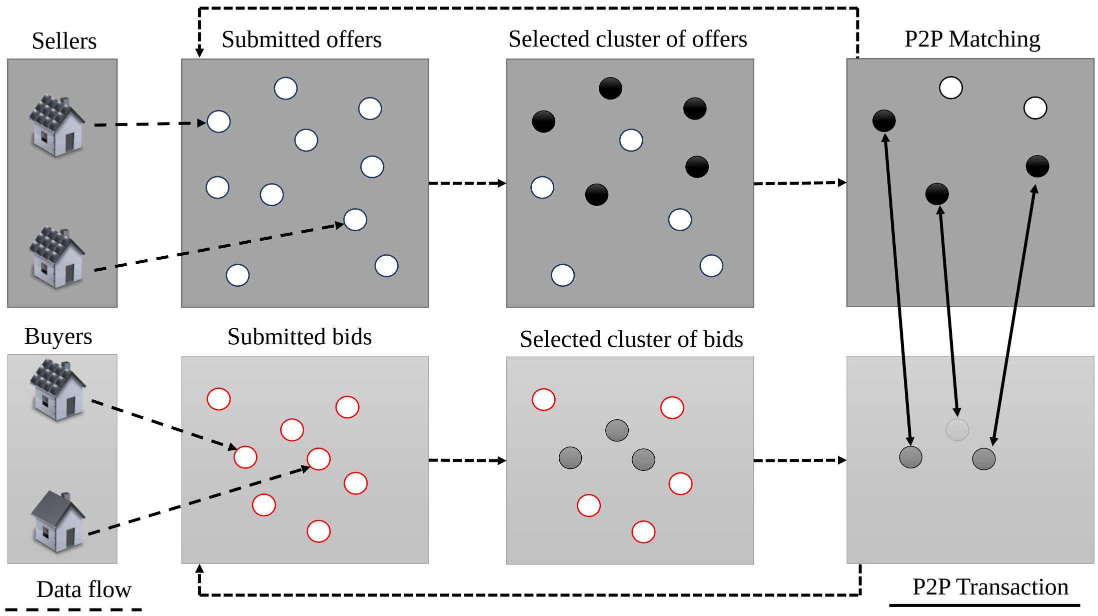

Figure 3.2: Schematic of proposed advanced clustering model, after [131].

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RESEARCH ARTICLE

Advanced Clustering Approach for Peer-to-Peer Local Energy Markets Considering Prosumers' Preference Vectors

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ABSTRACT Local energy markets (LEMs) are utilized in a bottom-up power systems approach for reducing the complexity of the traditional, centralized power system and to enable better integration of decentralized renewable energy resources (RES). Peer-to-peer (P2P) energy trading creates opportunities for prosumers to trade their RES with other prosumers in the LEM. Although several scenarios were proposed in the literature for modelling P2P energy trading, there is still a gap in the literature considering the heterogeneous characteristics of prosumers' bidding preferences during P2P matching in the LEM. In this paper, we present heterogeneous characteristics of bidding preferences for prosumers considering energy quantity, bid/offer price, geographic location, location of agents on the local community and cluster welfare. Moreover, this paper proposes an advanced clustering model for P2P matching in the energy community considering the heterogeneous characteristics of bidding preferences for prosumers. For evaluating our proposed model performance, two German real case scenarios of a small and large communities were studied. The simulations results show that using price preference, as the criterion for clustering, offers more technical and economic benefits to energy communities compared to other clustering scenarios. On the other hand, clustering scenarios based on location of prosumers ensure that energy is traded among prosumers who are closer to each other.

INDEX TERMS Energy community, advanced clustering, local energy market, matching mechanism, peer-to-peer trading.

I. INTRODUCTION

A. MOTIVATION AND BACKGROUND

The transition from a fossil fuel-based centralized power system to a more sustainable, low-emissions and renewable-based system supported by the fast growth of distributed energy resources (DER) add higher complexity to the power system network [1]. Thus, because of the variability of the distributed energy resources, maintaining the reliability and stability of the the power system grid becomes more challenging and complex with the decentralization of assets. Local energy markets (LEMs) are introduced within the past two decades as a means to sustain grid balances at the distribution level and ensure that electricity is consumed closer to where it is produced [2], [3]. LEMs are platforms for trading locally sourced DERs among prosumers and consumers within a geographic and social neighborhood at the distribution level in a competitive and economic

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efficient way [4], [5]. Notwithstanding the numerous research already conducted in the field of the LEM, predominant market mechanisms have not yet been developed and the LEM business model is still unclear [1]. Consequent to the numerous advantages it promised, including the opportunity for prosumers to decide whom to buy/sell their electricity from/to, peer-to-peer (P2P) energy trading has been proposed for local electricity trading by many researchers [6], [7].

B. LITERATURE REVIEW

P2P energy trading is a transactional structure which is based on prosumers and consumers directly or indirectly negotiating their electricity requirements to exchange electricity among each other [8]. In most countries, the electricity market is based on time series. Therefore, the consumers and prosumers are required to consistently bid/offer and negotiate their trade(s) every time slot to achieve a full P2P trading with direct negotiation between consumers and prosumers. This is time consuming and inefficient. Thus, modelling agents and P2P matching algorithms considering prosumers' energy requirements, choices, preferences and price are developed.

In terms of negotiation, P2P energy trading can be classified into mediated and non-mediated P2P negotiations [9]. In a mediated P2P negotiation, a neutral mediator expedites the mediation of the trade between the consumers and the prosumers [10]. This can be based on a many-to-one P2P negotiation between prosumers with an aggregator [11] or a virtual agent as a mediator [12]. Authors of [13] presented a many-to-one P2P energy trading where the distributions system operator mediates between prosumers and consumers and uses a double auction mechanism to decide the P2P winners of the auction. In a non-mediated or full P2P trading, prosumers and consumers directly negotiate with each other for electricity trading. This can be a one-to-one negotiation between a buyer and seller or many-to-many negotiation between all prosumers and consumers [10]. Ref. [14] proposed a one-to-one full P2P trading model based on bilateral trading coefficients. The authors of [15] proposed a many-to-many P2P energy trading model for local energy and flexibility trading based on decentralized negotiation.

Moreover, P2P energy trading can be classified based on the matching or decision approaches. Different approaches used for P2P energy trading are based on game-theory, algorithms, optimization models and reinforcement learning [7]. Ref. [16] proposed Stackelberg game-based energy sharing framework for P2P energy trading within in a multi-sharing region. Ref. [17] proposed a P2P multi-energy market mechanism for electricity and heat trading based on cooperative behaviors between the peers in an LEM. Authors of [18] in their work proposed a model based on Nash bargaining fair sharing of trading benefits for P2P energy trading in interconnected LEMs. Ref. [19] proposed a two-tier P2P trading model based on dual decomposition and distributed consensus mechanism for a double layer hierarchical LEM. The authors of [20] proposed a P2P model, based on P2P coordination for energy. In recent research works, reinforcement learning is used for P2P model. Ref. [21] proposed a multi-agent deep reinforcement learning model based on the combination of the multi-agent deep deterministic policy gradient algorithm and technique of parameter sharing for P2P energy trading. Their simulation study show that the proposed model reduced daily electricity cost and demand peak.

Additionally, recent researches in the field of LEM focused on prosumers preference vectors. In order to consider and satisfy LEM participants' willingness, Ref. [22] proposed a new auction-based LEM model that takes into account the participants' preferences and willingness to pay more for a certain energy quality. The model promised to increase the coverage of local demand and local supply compared to the conventional periodic double auction mechanism. Authors of [14] proposed LEM model which provide opportunity for the prosumers to select their preferred trading partners in a P2P LEM platform. The work of Ref. [21] is based on grouping prosumers into different multiple clusters based on the type of their distributed energy resources(DERs). Ref. [23] proposed a two stage preference based merit-order market mechanism for valuation between green, local, and energy source. The model showed that different DERs supply prosumers according to their willingness to pay and market situation.

Clustering as an unsupervised learning algorithm is used in most studies to identify similarities between set of large data and group the large data into sets of smaller data with similar properties. Clustering is recently used in P2P energy trading to identify similarities in different groups of microgrid, and for coordinating trades in LEM [24]. This further results to proper decentralization of energy markets and access to renewable energy resources [24]. Ref. [25] proposed a virtual LEM that clusters prosumers daily based on their load profiles. Ref. [26] in their work proposed a game theoretic approach for clustering microgrids using particle swarm optimization in a P2P energy trading system. The concept of adaptive segmentation for P2P market clearing was proposed by Ref. [27]. The model use balanced k-means clustering algorithm to cluster energy players into different segments to negotiate energy trading separately among themselves.

The concept of clustering has been used mainly in power markets for classifying loads and forecasting the future electricity demands of the users within a cluster [28]. Ref. [29] used the known traditional K-means clustering to cluster electricity customers demand in order to make a forecast of the future customers load demand. Ref. [30] used the K-means and Fuzzy C-means clustering algorithms to model the electricity price time series patterns for forecasting future electricity price. Ref. [31] developed a semi-supervised automatic clustering algorithm based on a self-adapting metric learning process for determining the household electricity consumers demand patterns.

C. CONTRIBUTION AND ORGANIZATION

The literature contains several studies proposing different models for LEMs, P2P trading approaches, and prosumers preference vectors for LEM design. However, there is still a gap in literature concerning models considering the heterogeneous characteristics (i. e. preferences) of prosumers within the bids/offers during P2P matching. In this paper, we develop a non-mediated P2P matching model based on advanced clustering model that simultaneously takes into account the geographic location, location on the local community, bid/offer price, bid/offer quantity, and cluster welfare for prosumers in the energy community. The literature [32], [33], [34] contains several studies on clustering and application of clustering in energy systems, however, this is the first of its kind where clusters are built with developed weights instead of the distance or values of the sets. Hence, in this model, the developer can decide on a set of variables within the multi set that is of more importance to him or her and decide to manually give more weight to this variable before the start of clustering. By doing so, the model will perform the clustering while considering that a certain variable is of more importance to the model compared to others and therefore perform according to this instruction. The model was implemented on an interface and open source code-base of the Grid Singularity Exchange to simulate, and optimize energy trading in local communities [35]. Furthermore, we evaluate the model using performance indicators such as self-sufficiency, self-consumption ratio, share of market savings and traded energy quantity. Our model can be used for any multi set functions where the user wishes to cluster multi variables while attributing more importance to some variable compared to others. Thus the application of the developed novel clustering algorithm extends beyond LEM but also to other applications where similar multi sets need to be classified. The main contributions of the paper are summarized in the following:

- Proposing an advanced clustering algorithm for grouping of heterogeneous characteristics of bidding preferences for prosumers considering energy quantity, geographic location, location on the community and bid/offer price.
- Presenting novel P2P matching in energy communities based on our proposed advanced clustering algorithm.
- Implementation of the proposed model in a real case German community.
- Assessing the performance of our proposed P2P model based on performance indicators for the LEM.

The remaining sections of this work are structured as follows. Section II introduces clustering and the proposed advanced clustering algorithm. The proposed LEM model is described in Section III and sample discussion of the proposed model with example presented in Section IV. The community set-up, data and price components are presented in Section V. Section VI discusses the results of our case studies and the findings in details. Finally, the paper is concluded in Section VII.

II. PROPOSED CLUSTERING ALGORITHM

A. INTRODUCTION TO CLUSTERING

Clustering is an unsupervised learning algorithm with the objective of extracting underlying information of data samples and using the information to split the data into different groups so-called clusters [36]. Clustering is usually used for analyzing market research, pattern recognition, data analysis, image processing and categorizing genes with similar functionalities [37]. K-means clustering is one of the most popular clustering algorithms used in data mining because of its simplicity and computational efficiency [36], [38]. In K-mean clustering, the Euclidean[1] is used as a means to measure data that are nearby each other and as a means for determining the centroid for group of unlabelled data [38]. Hence, K-means clustering uses a local search to group the data sample by first; randomly selecting k points $\{\mu_1, \ldots, \mu_k\}$ as the corresponding initial centers for k clusters, then optimizing them iteratively until the objective function (Eq. 3) is minimized [39]. Supposed we have a multi-set of d-dimensional vector, X, then,

$$X = \{x_1, x_2, \ldots, x_p\}, \tag{1}$$

where p is number of observations and x_p is the p-th observation. The objective of K-means clustering is to cluster the p observations into k multi-sets of homogeneous clusters by minimizing the objective function represented by Eq. (3) [39], [40].

$$S = \{s_1, \ldots, s_k\}, \tag{2}$$

$$J = \sum_{i=1}^{k} \sum_{x_j \in S_i} ||x_j - \mu_i||_2^2, \tag{3}$$

Here, the number of clusters should be less than or equal to the number of observations ($k \leq p$). Moreover, x_j is the j-th observation belonging to s_i as i-th cluster. It is noticeable that in K-means clustering algorithm, the number of clusters must be defined initially. Hierarchical clustering is another popular clustering algorithm used recently in data mining. Hierarchical clustering algorithm consist of nested partitions in which homogeneous observations are grouped by recursively clustering only two observations at a time [41]. Unlike K-means clustering algorithm that has fixed number of clusters, the number of clusters in hierarchical clustering changes in every iteration cycle [42]. Hierarchical clustering is classified into agglomerative and divisive clustering algorithms which can simply be explained as bottom-up and top-down approaches of the clustering, respectively [42]. In an agglomerative clustering approach, the algorithm begins with a singleton observation by pairing similar clusters at each iteration. This process is repeated every iteration until all observations are included into a single cluster or a defined criterion is met [41]. On the other hand, in divisive clustering approach, clustering begins with one big cluster obser-

[1] Euclidean in this context is the study of solid geometry based on the work of Euclid and the corresponding elementary geometry.

vation and breaks down into clusters consisting of smaller observations in a hierarchical top-down manner. Thus, for p number of observations grouped into q sets of clusters, $\{c_1, c_2, \ldots, c_q\}$, using hierarchical clustering, it is given that

$$\{c_j \subset c_i\} \mid \{c_i \subset c_j\} \mid \{c_i \cap c_j\} = \emptyset, \quad \forall i \neq j, \tag{4}$$

hence, it is either one of clusters i and j is a subset of the other one hierarchically, or a disjoint of it [43].

In hierarchical clustering, different linkage criteria such as single linkage, complete linkage, unweighted pair group method average, the weighted pair group method average, the unweighted pair group method centroid, the weighted pair group method centroid, and the ward linkage are used to measure the distance between two clusters [44]. For the single linkage, the similarity between two clusters depends on the closest pair of members in the two clusters. Therefore, the closeness of the pairs in terms of distance are considered. However, for complete linkage, the similarity between two clusters depends on the farthest pair of members in the two clusters. Therefore, farther pairs are grouped first. For the unweighted pair group method average, the average distance between all individual clusters is calculated and clusters with the least average distance are joined to form the next hierarchy [44], [45]. For a weighted pair group method average, the hierarchical clustering are formed by joining to nearby clusters, the distance between the new formed cluster and any other cluster is the arithmetic mean of the average distances between members of the formed cluster and any other cluster [34]. The unweighted pair group method centroid is similar to unweighted pair group method average, however, for unweighted pair group method centroid, the proximity between two clusters is the proximity between their geometric centroids. Also, the weighted pair group method centroid is similar to weighted pair group method average, however, for weighted pair group method centroid, the proximity between two clusters is the proximity between their geometric centroids [33], [34]. For the wards linkage, two clusters are joined to form a hierarchy once they minimize the increase of sum of square error [34], [44], [45]. For instance in [32], the the unweighted pair average distance and ward linkage methods were used for grouping the clusters. In [33], the single linkage criterio was used. In [34], the single linkage, complete linkage, unweighted pair group method average, the weighted pair group method average, the unweighted pair group method centroid, the weighted pair group method centroid, and the ward linkage were used and compared.

B. ADVANCED CLUSTERING ALGORITHM

In this section, a novel advanced clustering algorithm is proposed. Theoretically, the proposed advance clustering algorithm is derived by combining k-means and agglomerative clustering algorithms. In this way, two different multi-sets, X and W, of d-dimensional vectors each with $\mathcal{N}$ and $\mathcal{M}$ number of observations, are given in Eqs. (5) and (6), respectively.

$$\mathrm{X} = \{x_1, x_2, \ldots, x_{\mathcal{N}}\} \tag{5}$$
$$\mathrm{W} = \{w_1, w_2, \ldots, w_{\mathcal{M}}\} \tag{6}$$

1) STAGE I: INITIAL CLUSTERING

First, the sets from (5) and (6) are clustered into $\mathcal{K}$ and $\mathcal{U}$ number of homogeneous sets, by minimizing (7) and (8), respectively.

$$J^x = \sum_{k=1}^{\mathcal{K}} \sum_{x_y \in c_k^x} ||x_y - \mu_k||_2^2, \tag{7}$$

Subject to:

$$\mathcal{K} \leq \mathcal{N},$$

$$J^w = \sum_{u=1}^{\mathcal{U}} \sum_{w_g \in c_u^w} ||w_g - \mu_u||_2^2, \tag{8}$$

Subject to:

$$\mathcal{U} \leq \mathcal{M}.$$

Here, x_y and w_g are the y-th and g-th sets from the observations X and W, belonging to the k-th and u-th clusters, c_k^x and c_u^w, respectively. Hence, μ_k and μ_u are the initial cluster points for sets X and W as given in (5) and (6), respectively. Eq. (9) and (10) represent the solutions for (7) and (8), respectively.

$$\mathrm{C}^x = \{c_1^x, c_2^x, \ldots, c_k^x\}, \tag{9}$$
$$\mathrm{C}^w = \{c_1^w, c_2^w, \ldots, c_u^w\}, \tag{10}$$

where ${c_1}^x$ to ${c_k}^x$ and ${c_1}^w$ to ${c_u}^w$ represent the selected homogeneous clusters for sets X and W, respectively.

2) STAGE II: HIERARCHICAL CLUSTERING BASED ON LINKAGE CRITERIA

The homogeneous clusters from (9) and (10) are further clustered by determining the individual heterogeneous features of the clusters elements and pairing them one after the other, hierarchically. This is achieved by solving the optimization problem given in (11).

$$(c_{k*}^x, c_{u*}^w) = \arg\max \sum_{c_k^x \in \mathrm{C}^x, c_u^w \in \mathrm{C}^w} \omega_{k,u}(c_k^x, c_u^w) \tag{11}$$

where c_{k*}^x and c_{u*}^w are clusters selected from C^x and C^w, respectively, as solution of (11). Moreover, $\omega_{k,u}$ is the chosen metric which is derived based on the properties of the d-dimensional observation sets X and W. To solve the optimization problem, Eq. (11) is reduced to Eq. (12) to compute the weighted linkage ω^*, and (12), and (11) are solved iteratively until (9) and (10) are reduced to a single cluster.

$$\omega^* = \max\{\omega_{k,u}(c_k^x, c_u^w) : c_k^x \in \mathrm{C}^x, c_u^w \in \mathrm{C}^w\} \tag{12}$$

The pseudocode of our proposed advanced clustering is represented in Algorithm 1. The output $R_1, R_2, \ldots R_{\mathcal{N}^*}$ is the result of matching two clusters c_{k*}^x and c_{u*}^w obtained as solution to Eq. (11).

Algorithm 1 Advanced Clustering Algorithm

Require: X $=\{x_1, x_2, \ldots, x_{\mathcal{N}}\}$, W $=\{w_1, w_2, \ldots, w_{\mathcal{M}}\}$.
Output: $\{R_1, R_2, \ldots R_{\mathcal{N}*}\}$
Solve: Eq. (7) and Eq. (8), to obtain C$^x=\{c_1^x, c_2^x, \ldots c_k^x\}$ and C$^w=\{c_1^w, w_2^w, \ldots c_u^w\}$

while (size(C^x x C^w) >1) **do**
  Determine: ω^* from Eq. (12)
  Solve: Eq. (11) with solution from Eq. (12)
  Merge: Merge clusters of Eq. (9) and (10) based on solution from Eq. (11)
end while

III. PROPOSED P2P MARKET MODEL

In this Section, our proposed P2P market model is presented. In the first step, each prosumer submits its offers and bids at each time slot to the energy community framework as shown in Fig. 1. Then, prosumers are clustered based on the proposed advanced clustering algorithm. P2P matching among prosumers occurs and the cluster weight matrix is updated. This process is repeated in the next time slot until end of the market as shown in Fig. 2. The motivation of clustering prosumers and consumers in P2P energy trading is to reduce mismatch during P2P matching, create cluster of markets where the members of the clusters have similar features and further reduce imbalance in the local community. By clustering prosumers, we reduce the big local market into smaller groups of markets. The participants in each of these smaller groups have similar features/properties, thereby creating opportunity for more bids and offers to be matched in the group levels which will lead to efficient LEM. Also, by creating clusters of members with the similar load profiles, the market reduce imbalance in the local community and ensure that more energy is matched at local level and that grid instability is reduced. Moreover, by creating clusters with similar bidding/offering strategies, the model ensure that there is no mismatch during the market clearing of bids and offers. Because of the establishment of previous works [6], [46], [47] in this area that P2P market for LEM trading offers economic and technical benefits to the LEM participants compared to merit order clearing mechanism, we use the P2P trading for our model. Also, P2P trading gives opportunity for consumers and prosumers to say how much they are willing to pay/receive per kW of their electricity thereby engaging both producers and consumers in the market which is the major idea of LEM unlike the merit order where only the producers gives their cost price and market is matched based on this. Also, P2P energy trading provides opportunity for more energy to be traded within the local community compared to merit order clearing mechanism.

A. STAGE I: BIDDING AND OFFERING BY PROSUMERS

For the proposed LEM model, the prosumers submit their bids and offers as a set of prosumers' preferences at each time slot to the local electricity market framework. Eq. (13) represents the bid of buyer i at time slot t.

$$b_{i,t} = [p_{i,t}^b, q_{i,t}^b, l_i^g, l_i^d], \quad \forall i, t, \tag{13}$$

where, $b_{i,t}$ represents the bidding vector of buyer i at time t which contains energy quantity ($q_{i,t}^b$), bid price ($p_{i,t}^b$), geographic location (l_i^g) of the buyer i in terms of latitude and longitude, and the location (l_i^d) of the buyer i in energy community. The location of the buyer, which is a prosumer in the energy community, is the area location consisting of the building block, street, zone and/or district location of the buyer. Hence, while l_i^g represents the distance location of the buyer, l_i^d represents the particular community the buyer belongs out of the energy communities located inside the LEM. Similar to Eq. (13), Eq. (14) represents the offer of seller j at time slot t.

$$s_{j,t} = [p_{j,t}^s, q_{j,t}^s, l_j^g, l_j^d], \quad \forall j, t, \tag{14}$$

where, $s_{j,t}$ represents the offering vector of seller j which contains the energy quantity ($q_{j,t}^s$), the offer price ($p_{j,t}^s$), the geographic location (l_j^g) of the seller, and the location (l_j^d) of the seller on the energy community. Similar to buyers, l_i^g represents the distance location of the seller, and l_i^d represents the particular community the seller belongs out of the energy communities located inside the LEM. Thus, the bidding/offering vectors submitted by buyers /sellers to the LEM frame work at time slot t are represented by (15) and (16), respectively.

$$\text{B}_t = \{b_{1,t}, b_{2,t}, \ldots, b_{\mathcal{N},t}\}, \quad \forall t, \tag{15}$$

$$\text{S}_t = \{s_{1,t}, s_{2,t}, \ldots, s_{\mathcal{M},t}\}, \quad \forall t, \tag{16}$$

where B_t and S_t represent bidding and offering vectors, respectively. Moreover, $\mathcal{N}$ and $\mathcal{M}$ express number of buyers and sellers, respectively.

B. STAGE II: ADVANCED CLUSTERING OF BIDS AND OFFERS

1) STEP I: INITIAL CLUSTERING

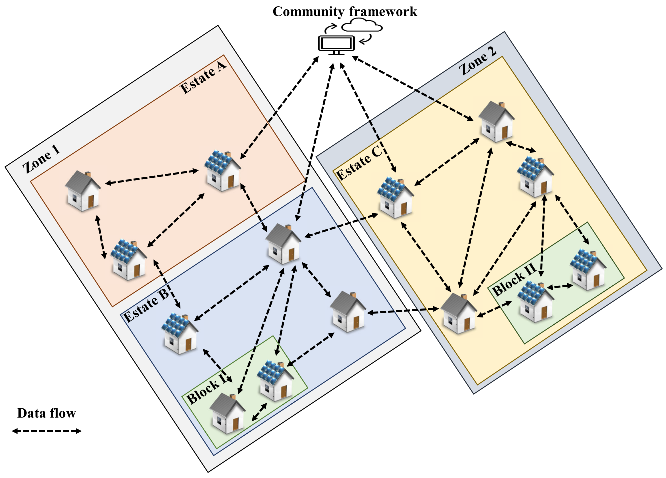
After bidding and offering vectors are submitted to the LEM framework, they are clustered based on the proposed advanced clustering algorithm. This way, similar to K-means clustering algorithm, bidding and offering vectors are defined as multi-sets and are clustered independently based on the defined criterion by minimizing Eqs. (17) and (18), respectively:

$$J_t^b = \sum_{k=1}^{\mathcal{K}} \sum_{b_{f,t} \in c_{k,t}^b} ||b_{f,t} - \mu_{k,t}||_2^2, \tag{17}$$

Subject to:
$$\mathcal{K} \leq \mathcal{N}.$$

$$J_t^s = \sum_{u=1}^{\mathcal{U}} \sum_{s_{g,t} \in c_{u,t}^s} ||s_{g,t} - \mu_{u,t}||_2^2, \tag{18}$$

Subject to:
$$\mathcal{U} \leq \mathcal{M}.$$



(a) (b)

FIGURE 1. Proposed (a) LEM design and (b) P2P market model.

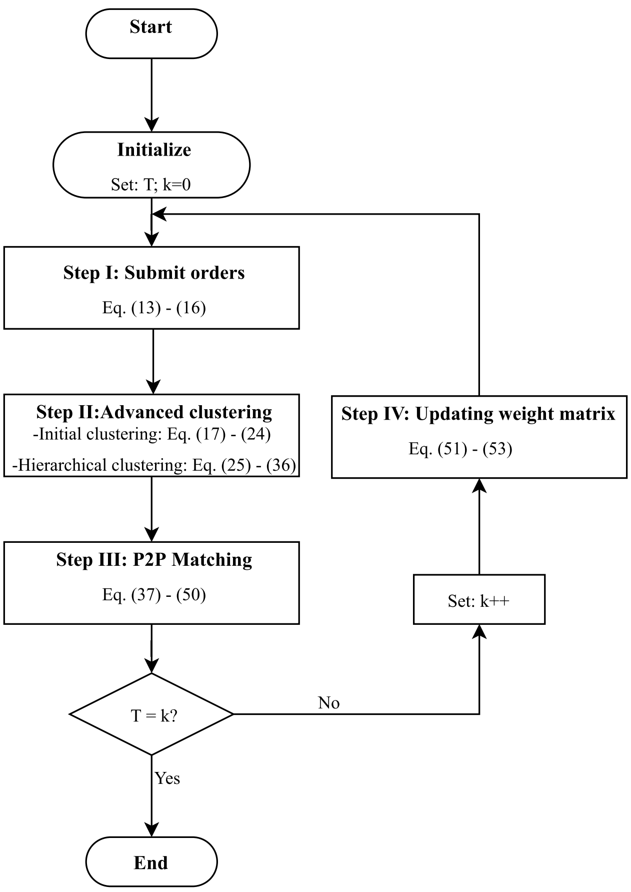


FIGURE 2. Flowchart of the proposed P2P market model.

According to Eqs. (17) and (18), $\mathcal{K}$ and $\mathcal{U}$ are the number of clusters for the bids and offers, respectively. The number of defined bidding clusters $\mathcal{K}$, must be less than or equal to the total number of bids at time step t. Also, the number of the defined offering clusters $\mathcal{U}$, must be less than or equal to the total numbers of offers at time step t. Besides, $b_{f,t}$ and $s_{g,t}$ are the f-th bid and g-th offer, belonging to the k-th and u-th clusters, $c^b_{k,t}$ and $c^s_{u,t}$, respectively. Moreover, μ_k and μ_u are the initial cluster points for bids and offers, respectively. The initial cluster points are selected randomly and minimization of Eqs. (17) and (18) is performed iteratively until the optimal cluster points are determined. Thus, for initial k-th cluster of bids and u-th cluster of offers, it is given:

$$c^b_{k,t} = \{b^k_{1,t}, \ldots, b^k_{n^k,t}\}, \quad \forall t, \tag{19}$$

$$c^s_{u,t} = \{s^u_{1,t}, \ldots, s^u_{m^u,t}\}, \quad \forall t, \tag{20}$$

where n^k is the number of bids belonging to k-th cluster of bids, $c^b_{k,t}$, which have similar homogeneous features based on the clustering criterion at time step t. Similarly, m^u is the number of offers belonging to u-th cluster of offers, $c^s_{u,t}$, which have similar homogeneous features based on the clustering criterion at time step t. In our proposed model, different criterion are defined for clustering bids and offers based on the elements of bids and offers submitted by prosumers, as represented by Eqs. (13) and (14), respectively, and cluster welfare. For a buyer i in $c^b_{k,t}$ and seller j in $c^s_{u,t}$ at time slot t, with bid and offer as represented by Eqs. (13) and (14), respectively, the welfare (π) of the pair is represented in Eq. (21),

$$\pi = \left\{ \begin{matrix} (p^b_{i,t} - p^s_{j,t}) \times q^s_{j,t}: \; q^b_{i,t} = q^s_{j,t} \\ (p^b_{i,t} - p^s_{j,t}) \times q^s_{j,t}: \; q^b_{i,t} > q^s_{j,t} \\ (p^b_{i,t} - p^s_{j,t}) \times q^b_{i,t}: \; q^b_{i,t} < q^s_{j,t} \end{matrix} \right\}, \quad p^b_{i,t} \geq p^s_{j,t}, \; \forall i, j, t. \tag{21}$$

For pairs with $p^b_{i,t} < p^s_{j,t}$, the welfare is not considered since there will not be matching of such pairs even after clustering. The social welfare of the clusters in Eqs. (19) and (20) termed cluster welfare is represented in Eq. (22). Hence, for our model, cluster welfare means social welfare of the clusters and not the social welfare of the local community. Hence, hierarchical clustering with cluster welfare as the chosen metric criterion means clustering pairs with higher $\pi*$ using the hierarchical clustering algorithm/method in the next step.

$$\pi* = \sum_{i=1}^{n^k} \sum_{j=1}^{m^u} \pi_{i,j}, \tag{22}$$

Additionally, Eqs. (23) and (24) represent the the set of all initial clusters for bids and offers:

$$\mathrm{C}_t^b = \{c_{1,t}^b, \ldots, c_{k,t}^b\}, \quad \forall t, \tag{23}$$

$$\mathrm{C}_t^s = \{c_{1,t}^s, \ldots, c_{u,t}^s\}, \quad \forall t, \tag{24}$$

where ${c_{1,t}}^b$ to ${c_{k,t}}^b$ and ${c_{1,t}}^s$ to ${c_{u,t}}^s$ represent the selected homogeneous initial clusters of bids and offers at time step t resulting from Eqs. (17) and (18), respectively. Eqs. (25) and (26) show that the selected initial clusters in Eqs. (23) and (24) are from the bids and offering vectors of buyers and seller represented in Eqs. (15) and (16), respectively.

$$\mathrm{B}_t = \{c_{1,t}^b \cup \ldots \cup c_{k,t}^b\}, \quad \forall t, \tag{25}$$

$$\mathrm{S}_t = \{c_{1,t}^s \cup \ldots \cup c_{u,t}^s\}, \quad \forall t. \tag{26}$$

2) STEP II: HIERARCHICAL CLUSTERING BASED ON LINKAGE CRITERIA

After initial clusters obtained by Eqs. (23) and (24), bids and offers are clustered hierarchically. Thus, initial clusters are inputs for the hierarchical clustering stage and its optimization problem represented by (27):

$$(c_{k*,t}^b, c_{u*,t}^s) = \arg\max \sum_{c_{k,t}^b \in \mathrm{C}_t^b, c_{u,t}^s \in \mathrm{C}_t^s} \omega_{k,u,t}(c_{k,t}^b, c_{u,t}^s), \quad \forall t, \tag{27}$$

where $c_{k*,t}^b$ and $c_{u*,t}^s$ are clusters selected from C_t^b and C_t^s, respectively. Moreover, $\omega_{k,u,t}$ is the chosen metric and is defined as the weight for clustering pair of bidding cluster k and offering cluster u into a single cluster at time slot t. Accordingly, Ω is defined as a chosen weight matrix as represented in Eq. (28).

$$\Omega_{k\times u,t} = \begin{bmatrix} \omega_{1,1,t} & \cdots & \omega_{1,u,t} \\ \vdots & \ddots & \vdots \\ \omega_{k,1,t} & \cdots & \omega_{k,u,t} \end{bmatrix}, \quad \forall t. \tag{28}$$

For reducing the computational burden, Eq. (27) can be restated as given in (29) and (30):

$$\omega_t^* = \max\{\omega_{k,u,t}(c_{k,t}^b, c_{u,t}^s) : c_{k,t}^b \in \mathrm{C}_t^b, c_{u,t}^s \in \mathrm{C}_t^s\}, \quad \forall t, \tag{29}$$

$$(c_{k*,t}^b, c_{u*,t}^s) = \arg(\omega_t^*), \quad \forall t, \tag{30}$$

where ω_t^* is the linkage criteria and is defined as the maximum value of the weighted linkage from the chosen weight matrix represented in Eq. (28). From (28), the chosen metric criteria, $\omega_{k*,u*,t}$, is defined as sum of the average weights of bidding and offering elements including bid and offer prices, energy quantity, location of the prosumers on the local community for bids and offers clusters combination of $c_{k*,t}^b$ and $c_{u*,t}^s$, respectively, which are given in (31):

$$\omega_{k*,u*,t} = \overline{\omega}_{k*,u*,t}^p + \overline{\omega}_{k*,u*,t}^q + \overline{\omega}_{k*,u*}^l. \tag{31}$$

From (31), $\overline{\omega}_{k*,u*,t}^p$ is the average price weight for possible matching bidding cluster, $c_{k*,t}^b$, and offering cluster, $c_{u*,t}^s$, as represented in the price weight matrix of (32) and given in (38).

$$\omega_{k*,u*,t}^p = \begin{bmatrix} w_{1,1,t}^p & \cdots & w_{1,m^{u*},t}^p \\ \vdots & \ddots & \vdots \\ w_{n^{k*},1,t}^p & \cdots & w_{n^{k*},m^{u*},t}^p \end{bmatrix}, \quad \forall t, \tag{32}$$

where n^{k^*} and m^{u^*} are number of bids and offers in bidding cluster, $c_{k*,t}^b$, and offering cluster, $c_{u*,t}^s$, respectively. Moreover, $w_{i,j,t}^p$ is the price weight for matching bid $b_{i,t}$ belonging to $k*$-th bidding cluster and offer $s_{j,t}$ belonging to u^*-th offering cluster at time slot t as represented by (33),

$$w_{i,j,t}^p = \left\{ \begin{array}{ll} 2: & p_{i,t}^b = p_{j,t}^s \\ 1: & p_{i,t}^b > p_{j,t}^s \\ \text{-1:} & \text{else} \end{array} \right\}, \quad \forall i,j,t. \tag{33}$$

From Eq. (33), a bid and an offer pair with equal bidding and offering price has the maximum weight which is 2, because, this pair provide the maximum satisfaction to both prosumers considering their bid and offer preference price. This pair also provide the maximum welfare for the both pairs while considering the bid/offer price of the prosumers. Therefore, giving the maximum price weight to prosumers with the same bid/offer price will ensure that more energy is traded within the community. For a bidding price greater than the offering price, the price weight is 1, because, this bid and offer pair provide less price preference satisfactions to both prosumers compared to the former. For a bidding price less than the offering price, the price weight is -1 because the bid and offer pair does not satisfy the sellers requirements and validation requirements and consequently, this bid and offer pair cannot match. This negative weight reduce the possibility of matching the bid and offer pair with sellers offer price greater than the buyers bid price.

Moreover, $\overline{\omega}_{k*,u*,t}^q$ and $\overline{\omega}_{k*,u*}^l$ represent weights of average energy quantity and location for possible matching of bidding cluster, $c_{k*,t}^b$, and offering cluster, $c_{u*,t}^s$, as represented by (34) and (36), respectively.

$$\omega_{k*,u*,t}^q = \begin{bmatrix} w_{1,1,t}^q & \cdots & w_{1,m^{u*},t}^q \\ \vdots & \ddots & \vdots \\ w_{n^{k*},1,t}^q & \cdots & w_{n^{k*},m^{u*},t}^q \end{bmatrix}, \quad \forall t, \tag{34}$$

where $w_{i,j,t}^q$ represents the energy quantity weight of a buyer i and seller j belonging to clusters $c_{k*,t}^b$ and $c_{u*,t}^s$, respectively, as given by (35):

$$w_{i,j,t}^q = \left\{ \begin{array}{ll} 2: & q_{i,t}^b = q_{j,t}^s \\ 1: & \text{else} \end{array} \right\}, \quad \forall i,j,t. \tag{35}$$

From Eq. (35), bid and offer pair with equal bidding and offering energy quantity has the maximum weight which is 2, because, this pair provides the maximum energy quantity preference satisfaction to both prosumers considering their bid and offer energy quantity. Thus, there is high probability that the buyer and seller will trade all their energy requirements with each other without requesting for another prosumer to take care of their energy requirements that is not satisfied by their pair. For pair with bidding energy quantity greater than the offering energy quantity or offering energy quantity greater than the bidding energy quantity, the price weight is 1, because, this bid and offer pair provide less energy quantity preference satisfactions to one of the prosumers unlike the former that provide maximum energy quantity preference satisfaction to both prosumers. Also, the prosumer with higher energy quantity requirements will still be paired in the next iteration meaning that all the energy requirements cannot be satisfied with the pair and hence, the reason for lesser energy quantity weight.

Additionally, Eq. (37) represents the location weight ($w^l_{i,j}$) of a buyer agent i and seller agent j belonging to clusters $c^b_{k*,t}$ and $c^s_{u*,t}$, respectively.

$$\omega^l_{k*,u*} = \begin{bmatrix} w^l_{1,1} & \cdots & w^l_{1,m^{u*}} \\ \vdots & \ddots & \vdots \\ w^l_{n^{k*},1} & \cdots & w^l_{n^{k*},m^{u*}} \end{bmatrix}, \tag{36}$$

$$w^l_{i,j} = \left\{ \begin{array}{ll} 4: & \{l_i \cup l_j\} \subset l^b \\ 3: & \{l_i \cup l_j\} \subset l^e \\ 2: & \{l_i \cup l_j\} \subset l^z \\ 1: & \{l_i \cup l_j\} \subset l^c \\ 0: & \text{else} \end{array} \right\}, \tag{37}$$

where l^b, l^e, l^z and l^c represent apartment block, estate, zone and local community, respectively. In other words, Eq. (37) expresses that the closer the seller and buyer are on the local community, the higher their location weight.

Thus, the average weight for all bidding/offering elements is determined by Eq. (38):

$$\overline{\omega}^{(.)}_{k*,u*} = \frac{1}{n^{k*} \times m^{u*}} \sum_{i=1}^{n^{k*}} \sum_{j=1}^{m^{u*}} w^{(.)}_{i,j}, \tag{38}$$

where $w^{(.)}_{i,j}$ can be weight for price (p), energy quantity (q) and location (l). In this way, the average weights calculated by Eq. (38) will be the inputs of (31).

3) STEP III: P2P MATCHING OF CLUSTERED BIDS AND OFFERS

After prosumers are clustered in bid and offer clusters separately, P2P matching occur among prosumers which their bids and offers belong to the selected clusters. This way, considering $c^b_{k*,t}$ and $c^s_{u*,t}$ are selected as optimum bidding and offering clusters from Eq. (30) which are represented by Eqs. (39) and (40), respectively.

$$c^b_{k*,t} = (b^k_{1,t}, \ldots, b^k_{n^{k*},t}), \quad \forall t, \tag{39}$$

$$c^s_{u*,t} = (s^u_{1,t}, \ldots, s^u_{m^{u*},t}), \quad \forall t, \tag{40}$$

where $c^b_{k*,t}$ contains n^{k^*} number of bids and $c^s_{u*,t}$ contains n^{u^*} number of offers at time t. Besides, bid i and offer j are vectors consisting of their corresponding bidding and offering elements as represented by Eqs. (13) and (14). Thus, prosumer i as a potential buyer and prosumer j as a potential seller are eligible to negotiate with each other directly for making P2P transaction because they belong to clusters $c^b_{k*,t}$ and $c^s_{u*,t}$, respectively. Hence, the matching among prosumers i and j can occur if Eqs. (41) and (42) as P2P validation criteria are satisfied.

$$p^b_{i,t} \geq p^s_{j,t} + g^l_{i,j,t}, \quad \forall i, j, t, \tag{41}$$

$$(l^d_i \subset l) \wedge (l^d_j \subset l) = 1, \quad \forall i, j, \tag{42}$$

where $g^l_{i,j,t}$ represents grid fee of P2P energy transaction among prosumers i and j in the local community l where l_j and l_i exist. In other words, the grid fee is amount of money in cent/kWh which the paired prosumers i and j pay for using the local grid for energy exchange in the energy community l. Eq. (43) represents the community grid fees,

$$g^l_{i,j,t} = \left\{ \begin{array}{ll} g^{l^b}_t: & \{l_i \cup l_j\} \subset l^b \\ g^{l^e}_t: & \{l_i \cup l_j\} \subset l^e \\ g^{l^z}_t: & \{l_i \cup l_j\} \subset l^z \\ g^{l^c}_t: & \{l_i \cup l_j\} \subset l^c \\ g^{l^u}_t: & \text{else} \end{array} \right\}, \quad \forall i, j, t, \tag{43}$$

where $g^{l^b}_t$, $g^{l^e}_t$, $g^{l^z}_t$, $g^{l^c}_t$ and $g^{l^u}_t$ represent grid fees for apartment blocks, estates, zones, local community and the upstream grid, respectively. Each grid fee is the combination of metering fee (g^m), local grid fee ($g_{i,j,t}$), upstream grid fee (g^u_t) and 19% value-added-tax (VAT) as represented in Eq. (44)

$$g^{l^*}_t = g^m + g_{i,j,t} + g^u_t + 0.19 \times (p^{p2p}_{i,j,t} + g^m + g_{i,j,t} + g^u_t); \quad \forall i, t, \tag{44}$$

If Eqs. (41) and (42) are satisfied among prosumers i and j, the selected pair of bid i and offer j are matched. Thus, $q_{i,j,t}$ and $p^{p2p}_{i,j,t}$ represent matched P2P energy quantity and price between buyer i and seller j at time slot t which are given in (45) and (46), respectively.

$$q_{i,j,t} = \left\{ \begin{array}{ll} q^b_{i,t}: & q^s_{j,t} > q^b_{i,t} \\ q^s_{j,t}: & \text{else} \end{array} \right\}, \quad \forall i, j, t, \tag{45}$$

$$p^{p2p}_{i,j,t} = \frac{p^s_{j,t} + p^b_{i,t}}{2}, \quad \forall i, j, t, \tag{46}$$

$$p^b_{i,j,t} = p^{p2p}_{i,j,t} + \frac{g^l_{i,j,t}}{2}, \quad \forall i, j, t, \tag{47}$$

$$p^s_{j,i,t} = p^{p2p}_{i,j,t} - \frac{g^l_{i,j,t}}{2}, \quad \forall i, j, t, \tag{48}$$

where $p^{b}_{i,j,t}$ is the bought price for buyer i to trade P2P energy with seller j, and $p^{s}_{i,j,t}$ is the sold price for seller j to trade P2P energy with buyer i at time slot t as represent by Eqs. (47) and (48), respectively. After P2P matching between seller i and buyer j, the bid and offer are updated by subtracting the matched energy quantity from the submitted bid/offer quantity as represented in (49) and (50), respectively.

$$q^{b'}_{i,t} = q^{b}_{i,t} - q_{i,j,t}; \quad \forall i, t, \tag{49}$$

$$q^{s'}_{j,t} = q^{s}_{j,t} - q_{i,j,t}; \quad \forall j, t, \tag{50}$$

where $q^{b'}_{i,t}$ and $q^{s'}_{j,t}$ is the deficit/excess bid and offer energy quantity for buyer i and seller j respectively, after P2P matching between them. In case, the selected bid and offer does not satisfy constraints (41) and (42), another bid and offer pair ($b_{i^*,t}$ and $s_{j^*,t}$) are selected according to (51) and (52), respectively.

$$b_{i^*,t} = [p^{b}_{i^*,t}, q^{b}_{i^*,t}, l^{g}_{i^*}, l^{d}_{i^*}]; \{b_{i^*,t} \subset c^{b}_{k^*,t}, i^* \neq i\}, \quad \forall t, \tag{51}$$

$$s_{j^*,t} = [p^{s}_{j^*,t}, q^{s}_{j^*,t}, l^{g}_{j^*}, l^{d}_{j^*}]; \{s_{j^*,t} \subset c^{s}_{u^*,t}, j^* \neq j\}, \quad \forall t. \tag{52}$$

Eqs. (51) and (52) imply that bids and offers paired earlier cannot be paired again in the same time slot, t. The proposed matching process from Eqs. (39) to (52) is repeated until all the bids and offers are selected.

4) STEP IV: UPDATING THE CHOSEN WEIGHT MATRIX

After matching bidding and offering clusters $c^{b}_{k^*,t}$ and $c^{s}_{u^*,t}$, respectively, according to Section III-B3, the chosen weight matrix will be updated. In this way, if all energy quantity of both bid i and offer j are fully matched, the chosen weight matrix is updated as given in Eq. (53) by deleting the corresponding bid's column and offer's row stated in Eq. (28). In other words, Eq. (28) is reduced to Eq. (53) by deleting matched bidding cluster, $c^{b}_{k^*,t}$, and offering cluster, $c^{s}_{u^*,t}$, from Eqs. (23) and (24), before solving (27) in the next iteration.

$$\Omega_{k\times u,t} = \begin{bmatrix} \omega_{1,1,t} & \cdots & \omega_{1,u-1,t} \\ \vdots & \ddots & \vdots \\ \omega_{k-1,1,t} & \cdots & \omega_{k-1,u-1,t} \end{bmatrix}, \quad \forall t. \tag{53}$$

However, if only the offered energy quantity of the cluster $c^{s}_{u^*,t}$ is fully cleared while the bid energy quantity of $c^{b}_{k^*,t}$ is not cleared completely, then Eq. (28) is updated to (54) by deleting the corresponding offer's row stated in Eq. (28).

$$\Omega_{k\times u,t} = \begin{bmatrix} \omega_{1,1,t} & \cdots & \omega_{1,u-1,t} \\ \vdots & \ddots & \vdots \\ \omega_{k,1,t} & \cdots & \omega_{k,u-1,t} \end{bmatrix}, \quad \forall t. \tag{54}$$

On the other hand, if only the energy quantity of the bid cluster $c^{b}_{k^*,t}$ is cleared completely, Eq. (28) is updated to Eq. (55) by deleting the corresponding bid's column stated in Eq. (28).

$$\Omega_{k\times u,t} = \begin{bmatrix} \omega_{1,1,t} & \cdots & \omega_{1,u,t} \\ \vdots & \ddots & \vdots \\ \omega_{k-1,1,t} & \cdots & \omega_{k-1,u,t} \end{bmatrix}, \quad \forall t. \tag{55}$$

Finally, if there are unmatched energy quantities of bid and offer within both ($c^{b}_{k^*,t}$ and $c^{s}_{u^*,t}$) clusters, the size of Eq. (28) remains unchanged. However, matched bids and offers are deleted leaving unmatched ones. Then the chosen weight matrix from Eq. (28) is computed again based on Eqs. (32), (34) and (36), and used to solve Eqs. (29) and (27). The process is repeated until the chosen weight matrix, represented in Eq. (28), forms a single matrix in which the input clusters cannot satisfy the matching criterion described in Eqs. (41) and (42), or all the bids and offers are fully matched. All deficit/excess bids and offers which are not cleared in the local energy market, will be traded with the utility using the upstream-grid price. The pseudocode and flowchart of our proposed advanced clustering approach for a single time slot t is shown in Algorithm 2 and Fig. 3, respectively. From Algorithm 2, $R_1, R_2, \ldots R_{\mathcal{N}^*}$ is the output of the algorithm which is the result of matching two clusters $c^{b}_{k^*,t}$ and $c^{s}_{u^*,t}$ based on Eqs. (39) to (52).

Algorithm 2 Advanced Clustering Algorithm

Require: $B_t = \{b_{1,t}, b_{2,t}, \ldots, b_{\mathcal{N},t}\}$, $S_t = \{s_{1,t}, s_{2,t}, \ldots, s_{\mathcal{M},t}\}$. ▷ Bids and offers

Ensure: $M_{criterion} = True$ ▷ All bids and offers contain no zero or empty set

Output: $\{R^{b,s}_{1}, R^{b,s}_{2}, \ldots R^{b,s}_{\mathcal{N}^*}\}$

Solve: Eq. (17) and Eq. (18), to obtain $C^{b}_{t} = \{c^{b}_{1,t}, \ldots, c^{b}_{k,t}\}$ and $C^{s}_{t} = \{c^{s}_{1,t}, \ldots, c^{s}_{u,t}\}$

while ($M_{criterion} = True$ | (size(C^{b}_{t} x C^{s}_{t}) >1)) **do**
  Calculate: Eq. (28)
  Determine: ω^* and ($c^{b}_{k^*,t}$, $c^{s}_{u^*,t}$) from Eqs. (29) and (30), respectively.
  Matching: Match the clusters ($c^{b}_{k^*,t}$, $c^{s}_{u^*,t}$) based on Eq. (39) to (52).
  if : All ($c^{b}_{k^*,t}$ & $c^{s}_{u^*,t}$) are matched **then**
    Reduce Eq. (28) to Eq. (53);
  else if : All ($c^{s}_{u^*,t}$) are matched **then**
    Reduce Eq. (28) to Eq. (54);
  else if : All ($c^{b}_{k^*,t}$) are matched **then**
    Reduce Eq. (28) to Eq. (55);
  else:
    Delete individual matched bids and offers;
  end if
end while

IV. PROPOSED P2P MARKET MODEL DISCUSSION

In this Section, our proposed P2P market model is described with a simple example to illustrate how bids and offers are clustered and matched according to prosumers' preferences.

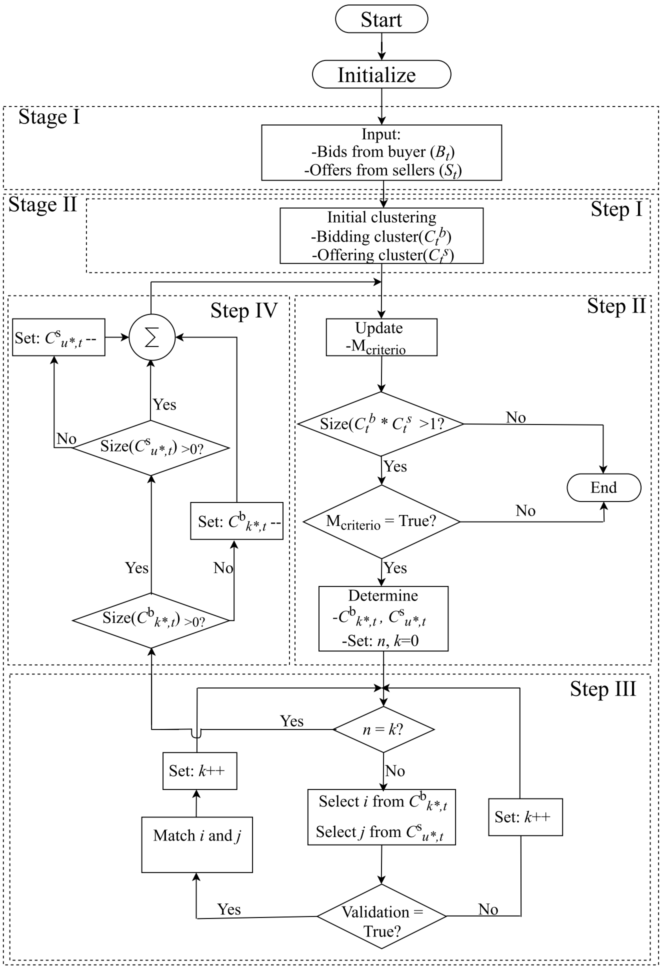


FIGURE 3. Flowchart of the proposed advanced clustering model.

Table 1 displays the sample of prosumers' bids and offers containing the prosumers preference vector for a single time step. The preference vector contains the prosumer's identification (ID), bid/offer price, energy quantity, geographic location and location of the prosumer on the energy community. The geographic location is the location of the prosumer in terms of latitude (La) and longitude (Lo). On the other hand, location of the prosumer in the energy community contains the its zone, estate and building block. According to Table 1, there are two zones consisting of zone A (ZA) and zone B (ZB). Moreover, there are three estates namely yellow (YE), ash (AS), and orange (OR), and six building blocks B1 to B6. In this way, as shown in first row of Table 1, ZA-YE-B1 means that the prosumer 1 belong to zone A, yellow estate and B1.

Fig. 4 displays the clustering and matching of the sample bids and offers of Table 1 based on the proposed P2P market model using advanced clustering algorithm. The bids and offers are arranged according to the bidding/offering price and energy quantity as shown on the lowest level of Fig. 4. The bids are b_1 to b_5, and the offers are s_1 to s_4. In the next level, bids and offers are clustered based on the initial clustering algorithm described in Section III-B1 with cluster welfare as the clustering criterion. The number of clusters for bids and offers are set as two for each of them. The initial clusters is shown on the second level from the bottom layer of Fig. 4. For the bids, the initial clusters are represented by c_1^b and c_2^b, while the initial clusters of offers are represented by c_1^s and c_2^s. Afterward, first two optimal clusters are selected from the four initial clusters by solving Eq. (27). In this sample, the first selected optimal clusters are c_1^s and c_2^b. This way, bids and offers within these selected clusters are matched using the matching algorithm described in Section III-B3 and forms a single cluster $c_{2,1}^s$ after matching. During matching, the first negotiation is between prosumers b_4 and s_4 because of their close price and energy quantity preference. Consequently, 2.85kWh is traded between both prosumers at 23.75 ct./kWh. Hence, b_4 is fully matched while s_4 is partially matched with a left over of 0.16kWh. In the same way, b_5 and s_3 negotiate to exchange 3.12kWh at 24.15ct./kWh. This results in s_3 been fully matched and b_5 been partially matched with a left over of 0.08kWh. Then, b_5 and s_4 negotiate to trade their left over. This results in 0.08kWh been traded among b_5 and s_4 at 25.5 ct./kWh. Hence, b_5 is now fully matched while s_4 is partially matched with a left over of 0.08kWh. Consequently, the formed single cluster contains two offers s_2 and s_4. While s_4 is partially matched, s_2 is not matched at all. Here, $c_{2,1}^s$ represents a combined cluster of bidding cluster c_2^b represented by first subscript 2, and offering cluster c_1^s represented by second subscript 1 and they both formed an offering cluster represented by superscript s. The fist hierarchy now contains three clusters namely $c_{2,1}^s$, c_2^s and c_1^b. For the next iteration, two clusters are selected from three clusters in the first hierarchy by solving Eq. (27) and are termed second selected optimal clusters. The second selected optimal clusters are $c_{2,1}^s$ and c_1^b. Bids and offers within these selected clusters are matched using the same matching algorithm described in Section III-B3 and forms a single cluster $c_{1,(2,1)}^b$ after matching. $c_{1,(2,1)}^b$ contains only one bid, b_1, which is partially matched. At this stage, only two clusters consisting of c_2^s and $c_{1,(2,1)}^b$ are left and form the second hierarchy. These two clusters are selected and matched to form the single cluster $c_{(1,(2,1)),2}^s$ which contains a single offer s_1 that is partially matched. In this way, the final cluster, $c_{(1,(2,1)),2}^s$, will trade with the upstream grid using the upstream grid price as it was not able to match in the local community.

Thus, our model considers similarities based on bidding/offering prices and load profiles. This way, two prosumers in an LEM with similar profiles will be able to trade P2P energy with each other. If the bidding price of the buyer is less than the offering price of the seller, there will be no matching notwithstanding the similarities in the load profiles. This shows the importance of bidding/offering price in an LEM. Bidding/offering price just likes prosumer profiles has effect in LEM trading which if not considered will lead to mismatch in trading and further result in trading with the upstream grid thereby making the market uneconomical and even cause grid instability. As our trading time step

TABLE 1. Prosumers bid/offer preferences.

S/N	ID	Price (ct./kWh)	Quantity (kWh)	Type (Bid/Offer)	Geographic location (La, Lo)	Energy Community
1	s_1	20.05	1.1	Offer	48.717548, 9.26708901	ZA-YE-B1
2	s_2	22.20	2.25	Offer	48.71766159, 9.26803016	ZA-AS-B2
3	s_3	20.80	3.12	Offer	48.71665553, 9.26887395	ZB-OR-B4
4	s_4	23.50	3.01	Offer	48.72076089, 9.26598559	ZB-OR-B5
5	b_1	25.45	0.42	Bid	48.72327604, 9.26718637	ZA-YE-B3
6	b_2	25.00	1.20	Bid	48.72433078, 9.27088607	ZA-YE-B1
7	b_3	27.00	1.00	Bid	48.72397379, 9.27069135	ZA-YE-B6
8	b_4	24.00	2.85	Bid	48.72325981, 9.27184345	ZB-OR-B4
9	b_5	27.50	3.20	Bid	48.71775895, 9.26848451	ZB-OR-B5

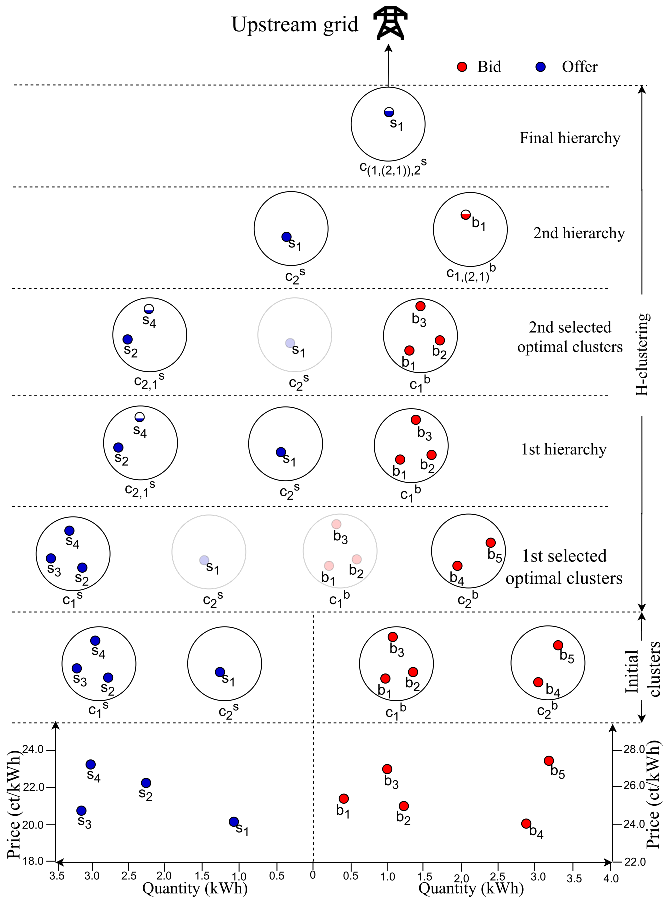


FIGURE 4. Clustering of bids/offers based on our proposed advanced clustering.

(15 minutes) is very short, uncertainty was not considered as it does not have high impact on the LEM. In the LEM, prosumers are allowed to take strategic actions that will benefit them and the market. However, they are not allowed to take actions that will result in inequality.

Clustering brings together prosumers into pools of their fellow prosumers where they all posses similar characteristics. This results in reducing mismatch in the LEM as clusters contain pairs with similar bidding/offering preferences which is used for the P2P matching. Clustering further ensures that more energy is traded at the local levels and creates more local economy for energy community. Hence, considering heterogeneous characteristics of prosumers is relevant to the economic goal of social welfare which is mainly creating additional savings for the local participants. This additional savings results in increase in the share of market savings of the local prosumers participating in the local energy trading. Moreover, clustering is based on considering the social welfare of clusters as defined in Eqs. (21) and (22) and not the social welfare of the local community. In comparison to existing clustering algorithms, the proposed clustering algorithm provides opportunity for the LEM operator managing the local market to give more importance to certain prosumers preferences that is more importance to the prosumers. Furthermore, the algorithm converges faster in lesser time when compared to the traditional clustering algorithms like K-means clustering.

V. SIMULATION SET-UP

A. SIMULATION FRAMEWORK

The proposed LEM advanced clustering model is developed as a Python code and implemented by integrating with the open-source Grid Singularity Exchange (GSy-E) [35], [48], [49] and bidding agent application programming interface (API) as represented in Fig. 5. Each consumer and prosumer is represented by a bidding/offering agent which communicates their bids and offers/bids, respectively, to the exchange engine. The exchange engine is responsible for (i) receiving the bids/offers from the bidding/offering agents of the prosumers, (ii) storing them in the ordered book, and (iii) sending them for onward clearing by the matching API. The matching API is responsible for matching the bids/offers among prosumer agents using the proposed advanced clustering model developed in this work. All unmatched bids and offers are transacted with the up-stream grid agent using the upstream grid price. In other words, any offer and bid of prosumers which is not matched with other prosumers in the energy community is traded with the up-stream grid. In our simulation model, each prosumer communicates their bids or offers individually to the exchange engine every 15 minutes time slot before the energy exchange time. Afterward, the results from the matching API is sent back to individual prosumers.

B. COMMUNITY SET-UP AND DATA

The proposed P2P LEM approach is verified in two simulation case studies for a period of one day. Case study I is a

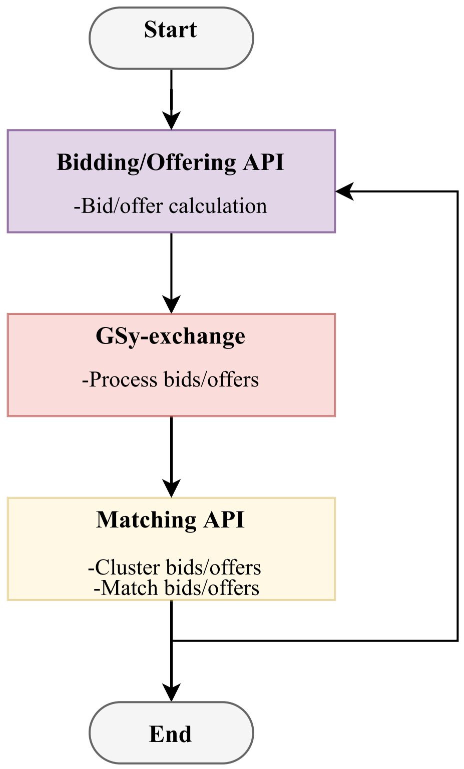


FIGURE 5. Flowchart of simulation framework for proposed model.

community with 25 prosumers consisting of 15 households with only consumption devices and 10 households with consumption and production devices. Case study II is a community with 120 prosumers consisting of 68 households consumers, 4 commercial consumers, 7 commercial prosumers, 6 industrial prosumers and 35 household prosumers. For both case studies, the load profiles are combinations of profiles from [50], LoadProfileGenerator [51], [52] and standard load profiles [53], [54]. These two case studies are chosen to show an in-depth and clear analysis of the advantage/benefits of our proposed model using case study I and further prove its application in a real-case LEM using case study II. Besides, the PV production profiles are from Renewables Ninja [55], [56] using Stuttgart region as a community. The PV system losses are also varied between 5% and 15% with a constant tilt angle of 35°. For prosumers with storage systems, the storage capacities are between 7.5 kWh to 13.5 kWh with maximum absolute power between 3.5 kW to 5.25 kW. Additionally, two community storage systems of capacities 140 kWh and 120 kWh, with maximum power of 40 kW are included in the local community of case study II. The minimum allowed state of charge for all storage systems is 10%. The profiles are randomly fitted into a community (Scharnhausen) in Stuttgart region as shown in Fig. 6(a) and (b) for case studies I and II, respectively, using the OpenStreet map and QGIS. In this study, prosumers in the same building like P1, C1 and P2, are considered to be in the same block. Moreover, prosumers in the same neighbourhood (street) like P1, P4 and C2 are considered to be in the same estate, and prosumers in the same post code (e.g P1, C6, C9 and P3) are considered to be on the same zone.

The price components of the simulation case studies are presented in Table 2. The price components of the local electricity market consist of energy price of the electricity producer, metering fee, local grid fee and 19% Value-Added-Tax (VAT) [57]. The energy price is the minimum amount of money (cents/kWh) a seller prosumer is willing to receive per kWh of electricity produced and traded with other prosumers. The metering fee is the surcharge paid by the consumer for maintaining the metering infrastructure while the local grid fees are for maintaining the local distribution grid infrastructure. The VAT is the tax paid for transacting electricity between prosumers. It is noted that the VAT is 19% of the sum of energy price, metering, local and up-stream grid fees. Additionally, the up-stream grid fee is added if the electricity is traded with the up-stream grid. Because of the average cost of electricity in Germany, the maximum cost of electricity which is the cost of buying electricity from the grid is capped at 31.5 cents/kWh [58]. Moreover, the minimum cost of electricity is 11.00 ct/kWh which is the feed-in tariff of PV. Hence, consumers (also prosumers during bidding) set their preferred bid price between 11.38 to 29.54 ct/kWh, that is the range of total cost for buying energy within a block. However, prosumers (during offering) set their preferred offering price between 11 to 24.5 ct/kWh. This is the range of energy price for selling energy within a block as shown in Table 2. The range of energy price is between the feed-in tariff price and the maximum price that prosumers can sell their energy within the community. Each prosumer within the LEM has an agent which is a software code that submit their bidding/offering vectors on their behalf to the LEM framework. The bidding price is chosen randomly by the agent within the range provided by the prosumer while the energy quantity is selected from the consumption/production profile of the prosumer. The agents on behalf of the prosumers and consumers can only send one bid or offer per time slot. Furthermore, electricity which is not traded within the LEM is exchanged with the up-stream grid at the grid price which is less profitable compared to trading within the LEM.

VI. RESULTS AND DISCUSSION

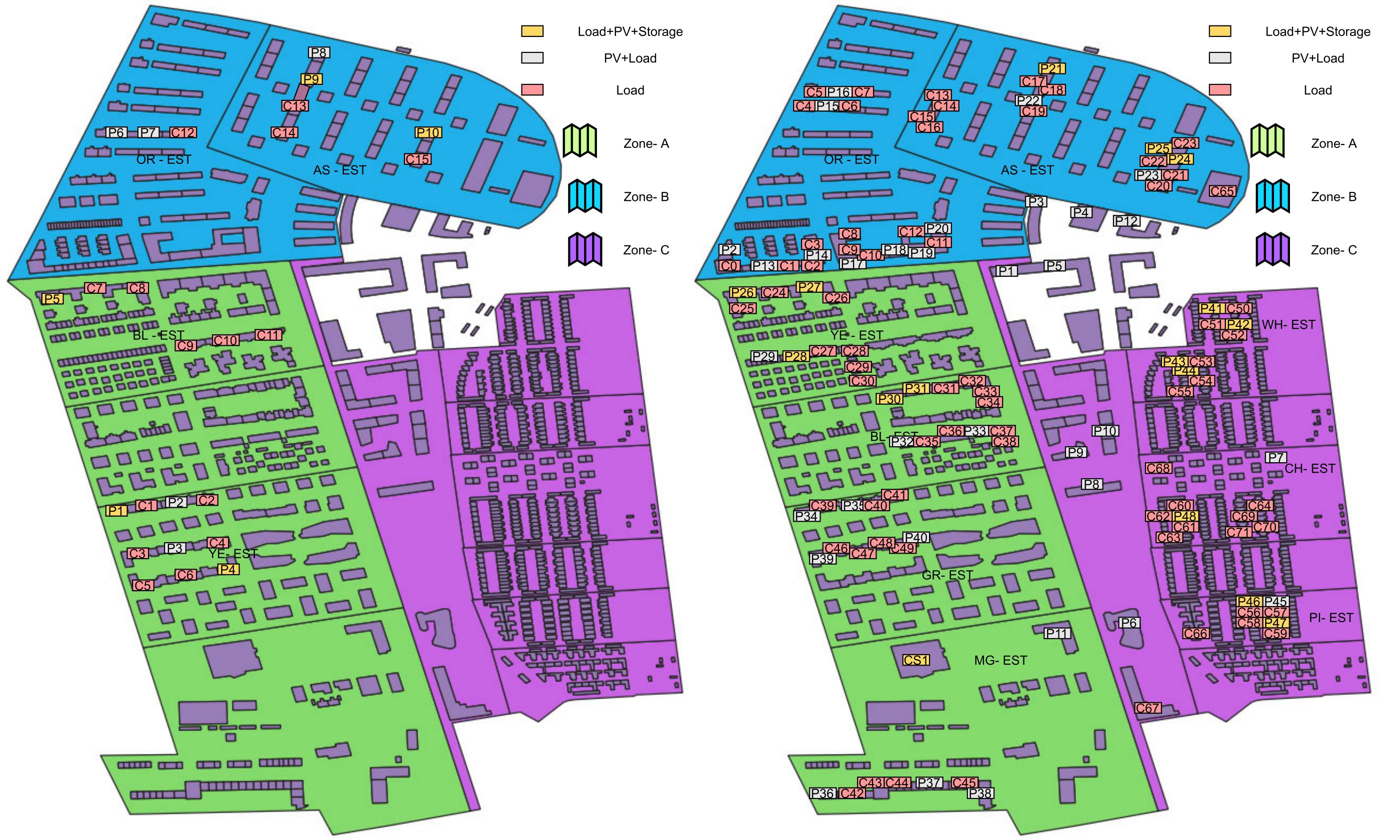
A. CASE STUDY I

The analysis and discussion of the simulations results for case study I are presented in this section.

1) GENERAL ANALYSIS OF SIMULATION RESULTS

To analyze the traded electricity volume and the electricity exchanged with the upstream grid, the geographic location and location of the agent in the local community are used as criteria for initial cluster grouping and hierarchical clustering chosen metric, respectively. The simulation is analyzed and presented in this subsection.

Fig. 7 shows the net electricity demand for (a) consumers, (b) prosumers and (c) the prosumers' electricity supply for



(a) (b)

FIGURE 6. Geospatial information for (a) case study I and (b) II.

TABLE 2. Price components for sub-communities and with the up-stream grid.

Components	Block Trades	Estate Trades	Zonal Trades	Community Trades	Up-stream Grid Trades
Energy price(ct./kWh)	[11 24.50]	[11 23.75]	[11 23.25]	[11 22.50]	[11 17.75]
Metering fee(ct./kWh)	0.32	0.32	0.32	0.32	0.32
Local grid fee(ct./kWh)	-	1.31	1.81	3.33	3.33
Up-stream fee(ct./kWh)	-	-	-	-	4.75
VAT(ct./kWh)	[0.06 4.72]	[0.31 4.82]	[0.40 4.83]	[0.85 4.96]	[1.60 5.35]
Total (ct./kWh)	[11.38 29.54]	[12.94 30.20]	[13.53 30.21]	[15.50 31.11]	[21.00 31.50]

the simulation period. As shown in Figs. 7a and 7b, the peak demand happens in the morning (around 6:00am) and late evening (around 8:00pm). This is typical of households as most people always prepare for their daily activities in the morning and consequently will need to use their electricity appliances. Moreover, at late in the evening, most people will be cooking their dinner, listening to local news, etc. Consequently, the peak electricity demand is obvious. The early morning peak electricity demand of the prosumer households is not noticeable in Fig. 7b. This is because the simulation is conducted for a summer day, and most of the prosumers' electricity demand in the morning of the simulation day is covered by the PV production and hence cutting off the morning peak demand of the prosumers. In addition, the households show an almost constant electricity demand from about 11:30pm until 5:00am. This is because most electricity consumers at this time are asleep and therefore only use their constant electricity demand appliances such as refrigerators. From Fig. 7c, net electricity supply starts early in the morning at around 5:30am with peak generation between 10:00am to 12:30pm, ending at around 4:00pm. This is a typical summer day, prior to and after this specified time, electricity generated by the prosumers is used to satisfy the internal demand of the prosumer households.

Fig. 8 displays the electricity traded within the LEM for selected (a) consumers (b) prosumers and (c) energy exchange with the upstream grid for the simulation period. As shown in Fig. 8, it is evident that electricity trading happens within the LEM mainly during the net PV production time. Since the batteries are not internally controlled, the prosumers that own batteries sell their charged electricity a few time steps after the PV generation within the LEM

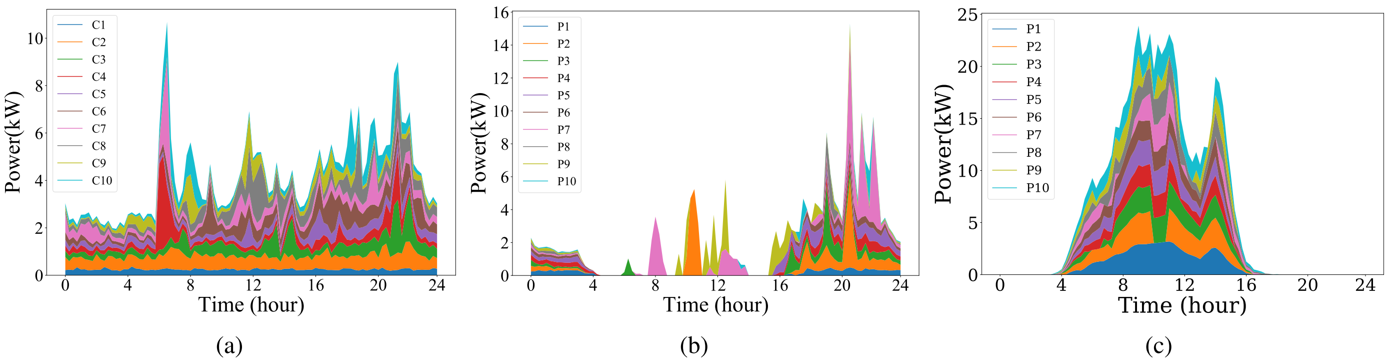


FIGURE 7. **Power demand for (a) Consumers (b) Prosumers and (c) Prosumers' supply.**

has stopped. The stacked area of the prosumers' (Fig. 8b) traded energy is bigger compared to the stacked area of the consumers' (Fig. 8a) traded energy. This is because prosumers can act as consumers in some time steps. At this instance, the traded energy between prosumers is recorded for both prosumers (i.e. prosumers that produce the energy and those that also consume the energy) thereby increasing the area of Fig. 8b compared to Fig. 8a where two consumers cannot exchange energy. Fig. 8c displays the energy imported/exported from/to the upstream grid to/from the LEM. From Fig. 8c, there is no energy export to the upstream grid from 12:00am until about 6:00am and from about 4:00pm until 12:00am. This is because there is no net PV production at this period. The major electricity import from the upstream grid also happens at this period. Since all prosumers within the LEM may not have the same price preference, some prosumers may not be able to bid the price that will enable them buy electricity from the LEM. At same time, some prosumers many not be able to offer the price that will enable them sell all their electricity at the LEM. This is the cause of the simultaneous imports and exports witnessed at some periods around 6:00am until about 4:00pm in in Fig. 8c. Comparing Figs. 8c and 7a, it is evident that the peak demand witnessed in Fig. 7a at around 6:30am which is cut off by the LEM (as shown in Fig. 8c) from 10kW to about 4kW showing about 60% cut off. The peak import (Fig. 8c) witnessed from around 9:00pm is because of the high demand from both consumers and prosumers at late evening and there is no PV production at this time to reduce it.

2) ANALYSIS OF CLUSTERING SCENARIOS

The analysis and discussion of the simulation results for the different clustering scenarios are presented in this section.

a: CONSTANT CLUSTERING CRITERIA FOR INITIAL CLUSTER AND HIERARCHICAL CLUSTER CHOSEN METRIC

In this subsection, we analyze the simulation for the constant clustering scenarios. The same approach is used for both initial cluster grouping and hierarchical clustering chosen metric. In this way, four scenarios are introduced based on location, offering/bidding price, energy quantity, and cluster welfare. These scenarios are analyzed in terms of how they affect electricity trading, and the economic and technical benefits of the LEM. Fig. 9 shows (a) the traded energy, (b) average trade rate and (c) number of trade per slot for four clustering scenarios. According to our study, the four clustering scenarios show similar behaviour for traded energy, average trade rate and number of trades per slot. In the proposed scenarios, from 12:00am until about 5:00am, the energy traded within the LEM is zero and consequently, the average trade rate and the number of trades per slot are 31.5ct/kWh and 0, respectively. At this time, there is no PV generation and all the electricity is bought from the upstream grid at a higher price. In the morning, the PVs start generating and consequently, the traded volume and the number of trades per slot increase gradually which further results in gradual decrease in the average trade rate. During the day, as the PVs are generating electricity, higher volume of energy is traded within the LEM resulting in higher value of number of trades per slot and lower value of the average trade rate. On the other hand, during the evening around 8:00pm, as the sun sets, the traded volume and the number of trades per slot reduce gradually to zero. The average trade rate increases in the same way to 31.5ct/kWh.

Fig. 10 displays the internal traded energy within the LEM, total energy import and export from/to the upstream grid for all clustering scenarios. The internal traded energy is the total energy traded between consumers and prosumers within the LEM. The energy imported/exported from/to the upstream grid are known as external energy exchange. As shown in Fig. 10, the price clustering scenario shows the best performance for the internal and external energy exchange compared to other clustering scenarios with location showing the least. This is evident with the high internal and lower external energy exchange of the price clustering scenario and the lower internal and higher external energy exchange of the location clustering scenario. Higher internal energy exchange means that more energy is traded within the LEM and hence, more benefits is expected to be created by this higher trade. On the other hand, higher external energy exchange means that most of the trades happens between the prosumers and the upstream grid, this is expected to create less benefits to the

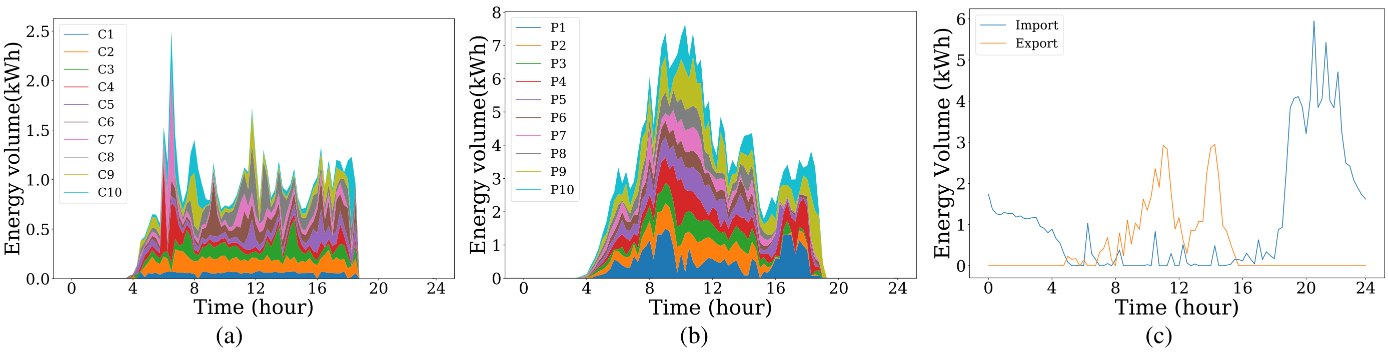


FIGURE 8. Electricity traded within the LEM for selected (a) Consumers, (b) Prosumers and (c) exchange with upstream grid.

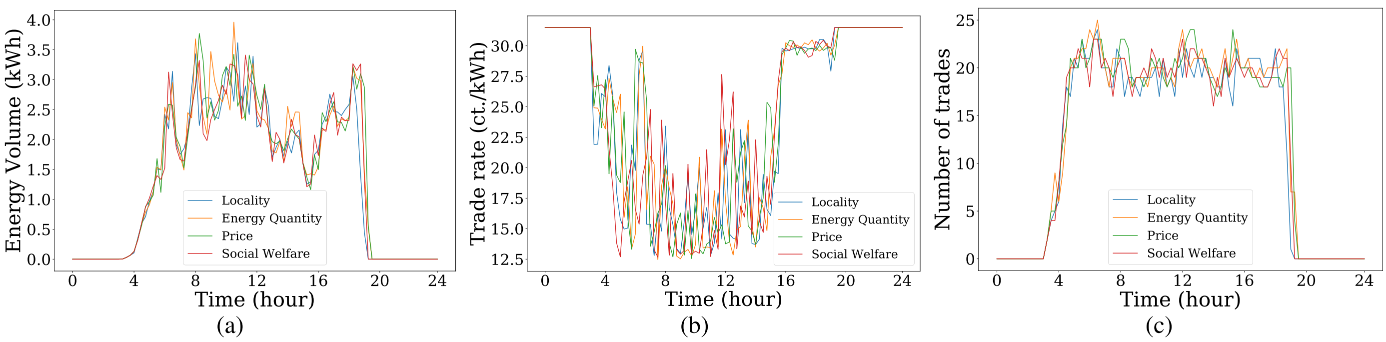


FIGURE 9. Comparison of (a) traded energy (b) average trade rate and (c)number of trades per slot for constant criteria for initial cluster grouping and chosen metric.

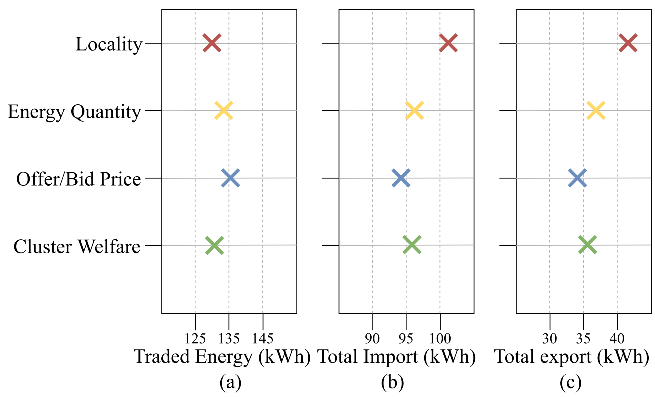


FIGURE 10. Comparison of internal and external energy exchanged for constant clustering criteria scenarios.

LEM. The least performance of location clustering scenario compared to the price clustering scenario is because, although some consumers and prosumers may be close to each other and may be clustered to trade electricity, but they will not trade if the bidding price is less than the offering price. This way, clustering prosumers and consumers who have the same price preference range will result in higher matching of bids and offers within the LEM, thereby creating more internal energy trade and less energy exchange with the upstream grid. The self-sufficiency (SS), self consumption ratio (SC) and the share of market savings (SMS) for the four clustering scenarios are shown in Fig. 11. The SMS is the share of profit made by the local consumers and prosumers for trading within the LEM compared to when there is no LEM [59]. The SS, SC and SM of the four scenarios share a close range with each other. However, for all the performance indicators (SS, SC and SMS), the price based clustering scenario has the best performance and location has the least. This is because, the price based clustering scenario provides more internal traded energy and less external traded energy compared to other clustering scenarios. Higher internal traded energy and lower external energy exchange results in higher performance of the LEM as the LEM does not depend much on the upstream grid for its energy production/consumption. Hence, clustering prosumers and consumers, who have the same price preference range will be more beneficial to the LEM as most trades will match in this cluster scenario, thereby increasing the LEM'S performance indicators.

Figs. 12 (a) and (b) show box plots of the net cost of trading electricity for consumers and prosumers, respectively, in twelve clustering scenarios (L1 to L12). For the consumers, Fig. 12a, the mean cost for all the clustering scenarios is between 2.6 to 2.8 ct./kWh. It is evident that the consumers are household consumers as this cost is within the range of the daily electricity cost for a households in Germany and this correspond to the household data used for the simulation of this case scenario. The minimum cost is 1.5 ct./kWh and all the clustering scenarios show the same minimum cost. However, the maximum cost varies for the different scenarios with L1, L3,L4, L6, L9 and L10 showing a lesser maximum

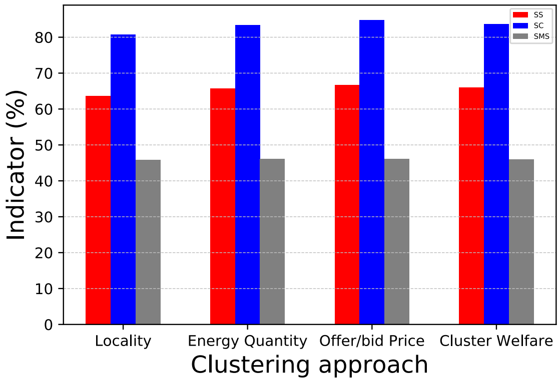


FIGURE 11. Comparison of SS, SC and SMS for constant clustering criteria scenarios.

TABLE 3. Varied clustering scenarios.

S/N	Initial cluster criteria	chosen metric criteria	Symbol
1	location	Offer/bid price + location	L1
2	location	Energy quantity + location	L2
3	location	Cluster welfare + location	L3
4	Offer/bid price	Offer/bid price + location	L4
5	Offer/bid price	Energy quantity + location	L5
6	Offer/bid price	Cluster welfare + location	L6
7	Energy quantity	Offer/bid price + location	L7
8	Energy quantity	Energy quantity + location	L8
9	Energy quantity	Cluster welfare + location	L9
10	Cluster welfare	Offer/bid price + location	L10
11	Cluster welfare	Energy quantity + location	L11
12	Cluster welfare	Cluster welfare + location	L12

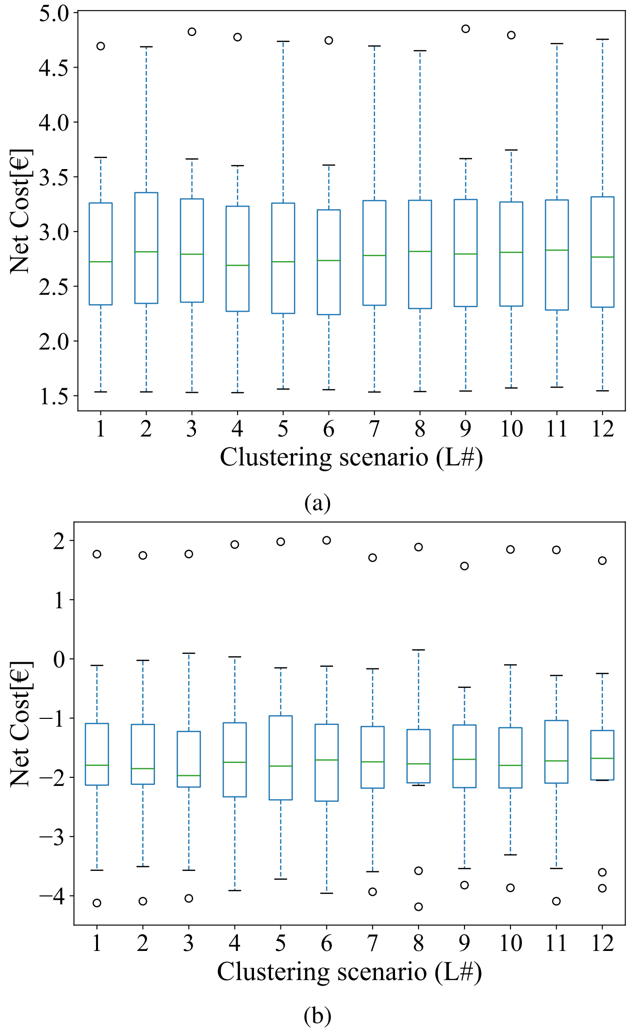


FIGURE 12. Net cost for (a) Consumers and (b) Prosumers based on variable clustering criteria scenarios.

cost value compared to L3, L5, L7, L8, L11 and L12 clustering scenarios. For the prosumers, Fig. 12b, the mean cost is between −1.8 to −1.6 ct./kWh for all the clustering scenarios. Negative mean cost means that the prosumers gained some monetary value for exchanging their electricity with the consumers. The maximum net cost of the prosumers is higher for L3, L4, and L8 compared to other clustering scenarios. On the other hand, the minimum net cost is lower for L4, L5, L6 and L7 compared to other clustering scenarios. L6, L7 and L9 show the best performance because of their lower mean, maximum, and minimum net cost.

Fig. 13 shows the internal traded energy within the LEM, total energy import and export from/to the upstream grid in twelve clustering scenarios (L1 to L12). As seen in Fig. 13, L4, L5 and L6 scenarios present the best performance for the internal and external energy exchange compared to other clustering scenarios with L1, L2 and L10 having the worst performance. This is evident with the high internal and lower external energy exchange of the L4, L5 and L6 clustering scenarios and the lower internal and higher external energy exchange of the L1, L2 and L10 clustering scenarios. L4, L5 and L6 have similar cluster criterion for initial cluster grouping which is the offering/bidding price. This similarity shows why the three scenarios perform better than the others in terms of energy exchange within the LEM and upstream grid. It is also evident that clustering prosumers and consumers who have the same price range based on initial cluster grouping will result in higher matching of bids and offers within the LEM which create more internal energy trade and less energy exchange with the upstream grid.

Fig. 14 shows the SS, SC and SMS for the clustering scenarios L1 to L12. The SS, SC and SMS of the twelve scenarios L1 to L12 show close range value to each other. However, for all the performance indicators, the price based initial cluster criterion's (L4, L5 and L6) clustering scenarios show the outstanding performance compared to other scenarios. The most outstanding clustering scenario is the L6 scenario which is based on initial grouping of bids and offers based on bids/offer price and advanced grouping based on location and cluster welfare. L6 has the highest SS, SC and SM compared to other clustering scenarios. This is because, the price based initial cluster grouping scenario provides more internal traded energy and less external traded energy compared to other clustering scenarios. Furthermore, the location and cluster welfare based criteria for chosen metric ensures that electricity is traded close to where they are consumed and further create additional welfare to the community. This provides additional SMS to the LEM.

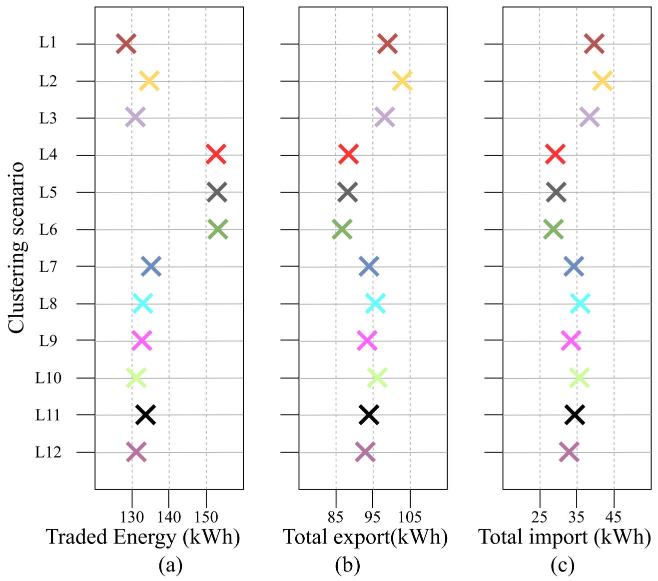


FIGURE 13. Comparison of internal and external energy exchanged for variable clustering criteria scenarios.

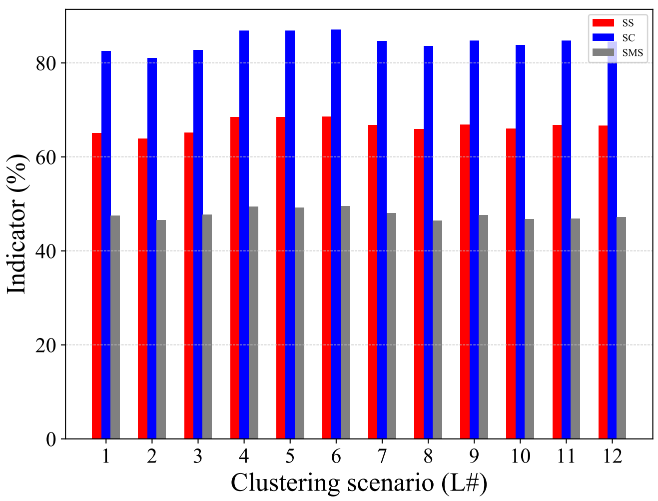


FIGURE 14. Comparison of SS, SC and SMS for variable clustering criteria scenarios.

b: P2P ENERGY TRADE

Fig. 15 shows the P2P energy trade between consumers and prosumers for the L6 clustering approach. Since the prosumers can act as consumers in some time slots, and consequently buy energy from other prosumers, the prosumers are further added to the horizontal axis. Comparing Fig. 15 with Fig. 6a shows that P2P energy is traded within the LEM according to the closest cluster that can be formed from Fig. 6a. Regions on Fig. 15 where higher quantity of energy is exchanged represent a particular region or cluster of household in Fig. 6a where households are close to each other. An example is the upper most center of Fig. 15 where higher quantity of energy is exchanged between P8, P9 and P10 as prosumers (producing) and; C13, C14 and C15 as consumers. This is evident in Fig. 6a where P8, P9, P10, C13, C14 and C15 are located in the same estate known as AS-EST. The higher quantity of energy exchanged between P2 and P13 is because they belong to the same block, therefore, the cluster model matches them easily and ensure that electricity is traded close to where it is produced. In the same way, the higher quantity of energy exchanged between P10 and C15 is also because they are located in the same block, therefore, exchanging energy among them will create additional welfare to the LEM.

B. CASE STUDY II

In this Section, we analyze the performance of the L6 clustering scenario with 120 households as described in Section V-B and varying number of clusters for initial cluster grouping and compare it with P2P matching where there is no clustering.

1) ENERGY EXCHANGE FOR VARYING NUMBER OF CLUSTERS

Fig. 16 displays the internal and external energy exchange for varying number of clusters. The external energy exchange are the energy export and import to/from the upstream grid. As shown in Fig. 16, the total energy exchange, that is the sum of the internal and external energy exchange, is constant for all the simulation scenarios. This is evident that the total energy requirements of the local community is constant throughout the simulations. Furthermore, the P2P matching model without advanced clustering scenario has higher external and lower internal energy exchange compared to all other scenarios. Higher external and lower internal energy exchange results in LEM depending totally on the upstream grid and impacts the LEM participants negatively. Moreover, increasing the number of clusters for initial cluster grouping increases the internal energy exchange and reduces the external energy exchange of the LEM. For the case scenario studied in this work, the simulation achieved its optimum when the number of clusters is four, therefore, increasing the numbers of clusters beyond four has no impact on the performance of the LEM. Based on the L6 advanced clustering approach, the number of initial cluster groups where the LEM reaches its optimum depends on the individual bidding strategies and location of the LEM participants on the local grid.

2) ECONOMIC AND TECHNICAL BENEFITS FOR VARYING NUMBER OF CLUSTERS

Fig. 17 displays the SS, SC and SMS for varying number of initial cluster groups. The P2P matching model without advanced clustering scenario has lower SS, SC and SMS compared to all other scenarios. This is because, the P2P matching model without clustering scenario has more external energy exchange and lower internal energy exchange compared to all other scenarios, making the LEM less beneficial to the local markets participants. Also, increasing the number of clusters for initial cluster groups increases the SS, SC and the SMS of the local community. This is because, increasing the number of clusters for initial cluster groups reduces the external energy and increases the internal energy exchange of the LEM and thereby creating additional benefits to the

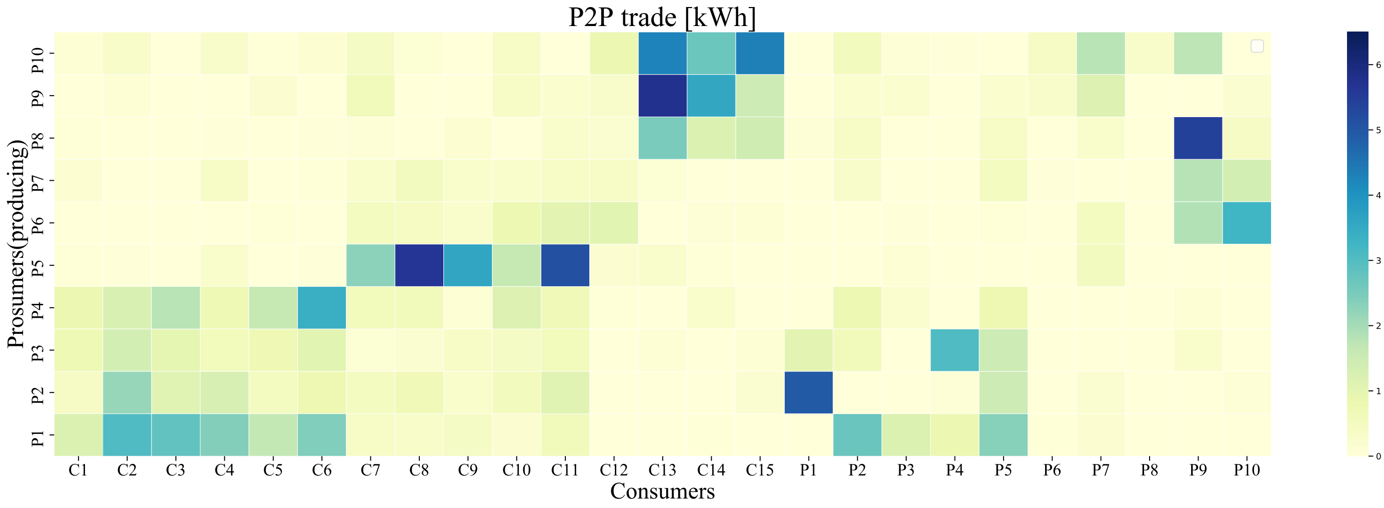


FIGURE 15. P2P energy trade for L6 clustering approach.

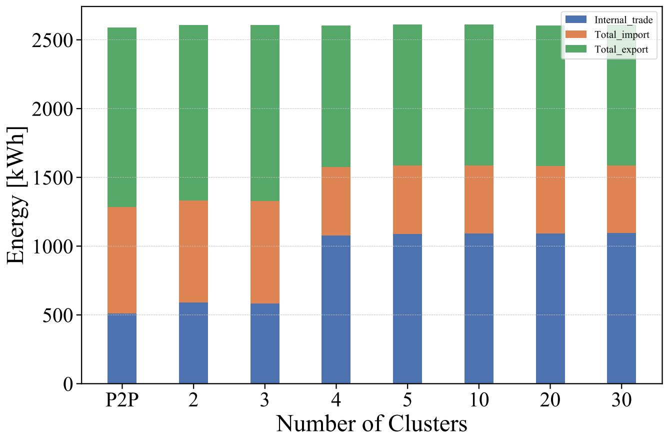


FIGURE 16. Comparison of energy exchange for variable number of clusters.

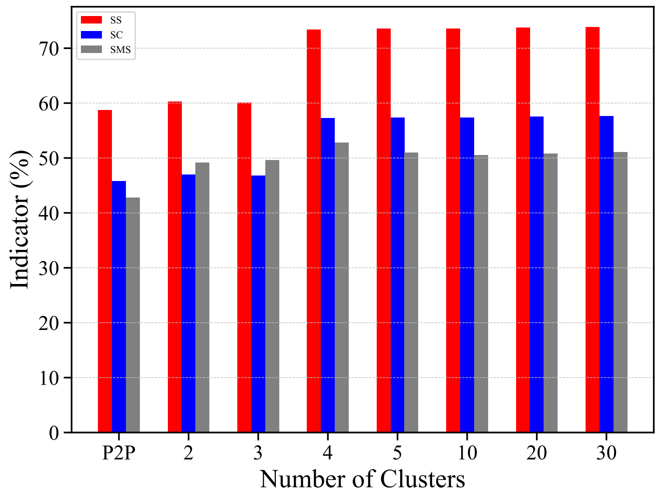


FIGURE 17. Comparison of SS, SC and SMS for variable number of clusters.

local community. The optimum SS, SC and SMS is achieved when the number of initial cluster groups is four. This is the same for internal and external energy exchange of the LEM. This is evidence that the technical and economic benefits of the local community depend on the energy exchange between the community and the upstream grid.

3) TIME COMPLEXITY

The proposed clustering algorithm takes less than 1 seconds to solve a given problem in an Ubuntu operating system computer. This means running the model only, without a market framework such as GSy-exchange. Running it with a market framework takes more time as simulation data needs to be stored and read from different files. Table 4 shows the average simulation computational time per slot to complete the matching in the GSy-exchange matching API for varying number of clusters. The P2P matching mechanism without clustering has the least computational time per slot compared to all other scenarios. This is because the P2P matching mechanism without clustering is a simple random matching and has no clustering model. With the smallest number of clusters which is 2, the run time is 22.55 seconds per slot for a community of 120 prosumers. Increasing the number of initial cluster groups increases the computational time. This is because increasing the number of clusters will require more time for k-means clustering to determine the individual cluster centroids, additionally, it will require more time for advanced clustering to build up the hierarchical model as there will be a greater number of branches from the initial

TABLE 4. Average computational time per time slot for varying number of clusters.

Number of cluster	Average computation time per slot (s)
P2P	15.5
2	22.55
3	28.36
4	32.1
5	42.02
10	60.08
20	73.05
30	82.5

cluster groups. Also, comparing the average computational time of our model with that of a multi-layer LEM model proposed in [48], where a similar community was simulated with the Grid Singularity platform shows that our proposed model has the capability of reducing the average computational time by half when the number of clusters is less than 5. However, with large number of clusters, it may take more time for the algorithm to complete its calculation and matching. For our simulation case scenario, our model achieved its optimum when the number of clusters is four as discussed in Sections VI-B1 and VI-B2, this is evidence that the model is computational efficient when compared to previous works already published in the same area.

VII. CONCLUSION

In this paper, an advanced clustering algorithm was proposed for P2P matching in the energy community considering the heterogeneous characteristics of bidding preferences for prosumers consisting of geographic location, location on the local community, bid/offer price, bid/offer quantity, and cluster welfare. The proposed model was tested in a German real-case scenario and simulated for 120 German households. The simulations results show that the model was able to leverage the preference opportunity to ensure that electricity was traded and consumed closer to where it is produced in a P2P trading structure. Thereby, reducing the peak demand of the local community, increasing the traded energy at the local community, and reducing the energy exchange of the local community and the upstream grid. Also, the model benefit the local prosumers as it can help to increase the share of market saving, self consumption and self sufficiency of the prosumers. By ensuring that energy is traded closer to where is is produced, the model further increase the local economy of the local prosumers.

Furthermore, in the proposed advanced clustering model, using price preference as the criterion for initial cluster grouping, and location of the prosumers in the community and cluster welfare as the criteria for the chosen weight metric, offered more technical and economic benefits to the local community compared to other clustering scenarios. Also, comparing our proposed model with a P2P model without clustering shows that the computational time of both models are closer in range and hence our model can be easily adopted without increasing the market computational time. In future work, we will investigate how reinforcement learning can be used by the prosumers to intelligently decide their bidding/offering preference and how the model will be implemented in a distributed blockchain platform to ensure efficient preservation of prosumers' privacy and conformation to data protection laws.

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3.1.3 Decentralized local energy market model

Contribution

The paper [132] in this section presents a decentralized LEM model for trading energy in a local community based on the consumers' and prosumers' preference. Fig. 3.3 displays the schematic of the decentralized P2P LEM model proposed in this paper. The model enables prosumers and consumers to form energy pools based on their energy or price preferences. Thus prosumers and consumers define their pool requirements and members that are willing to join a pool notify the pool members of their willingness to join the pool. A consumer or prosumer can join as many pool as they wish within the market. At the beginning of every market time step, the consumers and prosumers post their energy preference to each of the pools. Therefore, a prosumer has the opportunity to buy different energy qualities and quantities from different pools. The market at the pool level is cleared in a P2P manner. Members of each pool have the privilege to see the energy requirements of their pool members. This is to enable decentralized clearing. Therefore, each prosumer and consumer clears the market at their node and submit their results to members of their pool for verification. The model was also verified with a combination of load and production profiles from German households [121] and Renewables Ninja [124, 125] in a 15-minutes time step market. The results from the simulations show that the model is able to satisfy the individual energy preference of the consumers within the LEM up to 60%.

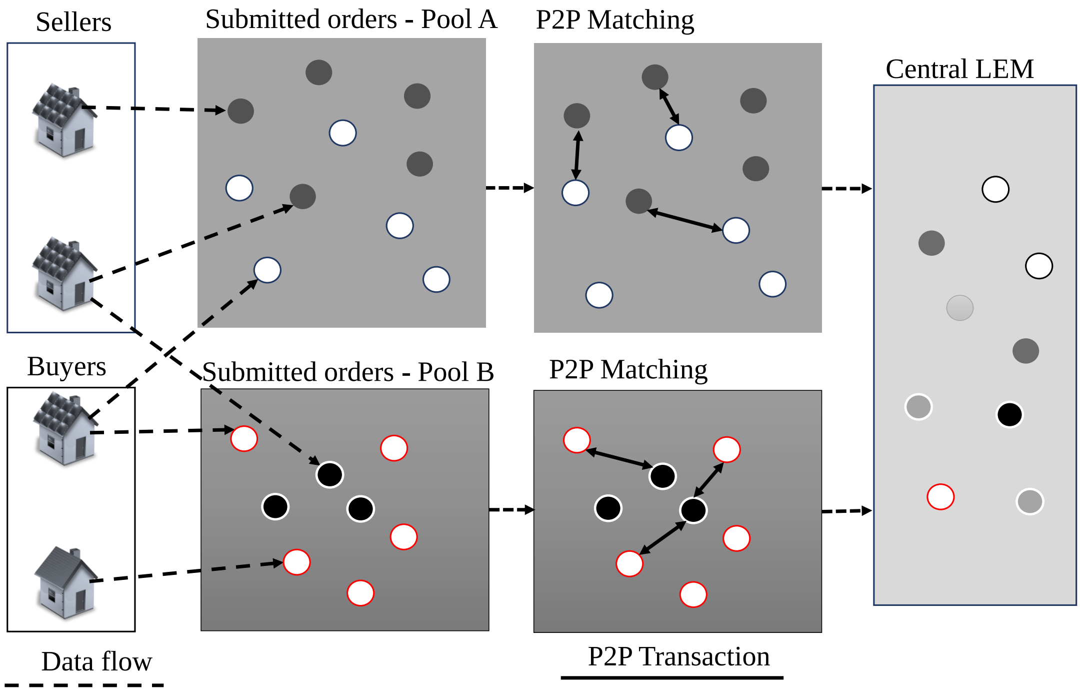

Figure 3.3: Schematic of proposed decentralized P2P LEM model, after [132].

Publication #5: Pooling platform: A decentralized Local Energy Market Platform Based on Clustered Prosumer's Preferences

Authors: Godwin C. Okwuibe, Ksenia Vinogradova, Sören Klingner, and Zhiwei Han.

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Authors contributions

Godwin C. Okwuibe	62%	Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Validation, Writing - Original draft, Writing - review and editing.
Ksenia Vinogradova	16%	Conceptualization, Methodology, Formal analysis, Writing—original draft, Writing—review and editing.
Sören Klingner	10%	Conceptualization, Software, Writing—review and editing.
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Pooling platform: A Decentralized Local Energy Market Platform Based on Clustered Prosumer's Preferences

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***Abstract*—Local energy markets (LEMs) have been introduced in the last few decades as a bottom-up approach solution to create a competitive market for prosumers/consumers to trade their energy and have control over their energy sources. However, there is still a gap in research for prosumers/consumers willing to exchange energy at defined price- and energy-preferences. In this work, we propose an open-source LEM model for matching prosumers and consumers with the same energy and price policy in a decentralized LEM. Our model was verified of its applicability by simulating it with the data from a German community. The simulation results showed that the model was able to satisfy the energy preferences of the consumers and prosumers in the local community to an average of more than 60%. Moreover, the model also demonstrated improved performance in terms of self-sufficiency and self-consumption ratio to the community compared to trading with the central LEM.**

***Index Terms*—Market mechanism, decentralized energy system, local energy market, multi agent system, peer-to-peer, prosumer preference.**

I. Introduction

A. Motivation & Background

Electricity markets were introduced in the past decades to ensure that all electricity fed into the grid is accounted for and that the complex power system is managed properly. The traditional method of managing this complex power system is the top-down approach where power flows unidirectionally. That is from large power plants generators to transmission, distribution and, finally, to the consumers. On the other hand, the money flows in the opposite direction - from the consumers to distributors, transmission, and finally, to the generators. The added value, decentralized nature, and technicalities associated with the new distributed renewable energy resources increased the complexity of the traditional power systems and raised new challenges for maintaining the reliability and stability of the power grid with the traditional top-down approach [1]. Local energy markets (LEMs) were introduced in the past two decades to enable proper coordination and management of the distributed renewable energy resources using a bottom-up approach [2]. LEMs provide an opportunity for prosumers to trade their electricity at the distribution level and have control over their electricity choices [3].

B. Relevant Literature

LEM models can be classified as centralized, decentralized and distributed market models [4]. A centralized market model is a model that relies on a trusted third party acting as an intermediate agent and responsible for making transactions between prosumers in an LEM [5]. The decentralized market model is developed to overcome the challenges of centralized market models such as: single point of failure, low transparency, risk of transaction manipulation, and cyber-attacks [4]. Distributed market models are LEM models that are based on distributed ledger technologies. Ref. [6] proposed centralized auction-based local energy market models that considers users' preference of paying a premium for heterogeneous energy properties such as a renewable energy source. The authors of [7] proposed a multi-layer LEM framework for energy trading in a centralized LEM. The model was evaluated using market performance indicators such as self-sufficiency, self-consumption, and share of market savings. Ref. [8] proposed a peer-to-peer (P2P) LEM model based on a multi-class energy management system for local prosumers in a community. Ref. [9] in their work proposed a P2P electricity trading mechanism based on a two-sided LEM model that enables aggregators to match consumer and producer agents energy requirements. Ref. [10] proposed a decentralized market mechanism for matching prosumers in a LEM that considers prosumers' preference for green energy trading, trading partners' reputation, and location in the distribution grid during P2P matching of prosumers. In [11], an agent-based simulation framework was presented to compare the P2P sharing market mechanisms of prosumers in a local community. [12] proposed a distributed multi-agent LEM model based on blockchain for P2P electricity trading in a local community.

C. Contribution and organization

The literature contains several studies proposing different LEM models for prosumers; however, there is still a gap in the literature proposing a market model for prosumers willing to trade electricity based on generally accepted price and energy policy. In this paper, we propose an LEM model for matching prosumers with the same energy and price policy preferences in a decentralized LEM. Our model is developed as an open-source code, accessible from [13], and can be used by local communities and researchers to model, simulate, and optimize energy trading among prosumers in a community. The model was evaluated for its applicability by a simulation with a real German case scenario. The remaining sections of this work are structured as follows. The proposed LEM model is described in Section II. The data, community setup, and trading strategies of the case study are presented in Section III. Section IV presents the results and discusses the findings in detail. Finally, the paper is concluded in Section V.

II. Pooling platform

In this Section, we present a decentralized P2P electricity trading platform (Pooling platform) with heterogeneous user preferences. First, the process of pool creation is described, followed by the bidding and offering by prosumers to the pools. Afterwards, the bids and offers are matched in a P2P manner and the matching results are verified by all prosumers. The unmatched bids and offers at the pool level are submitted to the central LEM platform for final matching. The goal of the pooling platform is not for economic benefits but to satisfy user preferences. Hence, the central LEM platform is used to match untraded energy requirements at the pool level in a competitive market to create more economic benefits to the users. The general framework of the proposed market model is as shown in Fig. 1.

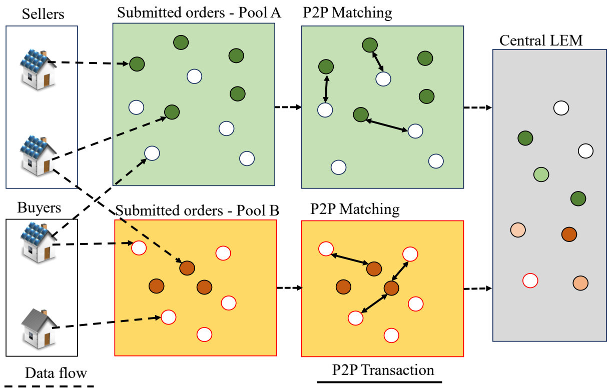


Fig. 1. Proposed decentralized P2P market model.

A. Pool creation

In this paper, the term prosumer refers to a household owner who consumes/produces energy from/to the local community. A pool is a cluster of prosumers who have similar heterogeneous bidding/offering characteristics and wish to exchange energy together with a pre-defined price policy. A pool is created by a prosumer through an application by giving the characteristics of the pool according to Eqn. 1,

$$c_k = [I_k, \alpha_k, p_k, m_k, [\beta_{1,k,t}, .., \beta_{m,k,t}]], \forall k, t. \quad (1)$$

I_k is the pool identity that is used to identify the pool. α_k is the energy selling price at the pool as a percentage of the predicted electricity market price. This is known as the dynamic price policy. The market price is referred to as the price from the retailers which is the last option of the prosumers when they cannot buy/sell from/to the LEM. p_k is the pool fixed price policy. This is the energy sell price at the pool if there is no defined dynamic price policy for the pool. m_k is the number of prosumers within the pool. $[\beta_{1,k,t}, .., \beta_{m,k,t}]$ is the individual characteristics of the prosumers within pool k. The individual prosumer characteristics of a prosumer i are given in Eqn. 2. The electricity trading time step is denoted as t.

$$\beta_{i,k,t} = [l_i, \gamma_{i,k,t}, \epsilon_{i,k,t}], \forall i, k, t. \quad (2)$$

From Eqn. 2, l_i is the location of the prosumer i in the local community in terms of the zone where the prosumer device is located. $\gamma_{i,k,t}$ is the prosumer preference coefficient which is the percentage of electricity that prosumer i will like to exchange in pool k at time t. $\epsilon_{i,k,t}$ is the prosumer type which signifies if the prosumer is buying/selling electricity from/to pool k at time step t. Whenever a new pool is created in the LEM, all prosumers participating in the LEM are notified of the new pool and the pool objective. The pool objective is usually defined by the member that created the pool. No prosumer is allowed to know the members of a pool that they do not belong to. A prosumer that wishes to join a new pool must send a join request to the members of the pool. The members within a pool have the right to see the individual characteristics such as the location of the prosumer, load/PV capacity, and the type of a prosumer that wants to join their pool. At this joining stage, the prosumers must state their role. That is, if they are joining as a consumer, producer, or both. A successful join requires the admissions of all pool members. Prosumers can join as many pools as they wish and are allowed to join in the LEM. The total pools in the LEM are represented by Eqn. 3. $\mathcal{K}$ is the number of pools in the LEM.

$$c = \{c_{1,t}, ..., c_{\mathcal{K},t}\}, \forall t. \quad (3)$$

B. Bidding/offering by prosumers

The future electricity market clearing price is predicted by a central client application and this price is communicated to the individual prosumer's pooling platform. In the same way, a prosumer client application at the prosumer household level is used to predict the future energy requirements of the prosumer. The future energy requirements of the prosumer is the quantity of energy that the prosumer wants to buy/sell in the future market time step.

At time step $(t-1)$, every prosumer pool receives the predicted market clearing price $(p_t^{'})$ and energy requirements$(q_{i,t}^{b,s})$ of the prosumer i for the next time step t from the centralized and prosumer's client application, respectively, as presented in Eqn. 4.

$$b_{i,t} = [p_t^{'}, q_{i,t}^{b,s}, \epsilon_{i,t}], \forall i, t. \quad (4)$$

Also, the pooling configurations presented in Eqn. 1 of the individual pools that every prosumer belongs to are sent to the prosumer's pooling platform from the prosumer's community platform, as represented in Eqn. 5.

$$c_i = \{c_{1,t}, ..., c_{\mathcal{N},t}\}, \forall t. \quad (5)$$

$\mathcal{N}$ from Eqn. 5 is the total number of pools the prosumer i belongs to. The prosumer role $\epsilon_{i,t}$ and energy requirements $q_{i,t}^{b,s}$ are sent to all prosumers, with whom that prosumer i is in the same pool with. In this way, all prosumers that belong to the same pools exchange their energy role and energy requirements which will be used for decentralized P2P matching at the pool's level.

C. Decentralized P2P matching & match verification

From Eqn. 4, buying and selling prosumers are represented as Eqns. 6 and 7, respectively.

$$b_{i,t} = [p_{(t+1)}^{'}, q_{i,t}^{b}], \forall i, t. \quad (6)$$

$$s_{j,t} = [p_{(t+1)}^{'}, q_{j,t}^{s}], \forall j, t. \quad (7)$$

where $q_{i,t}^{b}$ and $q_{j,t}^{s}$ are the bidding and offering quantity of buyer i and seller j, respectively. All bidding and offering prosumers in pool k are defined according to Eqns. 8 and 9, respectively.

$$B_{k,t} = \{b_{1,t}, ..., b_{n,t}\}, \forall k, t. \quad (8)$$

$$S_{k,t} = \{s_{1,t}, ..., s_{u,t}\}, \forall k, t. \quad (9)$$

n and u are the total number of buyers and sellers, respectively, in pool k at time step t. The matching of prosumer i willing to buy an energy quantity $q_{i,t}^{b}$ and prosumer j willing to sell an energy quantity $q_{j,t}^{s}$ at time step t, in pool k happens in three steps.

1) Step I: Select prosumers with lowest grid fees: The grid fees $(\omega_{i,j})$ between buyer i and seller j, is the fee the buyer pays for using the local grid to buy energy from the pooling platform. This depends on the zone location of the buyer and seller.

$$\Omega_{n \times u,k,t} = \begin{bmatrix} \omega_{1,1,t} & \cdots & \omega_{1,u,t} \\ \vdots & \ddots & \vdots \\ \omega_{n,1,t} & \cdots & \omega_{n,u,t} \end{bmatrix}, \forall k, t. \quad (10)$$

Eqn. 10 is the grid fees matrix considering the buyers and sellers within pool k. The buyers and sellers with the lowest grid fees are selected according to Eqn. 11.

$$(B_{k,t}^{n^*}, S_{k,t}^{u^*}) = \arg\min \sum \Omega_{n \times u,k,t}, \forall k, t, \quad (11)$$

n^* and u^* are the total number of buyers and sellers with the lowest grid fees within pool k. Hence, the buyers and sellers with the lowest grid fees are represented according to Eqns. 12 and 13, respectively.

$$B_{k,t}^{n^*} = \{b_{1,t}, ..., b_{n^*,t}\}, \forall k, t. \quad (12)$$

$$S_{k,t}^{u^*} = \{s_{1,t}, ..., s_{u^*,t}\}, \forall k, t. \quad (13)$$

2) Step II: Match prosumers with equal buy/sell quantity: In this step, prosumers with equal buying and selling energy quantity are matched. The sold price which is the price received by the seller is the pool dynamic price, α_k. For a pool where there is no dynamic price policy, the selling price is the pool price, p_k. The bought price which is the price paid by the buyer is the sum of the sold price and the grid fees as given in Eqn. 14.

$$p_{i,t}^{b'} = \alpha_k + \omega_{i,j}, \forall i, j, t. \quad (14)$$

The P2P matched quantity ($q_{i,t}^{b'}$) of prosumer i and j is the sell quantity of prosumer j as given in Eqn. 15.

$$q_{i,j,t}^{p2p} = q_{j,t}^{s}, \forall i, j, t. \quad (15)$$

The unmatched buyers and sellers from Eqns. 12 and 13 are updated according to Eqns. 16 and 17, respectively and matched based on Section II-C3.

$$B_{k,t}^{n^\oplus} = \{b_{1,t}, ..., b_{n^\oplus,t}\}, \forall k, t. \quad (16)$$

$$S_{k,t}^{u^\oplus} = \{s_{1,t}, ..., s_{u^\oplus,t}\}, \forall k, t. \quad (17)$$

$n^\oplus$ and $u^\oplus$ are the numbers of unmatched buyers and sellers, respectively after the matching of prosumers with equal energy quantity.

3) Step III: Fair energy sharing: The leftover energy within the pool is shared among the prosumers considering their energy requirements in a fair and peer-to-peer (P2P) manner. The total leftover energy demand and supply within the pools are calculated according to Eqns. 18 and 19 and compared.

$$Q_{k,t}^{n^\oplus} = \sum^{n^\oplus} q_{i,t}^{b}, \forall k, t. \quad (18)$$

$$Q_{k,t}^{u^\oplus} = \sum^{u^\oplus} q_{j,t}^{s}, , \forall k, t. \quad (19)$$

If $Q_{k,t}^{n^\oplus} \geq Q_{k,t}^{u^\oplus}$, the prosumers i and j are matched in a P2P manner using Eqn. 20.

$$q_{i,j,t}^{p2p} = \frac{q_{j,t}^{s} \times q_{i,t}^{b}}{\sum^{n^\oplus} q_{i,t}^{b}}, \forall i, j, t. \quad (20)$$

$q_{i,j,t}^{p2p}$ is the quantity of energy the buyer i bought from seller j. In this way, all prosumers in Eqns. 16 and 17 are matched one after the other.

On the other hand, if $Q_{k,t}^{n^\oplus} < Q_{k,t}^{u^\oplus}$, the prosumers i and j are matched in a P2P manner using Eqn. 21.

$$q_{i,j,t}^{p2p} = \frac{q_{j,t}^{s} \times q_{i,t}^{b}}{\sum^{u^\oplus} q_{j,t}^{s}}, \forall i, j, t. \quad (21)$$

All prosumers in Eqns. 16 and 17 are matched one after the other using this method. Steps I, II, and III are repeated until all the bids and offers within the pool k are matched. The matching process is repeated by all prosumer's pooling platforms for all the pools the prosumer belongs to. After matching, the matched transactions are sent by all prosumers to other prosumers that they are matched with in a P2P manner for verification. Each prosumer verifies the individual transactions from their peers before the transactions are considered valid. For any P2P matching that the seller and buyer do not have the same results individually, the transaction will be called invalid and hence canceled. All unmatched results from this stage are forwarded to the central LEM for matching using a two-sided uniform pricing market clearing mechanism [1]. The sequence diagram of the proposed decentralized clearing is shown in Fig. 2

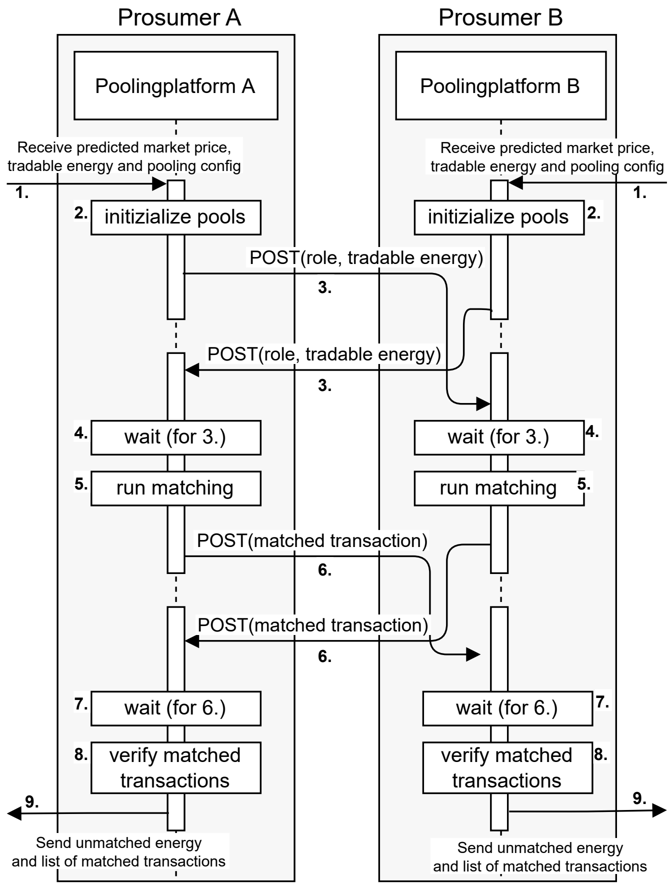


Fig. 2. Sequence diagram for the proposed decentralized LEM model

III. Case Study

The proposed model is verified in a simulation case study of 20 prosumers. Those 20 prosumers consist of 15 households with production and consumption devices and 5 households with only consumption devices. The simulation data are from [14], which is a one-year long 15-minutes time resolution data from a German community. The first three days of September were used for the simulation. To investigate the effect of the consumers-to-prosumers ratio and the production-to-consumption ratio in such a model, the community was classified into three types according to consumers-to-prosumers ratio. The experimented ratios of consumers to prosumers are 15:5 (15C5P), 10:10 (10C10P) and 5:15 (5C15P). For 15C5P and 10C10P, 10-prosumer and 5-prosumers, respectively, from the data were turned to active consumers for such simulation scenarios.

In addition, we further investigate three LEM model set-ups namely market-only (mOnly), pooling-only (pOnly) and market+pooling (P&M). Market-only is the type of LEM set-up where the prosumers/consumers post their offer/bid directly to the central LEM and the market is cleared using the double-sided uniform pricing market mechanism [1]. For the pooling-only LEM set-up, the prosumers/consumers offer/bid to the pooling platform only. For the market+pooling model, the prosumer/consumer offer/bid to the pooling platform and the central LEM. The excess/deficit from the prosumers/consumers in all the model types is traded with the upstream grid at feed-in tariff/upstream grid sell price. The feed-in tariff price is 11.00 ct/kWh. Table I summarizes the pool types, energy source, price and number of prosumers for the experimented pools. The four experimented pools are the green energy pool (GEP), altruistic sharing pool (ASP), family pool1 (FP1) and family pool2 (FP2). The electricity prices in all the pools are defined as a percent of the upstream grid sell price, which for simplicity was set to 33ct/kWh. The GEP is the pool where consumers agree to pay more in order to buy renewable energy. This is in accordance with the study by [15], which shows that most local consumers/prosumers are willing to pay more to buy renewable energy. The ASP pool is the pools where consumers and prosumers trade energy at a cheaper price than they would pay if they buy from the upstream grid. The family pools are the pools where family members exchange energy at 0 ct/kWh. Four different user preferences were randomly generated for each user for the pOnly and P & M experiment. This results in 27 simulation scenarios. Fig. 3 displays the first randomly generated user preference for consumers and prosumers for the different pools and central LEM. The user preference is the percentage energy a prosumer or consumer wishes to buy or sell from the different pools and central LEM.

TABLE I: Pool types and configurations.

S/N	Pool	Pool Name	Energy Source	Price (%)	Prosumers
1	Pool1	GEP	Only green	120	20
2	Pool2	ASP	Gray	60	20
3	Pool3	FP1	Gray & green	0	4
4	Pool4	FP2	Gray & green	0	4

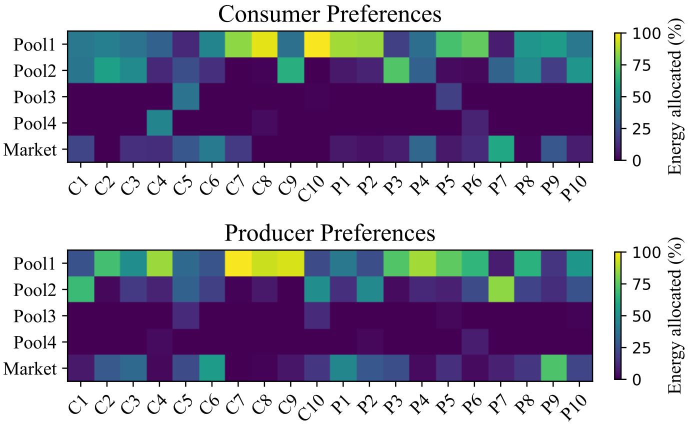
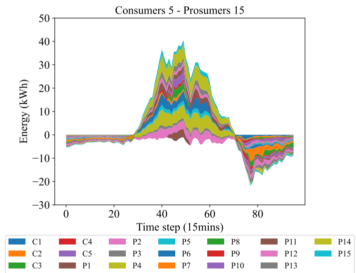


Fig. 3. User preferences in terms of energy allocation to different pools and the market.

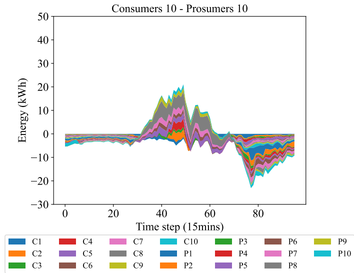
IV. Results and discussions

A. General characteristics

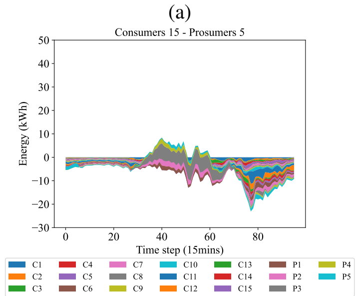
Fig. 4 shows the one day average energy supply/demand of the prosumers and consumers in different community configurations for the 3 days of the simulation. A major characteristics of all the communities is having excess production during the day time and more consumption during the night time. This is because more of the energy production is from PV systems which produces electricity mainly during the day when there is sunlight. On the other hand, Fig. 4a has more production during the day, followed by Fig. 4b before Fig. 4c which has the least production. This is because of the higher production in Fig. 4a followed by Fig. 4b which results from the higher number of consumers in the two community configurations (5C15P and 10C10P) compared to Fig. 4c. The average peak production is 40.5kWh, 20.3kWh and 8.5kWh for 5C15P, 10C10P and 15C5P community configurations. The peak demand is the same for all configurations which is 25.3kWh and happened around 8:00 to 9:00 pm when all the prosumers are at home and using their consumption devices.



(a)



(b)



(c)

Fig. 4. Prosumers/consumers average energy supply (positive) and demand (negative) for variable community configurations.

Fig. 5 displays a one-day average of the performance metrics for the 10C10P community configuration with pOnly LEM model for the 3 days of simulation. Fig. 5a displays the average self-sufficiency (SS) which raise steadily at about 6:00 am from 0 % to above 90% and decrease steadily from at about 3:00pm to 6:00 pm from 92% to 0%, respectively. This shows that the local community is mostly self-sufficient during the day and depends mainly on the upstream grid for their energy at night. This is also because most of the energy production at the local community is from the PV. Hence, most of the energy is traded during the day in the platform resulting in most energy demand of the community during the day being provided by the PV. The 10% average self-sufficiency witnessed at 12:00am are from the storage systems.

Fig. 5b displays the average daily self-consumption (SC) ratio of the community. The SC spiked up at about 6:00 am from 0 to 80%. Afterwards, it reduced to less than 30% and kept fluctuating during the day until the next spike to 75% which happened at about 3:00 pm. After this, it decreased to 0% at about 6:00 pm. The spikes in SC witnessed early in the morning and in the early evening are because of the lower quantity of PV production during these times which is traded and consumed in the community. During the afternoon, much PV energy is produced and therefore, not all of it is traded within the community. The excess PV production which is traded with the upstream grid results in reduced SC witnessed during the day. Fig. 5c displays the average share of market savings (SMS) of the local community. The share of market savings is the percentage of savings made by the community using the LEM compared to when there is no LEM [7]. The SMS of the local community is positive for producing prosumers from about 7:00 am to 5:30pm. This is because, at this time, most of the PV production is traded at the community at a price higher than the upstream electricity sell price thereby creating more savings for the producers. At high PV production hours (from 11:00 am to 2:00pm), the producers trade excess of their production with the upstream grid at a feed-in tariff price of 11.00 ct/kWh thereby reducing their SMS. The maximum SMS is 147% witnessed at about 4:15pm. The SMS for the consumers is negative for most time steps because, most of the energy traded within the community is from the green energy pool (GEP) where energy is traded at a higher price thereby making the market uneconomical for consumers in most time intervals.

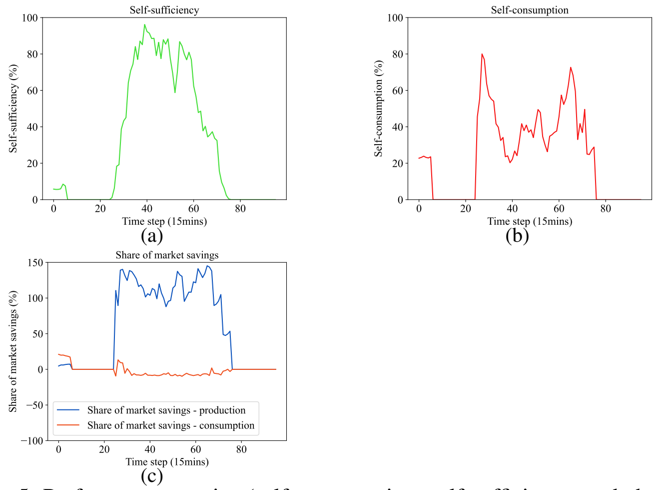


Fig. 5. Performance metrics (self-consumption, self-sufficiency, and share of market savings) throughout the day.

B. *Analysis of different pooling configurations*

Fig. 6 displays the average SMS for varying pools configurations for 10C10C community configuration and pOnly scenario for the 3 days of simulation. Figs. 6a, 6b, 6c and 6d displays the SMS for the green energy pool (GEP-pool1), altruistic sharing pool (ASP-pool2), family pool1 (FP1-pool3) and family pool2 (FP2-pool4), respectively. From Figs. 6a and 6b, the SMS for producing prosumers is positive during the day for the GEP and ASP pools. The average producing prosumers SMS of the GEP during the day is 145% which is higher than the average producing prosumers SMS of the ASP, that is 15%. This is because, for the GEP, energy is traded at 120% compared to ASP where energy is traded at 60% of the upstream grid price thereby creating additional savings for the producing prosumers during the day time. Also, the SMS of consumers in GEP (Fig. 6a) is negative because the energy trade price is higher than the price of electricity from the upstream grid. The ASP and family pools favour (positive SMS) the consumers because energy is traded at a price less than the upstream selling price. Moreover, the ASP is also favourable for producing prosumers, because, the price at which the energy is sold at this pool is still higher than the feed-in tariff price. The family pools are the most favourable for the consumers because they buy energy at 0 ct/kWh from their family members thereby achieving SMS of almost 98% during the day. The reverse is the case for the producing prosumers.

Fig. 7 displays the total P2P traded energy between prosumers and consumers at the different pool configurations for the 10C10P community configuration and pooling only scenario. Figs. 7a, 7b, 7c and 7d displays the P2P traded energy for GEP, ASP, FP1 and FP2, respectively. From the diagrams, the GEP and ASP pools

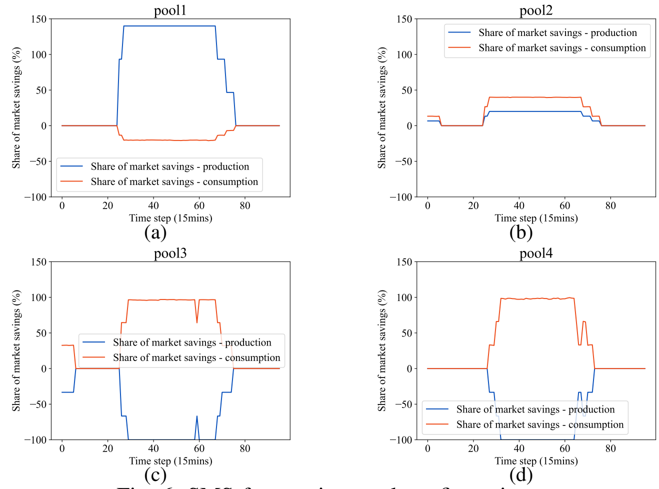


Fig. 6. SMS for varying pool configurations

have more transactions compared to FP1 and FP2 pools because there are more consumers and prosumers in the pools (GEP and ASP) compared to the family pools. Figs. 7a and 7b shows that there is no transaction between consumer to consumer. Also, the prosumer to prosumer transactions are small compared to consumer to prosumer transactions. The maximum P2P traded energy in the GEP is 28kWh and is traded between P9 and C1. In the ASP pool, the maximum traded P2P energy is 19.5kWh and is between P7 and P10. The maximum traded energy in FP1 and FP2 are 16.5 kWh and 7.2 kWh, respectively.

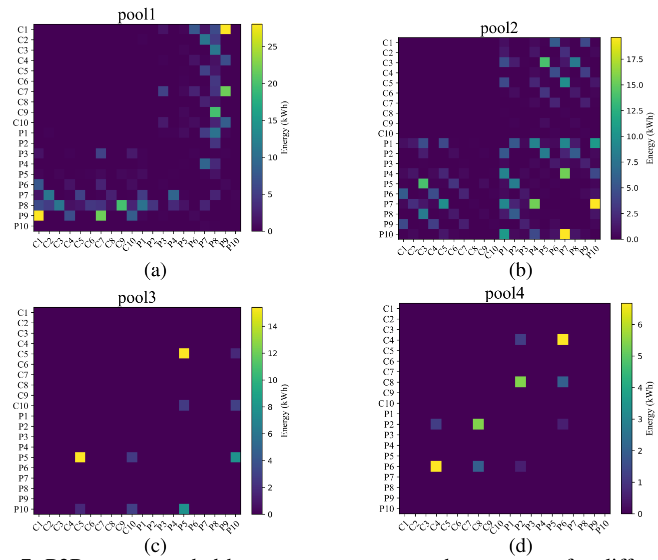


Fig. 7. P2P energy traded between prosumers and consumers for different pooling configurations.

C. *Analysis of different market configurations*

Fig. 8 display the average percentage satisfaction of the prosumers and consumers for the different community configurations. The prosumers and consumers have more of their energy requirements satisfied during the day (from 6:00am until 6:00pm) because, most energy production within the community is from the PV which can only produce energy during the day. The average percentage satisfaction of all the prosumers and consumers in C5P15, C10P10, and C15P5 community configurations during the day are 45%, 62% and 72%, respectively. Comparing Figs. 8a, 8b and 8c shows that the prosumers and consumers preferences are more satisfied in the C15P5 community configurations. This is notwithstanding that less energy is produced with the C15P5 configurations compared to other community configurations as shown in Fig. 4. This shows that more of the prosumers and consumers preferences are satisfied in a community where the prosumers have more opportunity to trade their energy compared to a community where the consumers have more opportunity to trade their energy. This is because, the prosumers are responsible for producing energy in the community, hence, creating opportunity for consumers and prosumers to trade more of their energy and thus satisfying the energy requirements of the community.

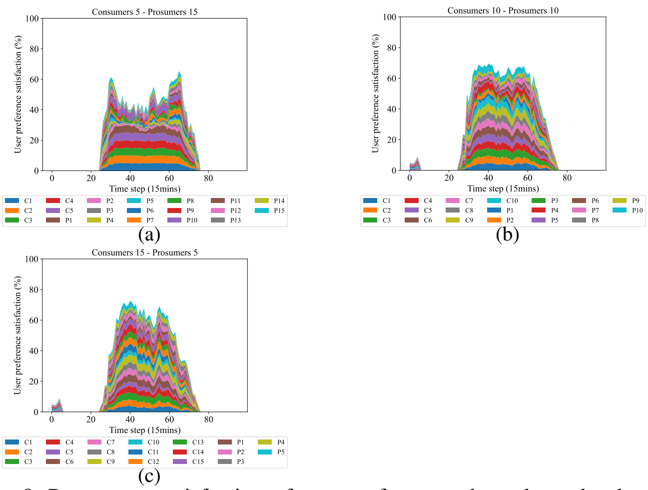


Fig. 8. Percentage satisfaction of user preferences throughout the day for different community setups.

Fig. 9 displays the community average SS and SC for the different simulation scenarios and community set-ups. From Fig. 9a, the SS is higher with 5C15P community configurations compared to the 10C10P and 15C5P. This is because the 5C15P community has more PV production thereby giving the prosumers and consumers the opportunity to be more self-sufficient compared to other communities. The pOnly and P&M simulation scenarios show higher SS compared to mOnly in all the community configurations. This shows that the pooling platform provides opportunity for the community to be more self-sufficient and not depend on the upstream grid for all their energy demand. The maximum SS is 42% which occurs with the P&M scenario in the 5C15P community configuration. From Fig. 9b unlike the SS, the SC is higher with 15C5P community configurations compared to the 10C10P and 5C15P. This is because the 15C5P community has less PV production thereby giving the prosumers the opportunity to trade all their energy production within the community. The pOnly and P&M simulation scenarios show higher SC compared to mOnly in all the community configurations. This also shows that the pooling platform provides opportunity for the community to consume all their energy within their community. The maximum SC is 35% which occurs with the P&M scenario in the 15C5P community configuration.

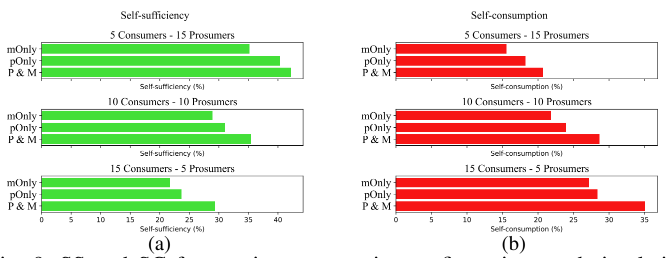


Fig. 9. SS and SC for varying community configurations and simulation scenarios.

V. Conclusions

In this paper, an open source model named pooling platform for matching prosumers with the same energy and price policy in a decentralized LEM was proposed and evaluated of its application in a German case scenario. The simulation results showed that the model was able to satisfy the energy preferences of the consumers and prosumers in the local community to 60% on an average. Also, by using the pooling platform, prosumers and consumers were enabled to trade energy at their preferred price which lead to increasing the self sufficiency and self consumption of the local community to additional 10% and 15%, respectively.

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3.2 Local energy market bidding/offering strategies

Scientific context
LEM is a time series market where prosumers and consumers are expected to post their bids/offers every 15 minutes to the market platform. Most prosumers and consumers may not be able to know the best price to bid/offer for their electricity requirements and it is not technically feasible to do this by hand. Hence, this responsibility requires an intelligent agent that is responsible for making complex and dynamic decisions involved in LEM trading by determining the optimal price the prosumer/consumer should offer-/bid per kWh of their electricity produced or consumed. The reinforcement learning approach which has its foundation from the Markov Decision Process (MDP) is used to model agents so that they are able to make decision or take actions based on their experience from past events or based on trial and error [135, 136, 137, 138, 139]. This shows that reinforcement learning has the capability to be used to develop strategic bidding agents for local prosumers and consumers participating in an LEM. Thus, the agent can learn from past events of the market by comparing their bid/offer price at a particular time with the median clearing price of the LEM or energy bought by a user in comparison with the total energy traded within the LEM. Therefore, the papers presented in this section show the different ways reinforcement learning could be used for modelling the agents bidding strategy in an LEM.

In this section, two papers are presented. The first paper [140] presents a comparison of the zero-intelligent and intelligent bidding strategy in an LEM. Both bidding strategies were analyzed for their application in an LEM during the “EEG” and “post-EEG” scenario. In the second paper [141], two reinforcement learning bidding strategies based on Q-learning and SARSA were developed and used for bidding/offering in a local energy market framework.

3.2.1 Q-learning bidding/offering strategy

Contribution
The paper [140] in this section presents a simulation analysis of bidding strategies for LEM design. In the first stage, a zero-intelligent bidding strategy was developed. For this strategy, the agent randomly selects a bid/offer price from a selected price range. In the second stage, a Q-learning intelligent bidding strategy was developed and evaluated with regards to its applicability in an LEM. Both models were evaluated for varying number of prosumers to consumers ratio and for varying production to consumption ratios. The pricing scenarios evaluated are the “EEG” and “post-EEG” scenario.

The models were also verified with a combination of load and production profiles from standard load profiles [122, 123], LoadProfileGenerator [126, 127] and Renewables Ninja [124, 125] in a 15-minutes time step market using the Grid Singularity exchange engine [120]. The simulation results showed that the intelligent bidding/offering strategy created added benefits for the local participants compared to trading with the zero-intelligent trading strategy.

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Mukund Wadhwa	15%	Conceptualization, Data curation, Formal analysis, Methodology, Validation, Writing - review and editing.
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Peter Tzscheutschler	5%	Methodology, Validation, Writing - review and editing.
Thomas Hamacher	5%	Supervision, Writing - review and editing.

Intelligent Bidding Strategies in Local Electricity Markets: A Simulation-based Analysis*

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***Abstract*—The integration of PV-generated electricity from households and commercial buildings into the electricity mix offers opportunity to reduce the greenhouse gas emissions released in the Earth's atmosphere. The rising quantity of these distributed energy resources (DER) and their fluctuating energy production makes it challenging for the grid operators to manage the grids. This in turn leads to an increase in retail electricity prices due to the rising grid fee. Local electricity markets (LEMs) have proven to be an effective and efficient tool to manage the local generated electricity and ensure that electricity is traded and consumed close to its point of production. The market design factors influencing the performance of an LEM are analysed using a decentralized autonomous area agent (D3A) simulation framework. The market design factors investigated are prosumers-to-consumers ratio (nPC), pricing scenarios and bidding strategies. The results were compared using performance indicators such as self sufficiency, share of individual savings (SIS) of the participants, share of market savings (SMS) and average buying rate. The simulation results show that the performance of an LEM on addition of new participant depends upon the type of participants added to the market. Furthermore, using intelligent bidding strategy like Q-learning increases the self sufficiency of the local community close to their threshold value without the addition of flexibility or storage options.**

***Index Terms*—energy trading, bid, trading agent, bidding strategy, intelligent agent**

I. Introduction

The German electricity sector is a highly complex and heavily regulated system which involves a lot of actors such as generators, retailers, speculators, grid operators, and regulatory bodies. Different types of markets have been created for efficient and fair trading of electricity [1]. According to Cramton [2], trying to create a perfect market with independent participants is an unrealistic idea as the participants cannot be expected to bid their original marginal cost. The main aim of every market participant is to maximize their profits. It is this profit maximization behavior by individual market participants that leads to efficient outcomes for the whole market. Therefore, it can be concluded that the bidding behavior of every participant in a real-life would reflect the principle of profit maximization. The strategies available for market participants in an auction setting can be categorised into zero intelligence (ZI) and intelligent agent (IA) strategy [3]. ZI strategy involves the agent bidding random bids or offers in the market while IA strategy involves using approaches such as estimating market-clearing, game theory or analysis of market behavior from historical data [4]. ZI strategy provides the minimum possible gains made by the market participant due to absence of rationality while IA strategy serves to reach the goal set by the agent for profit maximization. Learning algorithms such as genetic algorithms, Model-based adaption algorithms, Erev-Roth reinforcement learning, Q-Learning, and learning classifier systems are commonly used for creating optimization models for IA strategies [5].

Creation of LEMs has been explored as a solution to help integrate high shares of renewable energy (RE) into the power generation system and increase the involvement of end customers in the power distribution systems [6]. Thus, LEMs also fulfil one of the objectives stated in EU Clean Energy for all Europeans Directive (2016) by providing higher participation of the end consumers in the energy transition process [7]. LEMs create an alternative approach to the classical top-down hierarchy of power distribution by maximizing the utilization of DER in the vicinity of the consumption. Since small and medium scale PV systems are connected to the low voltage grid and a significant portion of the total PV installations are owned by private individuals, it is the main source of local

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generation in projects and research related to LEMs [6], [8]. Trading in LEM can take place between a producer (i.e. a participant that wishes to sell electricity) and consumer (i.e a participant that wishes to buy electricity) or a prosumer and consumer. A prosumer is as a consumer who also owns a source of electricity generation such as rooftop PV and therefore can act as a producer or a consumer in the market depending upon the condition at the given moment [9]. The role of a retailer can be limited to backup electricity provider or active electricity trader where it competes with the local generation sources to sell its electricity.

A lot of research have been conducted on the analysis of local market design factors, cost saving potential for prosumers and consumers, and regulatory requirements for creating LEMs [10] - [12]. Mengelkamp et al. [13] compared the market performance by using Modified Erev-Roth reinforcement learning as the IA bidding strategy and ZI strategy for an LEM participants. However, further research is required into other bidding strategies and the effects of market design factors on the performance of an LEM. Within this work, a Q-learning based IA strategy is investigated in this work along with the effects on performance of the market on addition of new participants. The remainder of this paper is structured as follows. Section II and III explains the design approach and simulation model, respectively. Section IV discusses the results in detail. Finally, Section V concludes the paper giving information on how to further explore the topic.

II. Methodology

This section describes the current day trading of energy at the local level (status quo) as well as in the presence of an LEM layer. LEMs performance evaluating parameters and the Q-learning based bidding strategy methodology are also described. This work is an extension of "in press" [14] research, hence, the design methodology and simulations set-ups are similar. Also, the simulation data are from the same source. The market clearing mechanism is explained in Section III.

A. Trading in the local grid

To determine the monetary and energy inflow and outflow within a local populace, we consider a neighbourhood encompassing of N local electricity traders (LETs) within the low-voltage grid. Retailers compensate the LETs with small-scale generators (e.g. rooftop PV system) for the electricity feed-in to the grid and satisfy the remaining electricity needs of the LETs at a constant rate of r_u^B and r_u^S, respectively. The anticipated net energy traded by an LET i at time step t is the algebraic sum of the forecast load consumption $E_{i,t}^{L}$ and PV generation $E_{i,t}^{PV}$ at slot $t+1$:

$$E_{i,t}^{Net} = E_{i,t}^{L} + E_{i,t}^{PV} \tag{1}$$

Status quo. Status quo is the current scenario where an LET i can only satisfy its net energy $E_{i,t}^{Net}$ requirements by trading with a retailer. Therefore, the energy and monetary balance for such LET i is given as:

$$E_{i,t}^{Net} = E_{i,t}^{ext} = E_{i,t}^{ext,in} + E_{i,t}^{ext,out} \tag{2}$$

$$\Pi_{i,t}^{S} = E_{i,t}^{ext,in} r_u^S + E_{i,t}^{ext,out} r_u^B. \tag{3}$$

$E_{i,t}^{ext}$ and $\Pi_{i,t}^{S}$ is the sum of traded energy between LEM and retailers, and the monetary net balance at the end of trading slot t, respectively. $E_{i,t}^{ext,in}$ and $E_{i,t}^{ext,out}$ represents the external inflows and outflows of energy respectively, within the household of an LET i at time step t.

With LEM. In other to enable LETs to simultaneously trade electricity among themselves and with the retailers, a layer of an LEM is integrated into the local community trading platform based on the smart grid architecture model (SGAM) as described by [15]. The LETs post their offers (bids and asks) for the next time step $(t+1)$ to the local market with $E_{i,t}^{Net}$ as the energy demand and the price determined from the bidding strategy. The offers are matched using the accepted market clearing mechanism. For LETs i and j matched to trade $E_{i,j,t}^{trade}$ energy at the rate of $r_{i,j,t}$ and time t. The excess generation $E_{i,t}^{ext,out}$ from the local community not sold within the LEM are sold to the retailer at r_u^S rate. Similarly, the community residual load $E_{i,t}^{ext,in}$ not provided by the prosumers and producers are fulfilled by the retailer at a constant buying rate of r_u^B. For an LET i within this trading scenario, the energy and monetary balance, at time step t now becomes:

$$E_{i,t}^{Net} = \Sigma_j^N E_{i,j,t}^{trade} + (E_{i,t}^{ext,in} + E_{i,t}^{ext,out}) \tag{4}$$

$$\Pi_{i,t}^{LEM} = \Sigma_j^N (E_{i,j,t}^{trade} r_{i,j,t}) + (E_{i,t}^{ext,in} r_u^B) + (E_{i,t}^{ext,out} r_u^S) \tag{5}$$

B. Parameters for evaluating LEM

Percentage of self sufficiency, share of individual savings, average buying rate, and SMS are the key performance indicators (KPIs) used to evaluate and compare the performance of different LEM designs. For an LEM with a total trading time of (T), the KPIs are expressed as follows.

Self-Sufficiency Ratio. This is the percentage of electricity demand within a local community or neighbourhood that is provided internally by the participants within the local community [10]. It is expressed as:

$$SS = \frac{\sum^N \sum^T |E_{i,t}^{PV} - E_{i,t}^{ext,out}|}{\sum^N \sum^T E_{i,t}^{L}} \times 100 \tag{6}$$

Share of Individual Savings. SIS is a union of the cost of a commodity and the benefit of the commodity measured by willingness to pay for it [17]. In context of LEMs, it is defined as the savings made by individual LEM participants compared to their status quo. Mathematically, it is represented as:

$$SIS = \frac{\sum_t^T (\Pi_{i,t}^{S} - \Pi_{i,t}^{LEM})}{\sum_t^T \Pi_{i,t}^{S}} \times 100 \tag{7}$$

Share of Market Savings. SMS is the sum of SIS made by the local electricity traders by trading among themselves in an LEM compared to trading without LEM. This is given as:

$$SMS = \frac{\sum_t^T \sum_i^N (\Pi_{i,t}^S - \Pi_{i,t}^{LEM})}{\sum_t^T \sum_i^N \Pi_{i,t}^S} \times 100 \quad (8)$$

Average Buying Rate. The average buying rate is given as:

$$ABR = \frac{\sum_t^T \sum_j^N \sum_i^N r_{i,j,t}}{2K} \quad (9)$$

where K is the total number of trades taking place within the LEM at time T.

C. Q-learning based Intelligent Bidding Strategy

Reinforcement learning based IA strategies are usually used to develop bid strategies in electricity markets. Markov Decision Process (MDP) is the bedrock for the development of reinforcement learning-based bidding strategies. According to Tijsma et al. [18], the five MDP factors which can be used to describe LEM participants using IA strategy are the unique set of states, actions, transition function, reward function and the discount factor. The unique set of n states $S = \{s_1, s_2, ..., s_n\}$ where $s_t \in S$ is a tuple made of future traded energy and solar irradiation at time step t. The unique set of m actions $A = \{a_1, a_2, ..., a_m\}$ represents all possible bids or asks (a_t) a participant can select at time step t. The probability relating the current state-action pair (s, a) to the next state s' is the transition function $T(s, a, s')$. The average reward participants receives while transiting from state s to state s' with action a is $R(s, a, s')$. The discount factor $(0 \leq \gamma \leq 1)$ is the basics for appropriating value to current rewards compared to future rewards.

The optimal policy of reinforcement learning is developed from the reward the participants received from past experiences for every state-action pair. For a Q-learning based IA strategy, increasing the state-action usage pair results in a proportional increase in the rate of convergence of the participant to an optimal Q-function. For a Q-function at time step t and state s_t, action a_t is chosen. If the reward received is r_t, the Q-value of a state-action pair at time step $t+1$, $Q_{t+1}(s_t, a_t)$ is represented as:

$$\begin{aligned} Q_{t+1}(s_t, a_t) = &Q_t(s_t, a_t) + \alpha[r_t + \gamma \max_a Q_t(s_{t+1}, a) \\ &- Q_t(s_t, a_t)] \end{aligned} \quad (10)$$

The learning rate and discount factor are α and γ, respectively, where $0 \leq \alpha, \gamma \leq 1$.

For efficient and modular design added with the diverse factors affecting production and consumption trading, the bidding strategies for PV and load are developed differently. To allow a convenient usage of the strategy, market data that are easily accessible are used for the design. The following subsections describe the steps used for creating our Q-learning based strategy for an LEM.

1) States creation: To ensure that all viable occurrences of past experiences are taken care of, historical data form the bedrock of unique figures used for creating states. Tuples of unique solar irradiation and excess PV production data are used for creating states for the production strategy. On the other hand, tuples of unique solar irradiation and the participants consumption profile are used for creating consumption strategy. LEM participants receive information on potential activities of the market from solar irradiation which link the production and consumption, and act as determinant for operation of the market. In order to ensure improved accuracy, 100 unique states are created for each individual device participating in the LEM trading. Each individual device determines the solar irradiation and future traded energy at every time step t and use the data to select the nearest state depicting the occurrence in the next time step $t+1$.

2) Exploration or exploitation factor: Household device use the exploration factor to choose between selecting a random action or action with the best historical record. The ϵ-greedy exploration method is utilized for both consumption and production strategy where the exploration rate is $0 \leq \epsilon \leq 1$. Given a random value x = [0,1], the household device chooses a random action if $x \leq \epsilon$, else, action with the highest Q-value. Consequently, increasing the exploration factor brings about higher orders (bids and ask). The current Q-value "(10)" is updated using the reward from the previous action of the Q-value. The limit to which newly received data predominates the historical data is calculated using the learning rate α. The importance of future rewards is determined using the discount factor γ and is assumed to have no effect on current reward.

3) Reward function (r): The trading objective of the participants are achieved using the reward function and it provides the fundamentals used to compare the value of actions taken under different states. As a result, the reward function is the sum of monetary value of the orders and percentage of absolute total traded energy. The monetary value is the percentage of profit or losses made by selecting an accurate or inaccurate order, respectively. The reward function of a participant at time step t can be represented as:

$$\begin{aligned} r_t = \lambda \frac{|r_{i,j,t} - r_u| E_{i,j,t}^{trade}}{|r_u - r_{opt}| E_{i,t}^{Net}} + \mu \frac{E_{i,j,t}^{trade}}{E_{i,t}^{Net}} \\ \lambda + \mu = 1 \qquad (\lambda, \mu \geq 0) \end{aligned} \quad (11)$$

From "(11)", r_u and r_{opt} represent the retailer's and most optimal trade rate, respectively. A value is assigned to two distinct factors λ and μ based on the trade choice of the participant. Higher λ value means greater preference to economic profit compared to local energy, however, the reverse is the case for μ. The range of reward is between -1 and 1 and the initial value of Q-function Q_0 is 1.

III. Simulations

The simulations were conducted using the Decentralized Autonomous Area Agent (D3A) framework back end code

[19]. Energy requirements not provided within the LEM are fulfilled by retailers who act as back up to the LEM, and flexible load and storage options were not considered. The market mechanism used is pay-as-bid in a double-sided auction intra-day market. Local electricity traders (LETs) can only post their bids and asks within the 15 minutes interval before the actual energy delivery time. Furthermore, the energy demand and PV production forecasts were assumed to be accurate and hence, no settlement was required after the market clearing was concluded. The markets were simulated for a year with 372 LETs made of 228 households, 48 bakeries, 48 office buildings and 48 small manufacturing facilities, in 48 microgrid scenarios. The base scenarios are combination of 4 residential households, a bakery, an office building with PV and a small manufacturing facility with PV. The base scenarios has a prosumers-to-consumer ratio (nPC) of 0.4. Two bidding strategies namely zero intelligent (ZI) and intelligent agent (IA) were investigated.

The production-to-consumption (PtC) ratio are categorized into low ([0.4, 0.6]), medium ((0.6, 0.8]) and high ((0.8, 1.0]). Two pricing types investigated are the "EEG scenario" and "post EEG scenarios". For a residential (H) or commercial (G) electricity consumer, Table I and II show the comprehensive cost of electricity derived from components of electricity price in Germany for the year 2019 when an LEM is integrated into the local community trading platform for EEG and post EEG time, respectively "in press" [14]. The total of the trading components that make up the price is the minimum and maximum trading rates for different seller-buyer pairs. For both EEG and post EEG time, trade between G-H has the same price as trade between H-H.

TABLE I
EEG MINIMUM AND MAXIMUM TRADING RATE FOR LEM

Components	H-H	H-G	G-G
Opportunity cost	12/18	12/18	11/18
Metering fee	0.32	0.32	0.32
EEG surcharge	6.756	6.756	6.756
Value-added-tax (VAT)	3.62/4.76	-	-
Total (Euro ct./kWh)	21.35/29.83	19.08/25.07	18.07/25.07

TABLE II
POST EEG MINIMUM AND MAXIMUM TRADING RATE FOR LEM

Components	H-H	H-G	G-G
Opportunity cost	0/18	0/18	0/18
Metering fee	0.32	0.32	0.32
EEG surcharge	6.756	6.756	6.756
Value-added-tax (VAT)	1.34/4.76	-	-
Total (Euro ct./kWh)	8.42/29.83	7.07/25.07	7.07/25.07

The simulations were performed by varying the nPC and bidding strategies. The addition of a consumer to the base scenario reduces the nPC of the LEM while the addition of a prosumer increases the nPC of the LEM. For each PtC category, the nPC is varied by adding more prosumers and/or consumers to the base scenarios. ZI with five update intervals bidding strategy whereby a random price is selected within a price range was used by the LETs to bid for electricity in the market for these scenarios. The IA bidding strategy based on Q-learning developed in Section II-C was simulated using the base scenarios and compared with the ZI with five update intervals. All the experiments were conducted for both the EEG (EG) and post-EEG (PE) pricing scenarios.

IV. RESULTS AND DISCUSSION

A. *Prosumers to consumers ratio*

1) Share of individual savings: Fig. 1 displays the change in SIS of a prosumer and consumer while varying the nPC of the LEM for EG and PE pricing scenarios with ZI bidding strategy. Increasing the nPC by the addition of a prosumer results in an increase in the PtC ratio. For a consumer, escalating the nPC slightly results in an increase in the SIS of the consumer. However, for a prosumer, increasing the nPC decreases the SIS of the prosumer. For a consumer, decreasing the nPC results in a decrease in the consumer's SIS. However, for a prosumer, decreasing the nPC increases the SIS of the prosumer. Increasing the nPC of the LEM leads to an increase in both the number of potential trading partners for the consumer, and the competition among the prosumers to sell to the same number of consumers. Therefore, increasing nPC increases the share of energy traded by the consumers, which increases their SIS compared to the base scenario. In the other hand, increasing nPC decreases the share of energy sold by the prosumers, which in turn decreases their SIS compared to the base scenario. The reverse is the case for decreasing nPC. The impact of an additional (decreasing or increasing nPC) participant is much higher on prosumers than on consumers. As the prosumers are smaller in number compared to the consumers, the addition of any kind of participant leads to a substantial change in the volume of energy traded. The resulting trends for varying nPC is the same for both EG and PE pricing scenarios only that the consumers have more benefits of buying at a lower average buying rate. This results in an overall higher SIS for the PE compared to EG for the consumers.

2) Self Sufficiency: Fig. 2 shows the change in self sufficiency of the local community while varying the nPC of the LEM for EG and PE pricing scenarios with ZI bidding strategy. Generally, for all PtC categories, increasing the nPC results in an increase in the self sufficiency of the local community for both EG and PE pricing scenarios. Varying the nPC at Low PtC results in a larger change in the self sufficiency compared to High PtC. Advancing the value of nPC increases the trade volume of the LEM. This is due to a higher possibility of trading by the addition of a prosumer as consumers are more in number. The self sufficiency saturates under 50% even when the PtC ratio reaches to 0.94. This is due to PV generation only being available during the presence of daylight. Hence,

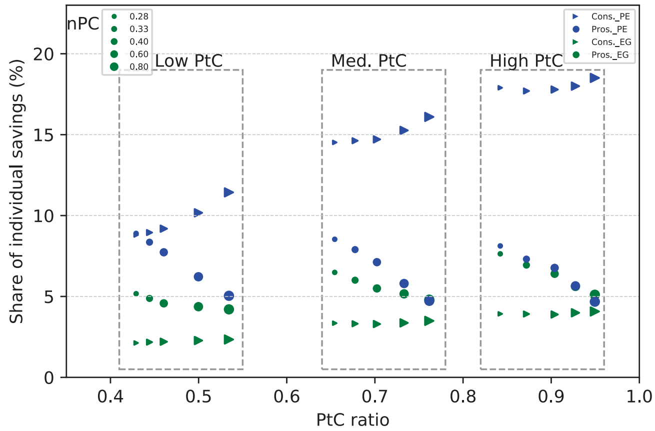

Fig. 1. Share of individual savings for varying nPC and PtC with ZI strategy

the generation from PV cannot supply during the absence of sunlight. Therefore, without unlocking the flexibility options in the form of smart appliances and energy storage options, the self sufficiency of the market cannot exceed the certain threshold even if the generation is enlarged. Finally, the self sufficiency is the same for EG and PE pricing scenarios because the same quantity of energy is sold at both sceanrios.

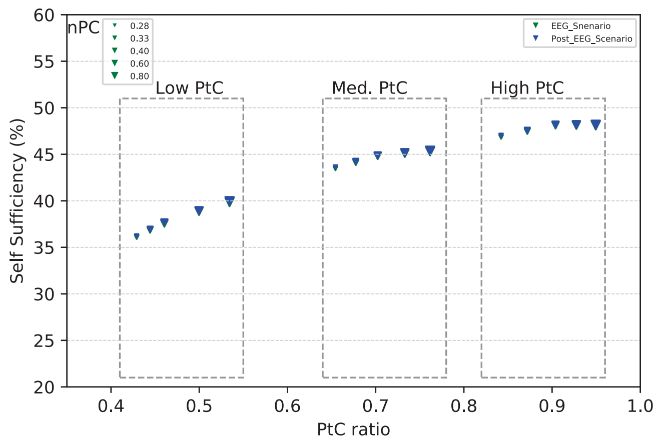

Fig. 2. Self sufficiency for varying nPC and PtC with ZI strategy

3) Share of market savings: Fig. 3 shows the change in SMS of the local community while varying the nPC of the LEM for EG and PE pricing scenarios with ZI bidding strategy. Decreasing the nPC of the base scenarios increases the SMS of the LEM for all the PtC categories. This is the same for both pricing scenarios. Furthermore, increasing the nPC from the base scenarios under Low PtC increases the SMS for both EG and PE scenarios. For high PtC and EG scenario, increasing nPC of the base scenario has only a slight increase on the SMS of the LEM. However, increasing the nPC of the base scenario under PE pricing scenario with high PtC, the SMS decreases from 13.7% to 13.4%.

Decreasing the nPC (addition of a residential consumer with high consumption) increases the energy being traded in the market which would otherwise be sold to the retailer in case of EG scenario, or would not have been produced in PE scenario. Therefore, under Low PtC, decreasing the nPC leads to a 13.4% increase in the energy traded. However, for high PtC, the addition of a small residential consumer leads to an increase of 3.2% in the energy traded. Therefore, the addition of a consumer has a more drastic increase in Low PtC compared to high PtC for SMS. In the PE scenario, the minimum opportunity cost for selling generation is reduced to zero and the consumers make higher profits with every trade. Thus, the overall SMS is increasing. The prosumer added has a significant portion of its excess generation produced during working hours and therefore, it can sell it to commercial consumers which have a high consumption at the same time. Under Low PtC, the generation already happening in the LEM is quite low. Therefore, the additional prosumer increases the energy traded in the market. The additional prosumer only increases the share of energy traded and the competition for selling to the same number of consumers. Consequently, the SMS increases due to significant increase in the share of energy traded in Low PtC and slightly reduces due to negligible increase in the share of energy traded in High PtC.

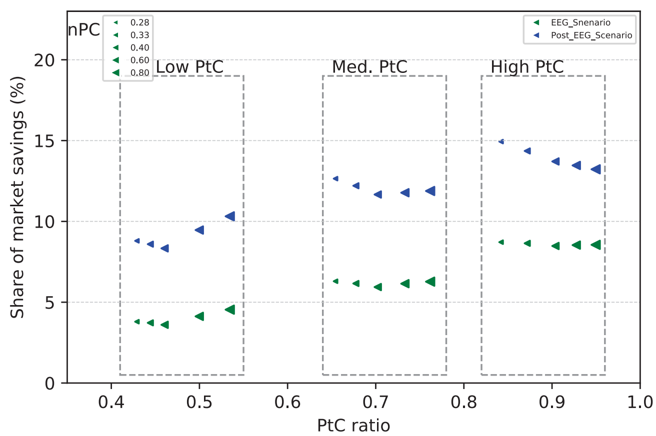

Fig. 3. Share of market savings for varying nPC and PtC with ZI strategy

4) Average Buying Rate: Fig. 4 shows the change in average buying rate (ABR) of the local community while varying the nPC of the LEM for EEG and post-EEG pricing scenarios with ZI bidding strategy. The ABR is relatively constant below 25.0 EUR ct./kWh across all the simulations for EG pricing scenario. However, for PE pricing scenario, increasing the nPC decreases the ABR in all PtC category. However, decreasing nPC increases the ABR in all PtC categories. Increasing nPC (addition of a prosumer) increases the supply of energy to the market, leading to lower competition among the buyers and hence, reducing the buying rate. Whereas, decreasing nPC (addition of a consumer) increases the total consumption to be fulfilled, leading to more competition among the buyers for the same amount of generation and hence, increasing the buying rate. These trends can be seen more prominently in the PE scenario as the range of possible bids is larger. Hence, the changes in the competition inside the market are more evident.

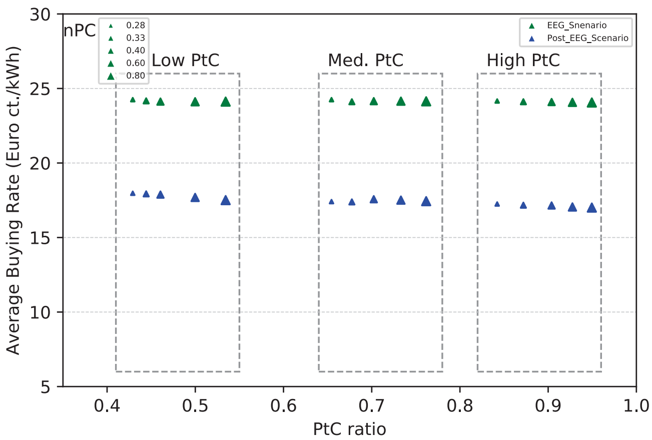

Fig. 4. Average Buying rate for varying nPC and PtC with ZI strategy

B. Bidding strategy

1) Self Sufficiency: Fig. 5 shows the changes in self sufficiency for different PtC categories and pricing scenarios with ZI and IA bidding strategy. An average increase of 1.1% in self sufficiency of the LEM is witnessed by using an IA strategy for all pricing scenarios as well as PtC categories. The share of the generation that remained unsold due to the mismatch of bids and offers is reduced from 3.1% to 0.1% on an average. Also, using Q-learning algorithm increases the probability of matching the bids and offers and hence, the self sufficiency reaches close to the maximum possible value for the market without the addition of flexibility or storage options.

2) Share of market savings: Fig. 6 shows the changes in the SMS for different PtC categories and pricing scenarios with ZI and IA bidding strategy. An average increase of 5.1% in SMS is witnessed by using intelligent bidding strategy for all pricing scenarios as well as PtC categories. The increase in the SMS is different across all the pricing scenarios and PtC categories. The increase in the SMS is the steepest at High PtC. This is due to a higher volume of energy being traded in the market under High PtC which helps the Q-learning algorithm to understand the market situation better and optimize the bids or offers better. Thus, it leads to higher profits for the participants and an increase in overall SMS.

3) Average Buying Rate: Fig. 7 shows the changes in the average buying rate for different PtC categories and pricing scenarios with ZI and IA bidding strategy. An average decrease of 5.3% is witnessed for the average buying rate of the LEM by using intelligent bidding strategy across all pricing scenarios as well as PtC categories except for EG scenario in Low PtC.

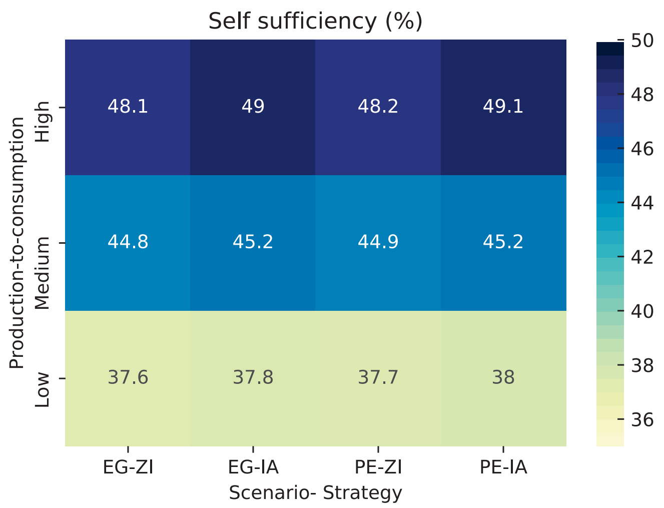

Fig. 5. Self sufficiency for varying bidding strategy

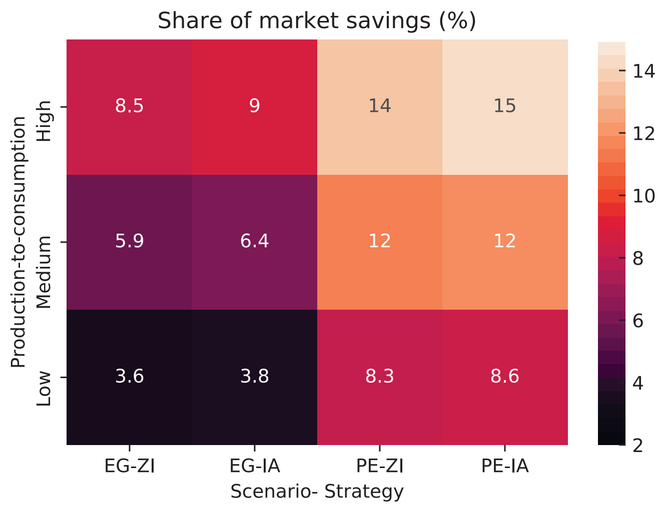

Fig. 6. Share of market savings for varying bidding strategy

For the IA strategy, factors that can influence the price on the market such as nPC, PtC ratio, and the pricing scenario were considered. The bidding was done in a manner to simulate human behavior and the true cost of electricity reflected as a result. Therefore, in situations of scarcity of generation, the consumers would be bidding higher than the average price in order to make a trade. Hence,the profit margin of the prosumers increases. However, in situations of an excess of generation in the market, the prices will drop as the prosumers would be competing to sell their generation. Consequently, the profit margin of the consumers increases.

V. Conclusion and Outlook

Within this work, simulation and analysis of LEMs using a multi-round auction with ZI and IA bidding strategy on

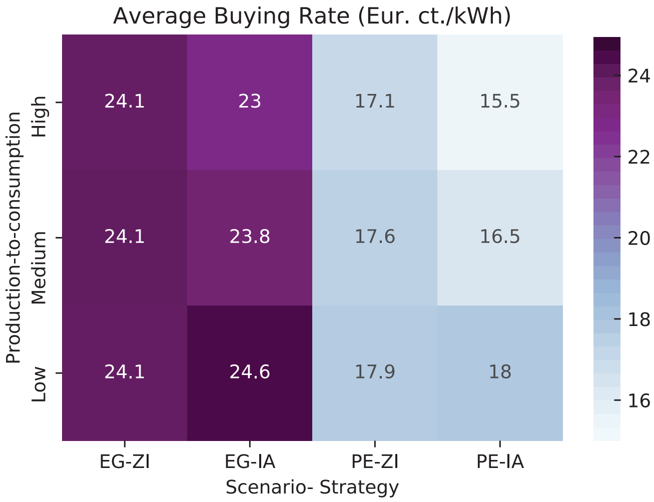

Fig. 7. Average Buying rate for varying bidding strategy

a D3A simulation framework are presented. Simulations of different local community markets configurations verified the opportunities and the importance of an LEM. The SIS of a participant in an LEM depends upon the number of competitors and the volume of energy available to be traded. The trends of SIS for prosumers and consumers are always reverse for increasing or decreasing nPC. The degree to which decrease or increase in nPC effects prosumers and consumers depends upon several market design factors such as the patterns of generation and consumption of participants, PtC, and the pricing scenario. In summary, LEMs can be beneficial to both prosumers and consumers, to fully exploit the potential of local energy resources in an efficient way without adding flexibility or storage options, a participant will need to integrate an IA bidding strategy in their household. The profit made by LETs from LEM can incentives them to keep their PV system running during PE time and thereby retaining the renewable energy capacity within the grid.

In future research, more bidding strategies such as Erev-Roth learning, long short term memory and convolution neural network will be investigated within this framework. Furthermore, the simulation will be extended to compare different market mechanisms and further validate the findings. The best-suited market mechanism will be implemented using a Hardware-in-the-Loop laboratory environment testing before the final stage which will be validating the results in a field test. A field test is planned with assets from our project partner WIRCON within the German SINTEG project “C/sells”.

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3.2.2 Q-learning and SARSA bidding/offering strategies

Contribution

The paper [141] in this section presents the modelling and evaluation of two reinforcement learning based bidding strategies for LEM design. The two intelligent bidding strategies are based on Q-learning and SARSA. The models were verified in different scenarios known as the classical, standalone and shared reward scenarios. For the classical bidding strategies, the agents are modelled to ensure that they take action that results in more benefits for the respective prosumer/consumer that own the agent. For the standalone scenario, only the prosumers or consumers have intelligent agents in the community. Hence, for this scenario, if the consumers have intelligent agents, the prosumers make an offer with a linear bidding agent. On the other hand, if prosumers have intelligent agents, the consumers bid with linear strategy. In this way, the effect of using the agents in a community where other participants have no intelligent agents was verified. The "shared reward" is a scenario where all the agents work towards a common goal of making benefits for the community. The model was also verified with a combination of load and production profiles from German households [121] and Renewables Ninja [124, 125] in a 15-minutes time step market. The results from the simulations show that when all the community member agents work towards a common goal, that it creates added economic and technical benefits to the community compared to when they work towards their own common individual benefits.

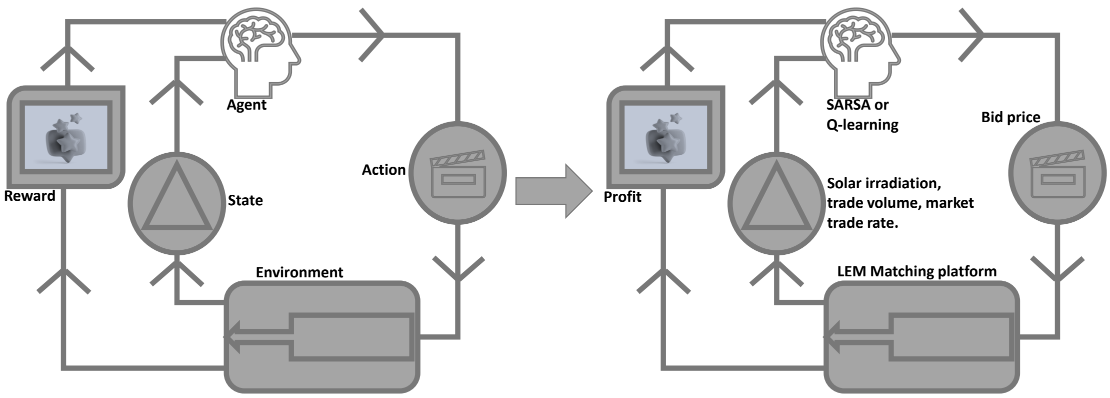

Figure 3.4: Schematic of proposed reinforcement learning bidding strategies for LEM, after [141]

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Publication #7: Intelligent Bidding Strategies for Prosumers in Local Energy Markets Based on Reinforcement Learning

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Jeel Bhalodia	15%	Conceptualization, Data curation, Formal analysis, Methodology, Validation, Writing - review and editing.
Amin Shokri Gazafroudi	4%	Methodology, Validation, Writing - review and editing
Thomas Brenner	5%	Methodology, Validation, Writing - review and editing.
Peter Tzscheutschler	5%	Methodology, Validation, Writing - review and editing.
Thomas Hamacher	5%	Supervision, Writing - review and editing.

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RESEARCH ARTICLE

Intelligent Bidding Strategies for Prosumers in Local Energy Markets Based on Reinforcement Learning

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ABSTRACT Local energy markets (LEMs) are proposed in recent years as a way to enable local prosumers and community to trade their electricity and have control over their electrical related resources by ensuring that electricity is traded closer to where it is produced. However, literature is still scarce with the most optimal and effective trading strategies for LEM design. In this work, we propose two reinforcement learning based intelligent bidding strategies for prosumers and consumers trading within an LEM. Our proposed models were evaluated of their performance by testing them in a German real case scenario. The simulation results show that intelligent bidding strategies create additional self sufficiency and market savings to the local community compared to the baseline strategy where the agents make their trading decision randomly without an intelligent agent. Moreover, modelling the intelligent agents to perform towards a common goal creates more share of individual savings for the prosumers and consumers compared to the classical intelligent bidding strategies employed in this work.

INDEX TERMS Bidding strategy, energy community, local energy markets, Markov decision process, peer-to-peer, reinforcement learning.

I. INTRODUCTION

A. MOTIVATION AND BACKGROUND

Local energy markets (LEMs) were introduced in recent years as a means to curb the challenges resulting from increasing share of variable distributed energy resources at the distribution grid level and thus creating an avenue to get small-scale producers, prosumers and consumers involved in the electricity market [1]. By transacting electricity closer to where it is produced, producers, prosumers and consumers create additional benefits for each other compared to transacting electricity to a far distance prosumers/consumers or with the upstream grid [2]. However, residential and most commercial prosumers/consumers are lay users and have little or no knowledge of the electricity markets. Therefore, they may not be able to decide the appropriate bidding/offering price for their energy demand/supply considering the dynamics and complexity involved [3]. On the other hand, the local electricity market is a time series market platform. Hence, consumers and prosumers are required to consistently post their bid/offer containing their desired energy quantity and price every time slot [4]. This is inefficient and time consuming and thus, the need for an intelligent bidding/offering agent responsible for making the complex and dynamic decision involved in LEM trading. The agent is also responsible for selecting appropriate price for prosumers/consumers to make benefits from their electricity assets and automatically posting the bids/offers on behalf of consumer/prosumers who own the agent [3], [4]. Consequently, researchers have proposed different bidding strategies for LEM design [5], [6].

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B. LITERATURE REVIEW

According to Ref. [7], LEM bidding strategies can be classified either as zero-intelligence or intelligent agent bidding strategies. Zero-intelligence agents randomly select their bid/offer price within the limit range of the maximum selling and minimum buying price, which is usually the upstream grid and feed-in tariff price, respectively. Intelligent agents bidding strategy usually derive their trading price based on some optimization model, algorithms, game theoretic approach and/or learning experience. The authors of [8], proposed a linear bidding/offering strategy for LEM that allows agents to linearly decrease/increase their bid/offer price, respectively, in an LEM time slot. This strategy allows prosumer agents to send multiple bids/offers in a single time slot thereby increasing their chance of being matched in the LEM without increasing the computational power requirements of the agents. Ref. [9] proposed an optimization based prediction-integration strategy called surrogate market prediction model based on Extreme Learning Machine. The model was used to learn the relationship between prosumer bidding actions and market responses from historical transaction data and the outcome was used for bidding/offering in a peer-to-peer(P2P) LEM.

The effective metrics and criteria for evaluating the performance of an LEM bidding strategy was introduced by Ref. [5]. Furthermore, the authors modelled the behaviors of both risk-neutral and risk-averse agents selling energy to the LEM taking into account the expected profit and risk criteria to obtain an optimal multi-step energy quantity-price bidding strategies of risk-neutral and risk-averse agents. PV is considered a major source of energy during the day for most intra community and inter community energy trading. Thus, considering the uncertainties in solar irradiance and temperature can result in an optimal P2P LEM bidding strategy [6], [10]. Ref. [6] proposed a dual bidding strategy for multi-hierarchical P2P energy trading in an LEM considering uncertainties in solar irradiance and temperature. By considering the uncertainty of renewable energy resources such as solar, wind and consumer demands in an LEM, the authors of [10] proposed a bi-level optimization model for prosumers to appropriately take advantage of their distributed energy resources in an LEM. The optimal bidding curve which described the cost-minimizing buying/selling strategy of prosumers was used to guarantee the optimality of bidding decisions and to reduce the computation and communication overhead of bidding agents by [11]. Ref. [12] proposed a two-stage bidding strategy for P2P LEM design. The first stage considered the supply-demand relationship for two-step price predictor with the aim to promote the usage of local renewable energy within the LEM. In the second stage, a trading preference based simultaneous game-theoretic approach was introduced and used to optimize the market equilibrium and social welfare of the P2P LEM. In [13], an optimal bidding/offering strategy was proposed for prosumers in an LEM to improve their savings and further increase the overall social welfare of the local community.

Before the introduction of LEM in the last two-decades and in recent years, reinforcement learning is used by electricity producers for making decision on their offering price in a competitive electricity market. In [14], a modified continuous action reinforcement learning automata algorithm was proposed to help power suppliers bid with the limited information in an electricity market. Ref. [15] proposed an experience weighted attraction reinforcement learning algorithm for bidding in an electricity markets. The authors of [16] used a deep deterministic policy gradient reinforcement learning algorithm to develop a bidding agent for a uniform pricing electricity market. Ref. [17] developed a fuzzy Q-learning method and used it to model the electricity producer strategic bidding behavior in a competitive and computational electricity market. In [18], the deep deterministic policy gradient method was combined with a prioritized experience replay strategy and used to model the strategic bidding decisions in a deregulated electricity markets. In the same way, Ref. [19] combined reinforcement learning with belief learning that converts experience-weighted attraction in a learning model for describing and improving individual learning behavior for effective bidding in a double auction electricity markets.

Similar to the main electricity markets and as a result of its numerous advantages, reinforcement learning is currently gaining the interest of researchers on how it can be utilized for decision making in an LEM. By solving the deep reinforcement learning technology with experience replay mechanism, Ref. [20] modified the deep Q-learning for local energy trading algorithm from deep Q-network to facilitate the decision-making process of local energy prosumers with an intelligent system and further promote prosumers' willingness to participate in the LEM trading. Ref. [21] proposed an intelligent bidding strategy based on an adaptive reinforcement learning model for prosumers within a local grid. In Ref. [22], a deep learning based on data-driven approach was developed and used to model the transaction behaviour of prosumers and consumers based on public information in a two-stage P2P local electricity market. A Q-learning based intelligent bidding strategy was proposed by [23] for prosumers in a competitive two-sided pay-as-bid LEM. To further integrate electric vehicle trading in an LEM, [24] proposed a data analytics and deep reinforcement learning based bidding strategy for electric vehicle aggregators in an LEM.

C. CONTRIBUTION & ORGANIZATION

Currently, the literature contains only few studies proposing intelligent bidding strategies for LEM design. Moreover, there is still a gap in literature proposing and comparing different reinforcement learning models for LEM bidding strategies and further suggesting the most optimal strategy for the different local energy participants types. In this paper, by answering the research question, which trading strategies are most suitable for effective performance of local energy markets? We propose two novel reinforcement learning based intelligent bidding strategies for prosumers and consumers in an LEM. The proposed models use information/data initially acquired from the LEM and the participants to formulate the most optimal bidding/offering prices for consumers and prosumers within an LEM for them to make optimal benefits from their consumption's/productions. The models were implemented on an interface and open source code-base of the Grid Singularity bidding application programming interface [25]. Furthermore, we evaluate the models using performance indicators such as self-sufficiency, share of market savings and traded energy quantity of the prosumers/consumers in the LEM. The main contributions of the paper are summarized below:

- Proposing two novel reinforcement based intelligent bidding strategies for prosumers and consumers in an LEM.
- Implementation of the proposed intelligent bidding strategy models in a real case German community.
- Assessing the performance of the proposed bidding strategies using LEM and reinforcement learning performance indicators.

The remaining sections of this work are structured as follows. Section II introduces reinforcement learning taxonomy and the proposed reinforcement learning algorithms. The proposed reinforcement learning bidding strategies are described in Section III. The simulation case study, community set-up and simulation data are presented in Section IV. Section V presents the simulation results, while Section VI discusses the findings, insights and improvements of the models. Finally, the paper is concluded in Section VII.

II. REINFORCEMENT LEARNING

A. REINFORCEMENT LEARNING TAXONOMY

Reinforcement learning (RL) is a branch of machine learning that uses trial-and-error strategy to learn from previous actions to make future decisions [26]. The reward strategy which gives positive reward to successful events/actions and negative rewards to unsuccessful events/actions is used by the agents to improve its learning and decision making [27]. The term ''value function'' refers to prediction of future benefits based on the present condition or state [28]. By comparing the outcome of each decision made by the agents, the agents get experience on how to perform better on future actions of the model based on its prior experience with the environment. In RL, this experience-based decision making process which helps the agents to maximize their reward for each action taken against the environment is referred to as a policy [26]. The Markov Decision Process (MDP), is a probabilistic model based on sequential decision making and provides the mathematical foundation for RL process [29]. The MDP property claims that ''the probability of the future is independent of the past given the present'' [29]. However, the optimal action of an agent is usually obtained when the agent evaluate not just the immediate reward but also the long-term quality of the action(s). Because of the high accuracy when given more data, the action-value function is preferable in the long term RL model [30]. This is why an action-value function is more suitable for intelligent agent-based bidding strategies for LEM.

RL algorithm can be classified based on their access to the model as model based and model-free algorithm [31]. Model-based RL algorithm is a type of RL in which the agent is privileged to know all possible state transition probabilities and rewards [32]. This type of RL is heavily influenced by control theory, and the objective is to obtain the optimum behaviours using a control function. The major draw back of this RL method is that since they have access to all potential state-actions, storing all the probabilities becomes impractical as the number of states and actions increases exponentially [32]. Model-free RL is a type of RL model that develops its own optimum strategy based on its own experience with its surroundings, state-action pairings, and their associated rewards [33]. Model-free algorithms are classified into policy iteration and value iteration [31]. For policy iteration model-free algorithm, the agent directly learns the policy function that translates state to action using policy optimization approaches [32]. Thus the policy is decided without the use of a value function. The policies here can be either deterministic or stochastic [32]. Value iteration model-free RL algorithm gains knowledge of the action-value function, calculates the expected discounted rewards received for taking a particular action and determines how beneficial it is to behave in a specific state [31]. Thus, a scalar value called Q-value is assigned to an action based on its state and the ideal results are obtained when the action with the highest Q-value is chosen. Value iteration algorithm can be further classified into off-policy and on-policy algorithms. Off-policy RL algorithms use greedy policy and learns the best policy and acts based on a different policy [34]. The updated policy differs from the behaviour policy. The Q-learning algorithm is an example of an off-policy algorithm. On the other hand, for the on-policy strategy, the actor captures the best policy and applies it to its actions [34]. The major difference between off-policy and on-policy is that for on-policy, the policy for updating and acting is the same, while it is different for off-policy. On-policy tries to evaluate the same policy that is used to make decisions [34]. State Action Reward State Action (SARSA) algorithm is an example of on-policy algorithm.

B. REINFORCEMENT LEARNING ALGORITHMS

1) OFF-POLICY ALGORITHM - Q-LEARNING

In Q-learning, the 'Q' stands for quality which refers to the usefulness of a certain action in obtaining a future reward which can be determined by the Q-value. Q-learning seeks to determine the best policy while pursuing a separate exploration strategy [35]. This class of algorithms updates the state or state-action values by calculating the difference between current and past estimations [33]. Eq. (1) is the general Q-learning function which states that the Q-value depends on the state-action combination [32].

$$\mathcal{Q} : \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{R} \tag{1}$$

where $\mathcal{S}$ is the state of the agent, $\mathcal{A}$ is the different actions that are available for the agent to take and $\mathcal{R}$ is the rewards the agents can receive for taking different actions. Eq. (2) represent the different states of an agent.

$$\mathcal{S}_t = \{[s_{1,t}^{x1}, s_{1,t}^{x2}, \ldots, s_{1,t}^{xm}], \ldots, [s_{n,t}^{x1}, s_{n,t}^{x2}, \ldots, s_{n,t}^{xm}]\} \quad (2)$$

where s_1 to s_n are the different states and x_1 to x_m are the state variables. The different state variables combine to form one sate s. n and m are the number of states and state variables, respectively. Therefore, at a time step t, the state of an agent is represented in Eq. (3),

$$s_t = s_t^{x1}, s_t^{x2}, \ldots, s_t^{xm}. \quad (3)$$

The different actions an agent can take at any time step is represented by (4).

$$\mathcal{A} = a_{1,t}, \ldots, a_{u,t} \quad (4)$$

where u is the number of actions. The available rewards for an agent at a time step is represented in Eq. (5),

$$\mathcal{R} = (-\infty, \infty). \quad (5)$$

Initializing Q-table: A Q-table is a matrix with the structure of [states, actions] used for Q-learning process as represented in Eq. (6).

$$\mathcal{Q}_{s\times a,t} = \begin{bmatrix} q_{1,1,t} & \cdots & q_{1,u,t} \\ \vdots & \ddots & \vdots \\ q_{n,1,t} & \cdots & q_{n,u,t} \end{bmatrix}, \forall t. \quad (6)$$

Q-table is first initialized with either 0 or 1 and updated every time step. It is the reference table for agents, which it uses to determine the optimal course of action taken.

Taking action: In order to interact with the environment, the agent needs to select an action. The agent chooses an action based on the maximum value in the Q-table or on a random basis [32]. The epsilon (ϵ) greedy approach is used by an agent to achieve a balance between exploration (chosen random action) or exploitation (chosen action with maximum Q-value) and to interact with its environment in either of the two ways throughout the experiment [36]. Eq. (7) represents that the total experiment time step is the sum of exploration and exploitation time represented as t^ϵ and $t^{1-\epsilon}$, respectively,

$$\mathcal{T} = \sum t^\epsilon + \sum t^{1-\epsilon}. \quad (7)$$

Eq. (8) represents how the agents select its action during time of exploration and exploitation. From Eq. (8), a_{u,t^ϵ} and $a_{u,t^{1-\epsilon}}$ represents actions selected by the agent during exploration and exploitation, respectively,

$$a_{u,t} = \left\{ \begin{array}{ll} a_{u,t^\epsilon}: & \epsilon = 1 \\ a_{u,t^{1-\epsilon}}: & \epsilon = 0 \end{array} \right\}, \forall t. \quad (8)$$

Eq. (9) represents that during exploration, the agent takes a random action by randomly selecting any action from the available actions at the time step. On the other hand, Eq. (10) represents that during exploitation, the agent takes action by selecting the action with the maximum Q-value,

$$a_{u,t^\epsilon} = rand.\{a_{1,t}, \ldots, a_{u,t}\}, \quad (9)$$
$$a_{u,t^{1-\epsilon}} = \arg\max \sum \mathcal{Q}_{s\times a,t}. \quad (10)$$

Updating Q-table: Q-values of Eq. (6) are updated every time step based on Bellman's equation as represented in Eq. (11) [32], [37].

$$Q_t(s_t, a_t) = \sum \left[r_{(t+1)} + \gamma \max_{a'} Q_t\left(s_{(t+1)}, a_{(t+1)}\right)\right] \quad (11)$$

where, s_t and a_t are the current state and action, $s_{(t+1)}$ and $a_{(t+1)}$ are the next state and action, respectively. r_{t+1} is the expected reward. γ is the discount factor and represents the amount of value the agent place on the future benefits. The discount rate ranges from 0 to 1 ($0 \leq \gamma \leq 1$). With a higher discount rate, the agent places a higher premium on future returns. Bellman's equation is used to calculate the value of a state and to estimate how beneficial it is to be in that state. The ideal state is the state that produces the optimal Q-value. Q-learning algorithms are based on the Bellman's equation used as the basic value of iteration update, based on the weighted average of the old and new Q-values and is defined according to Eq. (12) [37].

$$Q_{(t+1)}(s_t, a_t) \leftarrow Q_t(s_t, a_t) + \alpha \left[r_t + \gamma \max_a Q_t\left(s_{(t+1)}, a_t\right) - Q_t(s_t, a_t)\right] \quad (12)$$

where α is the learning rate and indicates the learning pace of the agent. This parameter gives information on how the agents' estimations should be updated considering the mistakes. The learning rate ranges between 0 and 1. A high learning rate adapts aggressively, which may result in variable — rather than converging — training outcomes. A low learning rate adapts slowly, which means that it will take longer time to converge. The terms in Eq. (12) are defined as follows:

- (1- α) $Q_t(s_t, a_t)$ is the current Q-value weighted by the learning rate.
- $\alpha\, r_t$ is the reward obtained in state s_t by taking action a_t, weighted by learning rate.

$$\alpha\gamma \max_a Q_t\left(s_{(t+1)}, a\right) \quad (13)$$

- Eq. (13) is the maximum reward to be obtained from the next state $s_{(t+1)}$.

$$r_t + \gamma \max_a Q_t\left(s_{(t+1)}, a\right) \quad (14)$$

- The term given in Eq. (14) which is derived from Eq. (12) is called the temporal difference target through which the estimated Q-value is adjusted.

The temporal difference is an estimate of the optimum Q-value which the agent strives to get and this varies as the agent is trained and the Q-value matrix updated. The Q-value of the agent's current state and action is updated by subtracting the previous Q-value and then adding the learned value. The learned value is a function of the reward for taking the current action in the current state and the discounted maximum reward from the subsequent state in which the present action is performed.

2) ON POLICY ALGORITHM : SARSA

SARSA is an on-policy reinforcement learning algorithm in which an action, A, is taken in the current state, S, and the agent receives a reward, R. The agent then moves to the next state, S', and performs action, A' in S'. As a result, the name SARSA is derived from the tuple (S, A, R, S', A'). SARSA is referred to as an on-policy algorithm because it adjusts the policy in response to actions and is part of temporal difference learning [36]. The algorithm's learning process is similar to Q-learning described in Section II-B1. The first step is to initialize the Q-table. Secondly, an action similar to that of Q-learning with its ϵ-greedy strategy is taken. Lastly, the Q-table is updated and this is where there is distinction between SARSA and Q-learning. Eq. (15) is used to update the Q-value for SARSA.

$$Q_{(t+1)}\left(s_t, a_t\right) \leftarrow Q_t\left(s_t, a_t\right) + \alpha \left[r_{(t+1)} + \gamma Q_t\left(s_{(t+1)}, a_{(t+1)}\right) - Q_t\left(s_t, a_t\right)\right] \tag{15}$$

The update equation of SARSA, Eq. (15) shows that the goal value in this case is dependent on the action the agent will take in the following state, s_{t+1}. Since this update is dependent on the next action a_{t+1}, which is determined by the current policy, this algorithm is termed on-policy [37]. While training the agent and the corresponding Q-value (and policy) is updated, the new policy may generate a different action for next time step $a_{(t+1)}$ for the same state $s_{(t+1)}$. It is not possible to improve the estimations by drawing on prior experiences. Hence, the algorithm utilizes each experience just once to update the Q-values and then discard it [34].

III. PROPOSED REINFORCEMENT LEARNING BIDDING STRATEGIES

In this Section, the proposed reinforcement bidding strategies is presented. Fig. 1 and 2 represents the process diagram and the flowchart, respectively, of the proposed bidding strategies. First, the state, actions and reward function are defined. Then, the Q-learning algorithm bidding strategy is introduced followed by SARSA bidding strategy.

A. STATE, ACTION AND REWARD DEFINITION

1) STATE

The state of the agent at any time t, is define by Eq. (16).

$$\mathcal{S}_t = \{[s^{\sqcup}_{1,t}, s^{\overline{p}}_{1,t}, s^{\overline{v}}_{1,t}, s^{\rho}_{1,t}], \ldots, [s^{\sqcup}_{n,t}, s^{\overline{p}}_{n,t}, s^{\overline{v}}_{n,t}, s^{\rho}_{n,t}]\} \tag{16}$$

where the state variable $\sqcup$ is the hour of the day where the trading occurs and this is split into 24 variables .i.e $\sqcup = \{0, 1, \ldots, 23\}$. $\overline{p}$ is the average market trade rate in cent/kWh for the previous market time step. The average trade rate has a range from feed-in tariff price ($p^{\perp}$) to the electricity buy price (p^b) from the upstream grid. In order to reduce the size of the Q-table for its optimal performance, the range of the state variable $\overline{p}$ is divided into six equal buckets as presented in Eq. (17)

$$\overline{p} = \{p^{\perp}, \frac{(4 \times p^{\perp} + p^b)}{5}, \ldots, p^b\}. \tag{17}$$

$\overline{v}$ is the average trade volume which is the average volume of the electricity traded internally within the local community without the help of the upstream grid in the last time step. The average trade volume is also divided into six buckets in order to have discrete data and to reduce the size of the Q-table as represented in Eq. (18)

$$\overline{v}_t = \{\overline{v}_{1,t}, \overline{v}_{2,t}, \ldots, \overline{v}_{6,t}\}. \tag{18}$$

ρ is the solar irradiation which gives information on the average solar radiation received per unit area of the simulation area. This state variable is divided into nine buckets to better refelect the different solar radiation intervals as given in Eq. (19)

$$\rho_t = \{\rho_{1,t}, \rho_{2,t}, \ldots, \rho_{9,t}\}. \tag{19}$$

Hence, at any time step t, the state of the agent is described as a tuple containing four state variables $\sqcup$, $\overline{p}$, $\overline{v}$ and ρ.

2) ACTION

This is a discrete set of potential bids/offers prices available to a consumer or prosumer. This varies from the lowest ($p^{\perp}$) to the highest price (p^b) allowed with the LEM. The range of bid/offer price is discretize into sixteen potential actions as represented in Eq. (20)

$$\mathcal{A} = \{p^{\perp}, \frac{(14 \times p^{\perp} + p^b)}{15}, \ldots, p^b\} \tag{20}$$

In RL, the agent learns what to do by itself and translate situations to actions to maximize a numerical reward signal [26]. The agent is not instructed on which actions to take; instead, through trial and error, it decides which action gives the maximum reward. For our model, ϵ greedy policy is used to handle the exploration/exploitation dilemma by applying simple strategy for balancing exploration and exploitation by randomly selecting between the two. For this, a random number λ is selected and the value compared with the given value of ϵ as represented in Eq. (21),

$$a_{u,t} = \left\{ \begin{array}{ll} a_{u,t^{\epsilon}}: & \lambda < \epsilon \\ a_{u,t^{1-\epsilon}}: & \lambda > \epsilon \end{array} \right\}, \forall t. \tag{21}$$

Hence, from Eq. (21), a random action (exploration) is selected if $\lambda < \epsilon$, while action leading to the maximum reward (exploitation) is selected if $\lambda > \epsilon$. The developed RL algorithm is a single agent RL method which contains a combined and evolved policy for both consumers and producers. Both consumers and prosumers take distinct actions as they have a different pricing strategy. However, their states and reward functions are identical. As a result, each actor uses a different Q-table inside a single RL agent, where one actor is not aware of the presence of the other actor.

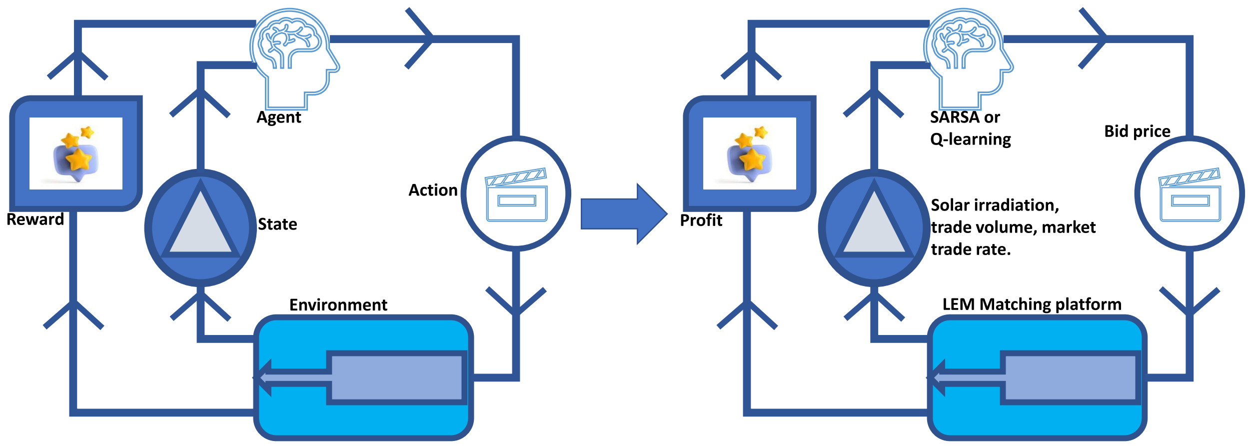


FIGURE 1. Proposed bidding strategies based on Q-learning and SARSA.

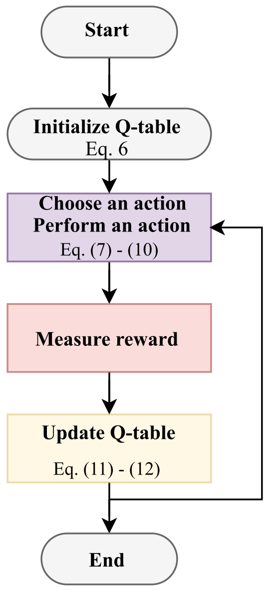


FIGURE 2. Learning process flowchart for Q-learning and SARSA.

3) REWARD FUNCTION

The reward function is used to compare the value of actions taken by the agent at different states. To encourage prosumer behaviour that results in greater consistency with their trading goals the reward function of our model is a mix of the monetary value of the bid/offer and how early trade occurs in a market time step. For this, the market model based on the work of Ref. [8] which allow prosumers and consumers to submit multiple bids and offers at a time step. Hence, each market time step is further divided into market ticks t_t^* as represented in Eq. (22).

$$t_t^* = \{t_{1,t}^*, t_{2,t}^*, \dots, t_{k,t}^*\}, \tag{22}$$

where k is the number of ticks in a time step t. The trade rate of prosumer agent i, at a time step is compared with the markets median trade rate at the same time step to obtain the monetary value of reward function. The median is used to prevent outliers from having impact if the mean was used as the measure. The monetary reward function of consumers is represented in Eq. (23).

$$r_t^{b,\$} = \left\{ \begin{array}{lr} 0.7 \times (\widehat{p}_t - p_{i,t}^b)/(p^b - \widehat{p}_t): & p_{i,t}^b > \widehat{p}_t \\ 0: & p_{i,t}^b = \widehat{p}_t \\ 0.7 \times (\widehat{p}_t - p_{i,t}^b)/(\widehat{p}_t - p^{\perp}): & p_{i,t}^b < \widehat{p}_t \end{array} \right\}, \forall t, \tag{23}$$

where $\widehat{p}_t$ is the median trade rate at time step t and $p_{i,t}^b$ is the trade rate of consumer agent i, at the same time step. Eq. (23) shows that if a consumer's trade rate is lower than the community's median rate $\widehat{p}_t$, the consumer's agent receives a positive reward since he/she (the consumer) paid less than the other members of the community and outperformed them. When a consumer's trade rate exceeds the market's median rate, the consumer's agent earns a negative reward. Eq. (24) represents the prosumer (producing) reward function.

$$r_t^{s,\$} = \left\{ \begin{array}{lr} 0.7 \times (p_{j,t}^s - \widehat{p}_t)/(p^b - \widehat{p}_t): & p_{j,t}^s > \widehat{p}_t \\ 0: & p_{j,t}^s = \widehat{p}_t \\ 0.7 \times (p_{j,t}^s - \widehat{p}_t)/(\widehat{p}_t - p^{\perp}): & p_{j,t}^s < \widehat{p}_t \end{array} \right\}, \forall t, \tag{24}$$

where $p_{i,t}^s$ is the trade rate of prosumer (producing) agent j, at time step t. Eq. (24) shows that if a prosumer's trade rate while producing is lower than the community's median rate $\widehat{p}_t$, the prosumer agent receives a negative reward since he/she (the prosumer) get less money compared to the other members of the community. When a prosumer's trade rate while producing exceeds the market's median rate, the agent earns a positive reward because the prosumer gets more money compared to other community members. The tick at which the trade takes place is compared to the total number of ticks per time slot to get the accuracy reward function. This is used to know how accurate and efficient the agent is in making their bids/offers at a time step. The degree of accuracy reward function is represented in Eq. (25).

$$r_t^{\mu} = 0.3 \times (t_{k,t}^* - t_{\mathcal{K},t}^*), \tag{25}$$

where $\mathcal{K}$ is the time tick at which trade took place. This means that the greater the disparity from the total number of ticks per time step, the greater the reward. This parameter does not result in a negative reward; rather, it results in a positive reward that is either increased or decreased. Eqs. (24) and (25) shows that the model places 70% value on monetary reward while the remaining 30% is on accuracy. The general reward function is the sum of the monetary and accuracy reward function. Eqs. (26) and (27) represent the total reward function for a consumer and prosumer (producing), respectively,

$$r_t^b = r_t^{b,\$} + r_t^{\mu}, \tag{26}$$

$$r_t^s = r_t^{s,\$} + r_t^{\mu}. \tag{27}$$

B. Q-LEARNING STRATEGY

1) STAGE I: INITIALIZE ALGORITHM

a: STEP I: INITIALIZE Q-TABLE

For the Q-learning algorithm, the defined state and actions acts as inputs to the Q-table. The defined state contains four state variables made of 24 time variables, 6 average trade variables, 6 average trade volume variable, and 9 solar irradiation variable. Consequently, we have a total of 7776 ($24 \times 6 \times 6 \times 9$) defined states for the Q-table. Eq. (28) represents the initialization of Q-table with ones for the 7776 defined states and 16 available action according to Eq. (20) at time step t. The Q-table is defined separately for consumers and producing prosumers because of their different trading interests,

$$\mathcal{Q}_{s\times a,t} = \begin{bmatrix} 1_{1,1,t} & \dots & 1_{1,16,t} \\ \vdots & \ddots & \vdots \\ 1_{7776,1,t} & \dots & 1_{7776,16,t} \end{bmatrix}, \forall t. \tag{28}$$

b: STEP II: SELECT INITIAL ACTION

At the first time step $t = 0$, a random action is selected by the agent from Eq. (20) at tick $t^*_{k^*,t}$. The action is a bid or offer price (p^b_{i,t,k^*} or p^s_{j,t,k^*}) depending on if the agent is a consumer or producer agent, respectively and $p^{\perp} < p^b_{i,t,k^*}, p^s_{j,t,k^*} < p^b$. If the agent was unable to make a trade at time tick k^*, another action is selected by the agent in the next time tick (k^*+1), following Eq. (29) or (30) for a buyer or seller agent, respectively.

$$a^b_{u,t^{\epsilon}} = \left\{ \begin{array}{cc} p^b_{i,t,(k^*+1)}: & k^*+1 < k \\ p^b: & k^*+1 = k \end{array} \right\}, \forall t, \tag{29}$$

Subject to:

$$p^b_{i,t,(k^*)} < p^b_{i,t,(k^*+1)} < p^b$$

$$a^s_{u,t^{\epsilon}} = \left\{ \begin{array}{cc} p^s_{j,t,(k^*+1)}: & k^*+1 < k \\ p^{\perp}: & k^*+1 = k \end{array} \right\}, \forall t, \tag{30}$$

Subject to:

$$p^s_{j,t,k^*} > p^s_{j,t,(k^*+1)} > p^{\perp}.$$

Here, $a^b_{u,t^{\epsilon}}$ and $a^s_{u,t^{\epsilon}}$ are the random actions taken by a buyer and seller agents, respectively. Eqs. (29) and (30) show that the agents buy/sell from/to the upstream grid at the last market tick k using the upstream grid buying/selling price $p^b/p^{\perp}$ if they are unable to buy from the local community. Assuming that trade took place at $\mathcal{K}$ time tick, then, $p^b_{i,t,\mathcal{K}}$ and $p^s_{j,t,\mathcal{K}}$ are the trade price for buyer and seller agents, i and j, respectively. Since this is the first market time step, there is no previous market results to define the current state, therefore, there is no need calculating the reward and updating the Q-table. However, the process of calculating reward and updating the Q-table after every action is done every time step except the first time step which is the initialization time step.

2) STAGE II: REWARD CALCULATION, TAKING ACTION, AND Q-TABLE UPDATE

a: STEP I: REWARD CALCULATION

At the next time step, $t + 1$, the result of the previous market time step containing the average market trade rate $\overline{p}$, average trade volume $\overline{v}$, the median trade rate $\widehat{p}_t$ and the agent trade price is used to calculate the reward functions as represented in Eqs. (31) and (32) for the buyer and seller agents, respectively.

$$r_t^{b',\$} = \left\{ \begin{array}{cc} 0.7 \times (\widehat{p}_t - p^b_{i,t,\mathcal{K}})/(p^b - \widehat{p}_t): & p^b_{i,t,\mathcal{K}} > \widehat{p}_t \\ 0: & p^b_{i,t,\mathcal{K}} = \widehat{p}_t \\ 0.7 \times (\widehat{p}_t - p^b_{i,t,\mathcal{K}})/(\widehat{p}_t - p^{\perp}): & p^b_{i,t,\mathcal{K}} < \widehat{p}_t \end{array} \right\}, \forall t, \tag{31}$$

$$r_t^{s',\$} = \left\{ \begin{array}{cc} 0.7 \times (p^s_{j,t,\mathcal{K}} - \widehat{p}_t)/(p^b - \widehat{p}_t): & p^s_{j,t,\mathcal{K}} > \widehat{p}_t \\ 0: & p^s_{j,t,\mathcal{K}} = \widehat{p}_t \\ 0.7 \times (p^s_{j,t,\mathcal{K}} - \widehat{p}_t)/(\widehat{p}_t - p^{\perp}): & p^s_{j,t,\mathcal{K}} < \widehat{p}_t \end{array} \right\}, \forall t, \tag{32}$$

Consequently, Eqs.(26) and (27) is updated as Eqs. (33) and (34), respectively.

$$r_t^{b'} = r_t^{b',\$} + r_t^{\mu}, \tag{33}$$

$$r_t^{s'} = r_t^{s',\$} + r_t^{\mu}. \tag{34}$$

b: STEP II: TAKING ACTION

In order to balance the exploration/exploitation challenges, the ϵ greedy strategy is used for taking action. Eq. (35) is used to select an action by first selecting a random number λ,

$$a_{u,t+1} = \left\{ \begin{array}{cc} a_{u,(t+1)^{\epsilon}}: & \lambda < \epsilon \\ a_{u,(t+1)^{1-\epsilon}}: & \lambda > \epsilon \end{array} \right\}, \forall t. \tag{35}$$

If $\lambda < \epsilon$, a random (exploration) action is taken by applying Eq. (29) or (30) for a buyer or seller agent, respectively. On the other hand, if $\lambda > \epsilon$, the action with the maximum Q-value is selected by applying Eq. (36).

$$a_{u,(t+1)^{1-\epsilon}} = \arg\max \sum \mathcal{Q}_{s\times a,t}. \tag{36}$$

c: STEP III: UPDATING Q-TABLE

In the same way, the Q-value is updated for both buyers and sellers agents as represented in Eqs. (37) and (38), respectively.

$$Q_{(t+1)}\left(s_t, a^b_{u,t^{\epsilon}}\right) \leftarrow Q_t\left(s_t, a^b_{u,t^{\epsilon}}\right) + \alpha$$

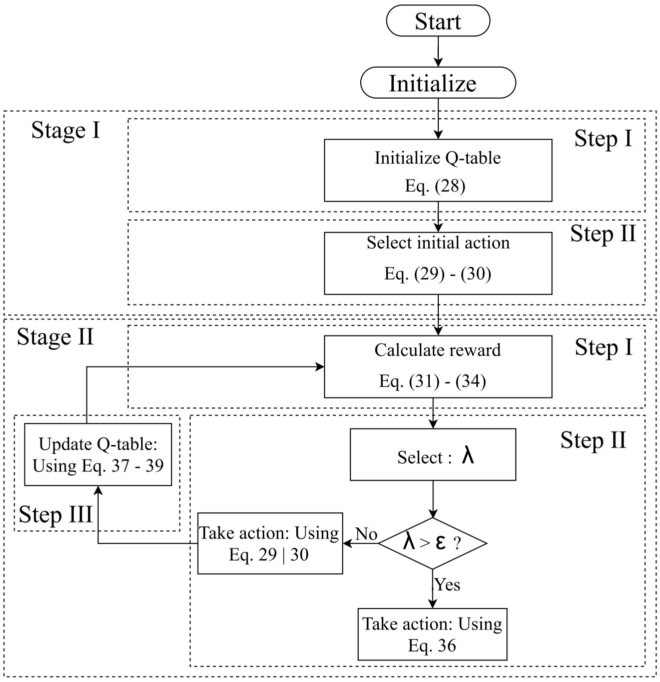


FIGURE 3. Flowchart for Q-learning algorithm.

$$\left[r_t^{b'} + \gamma \max_a Q_t\left(s_{(t+1)}, a_{u,t^\epsilon}^b\right) - Q_t\left(s_t, a_{u,t^\epsilon}^b\right)\right], \tag{37}$$

$$Q_{(t+1)}\left(s_t, a_{u,t^\epsilon}^s\right) \leftarrow Q_t\left(s_t, a_{u,t^\epsilon}^s\right) + \alpha \left[r_t^{s'} + \gamma \max_a Q_t\left(s_{(t+1)}, a_{u,t^\epsilon}^s\right) - Q_t\left(s_t, a_{u,t^\epsilon}^s\right)\right], \tag{38}$$

Here, a_{u,t^ϵ}^b and a_{u,t^ϵ}^s are the actions for the previous time step, t for buyer and seller agent, respectively and does not mean that the initial action is used for all time steps. Eqs. (37) and (38) are used to update the Q-table as represented in Eq. (39).

$$Q_{s\times a,t} = \begin{bmatrix} q_{1,1,t} & \cdots & q_{1,16,t} \\ \vdots & \ddots & \vdots \\ q_{7776,1,t} & \cdots & q_{7776,16,t} \end{bmatrix}, \forall t. \tag{39}$$

Stage II is repeated every time step until end of the experiment. The pseudocode and flowchart of the proposed Q-learning bidding strategy is represented in Algorithm 1 -Appendix A and Fig. 3, respectively.

C. SARSA STRATEGY

The methodology for the SARSA bidding/offering strategy is similar to the Q-learning strategy. The discrepancy between the two models is that in the SARSA strategy the Q-value is updated based on the temporal difference using SARSA update equation as represented in Eqs. (40) and (41) for buyer and seller agent, respectively. This is equally reflected on the flowchart of Fig. 3. The pseudocode of the proposed SARSA bidding strategy is represented in Algorithm 2 in Appendix A.

$$Q_{(t+1)}\left(s_t, a_{u,t^\epsilon}^b\right) \leftarrow Q_t\left(s_t, a_{u,t^\epsilon}^b\right) + \alpha \left[r_t^{b'} + \gamma \max_a Q_t\left(s_{(t+1)}, a_{u,(t+1)}\right) - Q_t\left(s_t, a_{u,t^\epsilon}^b\right)\right], \tag{40}$$

$$Q_{(t+1)}\left(s_t, a_{u,t^\epsilon}^s\right) \leftarrow Q_t\left(s_t, a_{u,t^\epsilon}^s\right) + \alpha \left[r_t^{s'} + \gamma \max_a Q_t\left(s_{(t+1)}, a_{u,(t+1)}\right) - Q_t\left(s_t, a_{u,t^\epsilon}^s\right)\right], \tag{41}$$

IV. SIMULATION CASE STUDY

A. SIMULATION FRAMEWORK AND DATA

The proposed LEM reinforcement bidding strategy model was developed as a Python code and implemented in the bidding agent application programming interface (API) of the open-source Grid Singularity Exchange (GSy-E) [8], [38]. The bidding agent API is used for creating the bids and offers and posting them to the exchange engine. The exchange matches the bids and offers using a two-sided pay-as-bid clearing mechanism and send the results with market information back to the bidding agents [38]. Bids and offers not matched at the local community are traded with the upstream grid. In our simulation model, each prosumer agent communicates its bids or offers individually to the exchange engine every 15 minute time slot before the energy exchange time. Each 15-minute time slot has 4 ticks, therefore, prosumer agents are able to update their bids/offers three times within a market slot. At the fourth market tick, the agent bids/offers the upstream grid price/feed-in tariff price for PV, respectively. The model is verified in a simulation case study of a community with 43 participants consisting of 26 households with only consumption devices and 17 households with consumption and production devices. Load profiles used are taken from [39]. Moreover, the PV production profiles are generation data from Renewables Ninja [40], [41] using Stuttgart region as a community and scaled down from hourly resolution to 15-minutes slot. To ensure that all PV of the same capacity do not produce exactly the same quantity of electricity, the PV system losses are varied between 5% and 15% with a constant tilt angle of 35°. Because of the cost of household electricity in Germany, the cost of buying electricity from the upstream grid is capped at 31.5 ct/kWh while the sell price to upstream grid is 11.00 ct/kWh which is the PV feed-in tariff price [42].

B. ASSUMPTIONS AND SIMULATION METHODS

In order to analyze the behaviour of the individual agents and to verify the implication of the agents working towards the same goal or benefits, the developed Q-learning and SARSA algorithms are verified in three different forms namely "classical", "standalone actor" and "shared rewards algorithms" The performance of the different reinforcement learning algorithms are compared to the baseline to establish a lower limit on the performance and complexity of the subsequent models. A random bidding agent is used as a baseline model

TABLE 1. Simulation parameters.

S/N	Parameter	Symbol
1	Learning rate	α
2	Exploration/exploitation rate	ϵ
3	Discount factor	γ
4	Episodes	Epi.
5	Simulation time	T

TABLE 2. Parameter for classical Q-learning and SARSA algorithms.

Environment	Algorithm	α	ϵ	γ	Epi.	T
Training	SARSA	0.1	0.8	0.4	182	17446
Testing	SARSA	0.1	0	0.4	56	5368
Training	Q-learning	0.1	0.8	0.4	182	17446
Testing	Q-learning	0.1	0	0.4	56	5368

TABLE 3. Parameter details for the Q-learning and SARSA standalone actor algorithms in training environment.

Algorithm	Actor	α	ϵ	γ	Epi.	T
SARSA	Pros.	0.1	0.8	0.9	182	17446
SARSA	Cons.	0.1	0.8	0.9	182	17446
Q-learning	Pros.	0.1	0.8	0.9	182	17446
Q-learning	Cons.	0.1	0.8	0.9	182	17446

in this research to compare it with the intelligent agent models. The agent randomly makes bids or offers based on the amount of energy required or available. The random strategy for generation (producer) begins with an arbitrary price and steadily decreases as the number of ticks increase. However, the consumer agent strategy steadily increases until a match is discovered. For a classical Q-learning and SARSA algorithm, the model is the traditional Q-learning and SARSA algorithm described in Section III. Table 1 displays the simulation parameters for training and testing of the simulations. T is the total simulation 15-minutes time steps and Epi. is the number of episodes.

Table 2 shows the simulation parameters for the classical Q-learning and SARSA algorithms for training and testing of the simulations. The standalone actor algorithm is used to get a better understanding of individual prosumers and consumers agents. Hence, for this algorithm, consumers trade using the intelligent bidding strategy while the prosumers use the baseline strategy and vice versa. This algorithm helps isolate each actor's policy and get a more refined knowledge into single actor's profits. Furthermore, it is evident that when two intelligent agents trade as a single entity, a difference between each of their profits is anticipated, unlike when just a single agent trades with an unintelligent agent. It is expected that in the first case that the model strikes a balance between the two, but in the latter, the model considers the relevance of just one actor. Here, the purpose is to experiment and analyse both scenarios. Table 3 shows the parameter details for training of Q-learning and SARSA standalone actor algorithms.

The goal of the shared reward case is to develop a model that will simultaneously benefit both prosumers and consumers since using the classical SARSA and Q-learning algorithms was unable to do that. Additionally, for our model, the consumer and prosumer actors do not communicate with one another and are unaware of each other's existence. To solve this, we define an element of cooperation between the actors for them to communicate information not directly but by working towards a certain goal. Consequently, the classical algorithms are modified to develop a shared-reward concept that allows agents to learn dynamically and coordinate with one another to motivate them to cooperate on the global reward aim, that is, to benefit the entire local community. Thus, the global reward is the sum of the individual prosumers and consumers agents rewards within the community. All agents now work towards maximizing this global reward. Table 4 shows the parameter details for shared reward algorithm.

TABLE 4. Parameter details for the Q-learning and SARSA shared rewards algorithm.

Environment	Algorithm	α	ϵ	γ	Epi.	T
Training	SARSA	0.01	0.8	0.9	364	34892
Training	SARSA	0.1	0.8	0.9	364	34892
Testing	SARSA	0.01	0.8	0.9	62	5933
Testing	SARSA	0.1	0.8	0.9	62	5933
Training	Q-learning	0.1	0.8	0.9	364	34892
Testing	Q-learning	0.1	0.8	0.9	62	5933

C. PARAMETER TUNING

After development of the SARSA and Q-learning model, parameter tuning was performed to determine the value of the input parameters that leads to optimal rewards. The three parameters used for the SARSA and Q-learning model are the learning rate (α), exploration/exploitation rate (ϵ) and discount factor (γ). The value of each of these parameters range from 0 to 1. The parameter tuning procedure is divided into 3 stages. First, sensitivity analysis was used to analyze the entire range of values of the parameters to determine the few optimal values of the parameters. In the second stage, the initial parameter tuning is carried out by using the optimal values selected from sensitivity analysis to repeat the simulations and the results compared to determine the parameters that outperforms the other. The optimal values from the second stage are then used to perform the final tuning simulations and the results compared. The best results are then determined as the optimal parameters of the model. As Q-learning and SARSA showed similar features, the parameter tuning was performed only for the SARSA algorithm.

V. RESULTS

In this Section, the simulation results are presented and discussed briefly. The first paragraph presents the general simulation analysis, afterwards, the results are analysed based on LEM performance indicators. Lastly, the simulations is analysed to determine the optimal parameters for the bidding agents.

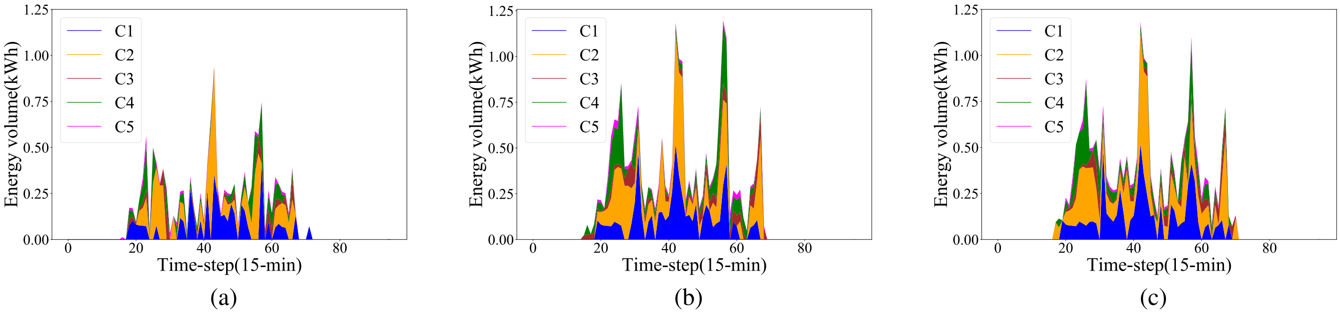


FIGURE 4. Selected consumers internal traded energy for (a) baseline, (b) classical Q-learning and (c) classical SARSA strategies.

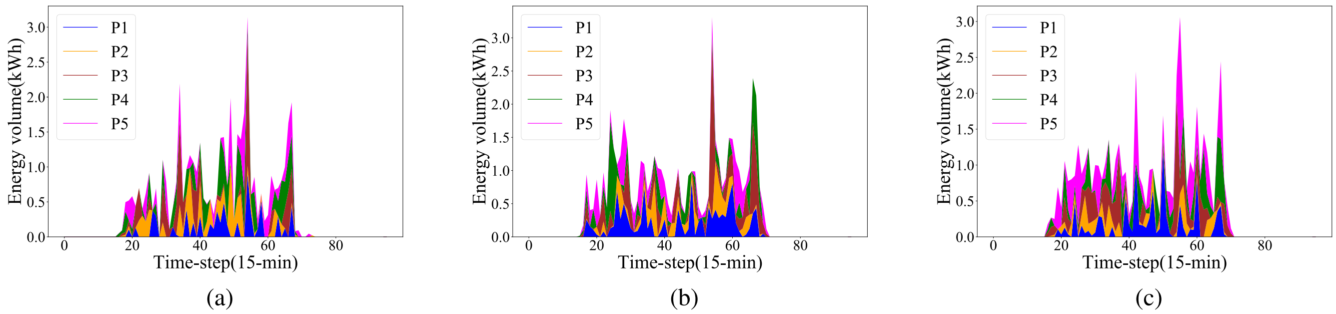


FIGURE 5. Selected prosumers internal traded energy for (a) baseline, (b) classical q-learning and (c) classical SARSA strategy.

A. GENERAL SIMULATION ANALYSIS

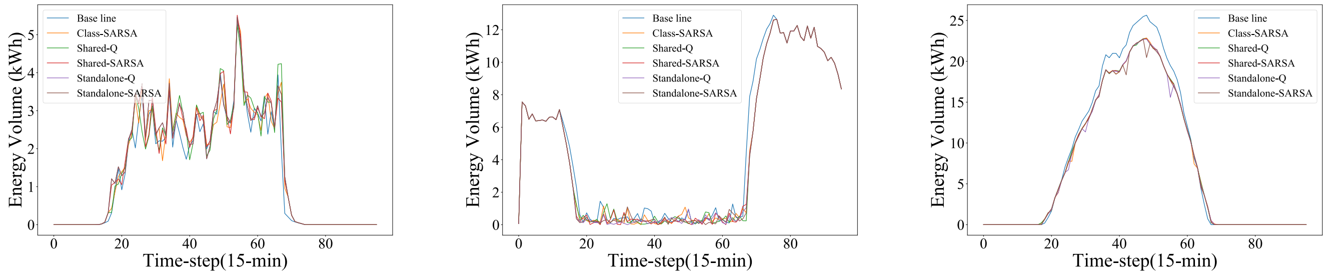
The results of the simulation are analyzed based on the quantity of energy traded between the prosumers and consumers, energy imported from the upstream grid to the community and energy exported from the local community to the upstream grid. Fig. 4 displays the internal traded energy of five selected consumers for the (4a) baseline, (4b) classical q-learning and (4c) classical SARSA strategies of a selected day with the training environment. The internal traded energy of the consumers is the energy bought by the consumers from prosumers within the local community. From Fig. 4, for all the scenarios, energy is traded majorly during the day. This is evident because the major source of energy within the community is PV and therefore, energy is generated and traded within the community mainly during the day. Furthermore, for the five selected consumers, the consumers trade more energy within the local community in the classical Q-learning and SARSA strategy compared to the baseline strategy. It is evident that the intelligent strategies (Q-learning and SARSA) provide opportunity for consumers to trade more energy within the local community compared to the baseline strategy.

Fig. 5 displays the internal traded energy of five selected prosumers for the (5a) baseline, (5b) classical q-learning and (5c) classical SARSA strategies of a selected day with the training environment. The internal traded energy of the prosumers is the energy sold/bought by the prosumers to/from consumers/prosumers within the local community. Similar to the consumers, as shown in Fig. 5, for all the scenarios, energy is traded majorly during the day because, the major source of energy within the community is PV. Therefore, energy is generated and traded within the community mainly during the day. Furthermore, for the five selected prosumers, the prosumers trade more energy within the local community in the classical Q-learning and SARSA strategy compared to the baseline strategy. This provides further evidence to support that the intelligent strategies create more opportunity for prosumers to trade energy within the local community compared to the baseline strategy.

Fig. 6 displays the community (6a) traded energy, (6b) energy import from the upstream grid and (6c) energy export to the upstream grid using the baseline, classical SARSA, shared Q-learning, shared SARSA, standalone Q-learning, and standalone SARSA strategies for a single day in the training environment. From Fig. 6a, the prosumers and consumers trade less energy using the baseline strategy compared to other strategies. This is because the internal traded energy of the baseline strategy is less compared to other strategies. Also, using the baseline strategy, the consumers and prosumers import more energy from the upstream grid compared to other strategies as shown in Fig. 6b. Furthermore, the prosumers export more energy to the upstream grid while using the baseline strategy compared to other strategy - Fig 6c.

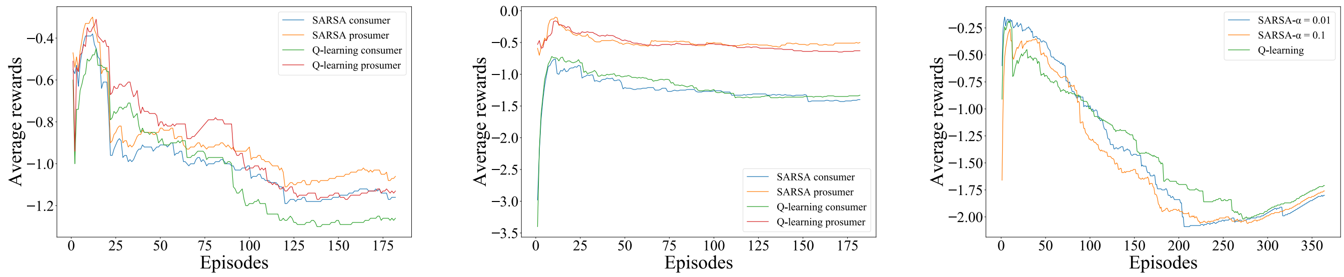
B. ANALYSIS OF SIMULATION BASED ON PERFORMANCE INDICATORS

Fig. 7 and 8 display the average and cumulative reward, respectively, of consumers and prosumers actors for the classical, standalone and shared reward strategies for the entire training period. Fig. 7 displays the average reward over the



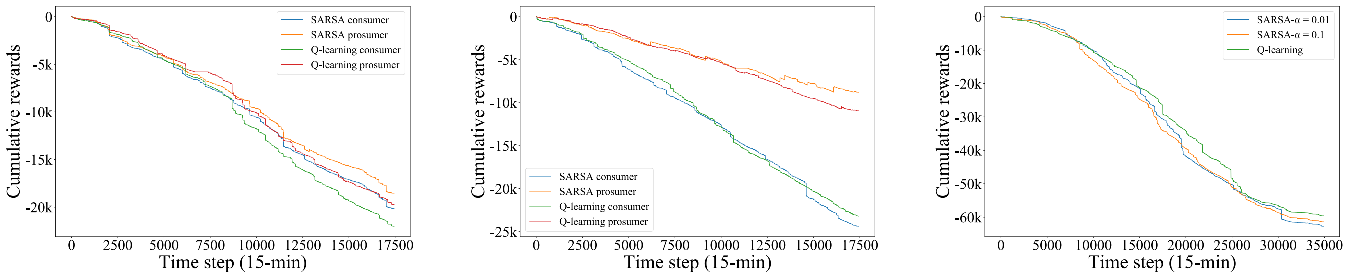
(a) (b) (c)

FIGURE 6. Community (a) traded energy (b) energy import and (c) export from/to the upstream grid.



(a) (b) (c)

FIGURE 7. Average reward for (a) classical (b) standalone and (c) shared reward strategy.



(a) (b) (c)

FIGURE 8. Cumulative average reward for (a) classical (b) standalone and (c) shared reward strategy.

entire episodes while Fig. 8 displays the cumulative reward over the entire 15-mins time step. The higher the average reward, the better the algorithm. Fig. 7a and Fig. 8b show that for the classical strategies, prosumers gather more rewards compared to the prosumers. At the same time, SARSA strategy gather more rewards compared to the Q-learning strategy. This shows that SARSA strategy has the capability of producing more benefits to the LEM compared to the Q-learning strategy while using the classical algorithm. Also, the classical algorithms has the capability of yielding more benefits for the prosumers compared to the consumers. From Fig. 7b and 8b, similar to the classical algorithms (Fig. 7a), the prosumers gather more rewards compared to consumers for the standalone strategies. However, the consumers gather more rewards using the Q-learning algorithm compared to the SARSA algorithm. On the other hand, prosumers gather more reward using the SARSA algorithm compared to the Q-learning algorithm. For the shared reward, the prosumers and consumers agents work towards a common goal of increasing their global reward. Therefore, the rewards of Fig. 7c and 8c are the global average and cumulative rewards, respectively. The Q-learning algorithm gathers more rewards compared to the SARSA algorithm. It is evident that Q-learning can provide more benefits to both consumers and prosumers while helping them to achieve a common goal. Generally comparing the classical, standalone, and shared reward strategies rewards show that the agents gathers most rewards with the standalone strategy and least reward with the shared reward strategy.

Table 5 presents the varied bidding strategies verified using the LEM performance indicators and their accompanying symbols. The performance indicators used are self sufficiency, market revenue, individual average consumer savings, individual average prosumer savings and average

TABLE 5. Varied strategies.

S/N	Simulation scenario	Symbol
1	Baseline	L_0
2	Classical Q-learning	L_1
3	Classical SARSA	L_2
4	Standalone SARSA - Consumer	L_3
5	Standalone SARSA - Prosumer	L_4
6	Standalone Q-learning - Consumer	L_5
7	Standalone Q-learning - Prosumer	L_6
8	Shared reward SARSA- $\alpha = 0.01$	L_7
9	Shared reward SARSA- $\alpha = 0.1$	L_8
10	Shared reward Q-learning	L_9

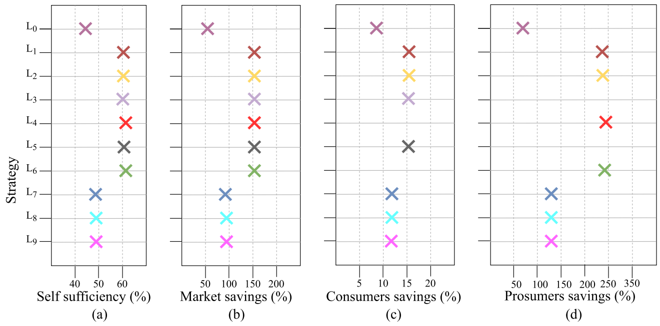


FIGURE 9. Performance indicators ((a) Self-sufficiency, (b) share of market savings, (c) share of consumer savings, and (d) share of prosumer savings) for varying scenarios in training environment.

trade rate. Fig. 9 and 10 display the self-sufficiency (SS), share of market savings (SMS), share of consumers savings (SCS), and share of prosumers savings for the different strategies L_0 to L_9, in training and testing environment, respectively. SMS is the percentage of savings made by the prosumers and consumers for trading within the LEM compared to without LEM. In the same way, the share of consumer/prosumer savings is the percentage of savings made by the consumer/prosumer for trading within the LEM compared to without LEM. The standalone strategies are not experimented with the testing environment because it is not obtainable in practice to keep some group of agents intelligent in a community while others are not. Therefore, the standalone strategies is used to verify the individual capabilities of the agents. For the training environment (Fig. 9), the community SS is higher with the classical and standalone strategies. This can be explained as consequent upon the rewards gathered by the classical and standalone strategy during training which is higher compared to the shared reward strategy. The maximum SS is obtained with the L_4 strategy. For this strategy, the prosumers use intelligent strategy based on SARSA while the consumers use the baseline strategy. Since trading energy within the community is more beneficial compared to the upstream grid, this strategy ensures that the prosumers trade all their energy within the community thereby making the community to be sufficient. This further results in higher SMS of the local community and share of prosumer savings. The baseline strategy (L_0) shows the least SS, SMS, SCS as well as share of prosumer savings. This is because the agents are not intelligent and do not bid/offer strategically to make the optimum benefit from the LEM. The

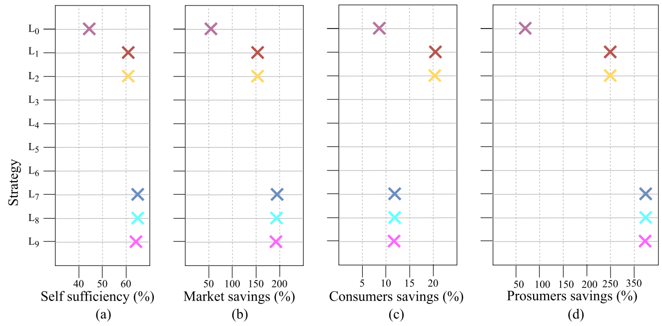


FIGURE 10. Performance indicators ((a) Self-sufficiency, (b) share of market savings, (c) share of consumer savings, and (d) share of prosumer savings) for varying scenarios in testing environment.

shared reward strategies (L_7 to L_9) have the least value of SS, SMS, SCS and share of prosumer savings compared to other intelligent strategies. This is highlighted by the least rewards collected by the shared reward strategies during training.

From Fig. 10, the SS and SMS of the shared reward strategies (L_7 to L_9) is higher compared to other strategies. It is evident that the shared strategy require more training time for the prosumers and consumers agents to determine their optimal trading strategy. Furthermore, trading towards a common community goal (global reward) results in higher SS and SMS of the community. However, the SCS of L_7 to L_9 is lower compared to other intelligent strategies. On the other hand, the share of prosumer savings is higher with L_7 to L_9 compared to the other strategies. Since the consumers and prosumers agents of the L_7 to L_9 strategies work towards a common goal of increasing the global reward, however, the offering/bidding strategy that results in more global reward benefits the prosumers compared to the consumers. This is because the prosumers own the PV's and batteries and thereby invested into the market, therefore, trading more of the energy from the PV in the LEM creates more benefits to the prosumers.

Fig. 11 shows the comparison of the different LEM strategies using LEM performance indicator in the training environment. At this stage, a new strategy termed the hybrid (H1) strategy is introduced. The Hybrid strategy is similar to the classical strategies. Hence, it is a combination of the Q-learning and SARSA classical algorithm strategies. For the hybrid strategy, the prosumers agents are modelled using the classical SARSA strategy while the consumers are modelled using the classical Q-learning strategy. From Fig. 11, the H1 strategy shows better SMS and SS compared to other strategies. However, the SCS of the H1 strategy is lower compared to the L_1 and L_2 strategies. By integrating the features of the SARSA and Q-learning strategies, the H1 strategy was able to leverage the features of the two strategies to create technical and economic benefits for the LEM.

Fig. 12 shows the comparison of the different LEM strategies using LEM performance indicator in the testing environment. Unlike the training environment, the L_7 to L_9 strategies show better SS, SMS and SCS compared to the L_1 and L_2 strategies. However, the H1 strategy still shows higher

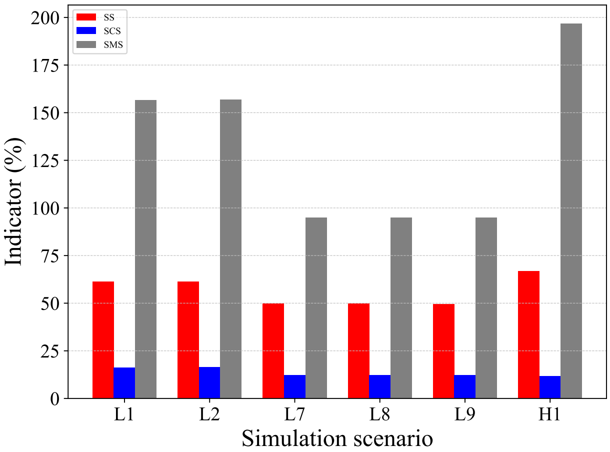


FIGURE 11. Comparison of performance indicators for varying simulation scenarios in training environment.

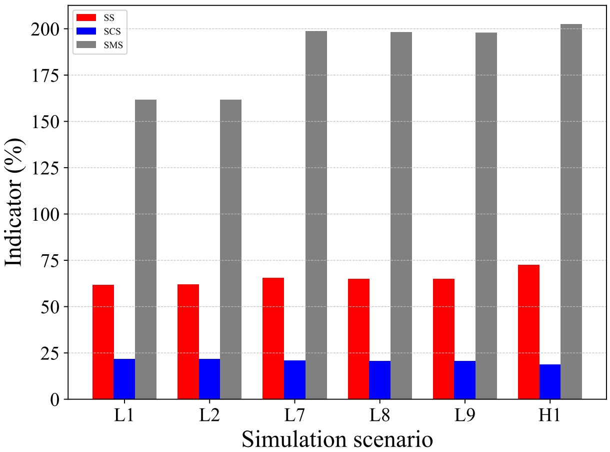


FIGURE 12. Comparison of performance indicators for varying simulation scenarios in testing environment.

SS and SMS compared to the L_7 to L_9. This is evident that utilizing SARSA strategy with prosumer agents while using Q-learning strategy for consumer agents creates more benefits to the local community compared to other strategies tested in this work.

C. PARAMETER TUNING

Appendix B-A (Table. 6, Fig. 13, and Fig. 14) contains the results of the sensitivity analysis of α, ϵ and γ parameter tuning. Four optimal values of α, ϵ and γ were selected from the sensitivity analysis and used for initial parameter tuning. The results of the initial parameter tuning is presented in Appendix B-B (Table. 7, Fig. 15, and Fig. 16). After the initial parameter tuning, two best values of α, ϵ and γ are then selected and used for the final parameter tuning. The results of the final parameter tuning are presented in Appendix B-C (Table. 8, Fig. 17, Table. 9, and Fig. 18) and a detailed discussion of the parameter tuning is presented in Section VI-D.

VI. DISCUSSION

The Section presents discussion about findings, insights and improvements of the model.

A. CLASSICAL MODELS COMPARISON

Firstly, the baseline model is used as a reference to assess the LEM performance indicators such as self sufficiency(SS), share of market savings (SMS), share of consumer savings (SCS), and share of prosumers savings. The baseline model and reinforcement learning (RL) algorithms are trained and compared, followed by testing of the RL algorithms. In general, the baseline model has satisfactory results of the LEM performance indicators with a SS of 44.75%, SMS of 56.99% and average trade rate of 23.63 ct./kWh. The SS and SMS increase significantly while the average trade rate decreased by deploying RL algorithm bidding strategy in the local community. The RL agent learns to bid/offer according to the current state which completely describes the observation needed to bid/offer. In the training environment, in comparison to the baseline model, average SS and SMS of the RL models increased from 44.75% to 61.20% and 56.99% to 156.65%, respectively, while the average trade rate of electricity is lowered from 23.63 ct./kWh to 22.01 ct./kWh. The SS and SMS in a testing environment compared to the training environment increase from 61.20% to 62.0% and 156.65% to 161.61%, respectively. However, the major changes is witnessed with the average trade rate which reduced from 22.01 ct./kWh to 19.75 ct./kWh. A lower community average trade rate is beneficial to the consumers and provides opportunity for them to buy locally produced electricity. This further results in additional technical and economic benefits of the community witnessed with the increase in SS and SMS, respectively. Comparing the increase in the share of savings of prosumers and consumers from baseline model to intelligent agents models reveals that the share of prosumers savings increase significantly higher than the consumers share of savings. Thus, the prosumers are the major contributors of the community SMS. This can be attributed to the investment made by the prosumers to the market by providing the PV and battery which are the source of power in the local community.

The RL rewards are the second criteria used for analysis and comparison of the model performance. However, throughout the comparison and evaluation, it is observed that the change in the RL rewards is higher compared to the changes in LEM performance indicators and so RL rewards are used as the deciding factors in most cases. Here, the ZI model is out of comparison because of lack of an agent. The consumers and prosumers act as a separate entity in a single agent model and so it is necessary to analyse their rewards differently. The average and cumulative rewards are negative in the training environment and can be attributed to be resulting from the high exploration rate (ϵ) used during the simulation. As the agent tries to explore new actions, it is possible that there are very few actions that result in positive rewards and so the agent is not able to compensate for the wrong actions received during the training process. This changes in the testing environment where no exploration is used, and the agent only chooses the action that leads to higher and positive rewards. Another observation to note is that the average reward per episode for consumer is higher than the average reward for the prosumer. This could be because the trades (demand) needed for the consumers are higher than the trades (supply) of the prosumers. In the training environment, the rewards collected by the SARSA algorithm is higher than Q-learning for both consumers and prosumers. In the testing environment, this is not the case. SARSA algorithm collects higher rewards for the consumer actor whereas Q-learning algorithm gains higher rewards for the prosumer. This means that one single-agent model does not work equally for both actors.

B. STANDALONE ACTORS

The standalone actor models are developed to isolate the behaviour of each actor and analyse their behaviour separately as the only intelligent agent in the system. Four models are developed in the training environment for this purpose. The two prosumer models have higher SS and SMS compared to the two consumer models. The average trade rate is higher for the prosumer models and lower for the consumer models showing the presence of only a single actor rather than two. The results of SS, average trade rate and SMS for the consumer models are close to the classical SARSA and Q-learning models, which means that the classical RL models are more influenced by the consumers rather than prosumers. The prosumer models are beneficial for the welfare of the community as it results in higher SS and SMS compared to the consumer models. The standalone consumer model is responsible for the lower average trade rate whereas the standalone prosumer model helps to increase the economic benefits.

The rewards gathered by the consumer and prosumer actors in the training environment are negative. The Q-learning algorithm provides opportunity to collect higher rewards compared to SARSA for the consumer models. However, for the prosumer models, the SARSA algorithm collect higher rewards compared to Q-learning model. It is important to note that the standalone actor models converged faster over time than the classical RL models. The average rewards gained by the prosumer models for the standalone algorithms are also comparatively higher than the prosumer rewards in classical RL models. This suggests that the standalone prosumer model performs better than the classical single-agent RL models in some criteria. This is because two entities in a single agent model might hinder each other's progress and can perform better as a standalone actor.

C. SHARED REWARDS CONCEPT

Shared rewards concept is implemented in SARSA and Q-learning models to analyze the possibility of prosumers and consumers to pursue the same goal in a single experiment. Two SARSA models with different learning rate and one Q-learning model are developed to analyse the shared rewards concept. The values of LEM performance indicators are lower in the training environment than the testing environment. The training was done for one year of simulation that includes both winter and summer season. That is one of the reasons why the SS and SMS is lower, as there is less solar production. The values of the LEM KPIs are higher in the SARSA algorithm rather than Q-learning algorithm with hardly noticeable difference which can results in the observed lower performance indicators. On the other hand, the RL rewards have a different outcome. For both the training and testing environment, Q-learning has constantly gained higher rewards than the SARSA models. Thus, there is no consistent model outperforming the other in both criteria. The graph of the global average rewards in the training environment is still increasing by the end of the training period which suggests that the algorithm might not have converged yet and would perform better if the training time was increased. However, because of the huge training time and lack of data, the training is only performed for 1 year. The lack of convergence can also be seen from the global average rewards in the testing environment which are negative. The LEM performance indicators in the testing environment show better performance compared to the testing environment of the classical RL models. The individual share of savings of both consumers and prosumers are substantially increased. The higher values of the LEM performance indicators of the shared reward models is evident that the shared reward models outperforms the classical models. However, the performance in the RL rewards is not as expected because of the insufficient training time. If the model was given enough training time for it to learn the cooperation between the agents, the shared reward model will outperform the classical RL models in terms of the obtained rewards.

D. PARAMETER TUNING

The three steps used are sensitivity analysis, initial parameter tuning and then, final parameter tuning. Starting with the sensitivity analysis, the change in the learning rate (α) does not result in significant change of the performance indicators. The lower values of α such as 0.1, 0.2, and 0.3 along with some higher values such as 0.7, result in comparatively higher LEM performance indicators. However, the RL reward criterion shows values of the learning rate such as 0.4 and 0.9 can help the algorithm collect more rewards compared to other values. Therefore, one optimum value from each criterion and one default and also most common learning rate are selected for the initial parameter tuning. The only parameter that has a linear relationship with the LEM performance indicator is the exploration rate (ϵ). The lower the values, the better the result. However, there are some outliers to this relationship in the RL rewards criteria. For example, ϵ equal to 0.6 and 0.7 collects higher rewards than 0.5 which is true for the consumer and prosumer rewards because of the exploration vs exploitation trade-off. Thus, the equal probability for both exploitation and exploration is not beneficial for the algorithm. To verify this anomaly further, ϵ equal to 0.2, 0.5 and 0.9 were chosen to compare further. The discount factor (γ) shows the most non-linear behaviour out of the three parameters. There is no rule of thumb on choosing γ, on the other hand, the value of 0.9 or 0.99 helps the algorithm converge faster. Considering

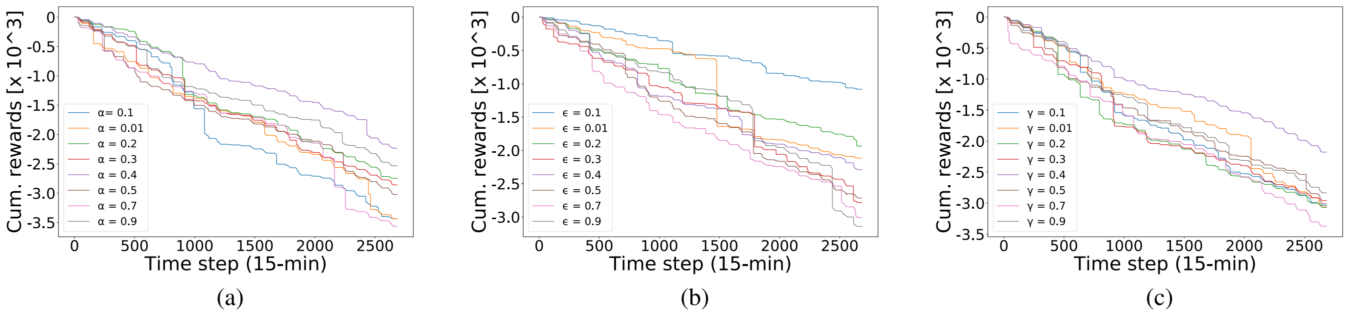


FIGURE 13. Sensitivity analysis of consumers rewards for (a) α, (b) ϵ and (c) γ.

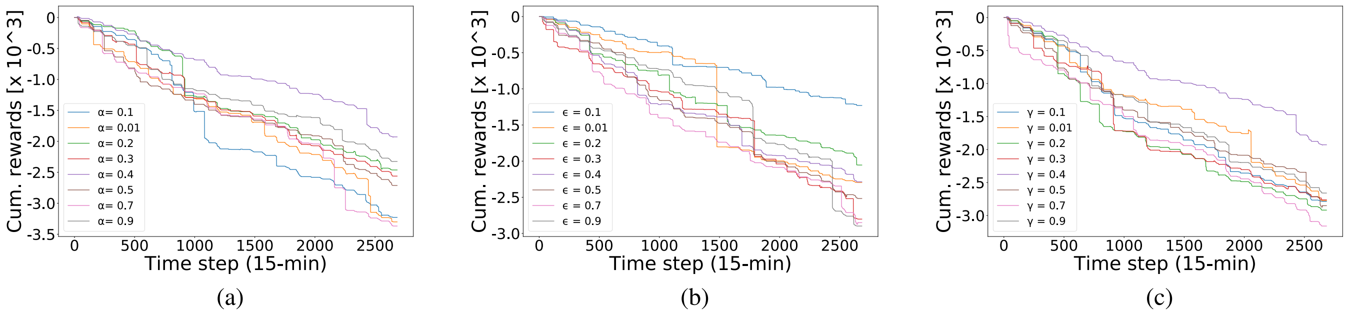


FIGURE 14. Sensitivity analysis of prosumers rewards for (a) α, (b) ϵ and (c) γ.

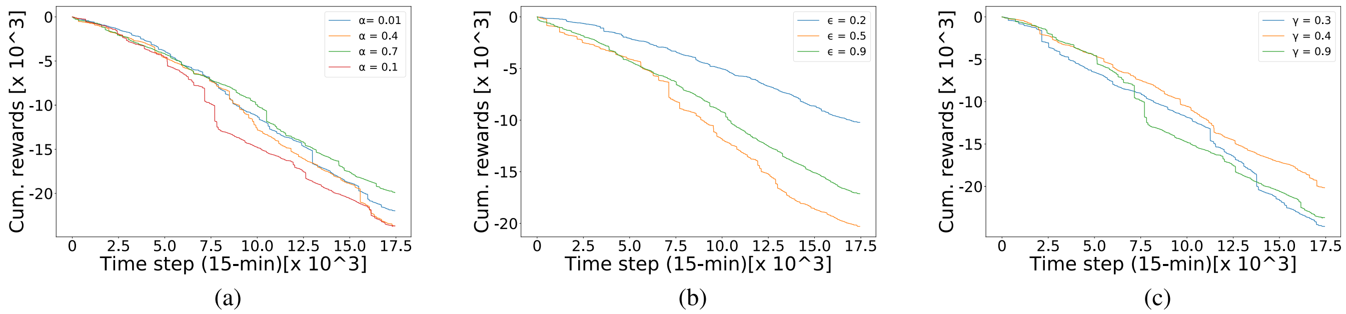


FIGURE 15. Initial parameter tuning of consumers rewards for (a) α, (b) ϵ and (c) γ.

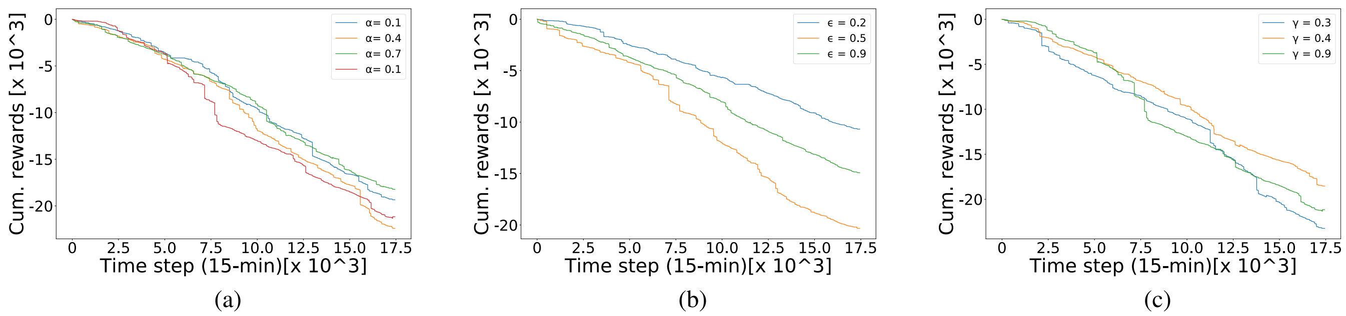


FIGURE 16. Initial parameter tuning of prosumers rewards for (a) α, (b) ϵ and (c) γ.

the LEM performance indicators, comparatively lower values of γ such as 0.1, 0.3 and 0.4 are better whereas for the RL rewards, higher values of gamma such as 0.5, 0.7 and 0.9 shows better performance. The value of the discount factor is usually higher compared to the learning rate and so three values, 0.3, 0.4 and 0.9 are used to further provide the comparison in the next step.

From the result of the initial parameter tuning for α, the default rate of 0.1 lead to the worst performance in the RL rewards criteria. Nevertheless, the LEM performance

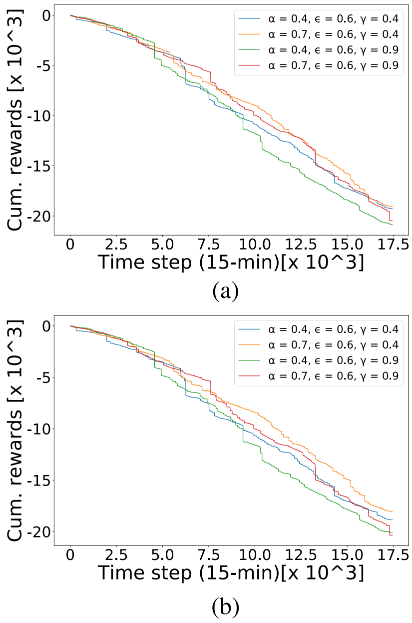


FIGURE 17. **Final parameter tuning of rewards for (a) consumers and (b) prosumers in training environment.**

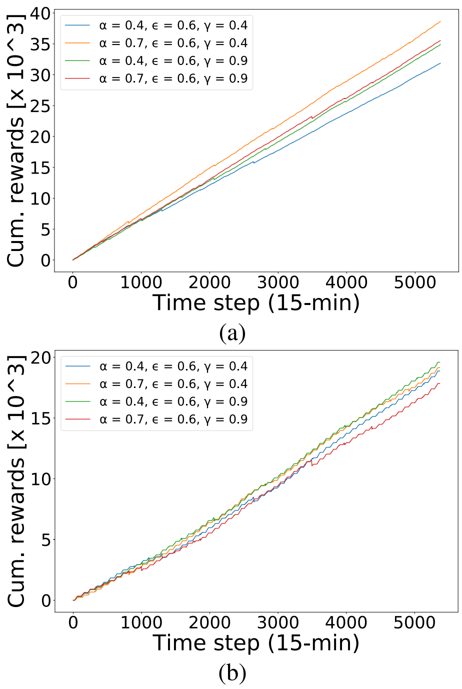


FIGURE 18. **Final parameter tuning of rewards for (a) consumers and (b) prosumers in testing environment.**

indicators for α equal to 0.1 and 0.4 were almost comparable. The initial parameter tuning of ϵ has the similar outcomes to its sensitivity analysis. $\epsilon = 0.5$ has lower rewards compared to $\epsilon = 0.9$. Given that the relationship of epsilon is quite straightforward with the evaluation criteria, only one value of epsilon 0.6 is used for the final comparison. The initial parameter tuning of gamma showed that there is no correlation between gamma and any of the KPIs. The two best values of 0.4 and 0.9 are selected from the criteria for the final

Algorithm 1 Q-Learning Algorithm Bidding/Offering Strategy

Require: $\mathcal{S}_t, \alpha, \epsilon, \gamma$. $\triangleright$ Initialize parameters and states
Initialize: $\mathcal{Q}_{s \times a,t}$ according to Eq. (28)
Initial action: according to Eq. 29 & 30

while (Epi > 0) **do**
  Calculate reward: according to Eq. (34) | 33
  Take action: according to Eq. 36 & 35
  Update Q-table: $Q_{(t+1)}\left(s_t, a^b_{u,t^\epsilon}\right) \leftarrow Q_t\left(s_t, a^b_{u,t^\epsilon}\right)$
   $+\alpha\left[r_t^{b'} + \gamma \max_a Q_t\left(s_{(t+1)}, a^b_{u,t^\epsilon}\right) - Q_t\left(s_t, a^b_{u,t^\epsilon}\right)\right]$ $\triangleright$ For buyers
   $Q_{(t+1)}\left(s_t, a^s_{u,t^\epsilon}\right) \leftarrow Q_t\left(s_t, a^s_{u,t^\epsilon}\right)$
   $+\alpha\left[r_t^{s'} + \gamma \max_a Q_t\left(s_{(t+1)}, a^s_{u,t^\epsilon}\right) - Q_t\left(s_t, a^s_{u,t^\epsilon}\right)\right]$ $\triangleright$ For sellers
   Update Eq. 39
end while

tuning. Hence, it is certain from here, that, the values of α, ϵ, and γ do not follow the common and default values used for them. Therefore, the behaviour of each value and parameter to the algorithm is challenging to interpret. Another important and common observation is that the best values of α, ϵ, and γ for the consumer and prosumer models are in most cases different from each other which also explains the reason for the development of standalone actor algorithms.

The final parameter tuning consists of two α and γ values and one ϵ value to determine the final optimal values. The results obtained from the training and testing environment are different from each other. Learning rate (α) of 0.7 and γ of 0.4 has the highest value in terms of LEM performance indicators and the RL rewards in the training environment. However, for the testing environment, the model with the best LEM performance indicators has $\alpha = 0.4$ and $\gamma = 0.9$. However, this is not the same for rewards collected by consumers. The model with the best rewards collected by consumer has $\alpha = 0.7$ and $\gamma = 0.4$. Therefore, the model with the most optimal bidding/offering strategy is the single-agent SARSA model with $\alpha = 0.4$, $\epsilon = 0.6$, and $\gamma = 0.9$.

VII. CONCLUSION

In this paper, two novel reinforcement learning based intelligent bidding strategies, Q-learning and SARSA, were proposed for effective trading of distributed energy resources for prosumers and consumers in an LEM. The proposed models were tested in a German real case scenario and simulated for 45 German households. The simulations results show that the intelligent bidding strategies create additional technical and economic benefits to the local consumers and prosumers compared to the baseline strategy. Furthermore, the proposed models reveal that when the intelligent agents within the local community work towards a common goal, in this case shared reward strategy, the model create additional benefits for the

TABLE 6. Comparison of participant revenue for sensitivity analysis.

Parameter	$\alpha = 0.1$	$\alpha = 0.01$	$\alpha = 0.2$	$\alpha = 0.3$	$\alpha = 0.4$	$\alpha = 0.5$	$\alpha = 0.7$	$\alpha = 0.9$
Consumer 1	16.48%	15.91%	15.94%	16.18%	16.36%	15.95%	16.43%	15.99%
Prosumer 1	261.24%	261.54%	261.43%	261.59%	261.51%	261.41%	261.27%	261.50%
Parameter	$\epsilon = 0.2$	$\epsilon = 0.3$	$\epsilon = 0.4$	$\epsilon = 0.5$	$\epsilon = 0.6$	$\epsilon = 0.7$	$\epsilon = 0.8$	$\epsilon = 0.9$
Consumer 1	22.90%	21.89%	20.38%	18.81%	18.09%	16.82%	16.0%	14.44%
Prosumer 1	259.57%	259.64%	259.92%	260.24%	260.27%	260.81%	261.49%	261.89%
Parameter	$\gamma = 0.1$	$\gamma = 0.3$	$\gamma = 0.4$	$\gamma = 0.5$	$\gamma = 0.7$	$\gamma = 0.9$	$\gamma = 0.99$	$\gamma = 0$
Consumer 1	16.16%	16.14%	15.89%	16.30%	15.83%	16.00%	15.99%	15.81%
Prosumer 1	261.52%	261.65%	261.22%	261.20%	261.28%	261.49%	261.49%	261.35%

Algorithm 2 SARSA Algorithm Bidding/Offering Strategy

Require: $\mathcal{S}_t, \alpha, \epsilon, \gamma$. ▷ Initialize parameters and states
Initialize: $\mathcal{Q}_{s\times a,t}$ according to Eq. (28)
Initial action: according to Eq. 29 & 30

while (Epi > 0) **do**
  Calculate reward: according to Eq. (34) | 33
  Take action: according to Eq. 36 & 35
  Update Q-table: $Q_{(t+1)}\left(s_t, a^b_{u,t^\epsilon}\right) \leftarrow Q_t\left(s_t, a^b_{u,t^\epsilon}\right)$
    $+\alpha\left[r^{b'}_t + \gamma \max_a Q_t\left(s_{(t+1)}, a_{u,(t+1)}\right)\right.$
    $\left.-Q_t\left(s_t, a^b_{u,t^\epsilon}\right)\right]]$ ▷ For buyers
    $Q_{(t+1)}\left(s_t, a^s_{u,t^\epsilon}\right) \leftarrow Q_t\left(s_t, a^s_{u,t^\epsilon}\right)$
    $+\alpha\left[r^{s'}_t + \gamma \max_a Q_t\left(s_{(t+1)}, a_{u,(t+1)}\right)\right.$
    $\left.-Q_t\left(s_t, a^s_{u,t^\epsilon}\right)\right]]$ ▷ For sellers
  Update Eq. 39
end while

TABLE 7. Comparison of participant revenue for initial parameter tuning.

Parameter	$\alpha = 0.01$	$\alpha = 0.1$	$\alpha = 0.4$	$\alpha = 0.7$
Consumer 1	16.09%	16.39%	16.05%	16.44%
Prosumer 1	244.23%	244.03%	244.02%	244.11%
Parameter	$\epsilon = 0.2$	$\epsilon = 0.5$	$\epsilon = 0.9$	-
Consumer 1	20.92%	18.91%	15.29%	-
Prosumer 1	242.87%	243.37%	244.42%	-
Parameter	$\gamma = 0.3$	$\gamma = 0.4$	$\gamma = 0.9$	-
Consumer 1	16.32%	16.29%	16.44%	-
Prosumer 1	244.14%	244.18%	244.11%	-

community compared to the classical strategies. The most optimal strategy is the hybrid strategy which is a combination of the classical Q-learning and SARSA strategies. In future work, we will investigate other artificial intelligent models such as deep learning and how they can be modelled for LEM trading and how the model will be implemented in a distributed blockchain platform to ensure efficient preservation of prosumers' privacy and conformation to data protection laws.

APPENDIX A ALGORITHMS PSEUDO CODES

See Algorithm 1 and Algorithm 2.

APPENDIX B FURTHER SIMULATION RESULTS

A. TABLES AND FIGURES FOR SENSITIVITY ANALYSIS

See Table 6, Figures 13 and 14.

TABLE 8. Comparison of participant revenue for final parameter tuning (training env).

Parameters	$\alpha = 0.4$ $\gamma = 0.4$	$\alpha = 0.7$ $\gamma = 0.4$	$\alpha = 0.4$ $\gamma = 0.9$	$\alpha = 0.7$ $\gamma = 0.9$
Consumer 1	18.10%	18.32%	18.07%	18.36%
Prosumer 1	243.52%	243.59%	243.65%	243.54%

TABLE 9. Comparison of participant revenue for final parameter tuning (testing env).

Parameters	$\alpha = 0.4$ $\gamma = 0.4$	$\alpha = 0.7$ $\gamma = 0.4$	$\alpha = 0.4$ $\gamma = 0.9$	$\alpha = 0.7$ $\gamma = 0.9$
Consumer 1	20.56%	20.26%	19.77%	19.54%
Prosumer 1	260.35%	260.39%	260.94%	260.59%

B. TABLES AND FIGURES FOR INITIAL PARAMETER TUNING

See Table 7, and Figures 15 and 16.

C. TABLES AND FIGURES FOR FINAL PARAMETER TUNING

See Tables 8 - 9 and Figures 17 - 18.

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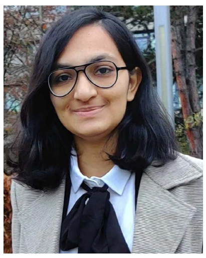

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4 DLT as an enabling factor for local energy market

Scientific context
An LEM market model is implemented in a platform and therefore needs a secured and tamper proof platform that will ensure that the data of LEM participants are highly secured, tamper proof, reliable, and execute transactions in a transparent manner while conforming to General Data Protection Regulation (GDPR) [142, 66]. Blockchain as a concept of DLT has several features which include distributed data structure, consensus mechanism, cryptographic signature, immutability, transparency, trust, and enhanced security that made it outstanding for application in LEM market model [102, 143, 144, 145, 146, 147]. Hence, blockchain provides an opportunity for LEM participants to post their transaction data to the market framework in a transparent, secured and tamper proof manner. The immutability feature of blockchain makes it impossible to tamper with data/transaction stored in the network as data/transactions are linked from one block to another using cryptographic hashes. For a person to falsify a data or transaction in the network, the person must be ready to start from the first block known as the genesis block which is almost impossible. Data stored in a public blockchain network are open to everyone that is willing to see it and thus the first challenge of blockchain since such kind of platform that deals with information about users need to conform with the GDPR. Although, these information are completely stored in pseudo-anonymous manner as one can only see the public key of the users and transactions belonging to a certain public key. This means that once you know the public key belonging to a particular user, you can easily read the users data such as electricity consumption from the network.

Also, another challenge facing the application of blockchain in LEM is scalability and high gas cost. Blockchain is less scalable and therefore has limited capability to handle large models/algorithms/computations in a short time. For example, running a simple merit order market clearing mechanism will require about 19 million gas which means extension of the block size which is limited at 8 million gas on any network that is running on the Ethereum virtual machine, such as the Energy Web Chain. Gas is the fee you pay to conduct a transaction in a public Ethereum network [142]. In this section, two papers are presented. The first paper [143] implemented a blockcain-based LEM framework and evaluated the applicability and challenges for a German case scenario. To the best of our knowledge, as at the time of the publication, this is one of the early papers that deals with the proof of concept of blockchain application for LEM. The second paper [148] focuses on solving the enumerated challenges of blockchain-based LEM which include scalability, transparency and conformity with GDPR, and high gas cost by applying a hybrid approach incorporated TEE.

4.1 Blockchain enabling a fully distributed local energy markets

Contribution

In this section, a proof of concept of blockchain-based LEM framework is presented. The paper [143] presents a blockchain-based double sided auction peer-to-peer local electricity market framework. As a proof of concept, four open-source smart contracts based on Ethereum blockchain network were developed and evaluated of their applicability to enable a fully distributed local energy trading [149]. The smart contracts implement the market model, LEM clearing mechanisms, token exchange, and token auction. The developed smart contracts were deployed to the Ethereum-based private blockchain network of the Chair of Energy Economy and Application Technology, Technical University of Munich (TUM), to verify their applicability. A hardware-in-the-loop simulation was performed with Raspberry Pis acting as blockchain light node that communicates bids/offers of the consumers/prosumers to the blockchain network at every time slot.

The framework was verified with a combination of load [121] and PV [150] profiles. The consumers/prosumers agents running on the different Raspberry Pis post the consumers'/prosumers' bids/offers every minutes. This was to evaluate the reliability of the blockchain network to handle data communicated to the framework every minute. The market was cleared hourly and token exchanged from the different consumers/prosumers account based on their consumed/produced electricity. The results of the simulations show that blockchain is not scalable to handle the transaction timely even with the two simple clearing mechanisms implemented known as uniform market clearing price and discriminative pricing. Furthermore, because of the cost of communicating, storing and transacting hourly bids/offers in the blockchain network that cost 67,369 gas which is equivalent to 270.2 ETH at the time of the publication, it is economically unfeasible to run the whole market model in a blockchain network, given the current maturity stage of blockchain.

Publication #8: A Blockchain-based Double-sided Auction Peer-to-peer Electricity Market Framework

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Michel Zade	15%	Conceptualization, Data curation, Formal analysis, Methodology, Validation, Writing - review and editing.
Peter Tzscheutschler	5%	Methodology, Validation, Writing - review and editing.
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Ulrich Wagner	5%	Supervision, Writing - review and editing.

A Blockchain-based Double-sided Auction Peer-to-peer Electricity Market Framework*

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***Abstract*—The framework presented provides an open-source, blockchain-based, peer-to-peer energy market platform which can be used for testing different setups or for creating a microgrid peer-to-peer trading platform. The framework offers the following possibilities:**

- **variations of the trading horizon, metering intervals;**
- **simulations within a fraction of the real time;**
- **variations of the number of participants;**
- **multiple operated microgrids within one smart contract;**
- **clearing mechanisms with discriminative prices or a market clearing price;**
- **functionality to log data exchanged with the blockchain; production and consumption data of each participant, electricity exchanged within the microgrid and the main grid, token balances of all participants,**
- **variation of the price ranges.**

***Index Terms*—peer-to-peer, blockchain, smart contract, energy trading, token (TEC)**

I. Introduction

In 2000, the Renewable Energy Sources Act (EEG 2000) came into force in Germany to encourage citizens to build renewable power plants with a capacity of up to 100 kW. To stimulate the construction of new power plants, a guaranteed feed-in tariff for 20 years has been implemented (see EEG 2000, §9 section 1). In 2020, the first power plants will drop out of the feed-in tariffs and an increasing number of renewable power plant owners will be responsible for the commercialization of their excess energy. Peer-to-peer (P2P) electricity markets offer an opportunity to trade renewable electricity in post-EEG times and within communities, close to their place of production. As such, potentially costly grid infrastructure expansions can be reduced.

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One general goal of a P2P market is the creation of trading relationships between a large number of distributed sellers and buyers [1]. Many definitions of P2P energy trading exist in several literature [2] - [7]; however, we will focus on selected definitions relevant to current electricity use case. According to Pouttu et al. [5], P2P energy trading is a platform that provides information about energy trading among buyers and sellers and matches their offers using the agreed or accepted regulations. This platform ensures that the quantity of energy matched is delivered to the buyer and that the price tagged for that quantity of energy is paid to the seller. The electricity producers are usually within the neighborhood or locality of the consumers, leading to reduced losses and overall cost [2]. Furthermore, P2P energy trading ensures that local funds remain within the local economy and provides prosumers/generators the opportunity to maximize their profits from electricity trading and have control over their distributed energy resources (DER) [2] - [3]. Some mechanisms proposed for P2P electricity trading are auction-based pricing strategy [2], [8], demand response approaches [9] and energy sharing models with price-based demand [10].

The electric energy demand and production in a microgrid show the patterns of a multi buyer and seller, respectively. Double-sided auction (DSA) market provides multiple buyers and sellers with the opportunity to trade their commodities simultaneously [11]. A DSA provides an efficient market for the allocation of energy based on quotes of sellers and buyers in a microgrid [12]. Sellers and buyers submit asks (sell orders), which set the minimum price they can receive, and bids (buy orders), which offer the maximum price they are willing to pay for the commodities [11] - [14]. The auctioneer collects the orders, sorts them and matches them if a buyer's bid price exceeds a seller's ask price [15]. Typically, a seller who has

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several quantities for sale may match different buyers, same with a buyer who wishes to buy several quantities [14].

Blockchain (BC) technology is a decentralized networking infrastructure that allows the execution and inspection of transactions in a decentralized and transparent manner. [16] and [17] describe BC as a P2P platform that uses a distributed and decentralized storage, initiates transactions and transmits them using a decentralized consensus algorithm while recording all transaction data in a tamper proof manner. Data is stored in blocks, created by means of consensus algorithm [17] and are protected by distributed sharing mechanisms and cryptographic signatures [18]. Smart contracts (SC) are applications (executed on the Ethereum Virtual Machine (EVM)) used to enforce agreement between parties or participating accounts and are executed only when the predefined constraints are satisfied [19]. BC technology uses SC, distributed ledgers, and decentralized consensus to enable decentralized markets, thereby solving the problem of conflict of interest [20].

In recent years, different research and projects have been conducted on P2P energy trading [6], [21] - [23]. The distinction between the model proposed in this work and the existing platforms is that the proposed model uses the novel BC technology for energy trading in a forward (intra-day) market on a rolling time horizon and promise a highly secured and tamper proof platform. DSA energy trading mechanism is used to calculate a market clearing for renewable electricity on a BC platform. The proposed model is open source [24].

II. Peer-to-Peer Energy Market

Prosumers that participate in the P2P electricity trading need to submit their ask ahead of the exchange period. The ask states the quantity of electricity they can produce, the minimum price per unit they wish to receive and the time of electricity production. Also, consumers who wish to buy electricity at a cheap price from prosumers within their microgrid need to submit bid ahead of the electricity exchange period. The bid states the quantity of electricity they need, the maximum price per unit they are willing to offer and the consumption time. At the end of the electricity auction, the market is cleared, and prosumers receive token (TUM Energy Coin (TEC)) paid by consumers for the energy they input to the microgrid. This TEC can be exchanged for fiat currency on the token market. Within this work, an energy-only market is modelled. Hence, network congestions and contingencies are not considered. The upcoming subsections will explain how this is achieved, describing the software architecture, event sequence, major functionalities and the implemented logic.

A. Market Architecture

Fig. 1 illustrates the involved actors, SC's, BC-nodes and software components necessary for the P2P electricity market. A Raspberry Pi operating a Parity Ethereum client (BC-node) and using Python software is installed on the smart meter gateway (SMGW) to form a SMGW-BC-node. Each consumer and prosumer (local electricity traders) owns a SMGW-BC-node for measuring consumed or produced electricity and communicating the data to the BC network. Furthermore, the local electricity traders (LETs) make use of a home energy management system (HEMS) to forecast future energy demand/production, receive user price input, optimize operations and communicate them to the BC network. The public electricity for this work is taken as a single entity called utility. The utility and LETs own a user application (APP) which they use to communicate with the BC network for selling of acquired TEC in exchange for fiat currency. The SC operator (SCO) on the other hand uses an APP to create new user accounts, transfer initial tokens to their accounts and update the SC during operation.

For the award and subtraction of TEC for energy exchange, transfer of TEC for fiat currency exchange, as well as TEC and energy market auctioning, four smart contracts were developed to ensure a modular structure. The scripting language for these contracts is Solidity, written on an Integrated Development Environment (IDE) known as Remix. Remix is also used to deploy the contract to the BC network. The contracts and their functions are explained in detail below.

- ERC20: This is the basic smart contract that all other contracts inherit. It initiates tokens (TEC) and manages their transfer from one address to the other. Once the TEC is created, it is assigned to the SCO.
- Double-Sided Auction: This is the contract that receives the various TEC bids and asks, sorts and matches the orders, before displaying them for payment confirmation. This contract inherits the ERC20 contract, checks the balance of users before approving and matching orders.
- Peer-to-peer Energy: This contract is responsible for receiving energy bids and asks, creating virtual microgrids and participant accounts, matching energy bids and asks, and settlement of TEC for energy sent to the microgrid. The SMGW-BC-node interacts with this contract by sending the energy produced or consumed to the contract via the Python script on the Raspberry Pi.
- Clearing: This contract serves two important functions: first, it is used to temporarily store TEC after TEC or energy market clearing, before transferring it to either the TEC buyer or the energy producer; second, it is used to trigger the clearing of energy and the TEC market.

B. Event Sequence

Fig. 2 provides an example of the P2P electricity auction and the exchange process for time interval t_0 to t_2, indicating the time that different events or transactions take place in the BC network. HEMS installed in the LETs households forecast the quantity of electricity the household can consume or produce in each time slot, in the next electricity exchange period (t_1 to t_2) (up to the next day (24 hours)). LETs can place and update their orders from 24 hours (t_0) until 1 minute before

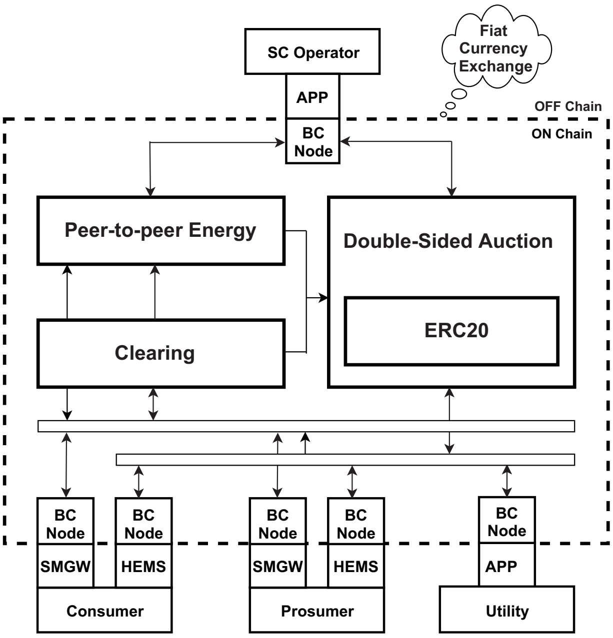

Fig. 1: Peer-to-peer market software structure

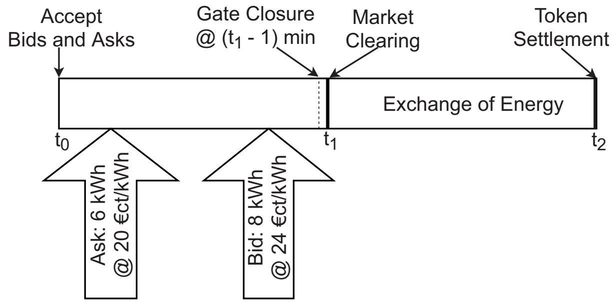

Fig. 2: Event sequence of the peer-to-peer energy market

(t_1 - 1) the electricity exchange period. Afterwards, they are obliged to follow the market clearing results by producing or consuming the quantity of energy allocated to them during market clearing. If the participants cannot produce/consume electricity according to the market clearing results, they must take counteractions themselves. Fig. 2 provides an example of a prosumer willing to sell 6kWh of electricity from t_1 to t_2, at 20 cent/kWh. Within the bid and ask interval, a consumer willing to buy 8kWh of electricity at 24 cent/kWh during the same energy exchange period (t_1 to t_2) also places a buy order. The market clearing mechanism is explained in Section II-C. Exchange of electricity takes place from t_1 to t_2 minutes. At the end of the electricity exchange period (t_2), the contract confirms that the prosumer fulfilled the agreement by producing the required amount of electricity. This process is known as token settlement (Section II-E) and prosumers that fulfill the agreement are rewarded with the equivalent ask token previously deducted from the consumer and temporarily stored at the Clearing account.

C. Energy Market Clearing Mechanism

Two market clearing mechanisms, market clearing price (MCP) and discriminative price (DP) were realized in the P2P Energy SC. This section illustrates the clearing mechanism of the DSA DP mechanism developed on the P2P Energy SC as depicted in the flow chart of Fig. 3. The bids, $b_{i,nB} = (p_{i,B}, q_{i,B}, t_{i,B})$ which consist of the maximum price ($p_{i,B}$) each participant is willing to offer per kWh of electricity, the quantity of electricity ($q_{i,B}$) in kWh each participant needs and the consumption time ($t_{i,B}$) are received in an array. Simultaneously, asks, $b_{k,nA} = (p_{k,S}, q_{k,S}, t_{k,S})$ which consist of the minimum price ($p_{k,S}$) per kWh of electricity the participants are willing to receive, the quantity ($q_{k,S}$) of electricity each participant is willing to sell and delivery time ($t_{k,S}$) are also received in an array.

Afterwards, the contract waits for a trigger from any of the participating smart meters within the microgrid to clear the energy market. Upon a trigger from the smart meters to the Clearing contract to clear the energy market, the Clearing contract checks if there is consensus within all participating smart meters in the microgrid. The clear energy market trigger is sent by all smart meters every minute; however, until there is above 51% consensus, the market will not be cleared. Once there is an up to 51% consensus to clear the energy market, the market is cleared as follows: Firstly, the bids and asks are arranged according to the consumption and delivery time, respectively, into different number of arrays for all the time slots in the next 24 hours. The total time slots $t_n = [0, 1, 2, ..., T_{n-1}]$ is equal for the bids and asks. T_n = 1440/(slot length), where the slot length is the time (minutes) of each slot and this is the energy trading time. Hence, for a 1 hour energy trading time, T_n = 24. Secondly, for each time slot, the bids are sorted in descending buy price order such that the price of $b_{i,nB} \geq b_{i+1,nB}$ and the asks in ascending sell price order such that the price of $b_{k,nA} \leq b_{k+1,nA}$. Thirdly, two integers "j" and "r" are initialized and set equal to zero for counting the matched row for the buy and sell orders, respectively. These integers are compared with the array length of the buy (n_B) and sell (n_A) orders, respectively, to find out if there exist orders to be matched. If n_B is equal to j or n_A equal to r, the program will end. This means that all orders have been matched or there are no order to match.

Fourthly, if n_B is not equal to j and n_A not equal to r, the first orders (r=j= 0) from the two sorted arrays are picked and their prices compared. If the sell price ($p_{0,S}$) of this first sell order ($b_{0,nA}$) is greater than the buy price ($p_{0,B}$) of the first buy order ($b_{0,nB}$) in the sorted array, the process will end; otherwise the quantities for the two orders will be compared. The two quantities are compared in three different case forms:

- Sell quantity (SQ) = buy quantity (BQ): For this case, the matched quantity is the SQ. The integers “r” and “j” are increased by one each. This means that the next matching should be selected from the subsequent rows of both seller and buyer offers.

- SQ < BQ: For this case, the matched quantity is the SQ. The integer “r” is increased by one. This means that the next matching should be selected from the subsequent row of seller offers and the current row of buyer offers as the quantities in the present row are not exhausted.
- SQ > BQ: For this case, the matched quantity is the BQ. The integer “j” is increased by one. This means that the next matching should be selected from subsequent row of buyer offers and current row of seller offers as the quantities in the present row are not exhausted.

For all three cases, the matched price is the average of the prices (cent/kWh) offered by the matched buyer and seller. The TEC equivalent of the matched price and quantity is calculated and transferred from the account of the buyer to the Clearing contract account, where it is stored temporarily. The same amount of TEC is approved for the seller by the Clearing account and can only be transferred to the electricity seller account during token settlement, if they supply the ask quantity of electricity. This process is repeated until either the sell price is greater than the buy price or all the offers in the ordered book are exhausted. For an easy onward process during token settlement, the quantity of electricity bought (BQty) or sold (SQty) by a LET during energy market clearing is recorded on the LET’s account. If a buyer is matched with two or more sellers, all the quantities bought are summed together as BQty. However, for a seller matched with different buyers, the SQty are not summed together; rather, they are put in an array with the corresponding sell price and stored on the seller’s account. Also, the number of participants a seller is matched is recorded as *sellcount* and is used during energy token settlement.

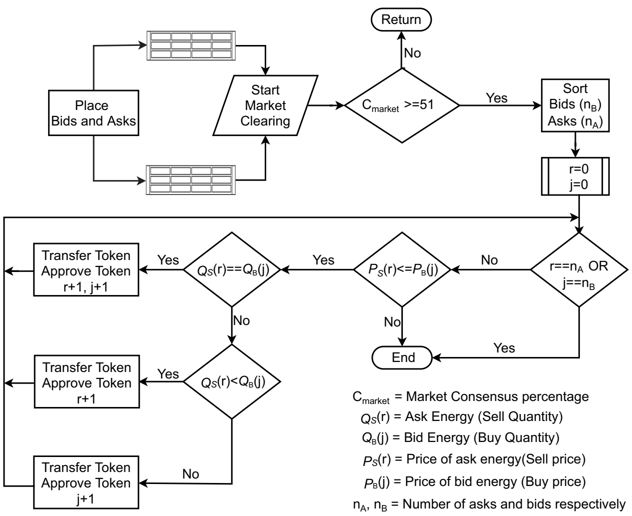

Fig. 3: Double-sided auction DP market clearing mechanism

D. Energy Exchange

Every minute, LETs communicate their consumed or produced energy measured from the SMGW to the BC network through their SMGW-BC-node. When this data is received on the network, the SC checks if its time for token settlement, and when this is not the case, the process will end and the transaction saved. Upon token settlement time, the participants smart meter node initialize transfer of token for energy produced or consumed, sign the market consensus and reset the energy exchange time. Signing of the market consensus indicates the acceptance by the participants to clear the energy market. Furthermore, the produced or consumed energy is added to the owners account and to the microgrid account.

E. Token Settlement

Consumers and prosumers participating in the P2P energy trading pay or get rewarded for energy consumed from or inputted to the microgrid, respectively. This section describes how this is achieved through the P2P Energy SC in the BC network and how LETs that do not follow the market clearing results in real-time are penalized. First, the consumed energy (CE) token settlement is described, followed by an explanation of the produced energy token settlement process.

1) Consumed Energy Settlement: During CE token settlement, the SC determines if the energy bought by the participant during the last energy market clearing is equal to zero, equal to CE, greater than CE or less than CE and makes the settlement for each case scenario as follows.

- BQty = 0: The TEC equivalent of the CE is transferred from the consumers account to the public utility account using the public utility sell price, which is costlier.
- BQty = CE: The bought quantity and CE are reset to zero.
- BQty > CE: The TEC equivalent of the excess (BQty - CE) energy the consumer bought and never consumed is calculated using the public utility buy price which is less than the original buy price. This serves as punishment for buying more than it can consume. The public utility transfers this TEC equivalent to the consumer during the next settlement. Furthermore, the quantity of energy bought and consumed are set equal to zero.
- BQty < CE: The TEC equivalent of the quantity (CE - BQty) consumed, which the consumer was unable to buy from the energy market is transferred from the user’s account to the public utility account, using the costlier public utility sell price. Following this, the quantity of energy bought and consumed are set equal to zero and the whole process is then returned.

Through the described method, consumers and prosumers pay for electricity they consume from the microgrid at the time interval (t_2 - t_1), during energy exchange.

2) Produced Energy Settlement: Produced energy token settlement occurs immediately after CE token settlement. The process of produced energy token settlement is done only for prosumers, who were matched during the last T_n energy market clearing to produce energy or prosumers that produce electicity within their microgrid during the current time slot. The quantity of energy a prosumer produced is evaluated in a loop for all the consumers and/or prosumers the prosumer was matched during the last energy market clearing to produce energy using the following two case scenarios.

- Produced energy $\geq$ SQty: The SQty is subtracted from the produced energy and the TEC equivalent of SQty is transferred from the Clearing contract account to the prosumers account.
- Produced energy $<$ SQty: The TEC equivalent of produced energy is transferred from the Clearing contract account to the prosumers account. Also, the TEC equivalent of the prosumer deficit (SQty - Produced energy) energy is transferred from the prosumer's account to the public utility account, using the difference between the public utility and the prosumer sell price. This is to penalize the prosumer for not producing the matched energy; as this energy was supplied by the public utility.

These steps are repeated for the number of times (sellcount) a producer was matched during the last T_n energy market clearing to produce energy. At the end of the loop, the prosumer is also evaluated to find out if the produced energy is greater than zero. This is a situation where prosumers produce more than they were matched during the last T_n energy market clearing. If this is true, the TEC equivalent of the excess produced energy is calculated using the public utility buy price. The public utility transfers this TEC equivalent to the prosumer during the next token settlement. After this, the process will end. By this, energy producers acquire some amount of token called TEC for the energy they input to the microgrid. TEC can be sold by energy prosumers whenever they want to receive fiat currency.

III. SIMULATIONS

The four SC's developed for this work were deployed at the Ethereum proof of authority (POA) private BC network of the Chair of Energy Economy and Application Technology, Technical University of Munich (TUM). The developed model was simulated for a day with seventy-two households in six different microgrid scenarios. Table I displays the six different microgrid scenarios of the simulations, the participants, the clearing mechanisms (Clear. Mech.) used for each scenario, and the auction bidding price range of the participants. The reference scenario is a scenario where there is no auction; thus, for this scenario, excess electricity produced by prosumers (Pros.) is sold to the utility at 12 cent/kWh and all consumers (Cons.) buy their electricity directly from the utility at 30 cent/kWh. Two different auction price range (PR) namely small (SR) and wide range (WR) were tested for the simulation. For SR, consumers start bidding for electricity from 15 cent/kWh and increase their bid price by 1 cent/kWh after every market clearing when they have not bought all the required electricity for a future time. Also, for this price range, prosumers set their initial electricity price at 20 cent/kWh and reduce their ask price by 1 cent/kWh after every market clearing if they have not finished selling all their forecast quantity. On the other hand, for WR, consumers make their first bidding at 12 cent/kWh and increase the bid subsequently by 1 cent/kWh if the bid was not successful while prosumers start their ask at 30 cent/kWh and reduce the price by 1 cent/kWh for the unsuccessful asks.

TABLE I: Microgrid Scenarios and Participants

Scenario	Participants	Clear. Mech.	PR
Reference	Varies	No auction	–
5P3C_DS	5 Pros., 3 Cons.	DP	SR
3P5C_DS	3 Pros., 5 Cons.	DP	SR
5P5C_DS	5 Pros., 5 Cons.	DP	SR
5P5C_MS	5 Pros., 5 Cons.	MCP	SR
5P5C_MW	5 Pros., 5 Cons.	MCP	WR

The consumption input data for consumers and prosumers are per minute resolution consumption data of PL1 (active power line1) from HTW Berlin [25]. The prosumers PV production data are from the Chair of Energy Economy and Application Technology, TUM [26]. Two different Python scripts were developed for each household to represent a SMGW and HEMS. The SMGW Python script was responsible for communicating the consumption per minute to the BC network for a day. And the HEMS Python script was responsible for making an energy forecast of the energy that will be consumed in the future, creating and, posting bids and asks to the BC network. All consumers and prosumers were given an initial TEC worth 100 cents. A single Python script per microgrid scenario was also developed for logging the output data from the BC network every minute. The data logged per user are the user's TEC balance, produced energy, consumed energy, BQty and SQty (prosumers only). The cost of deploying the SC to the network and user transaction cost were also determined. The simulation slot length is 1 hour, for a total of 24 slots. This means that the market is cleared after every 1 hour for the 24 hour simulation time.

IV. RESULTS AND DISCUSSION

Within this section, the results of the simulations introduced in section III are visualized and discussed. Fig. 4 displays the plots of produced/consumed energy (upper most graph (Fig. 4a)), accumulated energy (middle graph (Fig. 4b)) and TEC balance (bottom graph (Fig. 4c)) of Prosumer1 for the reference scenario. Positive energy means consumption while negative energy means feed-in. From Fig. 4a, Prosumer1 imports energy from the microgrid from 12:00am (0 min) until about 5:30am (330 min). Then it exports energy to the microgrid until about 4:40pm (1000 min) and afterwards, imports energy from the microgrid. From Fig. 4b, the accumulated energy increases linearly from 12:00am (0 min) until 5:45am

(345 min). It then decreases linearly until 4:40pm (1000 min) and increases afterwards. The TEC balance (Fig. 4c) decreases in steps from 12:00am (0 min) until 4:00 am (240 min), becomes almost constant until 6:55 am (415 min), increases in steps until 5:48 pm (1068) and decreases in steps afterwards. Comparing the three plots (Fig. 4 (a,b,c)), it is evident that as Prosumer1 imports energy (energy consumption) from the microgrid, its TEC balance decreases in steps while accumulated energy increases linearly; however, as it exports energy (energy production) to the microgrid, its TEC balance increases in steps while the accumulated energy decreases. The period (240 - 415 min) during which the prosumer balance (Fig. 4c) is almost constant signifies that the prosumer produces almost all its energy requirements by itself and does not exchange energy with the microgrid. The trends of Fig. 4c show a total of 24 steps which is the total number of time slots and the number of times the token settlement took place for the prosumer during the simulation.

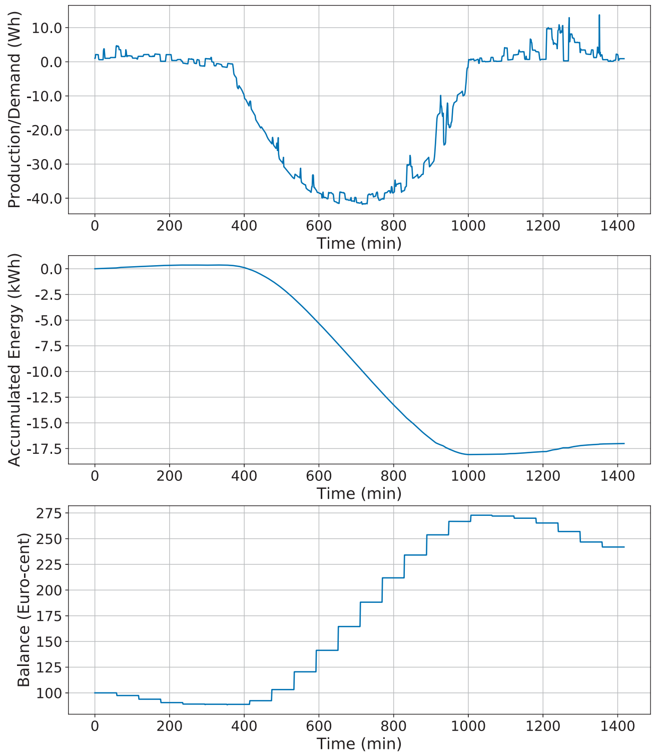

Fig. 4: Prosumer1 real time output data for reference scenario

Fig. 5 displays the real time plots of consumed energy (upper most graph (Fig. 5a)), accumulated energy (middle graph (Fig. 5b)) and TEC balance (bottom graph (Fig. 5c)) of Consumer1 for the reference scenario. From Fig. 5a, Consumer1 consumes energy from the microgrid for the whole day; peak load is witnessed from 9:04 am (544 min) until 11:50 am (710 min). The accumulated energy increases almost linearly from 12:00 am (0 min) until 9:04 am, increases in step until 11:50 am, then increases almost linearly afterwards. The TEC balance of Consumer1 decrease in steps from 12:00 am until 10:00 am (600 min), then a steeper decrease is witnessed until about 11:57 am (717 min) and decrease in steps afterwards (see Fig. 5c). Comparing the three plots (Fig. 5 (a,b,c)), it is evident that as the consumer consumes electricity, its TEC balance decreases in steps while the accumulated energy increases almost linearly. The step increase in accumulated load is because of the peak load witnessed at same time. Consequently, the steeper decreases in TEC balance witnessed between 10:00 am and 11:57 am in Fig. 5c is because of the peak load consumption that took place from 9:04 am until 11:50 am as shown in Fig. 5a. Since there is no auction, the consumer is unable to buy energy from the market prior to consumption time. Token settlement takes place every hour and results in the reduction of TEC witnessed in the form of step function which becomes steeper during peak load. Also, Fig. 5c show a total of 24 steps, which is the total number of time slots and the number of times token settlement took place for the consumer during the simulation.

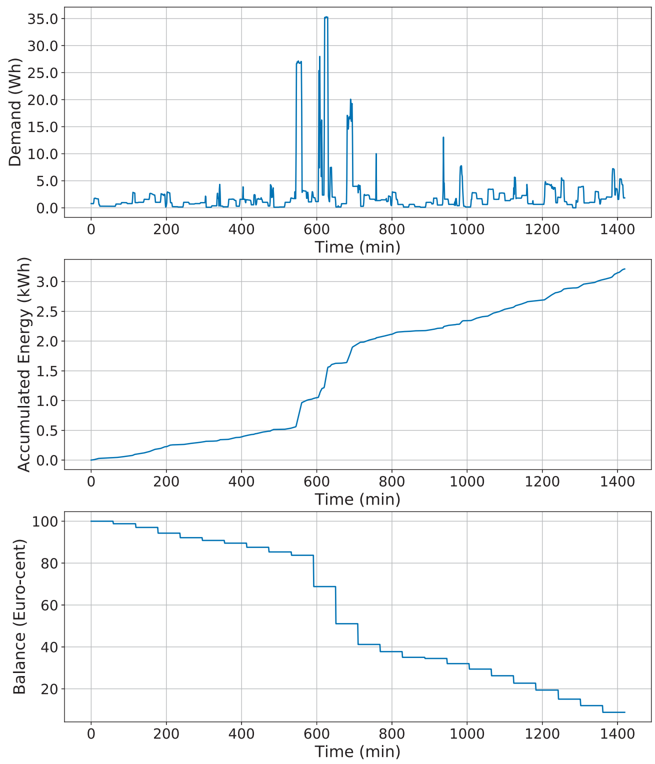

Fig. 5: Consumer1 real time output data for reference scenario

Fig. 6 displays the plots of real time TEC balance of Consumer1 at the six different microgrid scenarios. The blue plot is the reference scenario discussed on the previous paragraph and shown in Fig. 5c. The diagram shows that all plots demonstrate the same trend as the reference scenario from 0 mins until 184 min. This is the time interval where the bid and ask prices of the consumers and prosumers respectively, have not reached the market equilibrium price and hence, they all buy and sell their energies to the utility. At 185 mins, the bids and asks for 5P3C_DS, 3P5C_DS, 5P5C_DS, and 5P5C_MS reached the market equilibrium and this resulted market clearing and further deduction of TEC equivalent to the matched quantity of energy from the account of the consumers. However, since the energy bought is for a future time (307 - 1158 mins), the consumer continues to pay for its energy consumption to the utility hourly until 307 mins. This is evidence in the two step decrease in TEC balance of the consumer for the four scenarios from 185 - 307 mins. The TEC balance of the consumer is almost constant from 307 mins until 1158 mins for the four scenarios. This is because the consumer has previously bought energy for this time and does not need to pay again during hourly token settlement. The TEC balance of the consumer decreased in steps for the four scenarios from 1158 mins afterwards. This is because prosumers did not produce energy at this time interval and therefore, the consumers bought their energy from the utility for all the scenarios. The step decrease is similar for the four scenarios as the consumer buys energy at the same price from the utility for the four scenarios. The bids and asks for the 5P5C_MW scenario reached the market equilibrium at 550 mins. This was due to the wide price range which results in delayed time to reach market equilibrium. The market clearing took place at this time (550 mins) and further deductions of the TEC equivalent of the matched energy from the account of the consumer. Because of the energy bought during the market clearing, the consumer TEC balance for this scenario is constant from 550 mins until 1158 mins. The TEC balance of the consumer decreases in steps for this scenario from 1158 mins afterwards. This step decrease is because the consumer buys its electricity from the utility for this time interval and thereby pays for its electricity hourly just like the reference scenario. Consequently, there is likelihood of profit for a closer bidding range for a consumer. It is also evident from the plots that it is more profitable for the consumers to trade with prosumers on a P2P level than with the utility.

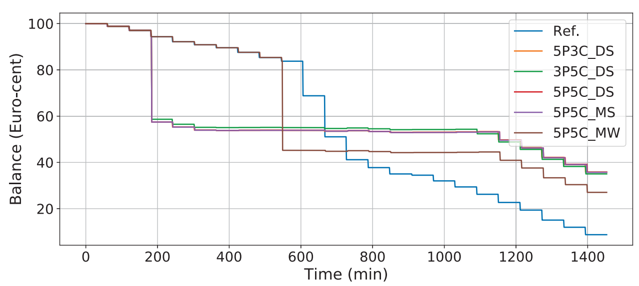

Fig. 6: Consumer1 balance at different microgrid scenarios

Fig. 7 displays the plots of real time TEC balance of Prosumer1 at the six different microgrid scenarios. The plots follow the same trend of step decrease as the reference scenario from 0 mins until 427 mins. This is because the prosumer buys energy from the utility for all scenarios within this time interval, thereby paying for its energy hourly. The hourly token settlement results to step decrease of TEC balance within this interval. The TEC balance of the prosumer for all the scenarios increases in steps from 427 mins until 1154 mins. This step increase is higher for the scenarios where there is auction than the reference scenario. This is because the prosumer trades with the consumers directly in these scenarios and makes higher profit than trading with the utility. The TEC balance of the prosumer show a similar decrease in steps for all the scenarios from 1154 mins afterwards. This is because, the prosumer consumes electricity from the utility within this time interval and pays for its consumption hourly during token settlement. Consequently, it is more profitable for a prosumer to trade with a consumer on a P2P level than trading with the utility.

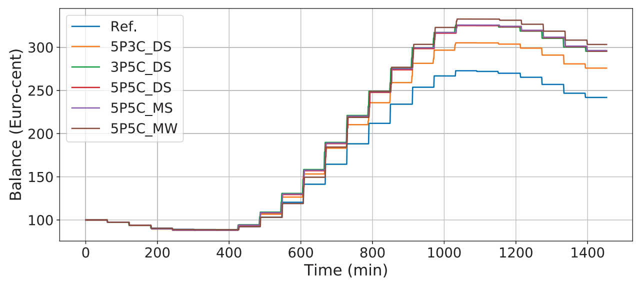

Fig. 7: Prosumer1 Balance at different microgrid scenarios

The unit used to measure the cost required for a particular transaction computation in a BC network is gas [27]. The transaction cost for deploying the P2P Energy SC is 19,896,454 gas against the gas limit of transaction in public Ethereum network of 8,000,000 gas. This makes it practically impossible to deploy the SC in the public BC network without increasing the gas limit of the network. Furthermore, communicating the consumption/production data to the BC network per minute has a transaction cost of 67,369 gas. This is equivalent to 270.2 ETH if deployed on Ethereum public BC network, using the prevailing exchange rate from [28]. Consequently, it is economically unfeasible to use the model for local energy trading on the popular public BC network - Ethereum network. This calls for a consortium public BC network with a lower transaction cost for energy trading.

V. Conclusion and Outlook

Within this paper, a product architecture, event sequence, algorithms for automated energy trading in smart contracts; using HEMS and SMGW functionalities of prosumers, consumers and utilities; are presented. Simulations for multiple microgrid configurations have verified the usability and the effectiveness of the P2P energy market on the blockchain network. The key findings are listed below.

- It is more profitable for prosumers and consumers to trade electricity with each other than trading with the utility.

- A BC operator(s) or consortium of authorities are necessary to trade energy on a P2P level on a BC (updating SC, adding new participants, transferring initial tokens).
- It is currently economically unfeasible to use public Ethereum BC network to trade electricity due to its high gas cost.
- Closer bidding range increases the likelihood of profit in a P2P energy market.

In future research, intelligent bidding systems will be developed and a more complex market with hundreds of households investigated. The functionalities of the SC will be split to allow a practicable and economically feasible contract, that can be run on public BC network with basic functionalities like consensus mechanism, encryption and storage ON-chain and others like market clearing off-chain. A forecast model will be developed for predicting future consumed/produced energy for a household. A Hardware-in-the-Loop laboratory environment testing will be conducted before the final stage which will be validating the results in a field test. A field test is planned with assets from our project partner WIRCON within the German SINTEG project "C/sells".

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4.2 Hybrid blockchain based local energy market

Contribution

The paper [148] presented in this section is focused on solving the scalability, transparency and high gas cost challenges that arise from using public blockchain networks for LEM applications. An open-source hybrid framework was developed, a framework that combines the on-chain features of blockchain with the side-chain features of TEE to provide a reliable, scalable, reduced operation cost, resilient, highly secured, and tamper resistant LEM model architecture that upholds transparent transactions while still conforming to GDPR [151]. The developed framework runs the market model inside a TEE enclave and proves the integrity of the enclave at all times to show that it is trustworthy by sending attestation of the enclave quarter-hourly to the blockchain network. A Merkle root hash encryption is used to safeguard the bids and offers in the blockchain network by ensuring the consumers/prosumers are able to generate a Merkle root proof to show that their bids/offers are part of bids used for the market clearing without seeing the bids/offers of other participants. By doing this, the framework complies with GDPR requirements while proving to the participants that they are not cheated and that their data were not falsified. Fig. 4.1 shows the architecture of the developed model framework.

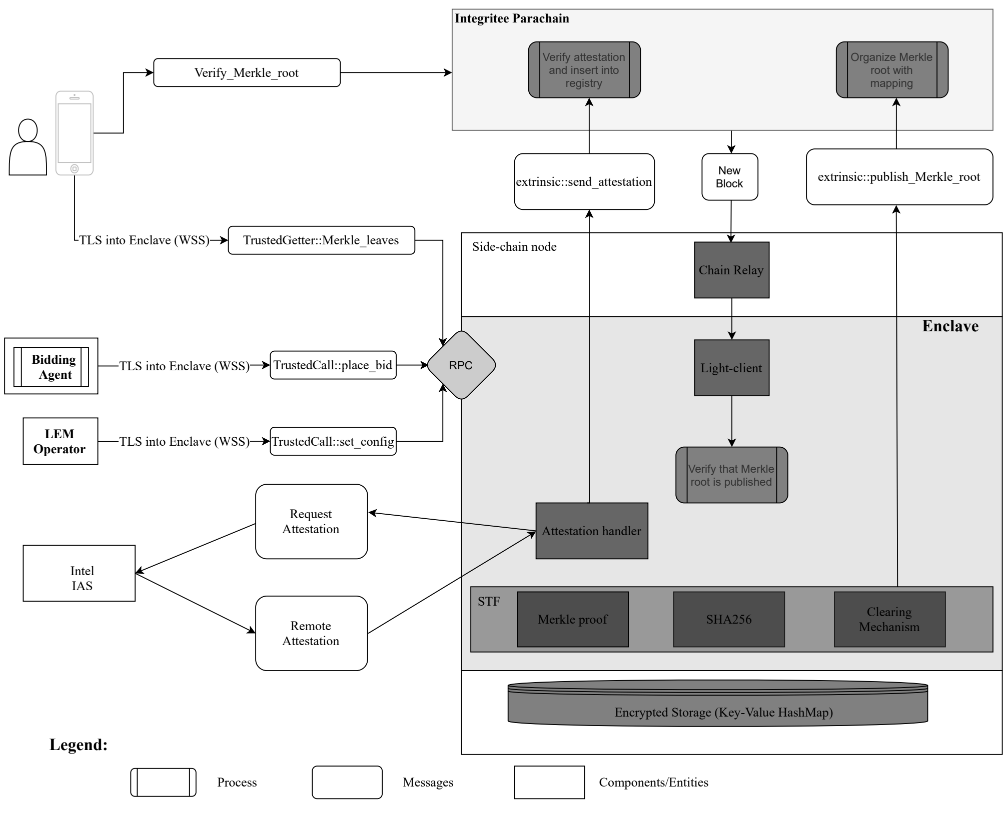

Figure 4.1: Schematic of the developed hybrid blockchain architecture for LEM, after [148].

A one-year economic analysis of the model framework was conducted to evaluate the economic feasibility of the model. Furthermore, a one year simulation result of energy exchange was received from [118] for varying number of prosumers/consumers trading in the local community. The number of participants (prosumers and consumers) were varied from 10 to 10,000. The cost of maintenance, operations, updates, and management of the model were calculated for the period of one year. Then, with a transaction cost of 2 ct./kWh, the total profits of the LEM operator and the prosumers/consumers for the period of one year were calculated for varying number of participants. The results of the economic analysis show that the framework is always profitable to the consumers and prosumers, notwithstanding the number of prosumer/consumers in the LEM. However, with a charge of 2ct./kWh, the market is profitable to the LEM operator when the number of participants is more than 500 members. Hence, for an LEM operator to make profit from the model framework with less than 500 participants, it is either the charge per kWh is increased or the LEM operator will have to provide more production devices in the community to ensure that more trade takes place in the community, thereby increasing their total profit.

Publication #9: Design and Evaluation of Architectural Framework for Local Energy Market Model Based on Distributed Ledger Technologies

Authors: Godwin C. Okwuibe, Thomas Brenner, Muhammad Yahya, Peter Tzscheutschler, and Thomas Hamacher.

Publication medium: IET Smart Grid, Under Review.

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Authors contributions

Godwin C. Okwuibe	75%	Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Validation, Writing - Original draft, Writing - review and editing.
Thomas Brenner	5 %	Conceptualization, Formal analysis, Validation, Writing - review and editing.
Muhammad Yahya	10%	Software and Visualization.
Peter Tzscheutschler	5%	Methodology, Validation, Writing - review and editing.
Thomas Hamacher	5%	Supervision, Writing - review and editing.

Design and Evaluation of Architectural Framework for a Secured Local Energy Market Model Based on Distributed Ledger Technologies

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Blockchain-based local energy markets have been proposed in recent years to provide a market platform for local prosumers and consumers to exchange their energy in a secured, transparent and tamper proof manner. However, there are still some challenges regarding the scalability of blockchain to handle high computational models/algorithms/contracts as this may result in extension of the block size of the blockchain network and very high gas costs. Also, there is still problem of transparency as regards General Data Protection Regulation because, the full visibility of data in the blockchain may collide with privacy in some settings. This paper presents a framework that combines the on-chain features of blockchain with trusted execution environments to develop a transparent, tamper resistant, low operation cost, scalable and resilient hybrid model architecture for local electricity trading. The model architecture was simulated in German community case scenarios for varying number of prosumers and consumers to show its applicability. The simulation results show that the model was able to solve the scalability problem of blockchain for local energy market application as the market model is run in a trusted environment where the integrity of the model can be verified by the participants.

Index Terms—**Blockchain, trusted execution environment, local energy market, market models, market platform.**

I. Introduction

A. Motivation and Background

Local energy markets (LEMs) have been introduced in recent years as a solution to the high grid congestion management cost caused by variable renewable energy resources in the power system grid [1], [2]. Hence, by ensuring the energy is consumed closer to where it is produced, LEM provides a market platform for trading locally produced energy at the distribution grid level [3]. Thereby providing an opportunity to utilize a bottom-up approach to solve the complex power system problem of distributed generation [4], [5]. The LEM market model usually implemented in the market platform is used to furnish the market event sequence, trading format, and matching process [6], [7]. An LEM market platform can be either centralized, decentralized or distributed. A centralized market platform is a platform that is based on a trusted third-party that is responsible for hosting, updating, and maintaining the market platform [8]. A decentralized market platform is a type of platform that is made of different sub-platforms responsible for data storage, update and record keeping in the platform. A distributed market platform is a platform made of synchronized nodes that utilize a distributed ledger for its record keeping and consensus mechanism for writing data into platform [8], [9]. In summary, for a centralized market platform, an attack on a node of the platform will result in complete failure of the whole platform. On the other hand, for a decentralized market platform, an attack on a node will result on the failure of some part of the platform. However, for a distributed market platform, an attack on a single or even several nodes will not affect the platform.

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B. Introduction to Distributed Ledger Technology

Distributed ledger technology (DLT) is a variant of distributed computing that is used to validate, access, transcribe and record transactions in a manner that it is transparent [10], and easily accessible by each participating node spread over different locations in the network and has the ability to enforce consensus among the participating nodes [11], [12]. Data stored in a DLT network is also accessible to everyone running the DLT client or through a block explorer. The features of DLT include transparency, distributed consensus [13], high security, immutability, pseudonymity [14], trust-free, and decentralized storage [15]. The concept of blockchain was introduced by Nakamoto in his paper titled "Bitcoin: A Peer-to-Peer Electronic Cash System" published in 2008 [16]. The paper presents a solution to double spending by proposing electronic cash based on cryptographic signatures in a peer-to-peer (P2P) network. The model propose a cryptographic linked blocks data structure that utilize the proof-of-work consensus mechanism [11]. A block contains transactions within the network at a stipulated time and a reference of its predecessor block in the form of hash [17]. This intrinsic features of blockchain attracted different researchers to research on how blockchain can be used for their field of study. Moreover, this features also attracted researchers in the field of LEM to investigate how blockchain could be used to develop the LEM market platform.

C. Blockchain based LEM platform

After the introduction of smart contracts and the launch of Ethereum blockchain project by Butterin in 2015 [18], many researchers began to investigate on how blockchain can be used in the energy sector. Ref. [19] proposed a decentralized electricity transaction model based on blockchain for exchanging digital certificate of power and expenditure. A consortium blockchain was used by [20] in their work to increase transaction security and privacy for localized electricity trading among plug-in hybrid electric vehicles. Ref. [21] proposed a model for peer-to-peer transactive microgrid for exchanging electricity among prosumers that is based on Ethereum blockchain model. This was also followed by research on the application of blockchain for LEM as the first notable blockcain based LEM project, the Brooklyn microgrid was launched in 2016 [7]. Following this, numerous research works have evolved introducing and describing how blockchain can be used for LEM application. The major drive for using blockchain for LEM application as discussed by many researchers is usually the ability of blockchain to provide a transparent and trustless platform to enable trading of electricity at the local grid level without the need for a third party. Ref. [22] proposed a framework for a blockchain based doubled sided auction mechanism for P2P local electricity trading market. A similar study by Ref. [23] investigated the application of a blockchain-based LEM by using smart contract to develop a merit order clearing mechanism implement in a private Ethereum network. Ref. [24] used the IBM Hyperledger Fabric to implement their proposed strategies for determining the trading preferences of prosumers participating in local energy market.

Ref. [8] proposed a hierarchical blockchain-based local electricity market framework for trading electricity in a microgrid. The concept of proof of energy as a modification of proof of stake was proposed by Ref. [25] as a consensus mechanism for trading energy in a P2P LEM. The proposed model created added self-consumption, and further contributed to reducing power losses in the local community. Ref. [26] proposed a blockchain based solution for energy trading in a local community based on the concept of ERC-1155 compliant solution for use in an Ethereum blockchain network. The proposed Ethereum prototype promised a reduced gas cost by 97% compared to the public Ethereum network. A blockchain based decentralized local market was proposed by [27]. The model was implemented using a Cosmos framework implemented as a side-chain and used for implementation of the developed market mechanism. To provide insight on the design of the trading platform of a blockchain based LEM framework, Ref. [28] proposed and described the general architecture and elements needed to implement a blockchain-based LEM. The seven functional layers architecture for designing a community based LEM was proposed by [10]. The proposed layers were evaluated of their applicability by comparing them to a case study of the Brooklyn microgrid. Ref. [7] proposed the seven market components for designing an efficient community based LEM. The proposed components were also evaluated using the Brooklyn microgrid as a reference.

The permissioned Hyperledger Fabric network was used by Ref. [29] to proposed a framework for designing and evaluating a realistic blockchain-based local energy markets. The proposed model framework showed that changes in the data model can affect the efficiency of the framework up to 90%. ETradeChain which is a blockchain-based platform for local energy trading was proposed by [30]. The platform is based on Byzantine proof-of-stake consensus mechanism. Hence, the coins (called Pcoin) used for transaction exchange is based on energy generated by the participating prosumers. Ref. [31] implemented a blockchain-based local energy market to evaluate the impact of hardware and communication protocol in such application. The model was based on Byzantine fault tolerant blockcain network. The field test evaluation showed that the model has lower/limited scalability (10 transaction per second). The Ethereum blockchain network was used by Ref. [32] to show the application of a community battery energy storage system in a blockchain-enabled local energy market. The results from the experiment show that the proposed model is relatively expensive and the transactions are slow to execute.

Moreover, Ref. [33] proposed a system architecture for implementing local energy markets in a blockchain infrastructure. The model was evaluated in a case study of the Landau Microgrid. Ref. [34] demonstrated the implementation a local energy market based on private Ethereum network in 37 households in Walenstadt, Switzerland. In the same way, Ref. [35] demonstrated how blockchain can be used to enable local prosumers to exchange energy in a secured manner. The model was implemented by developing smart contracts used for running the merit-order market clearing mechanism and implementing it in the Allgäu microgrid. Notwithstanding the research works already developed in the field of blockchain-based LEM and few projects already conducted in this area, blockchain is still not matured for application in LEM [36]. Zade et al. [37] compared a blockchain-based and a centralized LEM using their derived basic LEM requirements such as reliability, scalability, data security, tamper resistance, and low operation cost. The findings of the research showed that blockchain-based LEM is less reliable, has limited scalability, difficult to implement, less stable, and does not fulfil the data security requirements when compared to centralized LEM. In terms of the operation cost, this depends on the type of blockchain network. While it is significantly low in a private blockchain network compared to a public blockchain, it is also important to mention that the cost of running this private blockchain network need to be considered before implementation and may need a third party maintenance. Also, with the number of transactions expected to take place in an LEM, scalability is important in LEMs to ensure that the market is cleared within the market time slot without tampering with the market results. Ref. [38] proposed a clustering model for splitting LEM into different clusters to ensure that the market is trackable in time while maintaining the integrity of the market outcome. Table I summarizes the literature presented highlighting clearly the advantages and challenges of each proposed model.

D. Contribution and organization

The evolution of blockchain has lead to different studies proposing the use of blockchain for LEM trading. However, the limited reliability, scalability, difficulty in implementation, less stability, and inability to fulfil data security requirements of blockchain has lead to low adoption of blockchain for

TABLE I: Summary of several proposed blockchain-based LEM models with their characteristics.

S/N	Reference	Blockchain platform/major characteristics	Advantages	Challenges
1	[7]	Fully blockchain-based, Ethereum private blockchain network, proof-of-work consensus mechanism, and double auction market mechanism.	Secured and transparent platform, distributed consensus platform.	Data is open to all participants, scalability challenges, high gas cost and high operating cost.
2	[22]	Fully blockchain-based, Ethereum private blockchain network, proof-of-authority consensus mechanism, and double auction market mechanism.	Secured and transparent platform, relatively low operating cost	Data is open to all participants, scalability challenges, high gas cost.
3	[23]	Fully blockchain-based, Ethereum private blockchain network and two step merit-order market mechanism.	Secured and transparent platform,	Data is open to all participants, scalability challenges
4	[24]	Fully blockchain-based, IBM Hyperledger Fabric network, permissioned platform and peer-to-peer strategies.	Secured and confidential transactions	Lack of transparency hinder transaction verification and scalability challenges.
5	[8]	Hierarchical blockchain-based framework.	Secured and transparent,	Higher energy cost, Not fully scalable
6	[25]	Fully blockchain-based network, proof-of-energy (similar to proof-of-stake) consensus mechanism.	Increase self consumption	limited decision making contribution by participants, not scalable.
7	[26]	Ethereum based prototype, ERC-1155 compliant solution.	Reduced gas, increased transparency	limited scalability
8	[27]	Cosmos side-chain, proof-of-stake (POS) consensus mechanism.	less hardware requirement	limited decision making contribution by participants, not scalable, require more memory.
9	[29]	Fully blockchain-based, Hyperledger Fabric network, permissioned platform and closed-order book auction	Secured and confidential transactions	Lack of transparency hinder transaction verification and scalability challenges.
10	[30]	Decentralized P2P network, Byzantine POS consensus double auction mechanism	Secured and low computation overhead	scalability challenges
11	[31]	Fully blockchain-based, Tendermint protocol Byzantine Fault Tolerance, POS consensus mechanism, Peer-to-peer LEM	Secured transaction	High computation data, scalability challenges.
12	[32]	Ethereum blockchain network, peer-to-peer trading strategy	Secured transaction	Relatively expensive, scalability challenges.

LEM application. Hence, this work is aiming to determine the required conditions for implementing an economically feasible blockchain based LEM architecture model. We propose a hybrid blockchain based LEM model architecture by leveraging the features and value propositions of trusted execution environment (TEE), and using them to create a model solution to the enumerated limitations of blockchain for LEM application. The proposed model was verified of its application by simulating it in a German community case scenario of more 10,000 consumers and prosumers and further evaluated of its suitability for LEM application by performing an economic analysis of the use case scenario. Our proposed model is open-source and available at [39]. The main contributions of the paper can be summarized as follows:

- We propose a hybrid blockchain based architecture model for LEM.
- The proposed framework proves to be highly secured and scalable while maintaining privacy requirements of an LEM.
- Simulating the proposed model for a German case scenario to verify its applicability with more than 10,000 prosumers.
- Performing an economic analysis of the proposed model to evaluate its economic feasibility and the necessary conditions required for this.

The remaining sections of this work are structured as follows. The proposed LEM architecture model is described in Section II. The model is verified and evaluated in Sections III and IV, respectively. Finally, Section V concludes the paper and proposes how the work can be further extended in future.

II. Proposed architecture design of a hybrid blockchain-based LEM

In this Section, the proposed hybrid blockchain-based LEM is presented. In order to provide a highly secured, tamper-proof, transparent and a trusted LEM model that satisfies the LEM participants' requirements as described in [40] and [37], and still compliant with the General Data Protection Regulation (GDPR), we propose a model that combines on-chain mechanism and side-chain Trusted Execution Environment (TEE) for our LEM platform. Using only blockchain for deploying the LEM model to provide tamper-proof and secured data is gas intensive and will require extension of the block size of the public blockchain in most cases [22], [37]. Also, public blockchain is open and therefore data stored on the blockchain is open to everyone willing to see it, consequently, it is difficult to build it in such a way that it has no issue for privacy protection especially with regard to GDPR. Consequently, the TEE is considered important because, it will provide a secured environment for running the LEM model in a secured and tamper-proof manner while being compliant with GDPR. TEE provides a hardware encrypted environment for executing code and protecting it from external attacks, and even prevents the system administrator and the operating system from accessing sensible data. In general, a TEE provides confidential code execution and can deliver a proof that it has not been tampered with. It can also handle authentication with cryptographic signatures. Finally, remote attestation can proof to a remote third party what code is executed in a TEE making it most suitable and interesting to use for LEM application [41], [42], [43].

A. General architecture description

The proposed architecture of the proposed hybrid blockchain-based LEM model platform is presented in Fig. 1. The framework is classified into four basic components namely prosumer side components, on-chain components, side-chain components, and LEM operator. The prosumer side components are the user application (App) and bidding agent. The user App is used by the consumer/prosumer to communicate their trading preferences and verify bids/offers, tampering of market mechanism and market results. The bidding agent is a software code used to decide the bidding/offering price and energy quantity at every market time step. The development and working of the bidding agent is presented in [44]. The on-chain component used is the Integritee parachain which is a blockchain network responsible for storing the Merkle root hash, verifying the remote attestation, and inserting the attestation data into its public registry. The Integritee parachain blockchain network is a second-layer blockchain network built on Polkadot relay chain which enables transactions to be performed in parallel [45], [46]. Polkadot relay chain allows different blockchain networks to run on them thereby increasing the scalability and flexibility of the blockchain network [45].

The side-chain components are the enclave, chain relay and encrypted storage. The enclave contains all the code that needs the guarantees of the TEE such as confidentiality and integrity, these include the enclave state transition function (STF), the attestation service handler and the light client. The STF contains all the business logic specific code. The most important parts in this use case are the LEM clearing mechanism, the Merkle proof generation component, and the SHA256 library which the Merkle proof component uses.

The attestation service handler client is responsible for formulating the attestation quote and communicating it with Intel attestation service (Intel IAS) to verify that the integrity of the TEE is not tampered with and that the TEE is genuine, secured and running the expected code. The Intel IAS is the service provided by Intel's Software Guard Extensions (SGX) in order to guarantee integrity, confidentiality and security of Intel architecture from malicious software [43]. Chain relay is responsible for importing new blocks from the Integritee parachain. The light client is used to read the imported data to verify that the Merkle root was published on the blockchain network. Encrypted storage is used for storing the bids/offers and the market results. The LEM operator is responsible for developing the market matching algorithm that runs on the TEE enclave. The remote procedure call (RPC) is the software communication used for this design which allows a programme to use it to request a service from another programme located on another computer on a network without the need to understand the details of the network [47]. In order to better describe the working of the model, we explain the process of verification and attestation of the model integrity as a use case scenario using a sequence diagram. The verification/attestation process is classified as verification of bids/offers, attestation of market mechanism/TEE enclave and verification of results. These verification/attestation processes are sequentially described in the following subsections.

B. Hash verification process - bid/offer verification

This process provides opportunity for a consumer/prosumer participating in the LEM to verify if their bid/offer is part of the bids/offers used for market clearing of the LEM within a predefined previous market slot. Fig 2 displays the sequence diagram for the bids/offers verification process. The actors are the consumers/prosumers, TEE and the blockchain network, which is the public Integritee parachain in this case. The bidding agent and user application are used to represent the consumers/prosumers in the network ecosystem. The consumer/prosumer bidding agent creates the bids/offers (orders) for a consumer/prosumer at a particular time slot. The order contains user identification, market time slot, bidding/offering energy quantity, price, and type. The order type is either bid or offer which is used to show if the consumer/prosumer is buying or selling the proposed quantity of energy, respectively. All consumers/prosumers post their orders using transport layer security (TLS) communication method through a secure websocket (WSS). The TLS protocol facilitates an encrypted communication channel and thus its certificate of the TEE contains the TEE's unique public key. So the client application can check that this key matches the one that the TEE registered on the blockchain to verify that it is talking to a genuine TEE. The orders are then stored in the encrypted storage database. At the end of bidding/offering for each time slot, individual consumer/prosumer order is used to generate a hash called leaf hash by passing it through the SHA256 function. The leaf hashes through the process of Merkle root generation are used to generate a single hash called the root hash. The root hash for the time slot is then stored on the blockchain network. This root hash can be seen by everyone since the blockchain is public, however, cannot be interpreted or translated by humans which implies that it is completely GDPR compliant.

The consumer/prosumer at any time after the end of bidding/offering may wish to verify if their bid/offer was part of the bids/offers used for market clearing at a defined time slot. This can be done by the consumer/prosumer sending a bid/offer verification request for a defined previous time slot to the TEE enclave using their user application. The RPC request is sent via the TLS communication protocol. Hence, it is encrypted and secured from external attacks. The orders of the specified previous time slot is retrieved from the database and passed through SHA256 function to generate a leaf hash for the individual consumers/prosumers orders. The leaf hashes are then sent to the consumer/prosumer use application that made the request through TLS communication protocol. The first stage verification is carried by the user application client by generating the hash of the consumer/prosumer order at the defined time slot and comparing it with the received

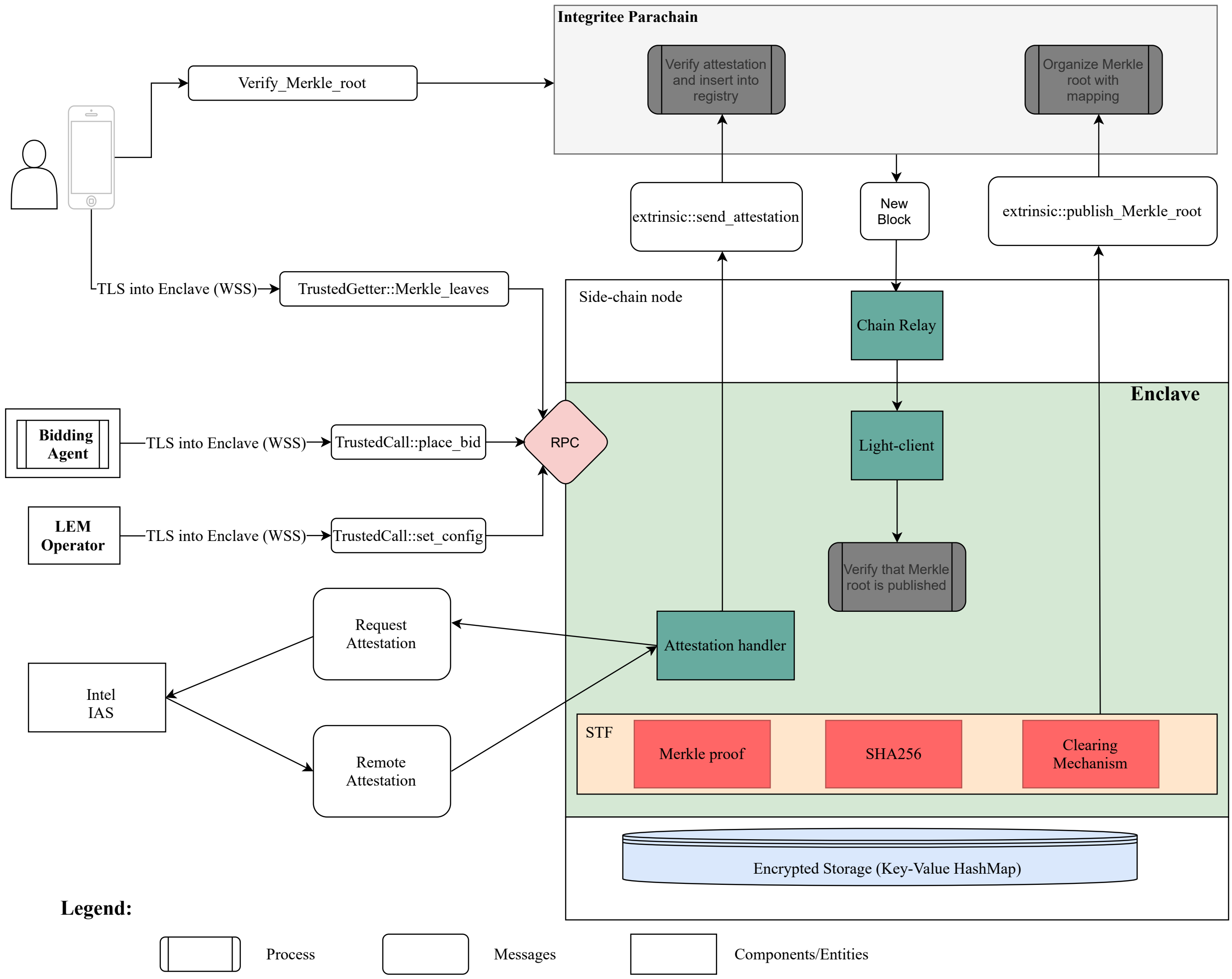

Fig. 1: Proposed hybrid blockchain-based LEM model architecture.

leaf hashes to know if its part of the hashes. If this is successful, the user application client will request the root hash of the orders at the defined time slot from the Integritee parachain blockchain network. The application client then uses the received leaf hashes to construct a Merkle root hash by itself and then compare the constructed root hash with the root hash it received from the blockchain network. If they are the same, this is evidence that the consumer/prosumer bid/offer is part of the bid/offer used for market clearing. In this way, the consumer receives a confirmation that they are part of the trade without seeing the orders from other participants.

C. Attestation of market mechanism/TEE enclave

Fig. 3 displays the sequence flow of the attestation of market mechanism and TEE enclave. Step I describes the sequence of matching algorithm development and storage in the open source environment, and TEE enclave. In Step II, the user verifies the stored mechanism and attest that the TEE enclave has not being tampered with. The LEM operator is responsible for developing the market matching algorithm. The algorithm is uploaded to an open source code hosting platform (i.e. GitHub) and made open to the LEM participants. The market clearing mechanism, and its configuration is compiled with the rest of the enclave code by GitHub into an enclave binary and deployed to the TEE enclave. Upon start-up of the enclave, it takes a measurement of itself, which is essentially the hash of the business-logic, the enclave code and other security related details, and publishes this via the remote attestation on the Integritee Parachain. The time interval for performing remote attestation is usually set before starting the enclave.

The attestation is performed by Intel IAS. The attestation handler formulates a so-called enclave quote. The enclave quote is data about the enclave that contains the TEE's unique identifier, security related hardware context, and hash of the enclave binary. This data will be sent to Intel along with a remote attestation request. Intel verifies the enclave quote and returns a remote attestation, which proves that the TEE is genuine, patched against the latest security vulnerables, and that the expected code is running inside the TEE. The result of the TEE attestation is sent back to the Integrity parachain by Intel IAS through the enclave, and it's stored on the blockchain

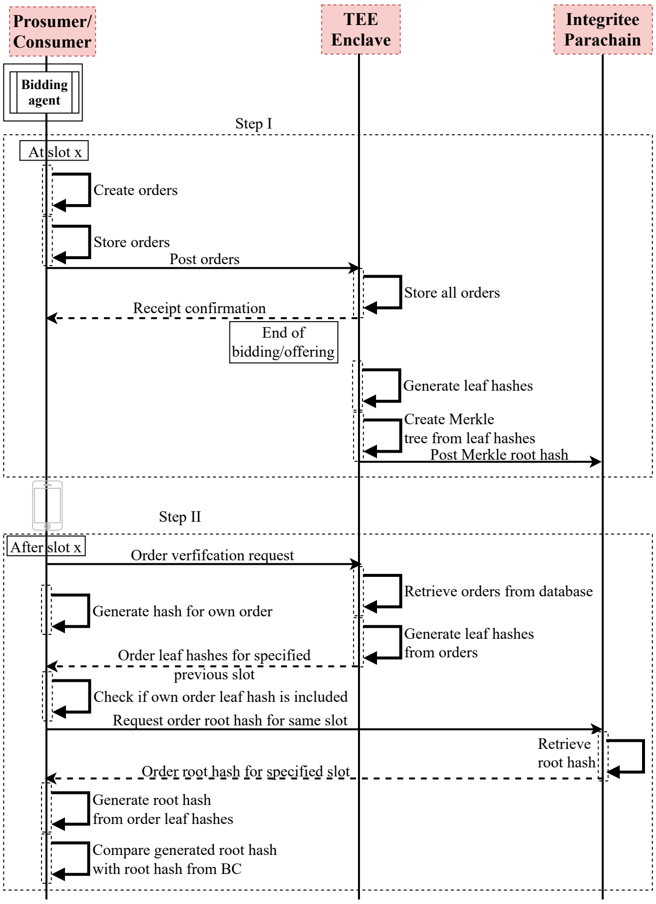

Fig. 2: Sequence diagram of bidding/offering verification.

network.

At any time in the future, a consumer/prosumer may wish to verify if the algorithm in the enclave has being tampered with and/or if the mechanism running in the enclave is the same with the mechanism published in the open source environment. The consumer/prosumer can achieve this by using their user App to request for the mrenclave published by Github for the latest version of the code on the open source environment. In the same way, the user App will request for the latest verified attestation result from the Integritee parachain which contains the enclave measurement. By comparing the two enclave measurements and verifying that they are the same, the user is assured that the TEE enclave is not tampered with and that the clearing algorithm running in the enclave is the same with the algorithm in the open source environment. Hence, this process helps to prove to an LEM participants that the integrity of the market mechanism in a transparent manner.

D. Hash verification process- results verification

The sequence diagram for the market results verification process is shown in Fig 4. The results verification process is similar to bids/offers verification process described in Section II-B. At the end of the bidding/offering interval for a defined time slot, the market is cleared for the time slot using the accepted market clearing mechanism developed by the LEM operator. The consumer/prosumer authenticates themselves with a cryptograhic signature of their private key. The enclave then sends the individual consumer/prosumer result to the consumer/prosumer only if the signature matches their the public key of their account. As the communication is done with TLS, it is encrypted so no data is leaked. The results are further stored in the encrypted storage in the the TEE enclave so that they can be used at a future time. To create opportunity for a consumers/prosumers to verify their results at a future time, the individual consumers/prosumers results are used to create leaf hashes by running it with the SHA256 function. The resulting leaf hashes are used to generate a Merkle root hash. The resulting Merkle root hash is sent to the blockchain network.

The consumer/prosumer at any time after the end of clearing may wish to verify if their result was part of the market results for the particular time slot. This can be done by the consumer/prosumer sending a result verification request for the time slot to the TEE enclave via a TLS call with their user application. The market results of the specified previous time slot is retrieved from the database and passed through SHA256 function to generate a leaf hash for the individual consumers/prosumers results. The leaf hashes are then sent to the consumer/prosumer application that made the request through encrypted TLS channel. The first stage verification is carried by the user application client by generating the hash of the consumer/prosumer result at the defined time slot and comparing it with the received leaf hashes to know if it's part of the hashes. If this process is carried out successful, the user application client will request the root hash of the results at the defined time slot from the blockchain network. The application client then uses the received results leaf hashes to construct a root hash by itself and then compare the constructed root hash with the root hash it received from the blockchain network. If they are the same, this is an evidence that the consumer/prosumer result is part of the market results for the defined time slot.

III. Verification of Proposed Architecture

The designed LEM architecture was verified by implementing a use case scenario of energy exchange in a local community where random bids/offers are posted by agents to the market, the bids/offers are matched within the TEE and results posted back to the agents. Each bid/offer contains the bidding/offering price, the quantity of energy required and time slot of the energy exchange. The market time step is 15-minutes time slot. The TEE was developed within a docker container environment with XMG FUSION 15 _XFU15L19_ PC using Ubuntu 22.10 operating system (OS). Since the verification is architecture evaluation, the simulation was performed for one time slot. The number of orders posted per time slot was increased from 10 until 10,000 as follows; 10, 50, 100, 500, 1000, 2500, 5000, 7500, 10000. Each simulation was repeated 10 times to ensure and the average result calculated. The 10 simulation samples is to ensure easy comparability with a previous model by Ref. [37] that compared a centralized and distributed framework for local energy

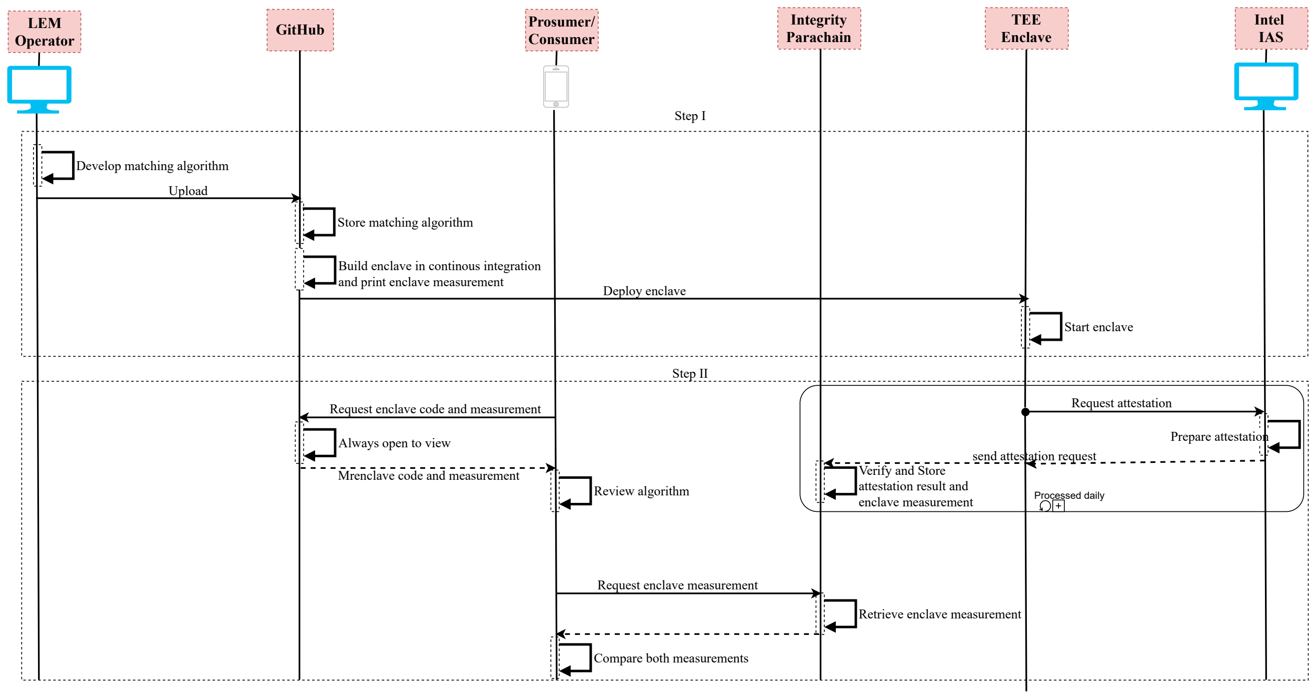

Fig. 3: Sequence diagram for TEE enclave/market algorithm attestation.

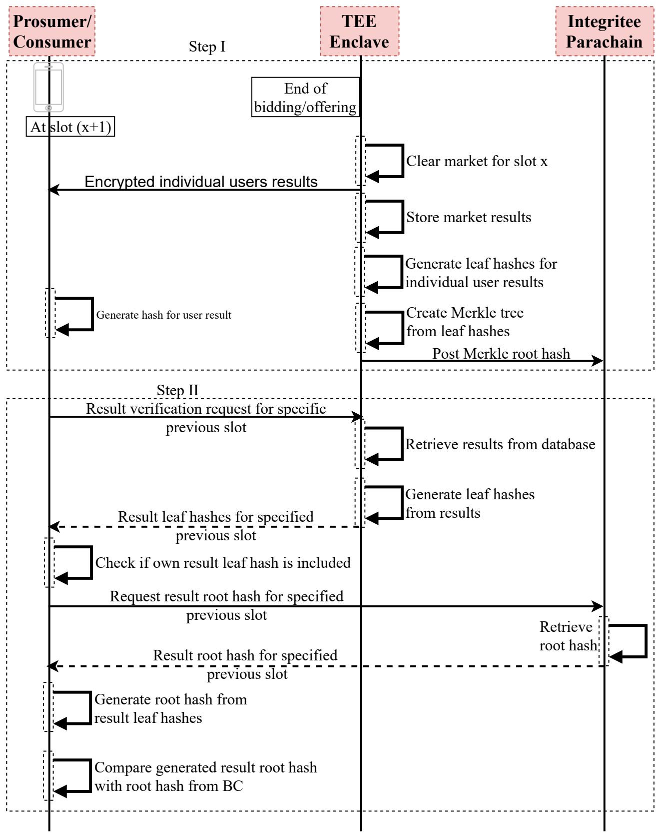

Fig. 4: Sequence diagram of results verification.

market. The matching mechanism used for the evaluation is two-sided merit order clearing mechanism with discriminative pricing [22]. The bidding strategy is based on random bidding strategy within the feed-in tariff and retail price range. Hence, consumers and prosumers agents are allowed to randomly bid between the range of the feed-in tariff and retail electricity price range to ensure that all the agents are not behaving the same way. This is also to ensure that the economic benefits from the market is the minimum economic benefits that can be obtained.

For each simulation, the orders arrival time, market clearing time, orders hashing time, result hashing time and result arrival time were measured. The orders arrival time is the time taken by the TEE to receive the orders from the agents. The market clearing time is the time taken by the enclave to match bids and offers using the market clearing mechanism. Orders hashing time is the time it takes the enclave to create leaf hashes of orders and use them to generate root hash and post the root hash to the Integritee parachain. In the same way, results hashing time is the taken by the enclave to create leaf hashes of results and use them to generate root hash and post the root hash to the Integritee parachain. Result arrival time is the time the agents receive the market clearing results from the enclave after clearing. The cost for posting hashes to the blockcahin network was measured. To simulate the verification and attestation process of the users, Postman desktop App was used as user App to verify the the working of this process.

IV. Results, evaluation and discussion

A. Time complexity analysis

The clearing time of the developed architecture model was compared with the clearing time of running the market mechanism without a TEE. Table II displays the average market clearing time (CT) for varying number of bids/offers in the Ubuntu OS environment, TEE, and full blockchain (BC) network. The results of CT in blockchain is from [37] and is used to compare CT for Ubuntu OS environment and TEE for the same number of bids/offers. CI is the confidence interval limit of the mean clearing time for the proposed model in TEE. CI is given in Eqn. 1, where $\bar{x}$ is the mean value of the CT, s is the standard deviation and n is the number of observation which is 10. The CI shows the range of values of the clearing time if the experiment is repeated in the same scenario. The ratio of mean fully blockchain based clearing time to the proposed hybrid blockchain clearing time represented as RBT is used to show how efficient the proposed model is compared to using fully blockchain-based model. From Table II, increasing the number of bids/offers increase the computation time of the LEM for running the market in both Ubuntu OS, TEE, and BC. Although it takes lesser computational time to clear the market in the Ubuntu OS compared to the TEE for varying number of bids/offers. However, both computation times are still within milliseconds and therefore it is computationally efficient for running the market in both systems compared to running the clearing mechanism in BC. Running similar market clearing mechanism in BC takes more than 500 times more time as required to run the same mechanism in TEE for the same number of bids/offers. The least value of RBT is 500 and this shows that the efficiency of the proposed model in terms of clearing time is far higher than a fully blockchain-based model. In general, the model architecture was able to handle a market volume of up to 10,000 members and the market was cleared within 40 milliseconds. This shows that developed architecture is computationally efficient as the market results are computed in milliseconds which is far less than the 15-minutes market time step of the LEM. However, running the clearing mechanism with more than 500 bids/offers in BC becomes computationally inefficient as the required time is more than 15-minutes which is the market time slot.

$$CI = \bar{x} \pm \bar{x}\frac{s}{\sqrt{n}} \tag{1}$$

Table III displays a comparison of the computational time for hashing (HT), market clearing time (CT) and overall time (OT) in the TEE environment for varying number of orders. The hashing time is the sum of the time it takes to generate the individual leaf hashes of the bids/offers, create the Merkle root hash from the leaf hash and post the root hash in the blockchain network. This value range from 0.096 ms with 10 prosumers and consumers to 112.98 ms with 10,000 prosumers and consumers. If the hashing time is compared with the clearing time (CT) in the TEE environment, it is obvious that it takes more time to create the leaf hashes and the Merkle root hash than clearing the market. The overall time for clearing the market and posting the Merkle root hash is within milliseconds even with a market of up to 10,000 orders. This makes the proposed architecture model to be computationally efficient for application in LEM.

Table IV displays the overall clearing time of the hybrid framework with higher number of orders. The orders were randomly generated and used to evaluate the maximum scalability of the framework. Interpolating the results of Table IV shows that the maximum number of bids/offers the framework could match within 15 minutes market slot is 900000. This shows that there is more room for application of the framework in a large community and wide regional area/market.

B. Attestation and hash verification process

Fig. 5 displays the screen-shot of the Ubuntu terminal that runs the market model test scenario and the Integritee blockchain interface which is a parachain in the Polkadot ecosystem. The highlighted hash is to show that the market transaction of the Merkle root hash sent through the TEE via command line of the Ubuntu terminal arrives the blockchain network. Also, shown on the right side is the weight of the transaction, that is 2218474000 weight. The weight is the bench-marked amount of execution time of a transaction in nanoseconds on a reference hardware. Similar to gas in Ethereum, it is the basis of the actual transaction cost. The model architecture was able to communicate with the blockchain network for the storage of its transaction and attestation data.

The architecture model is evaluated in two stages. In the first stage, we evaluate the model based on infrastructure requirements and quantifying factors for participating in an LEM based on distributed ledger technologies already discussed in references [40] and [37]. In the second stage, we perform an economic analysis of the developed architecture to evaluate if its economically promising to implement the model.

C. Evaluation based on LEM infrastructure requirements and performance indicators

The developed model is evaluated based on its reliability, scalability, data security, tamper resistance, operation cost and transparency.

1) Reliability

In the context of LEM, reliability is defined as the availability of the LEM model to the LEM participants and accurate processing of the market data [37]. Throughout the simulation, the different components of the model architecture were available and all data were processed accurately. The market results were processed in milliseconds and hence it was very difficult to recognize failure of the system interactions. The time slot of energy trading is usually 15-minutes and hence the model satisfies the reliability requirements for an LEM application. Since only two transactions containing the root hashes of the orders and market result are communicated to the blockchain per market slot, the communication to the blockchain network was also efficient and failure free.

2) Scalability

Scalability in the context of LEM is the ability of the market model to maintain a certain quality notwithstanding the increase in the volume of orders or transactions in the market [48]. The volume of the orders were increased for the simulation from 10 until 100,000 units, however, the computation time remains within less than one second and the results were very accurate. This shows that the quality of the model architecture was maintained notwithstanding that the model was stressed with too many orders. Since the market

TABLE II: Comparison of market clearing time in Ubuntu OS and TEE environment.

S/N	No. of participants [-]	CT in TEE [ms]	CI [ms]	CT in Ubuntu [ms]	CT in BC [s] [37]	RBT [-]
1	10	0.107	0.107 $\pm$0.0019	0.002	$< 10^2$	< 581392.3
2	20	0.116	0.116 $\pm$0.0046	0.002	$< 10^2$	< 581392.3
3	50	0.172	0.172 $\pm$0.0042	0.003	10^2	581392.3
4	100	0.216	0.216 $\pm$0.0053	0.003	$2.5X10^2$	1157407.4
5	500	0.763	0.763 $\pm$0.0187	0.006	$1.2X10^3$	1572739.2
6	1000	1.430	1.430 $\pm$0.0701	0.008	-	-
7	2500	5.870	5.870 $\pm$0.2876	0.016	-	-
8	5000	17.320	17.320 $\pm$1.2728	0.029	-	-
9	7500	25.920	25.920 $\pm$1.9047	0.040	-	-
10	10000	40.310	40.310 $\pm$2.9623	0.045	-	-

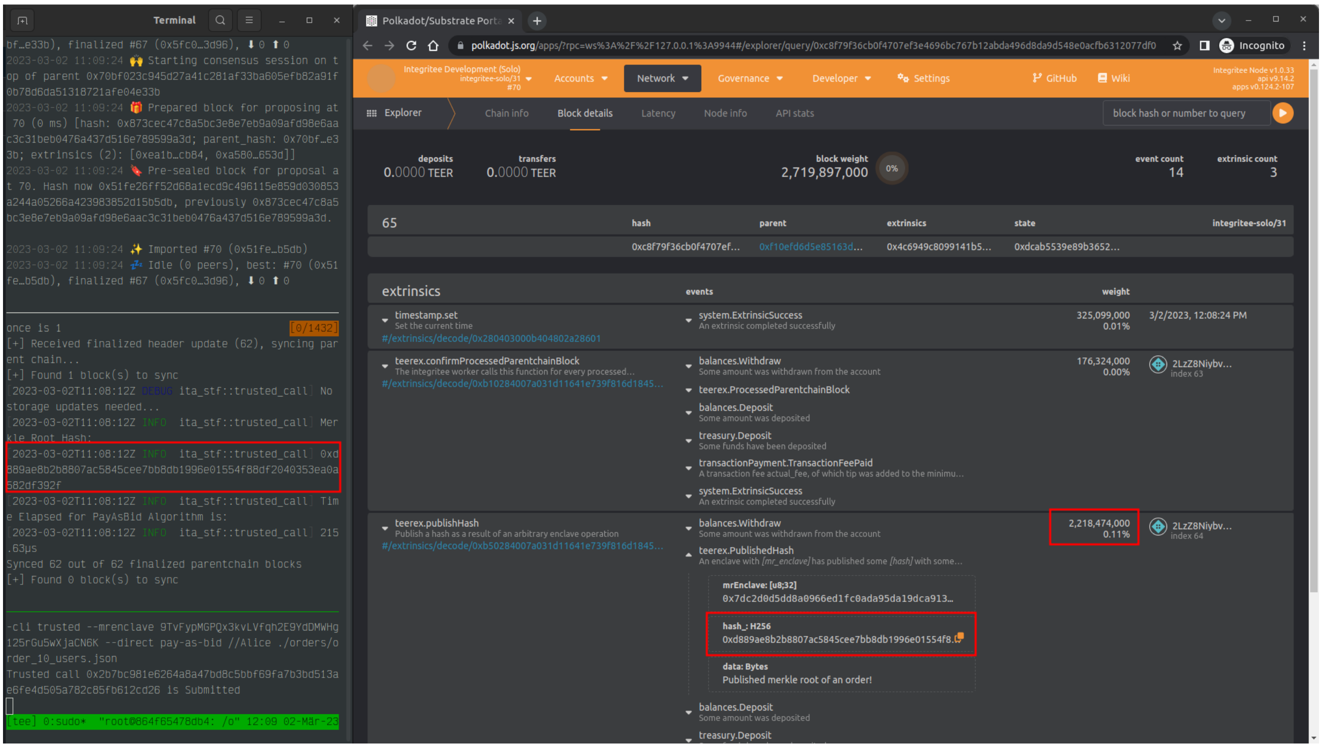

Fig. 5: Computational time for hashing and clearing.

TABLE III: Computational time for generating Merkle root hash and market clearing.

S/N	No. of participants [-]	CT [ms]	HT [ms]	OT[ms]
1	10	0.107	0.096	0.203
2	20	0.116	0.659	0.775
3	50	0.172	1.288	1.46
4	100	0.216	1.484	1.700
5	500	0.763	6.337	7.100
6	1000	1.43	14.480	15.91
7	2500	5.87	34.58	40.450
8	5000	17.32	82.25	99.570
9	7500	25.92	91.87	117.79
10	10000	40.31	112.98	153.29

TABLE IV: Overall computational time in TEE with higher number of orders.

S/N	No. of participants [-]	OT
1	50000	1.87s
2	100000	5.53s
3	500000	4 min 15.26s
4	1000000	17 min 49.65s

time is 15-minutes per time slot, the architecture is scalable enough to maintain the quality of an LEM and ensure that market of a certain time slot is cleared before the next time slot. The scalability of the market framework is limited to 900000 orders. Beyond this, it is not certain that the market can be cleared within the 15 minutes market slot. With the systems capability of clearing market of hundreds of thousands of orders in less than six second, millions of transactions will be handled within minutes if not seconds. Furthermore, comparing the maximum number of transaction (based on number of units of orders) the hybrid model can handle which is 900000 to the maximum number of transaction that can be handled using a fully blockchain-based model which is 500, the proposed model is at least 1800 times more scalable than a fully blockchain-based model. Thus 900000 orders is the maximum limit of the proposed approach considering 15-minutes market time slot.

3) Data security

Data communicated to the TEE enclave is encrypted and non-human readable. Also, only hashes that are non-human readable are stored on the blockchain network. During verification of bids/offers and market results by prosumers/consumers, only hashes are communicated to prosumer/consumers App for verification. This means that it is not possible for prosumers/consumers to have access to the data of their fellow prosumers/consumers within the LEM. Hence, the model architecture is highly secure of personal and sensitive data of the participants and also GDPR compliant. Also, model running on the TEE cannot be falsified. At any instant, participants can request to know the state of the TEE enclave to know if the model running in the enclave has been tampered with. This is when the Intel attestation service will provide the participants with the attestation history of the enclave to show the integrity of the models and that it was/was not tampered with. This is a special feature of the proposed hybrid model which made it to be highly secured and can attest integrity of the models running inside it through another service provider (Intel IAS).

4) Tamper resistance

Tamper resistance is the ability of any developed model architecture or infrastructure integrated to a network to ensure that its data cannot be manipulated, it's trustworthy and can detect any attempt to manipulate its data [49]. The enclave ensures that not even the system administrator or its operating system can manipulate the data or business logic in the enclave. Furthermore, the verification of orders and results, and attestation process is used to detect any attempt to manipulate the input or output data to/from the enclave. This shows that the developed architecture is tamper resistant and can prevent any foreseeable attempt to manipulate its data or business logic.

5) Operation cost

The prosumers and consumers pays no operation cost for posting their bids and offers to the LEM. The major operating costs identified are the cost of storing root hashes (for orders and results) and attestation results on the blockchain.The root hashes and the attestation results are stored every time slot. Currently the cost of storing root hashes and attestation data per time slot is less than 1 Euro cent. This shows that the operating cost of the model architecture is low and very feasible for large scale operation. Hence, the model is cost efficient.

6) Transparency

A transparent market model provides opportunity for market participants to verify that they are not unfairly treated in the market. Even though the market data is encrypted due to GDPR and hence, participants are not allowed to see the data of other participants. The model still provides opportunity for the participants to verify that they are not cheated in the market and that their data is not manipulated.

Table V displays the summary comparison of the proposed hybrid model to a centralized and blockchain-based (BC) LEM framework. The comparison is based on the identified features of blockchain-based LEM and centralized LEM proposed in Refs. [22], [37] and [8]. In terms of reliability, the proposed model is more reliable compared to the blockchain-based model proposed in [22] and [37]. The blockchain-based LEM models are less reliable as they are not always continuously available because the blockchain node frequently loss connection to the network. This is not the same with the proposed model in this work. The time it takes to complete a transction is our proposed model is far less than the time it takes to complete a transaction in [22], [37] and [8]. This is seen as our model handles thousands of transactions in milliseconds unlike the model in [22] and [37] that takes minutes to handle hundreds of transactions. The hierarchical blockchain-based LEM model proposed in [8] is more scalable compared to [22] and [37]. However, our model is far more scalable compared to the hierarchical model of [8] as it was able to handle up to 900000 transactions within 15 minutes. The scalability of the blockchain-based models are far less than than as they cannot handle such number of transactions. Also, at all times, the integrity of the proposed model can be attested and this is not so with other blockchain models. Hence, our proposed model has distinguished features (Table V) which made it outstanding for LEM application.

TABLE V: Comparison of the proposed hybrid framework with different LEM frameworks.

S/N	LEM requirement	Centralized LEM	BC LEM	Proposed Hybrid model
1	Time complexity	++	-	+
2	Reliability	++	-	++
3	Scalability	+	−	++
4	Transparency	−	++	+
5	Data security	−	++	++
6	Operation cost	++	−	++
7	Tamper resistant	−	++	++
8	Integrity	−	+	++
9	Participants privacy	-	−	++
10	Transaction cost	++	−	++

D. Economic analysis for operation of proposed architecture

The economic analysis was conducted using data from previous work in order to analyze and show that the proposed model is economically feasible. Table VI displays the economic analysis of the developed hybrid blockchain based LEM architecture for a period of one year. The number of participants is varied from 10 to 10000 participants. The traded energy (TE) is the quantity of energy traded between consumers and prosumers for the one year period in a 15-minute market time slot. The data for traded energy quantity is taken from previous work of community simulation analysis of local energy market conducted for a German case scenario in Ref. [40]. From Ref. [40], LEM participants are combination of households consumers, household prosumers, commercial consumers, consumers prosumers and industrial prosumers. The portfolios of the participants are only load, PV and load, and few participants with PV, load and storage. In the LEM simulation, energy not traded within the LEM is exchanged with the upstream grid through a retailer who participates in the LEM to buy/sell excess/deficit generation/demand from/to the prosumers/consumers. Furthermore, only the function layer of LEM as described in the smart grid architecture model (SGAM) [50] is used for the simulation and therefore the grid constrained is not considered. The expected market yield (EMY) is the expected prosumers and consumers gain for trading in an LEM compared to trading with the upstream grid. Eqn. (2) describes the expected marketed yield. r_b is the average kWh cost of buying electricity from the upstream grid. For this work, r_b is equal to 35 ct./kWh which is the average cost of buying electricity from the upstream grid in Germany for the year 2022. r_s is the feed-in tariff price which is placed at 11ct./kWh for this work. g is the local grid fee which is assumed to be 4ct./kWh for the experiment. Total transactions per annum (TT/a) is the total number of transactions that occur in the LEM within the one year period. Market clearing happens every 15 minute market time slot and is modelled as a single transaction. Hence, a total of 35040 transactions is expected to happen per year.

$$EMY = (r_b - r_s - g) \times TE \tag{2}$$

Total transaction cost per annum (TTC/a) is the total cost spent by the LEM operator for handling the transactions with the developed market architecture. It is basically the cost of storing the Merkle root hashes of market result and bids/offers in the Integritee blockchain network every market time slot summed over one year. Storing the Merkle root hash of bids/offer or market result in the Integritee blockchain network takes 2218474000 Weight. A weight is the unit used to measure the time it takes to validate a block for a certain transaction in a Subrate-based blockchain network [51]. The cryptocurrency of Integritee blockchain network is TEER and it cost 0.285 milliTEER to publish the bids/offer or market result in the blockchain network. As the time of this publication, one TEER is equivalent to 0.42 USD. Hence, it will cost a total of about 8.39€ yearly to publish the Merkle root hashes on the blockchain network.

Attestation cost per annum (AC/a) is the cost of storing the quarter-hourly attestation result in the blockchain network over a period of one year. Storing the attestation result in the Integritee blockchain network takes 1388799000 Weight and this amounts to 1.2 milliTEER. Hence, it will cost a total of 17.66 € per year to store the attestation result every quarter hour. Cloud operation charge per annum (COC/a) is the cost of maintaining the cloud space that is running the TEE and other side chains of the market architecture for a period of one year. The cost of cloud space increase with increasing in storage space. Since, increasing the number of LEM participants will significantly increase the transaction data and thereby require more storage space. Increasing the number of participants significantly increase the COC/a. Hence, for [10, 50], [100, 1000], [2500], and [5000, 10,000] ranges of numbers of participants, the COC/a are 1200, 1800, 2400, and 3600 €, respectively. The personnel and maintenance cost (P&MC) is the personnel cost of maintaining the software and doing upgrade when necessary. This is basically the cost of hiring a software engineer to perform annual upgrade of the software when necessary. This is placed at constant cost of 12000€ per annum. Total operation cost per annum (TOC/a) is the sum of the COC/a, AC/a, P&MC and TTC/a.

LEM operator charge (OC*) is the proposed charge per kWh the LEM operator will receive from prosumers and consumers for clearing the market. This is assumed to be 2 cent/kWh. Total charge per annum is the total expected charge the LEM operator will receive from the prosumers and consumers for the period of one year. It is the product of LEM OC*[€/kWH], and TE [kWh]. The operation profit is the expected profit the LEM operator will make from this market by using the architecture in a period of one year. It is the difference between the total charge/a and the TOC/a. The expected participants profit per annum (EPP/a) is the expected total profit the prosumers and consumers will make for trading in the LEM for a period of one year. It is the difference between the EMY/a and the total charge/a. The EPP/participant is the expected profit a prosumer or consumer is expected to get for participating in the LEM using the model architecture.

From Table VI, the proposed model architecture is profitable for prosumers willing to participate in the market notwithstanding their number of prosumers in the community. This is because the EPP/a and EPP/participant is positive for all number of participants in the community. The average annual participant profit for using the model is between 226 to 328 €. For an LEM operator who is willing to be managing the market and handling updates and maintenance of the model architecture, the market is profitable for the market operator only with a community of up to 1000 members upwards given a transaction charge of 0.02 €/kWh. Hence, this happens to be the lower limit of the proposed model as implementing the market for less than 1000 members may not yield enough economic benefits for the market operator. Therefore, with a smaller community, the LEM operator may need to increase the charges per kWh of energy traded in the community to be able to make profit. On the other hand, adding more energy devices such as batteries and CHP to the community will help to increase the amount of traded energy in the community and consequently, the LEM operators' profit. Also, the major cost of operating the model architecture is the P&MC which is the personnel cost of running the upgrades and maintenance of the software architecture. This cost can be removed in the first few years of the project where the model is to be adopted until the number of participants in the community has grown to the extent that upgrade and expansion are needed. In summary, increasing the number of participants increase the amount of profit for the LEM operator.

The major variable that can have uncertainty value in Table VI is the traded energy quantity [TE]. This value can vary according to the size and type of community, the matching mechanism and the bidding strategy of the individual bidding agents. The matching mechanism used for the LEM simulation is two-sided merit order clearing mechanism with discriminative pricing. This is to ensure that the expected minimum economic benefits is calculated from the LEM. Since the work of [52] has established that peer-to-peer clearing mechanism match more energy within the LEM and create more economic benefits compared to merit order clearing mechanism. Hence, using peer-to-peer clearing mechanism for the proposed model will create more economic benefits for the LEM participants

TABLE VI: Economic analysis of hybrid blockchain based LEM architecture. [TE = Traded energy, EMY = expected market yield, TT/a = Total transactions per annum, TTC/a = Total Total transaction cost per annum, AC/a = Attestation cost per annum, COC/a = Cloud operation charge per annum, P&MC = Personnel and maintenance cost, TOC/a = Total operation cost per annum]

S/N	No. of participants	TE [kWh]	EMY [€]	TT/a [-]	TTC/a [€]	AC/a [€]	COC/a[€]	P&MC [€]	TOC/a[€]
1	10	18222.99	3644.59	35040	8.39	17.66	1200	12,000	13,226.05
2	20	32641.56	6528.38	35040	8.39	17.66	1200	12,000	13,226.05
3	50	81074.22	16214.84	35040	8.39	17.66	1200	12,000	13,226.05
4	100	129028.41	25805.68	35040	8.39	17.66	1800	12,000	13,826.05
5	500	645400.12	129080.02	35040	8.39	17.66	1800	12,000	13,826.05
6	1000	1458021.03	291604.21	35040	8.39	17.66	1800	12,000	13,826.05
7	2500	3139261.22	627852.24	35040	8.39	17.66	2400	12,000	14,426.05
8	5000	6386906.30	1277381.26	35040	8.39	17.66	3600	12,000	15,626.05
9	7500	9695822.85	1939164.57	35040	8.39	17.66	3600	12,000	15,626.05
10	10000	13371232.03	2674246.41	35040	8.39	17.66	3600	12,000	15,626.05

Table VI continues. [OC* = Operator charge, EPP/a = Expected participants profit per annum]

S/N	No. of participants	LEM OC*[€/kWh]	Total charge/a [€]	Operation profit [€]	EPP/a [€]	EPP/participant [€]
1	10	0.02	364.46	-12,861.59	3,280.14	328.01
2	20	0.02	652.83	-12,573.22	5,875.49	293.77
3	50	0.02	1621.48	-11,604.56	14,593.36	291.87
4	100	0.02	2580.57	-11,245.47	23,225.11	232.25
5	500	0.02	12908.00	-918.05	116,172.02	232.34
6	1000	0.02	29160.42	15,334.37	262,443.79	262.44
7	2500	0.02	62785.22	48,359.18	565,067.02	226.03
8	5000	0.02	127738.13	112,112.08	1,149,643.13	229.93
9	7500	0.02	193916.46	178,290.41	1,745,248.11	232.70
10	10000	0.02	267424.64	251,798.60	2,406,821.77	240.68

and consequently, it is expected that this will yield a positive effect on Table VI. On the other hand, using Multiple-unit Double Auction (MUDA) [53] would reduce the economic benefits of the LEM as splitting the market into different market during matching will result in reducing the traded energy. Furthermore, it is expected that the bidding strategy has impact on economic outcome of the market. Using intelligent bidding strategy creates more economic benefits in an LEM compared to using random or zero-intelligent bidding strategy [52]. This is because intelligent bidding strategy enable the agent to bid strategically and thereby exchange more energy within the LEM resulting in an increase in traded energy. Hence, it is expected that using intelligent bidding strategy will affect Table VI positively. In summary, the LEM clearing mechanism and agents bidding strategy can affect the outcome of the economic analysis obtained in Table VI.

V. Conclusion

In this paper, a hybrid blockchain based architecture was proposed for building and operating a local energy market. The model is based on combining the on-chain features of blockchain such as secured hashed data storage and side-chain features of trusted execution environment (TEE) such as confidential code execution, proof of integrity, and authentication with cryptographic signatures. Furthermore, the developed model was verified of its applicability by simulating it in German community case scenario for varying number of prosumers/consumers from 10 to 10,000 members. The evaluation of the simulation results using the LEM infrastructure requirements show that the architecture model is computationally efficient, reliable, scalable, has low operation cost, tamper resistant and provides highly secured environment for LEM data. Also, the model was able to comply with GDPR while providing opportunity for the participants to verify that their data is not manipulated in a transparent manner. A one year economic analysis of the proposed model was performed and the results shows that the model will be beneficial for both LEM operators that will be responsible for managing and updating the model architecture and prosumer/consumers that will be exchanging their energy using the model architecture. However, the model may not be beneficial to the LEM operators if the number of participants is low (below 500 members) coupled with a low (below 2.0 ct/kWh) charge per kWh of energy traded.

In future work, the framework will be implemented in a field test case of a German community where energy will be exchanged within the platform. This will happen within the scope of the project BEST. Also, further research will focus on proposing the regulatory requirements for establishing an LEM. Due to the high scalability of the proposed framework, future work will focus on trading multi-energy system product such as flexibility and ancillary services.

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5 Conclusion & Outlook

This dissertation presents studies on how consumers and prosumers can become active participants in the electricity market through engaging in an LEM, that enables the exchange of energy within their local community. Different LEM market models including centralized, decentralized and distributed models were developed and their applicability to local community evaluated using the derived key performance indicators.

5.1 Conclusion

The articles in this dissertation starts with a survey analysis of the quantifying factors that make consumers and prosumers participate in an LEM based on DLT. Then, a community simulation followed by key performance indicator based analysis to determine the necessary conditions for optimal performance of an LEM was conducted. The development of the market models started with deriving the mathematical models and the evaluation of an open-source hierarchical multi-agent local energy market framework developed by Grid Singularity [120]. An advanced clustering market model for matching prosumers and consumers in a centralized LEM based on the consumers/prosumers preference vectors was developed. This was followed by a decentralized LEM model for matching consumers and prosumers in a local community based on the consumers/prosumers pool preferences. Different consumers/prosumers bidding/offering strategies based on reinforcement learning approaches for LEM were developed and evaluated with regards to their applicability in an LEM. A proof of concept blockchain-based fully distributed LEM framework was developed and its applicability in a local community evaluated. From the findings of the blockchain-based fully distributed LEM framework, a hybrid blockchain-based LEM framework was developed; that combine the on-chain features of blockchain network and side-chain features of trusted execution environments (TEEs) to overcome the main limitations of a fully distributed LEM framework and satisfy all the requirements of LEM platform. Based on the findings from the research articles, the research questions presented in Section 1.2 are answered as follows.

1. **What are the quantifying factors for participation on local electricity markets based on distributed ledger technologies and the necessary conditions for most beneficial LEM?**

   The articles presented in Publications 1 and 2 focus on answering this research question. The survey result of Publication 1 shows that the major drive or quantifying factors for local consumers/prosumers to participate in a blockchain-based LEM are their willingness to support renewable energy integration, transparency, and trust offered by a blockchain network. Furthermore, the result of the simulation based analysis of Publication 1 shows that the most beneficial LEM is obtained in small and medium communities with prosumers to consumer ratios between 0.3 to 0.5, as this type of LEM creates more economic and technical benefits for local consumers/prosumers compared to large communities. The key performance indicator analysis of Publication 2 shows that increasing the share of the local generation in the LEM creates high liquidity in the market, which in turn leads to an increase in the share of market savings of local community. However, bidding strategy affects the performance of an LEM compared to the share of the local generation. Therefore, for a consumer/prosumer/community that wishes to make more benefits from the LEM, their priority should be having an intelligent bidding/offering agent(s).

2. **Which market models and clearing mechanisms are most suitable for local electricity markets?**

   The articles presented in Publications 3-5 focus on this research question. According to the studies from Publications 3-5, in a community where a lesser time computational market model is required, a hierarchical LEM model as presented in Publication 3 is most suitable. From this study, the multi-layer hierarchical model is more profitable for household consumers and prosumers compared to a single-layer hierarchical LEM model. However, the single-layer LEM is more beneficial for industrial prosumers. By coordinating the market in a multi-layer levels, the multi-layer LEM community model reduces the total energy exchange between the LEM and upstream grid, increases the internal energy exchange within the LEM, individual savings of the consumers/prosumers, self-consumption and share of market savings of the local community as compared to the single-layer LEM model. In a community where the computational time and consumers/prosumers trading preference are less important, an advanced clustering P2P market model as presented in Publication 4 is most suitable. The results from the simulations show that using price preference as the criterion for clustering offers more technical (i.e. self sufficiency and self consumption) and economic benefits to energy communities compared to other clustering scenarios tested in the model. In a community where the trading preference (i.e where a consumer/prosumer is allowed to select their choice of electricity quality and trading partner) is more important, a decentralized LEM platform based on grouped prosumers' preferences as presented in Publication 5 is most suitable. The results from the article show that the developed decentralized LEM model was able to satisfy the energy preferences of the consumers and prosumers in the local community to an average of more than 60%. In summary, suitability of a market model depends mainly on what the local community desire. Different models provide different benefits to the local participants.

3. **Which trading strategies are most suitable for effective performance of local electricity markets?**

The two articles presented in Publications 6 and 7 addresses this research question. Publication 6 shows that intelligent bidding/offering strategy is more effective and creates added self-sufficiency and share of market savings to the local consumers compared to a random bidding/offering strategy. In Publication 7, different intelligent bidding/offering strategies based on reinforcement learning were developed and compared with respect to their ability to provide added technical and economic benefits to the LEM. The developed reinforcement learning strategies were based on Q-learning and SARSA. The results of the simulations reveal that the most effective performance of LEM is obtained when the intelligent agents within the local community make their bidding/offering with a common goal. This is known as the shared reward strategy, which creates additional benefits for the community compared to the classical strategies. The most optimal strategy obtained from the results is the hybrid strategy which is a combination of the classical Q-learning and SARSA strategies. In this strategy, while trying to create additional benefits for the local community, it also weighs the individual benefits of the prosumer that own the agent.

4. **Is it economically reasonable to use blockchain for local energy trading? If yes, what conditions must be fulfilled?**

   The articles presented in Publications 8-9 answer the research question. From the proof of concept results of Publication 8, it is economically unreasonable to use a public blockchain network for LEM with the current state of maturity of blockchain. This is mainly because of the high gas cost of most public blockchain network and blockchain is less scalable. It can be argued that a private blockchain network can be used to replace public blockchain in the implementation of LEM trading. However, this may destroy the major reason of using blockchain for LEM trading which is to show transparency and trust. To provide a blockchain-based LEM model that satisfies all the LEM requirements, a hybrid blockchain-based LEM model architecture as presented in Publication 9 is most suitable. The basic conditions required to achieve this type of model architecture is combining the on-chain features of blockchain with the side-chain features of systems like TEE, which solves the on-chain challenges or limitations of blockchain. For consumers and prosumers participating in this kind of market, this model architecture is profitable to them notwithstanding the number of participants. However, for LEM operators that will be responsible for managing the market, this model architecture is profitable to them only when the number of consumer and prosumers are more than 500 in a market with low internal traded energy and with a charge of 2.0 ct./kWh. Low internal traded energy can result from a community where the local prosumers own only load and PV devices, thereby trading energy with each other during the day where there is sunlight and buying from the upstream grid when there is no sunlight. Hence, with more devices like batteries and Combined Heat and Power (CHP), there would be more trades in the LEM resulting in more profit for the LEM operator.

5.2 Outlook

Policy recommendation

The analysis [119] conducted in this dissertation shows that LEM can create valuable financial support for prosumers that own PV devices after the fixed feed-in tariff under German EEG expires. This means that they can be able to retain their electricity production during the post-EEG time and, consequently, maintain their contribution to the share of renewable energy within the electricity grid. Since LEM provides better financial incentives for prosumers to invest in energy assets compared to government sponsored tariffs, it can stand as the major force to increase small-scale renewable energy generation. Thus LEM has a major role to play in reaching the decarbonization goal within the electricity sector. For efficient running of LEM, I further stress that there is need for a regulatory framework that is responsible for the sharing of taxes and levies among consumers and prosumers within the LEM only, without involving consumers that do not trade in the LEM. Additionally, the German regulatory body needs to extend its framework to include requirements for creating LEMs and further define the roles and responsibilities of all the actors required for effective and efficient performance of an LEM.

Future research

LEM is still at its growing stage and therefore there is still a lot of opportunities to further extend the studies in this area. It is recommended that further research should focus on proposing regulations for implementing LEM at the regional and community levels. If the appropriate regulations are approved and implemented, it will allow firms and commercial ventures to start implementing various research works and models already developed in the field of LEM. Thus, there is need to define adequate hardware components and metering devices that will be used for this type of time series market that happen every 15-minutes. This area of regulation and the needed hardware infrastructure has not been addressed in this dissertation.

The role of EV in reducing CO_2 especially in the mobility sector cannot be over emphasized. There is still need to look into the role of EV in LEM trading for effective performance of the market. Hence, we recommend the proposition of market models to enable inclusion of EV in LEM trading for future research. This include enabling Grid to Vehicle (G2V), Vehicle to Vehicle (V2V) and Vehicle to Grid (V2G) trading all in the same LEM where household prosumers and consumers exchange their energy. Flexible EVs that participate in such kind of market can also take advantage of the market by trading their flexibility in a strategic way. It is also important to further develop bidding strategies for this kind of market as the prosumers and consumers need to be more strategic in taking advantage of buying electricity from the EVs as well as for their owners to sell flexibility effectively.

List of Figures

List of Tables

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