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Towards cross-commodity energy-sharing communities – A review of the market, regulatory, and technical situation

Satu Paiho [a,*], Jussi Kiljander [a], Roope Sarala [a], Hanne Siikavirta [a], Olli Kilkki [b], Arpit Bajpai [c], Markus Duchon [c], Marc-Oliver Pahl [d,e], Lars Wüstrich [d], Christian Lübben [d], Erkin Kirdan [d,f], Josef Schindler [f,g], Jussi Numminen [h], Thomas Weisshaupt [h]

[a] VTT Technical Research Centre of Finland Ltd, P.O Box 1000, FI-02044, VTT, Finland
[b] Enerim Ltd, Valimotie 16, Helsinki, Finland
[c] Fortiss GmbH, Guerickestraße 25, 80805, München, Germany
[d] Technical University of Munich, Boltzmannstr. 3, 85748, Garching, Germany
[e] Institut Mines Télécom Atlantique, 2 Rue de La Châtaigneraie, 35510, Cesson-Sévigné, France
[f] Framatome GmbH, Paul-Gossen-Str. 100, 91052, Erlangen, Germany
[g] Friedrich-Alexander-University Erlangen-Nuremberg, Schlossplatz 4, 91054, Erlangen, Germany
[h] Wirepas Oy, Visiokatu 4, 33720, Tampere, Finland

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ABSTRACT

Meeting the energy goals of the European Union requires new ways of managing energy. Decentralized energy management, cross-commodity energy production and usage optimization are promising means. Future neighbourhoods will include multiple forms of energy such as electricity, heat, and cooling. According to our vision, the smart neighbourhoods, can optimize energy across different vectors by sharing resources in a controlled way.

The first contribution of this paper is a comprehensive review on market, regulatory and technological status to support the transition towards distributed cross-commodity energy management with focus on Germany and Finland. Markets disruption could lead to more decentralized structures. Mechanisms therefore have been proposed, but mostly without sector integration.

Clean Energy Package includes legislation that is supportive towards cross-commodity energy sharing solutions. Corresponding implementation in Germany and Finland may be successful in both countries even though it differs.

Regarding technology, the article identifies required technical components (IoT, AI and blockchain) focusing on their support decentralized and cross-sector energy systems. Key components of IoT are wireless communication and interoperability middleware. AI provides key technologies for modelling and optimization of sector-integrated and distributed energy systems. Even if there has been lots of research, practical implementations are still lacking. Furthermore, many technical challenges still exist for blockchain based solutions in decentralized energy systems. Moreover, organizational, and legal responsibilities need to be clarified to support the adoption of blockchains in decentralized energy systems. Finally, the article gives recommendations regarding an increasing implementation of cross-commodity sharing and how it can contribute to the energy transition.

1. Introduction

According to the special report [1] by the Intergovernmental Panel on Climate Change, energy transition is required as a means to limit global warming to 1.5 °C above pre-industrial conditions. In Europe, consumers, prosumers, and their collectives are seen as core part of the energy transition, and the aim is to strengthen their role [2]. Key concepts to realize this include energy communities and the so-called Positive Energy Districts. As decentralized and renewable-based energy

* Corresponding author.,
E-mail addresses: Satu.Paiho@vtt.fi (S. Paiho), jussi.kiljander@vtt.fi (J. Kiljander), roope.sarala@vtt.fi (R. Sarala), hanne.siikavirta@vtt.fi (H. Siikavirta), olli.kilkki@enerim.com (O. Kilkki), bajpai@fortiss.org (A. Bajpai), duchon@fortiss.org (M. Duchon), pahl@net.in.tum.de, marc-oliver.pahl@imt-atlantique.fr (M.-O. Pahl), wuestrich@net.in.tum.de (L. Wüstrich), luebben@net.in.tum.de (C. Lübben), josef.schindler@framatome.com, josef.s.schindler@fau.de (J. Schindler), jussi.numminen@wirepas.com (J. Numminen), thomas.weisshaupt@wirepas.com (T. Weisshaupt).

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Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
CoAP	Constrained Application Protocol
con	conventional
CHP	Combined Heat and Power
DECT	Digital Enhanced Cordless Telecommunications
DH	District Heat/Heating
DSO	Distribution System Operator
ERC	European Radiocommunications Committee
ETSI	European Telecommunications Standards Institute
EU	European Union
EV	Electric Vehicle
HART	Highway Addressable Remote Transducer
HVAC	Heating, Ventilation, and Air-Conditioning
ICT	Information and Communications Technology
IMS	Intelligent Metering System
IoT	Internet of Things
LoRa	Long Range
LoRaWAN	Long Range Wide Area Network
LTE	Long Term Evolution
ML	Machine Learning
MNO	Mobile Network Operator
MPC	Model Predictive Control
MQTT	Message Queuing Telemetry Transport
P2P	Peer-to-Peer
PV	Photovoltaic
RES	Renewable Energy Sources
RL	Reinforcement Learning
SRD	Short Range Devices
TSO	Transmission System Operator
UA	Unified Architecture

projects, energy communities can promote sustainable energy production and consumption practices in addition to citizens' participation [3]. The Positive Energy District [4] in turn aim at increased and optimized use of local energy resources across different energy vectors. To support these trends, the International Energy Agency [5] highlights Information and Communication Technologies (ICT) in energy and its ability to break down boundaries between energy sectors, increasing flexibility and enabling integration across entire systems.

This paper subscribes to the viewpoint where ICT, including Internet of Things (IoT), Artificial Intelligence (AI), and blockchain play an important role in the transition towards distributed and sector-integrated energy systems. To elaborate, we envision a decentralized and sector-integrated energy system, where trading energy between consumers and prosumers is a core part of the daily operation. Networked prosumers can negotiate and form smart contracts based on blockchain [6–11] technology to match production with consumption (and storage) as locally as possible. Building from bottom-up, locality and timely management of distributed cross-commodity resources will be the key to ensure energy efficiency and stability at smart city level. In this context, IoT [12,13] technologies are needed for real-time monitoring and control of Distributed Energy Resources (DER). AI technologies such as machine learning and automated decision-making in turn ensure optimal control of DER in different climate and temporal conditions [14,15].

It is not, however, enough to have the ICT-enablers in place. Proper regulation and market structures are also needed to realize the energy transition. In this paper, we focus especially on the regulation and market situation in Finland and Germany, two countries that have set high targets towards carbon neutrality. For instance, the Finnish government [16] has set ambitious climate targets and defined that Finland should achieve carbon neutrality by 2035. There are also several activities going-on to phase-out coal in energy production, e.g., Refs. [17–19]. The German "energy transitions" started in the early 2000s. Since then, Renewable Energy Sources (RES) represent a steadily increasing share of the electricity supply [20,21]. However, to achieve set climate goals, the German government enacted the coal phase-out by 2038 [22,23]. Together with the shutdown from nuclear power plants by 2022, a major redirection of the power system is declared [24].

Local energy systems are not a new topic and there is a large number of review papers focusing on local energy systems that consider only a single energy vector such as microgrids [25–27], and district heating and cooling systems [28–30]. In many situations, it would be more energy efficient to be able to manage and trade energy across many vectors in local context. Consequently, there exists research (and review papers) on local energy systems that integrate different energy vectors to improve energy efficiency [31–36]. However, these review papers focus mainly to the design and physical infrastructure needed to implement energy efficient and local energy systems. More studies and reviews are needed for properly addressing the ICT, regulation, and market viewpoints.

To address this need, this article provides an overview of the market, regulation, and technical situation towards cross-commodity energy sharing communities. More specifically, we aim to answer the following research questions: 1) Are the existing and foreseen market development supporting cross-commodity energy sharing in Finland and in Germany, 2) What is the role of core European Union (EU) regulations in realizing cross-commodity energy sharing solutions, and 3) How could the core ICT enablers such as IoT, AI and blockchains support the realization of cross-commodity energy sharing in local context?

The subsequent sections are organized as follows. Section 2 describes the vision on decentralized cross-commodity energy markets and principles of how the work was performed. Section 3 deals with recent energy production trends, shares of main market components and liberalization of energy markets in Finland and Germany as well as potential functioning of multi-energy markets. Section 4 compares regulations of core components of multi-energy systems between Finland and Germany. Section 5 analyses how AI, IoT and blockchains could support multi-energy systems. In Section 6, we discuss the findings. Finally, in Section 7 we conclude our study and give recommendations for future research.

2. Vision for and principles of the work

Future neighbourhoods will be prosuming [37]: not only the consumption of energy but also its production and storage will be decentralized [38]. This includes multiple forms of energy such as electricity, heat, and cooling. With solar panels or block heating devices this is already the case in single-family houses today.

Decentralization may make it difficult to benefit from scaling factors. For a smart grid operator, it might be cost efficient to invest in large storage or production capacities. For a single prosumer, it often makes no sense resulting in non-optimal energy management.

To compensate for scalability and resilience aspects of decentralized energy production and storage, communities can be formed. Our vision is to build Smart Cities within which, participants share resources in a controlled way including monetary exchange. This is schematised in Fig. 1. There, Smart Buildings organised in Smart Districts offer their flexibilities to the market. For example, one participant uses an intelligent Electric Vehicle (EV) charger to shift its load if needed. The next house owner installs a high-capacity battery offering electricity storage

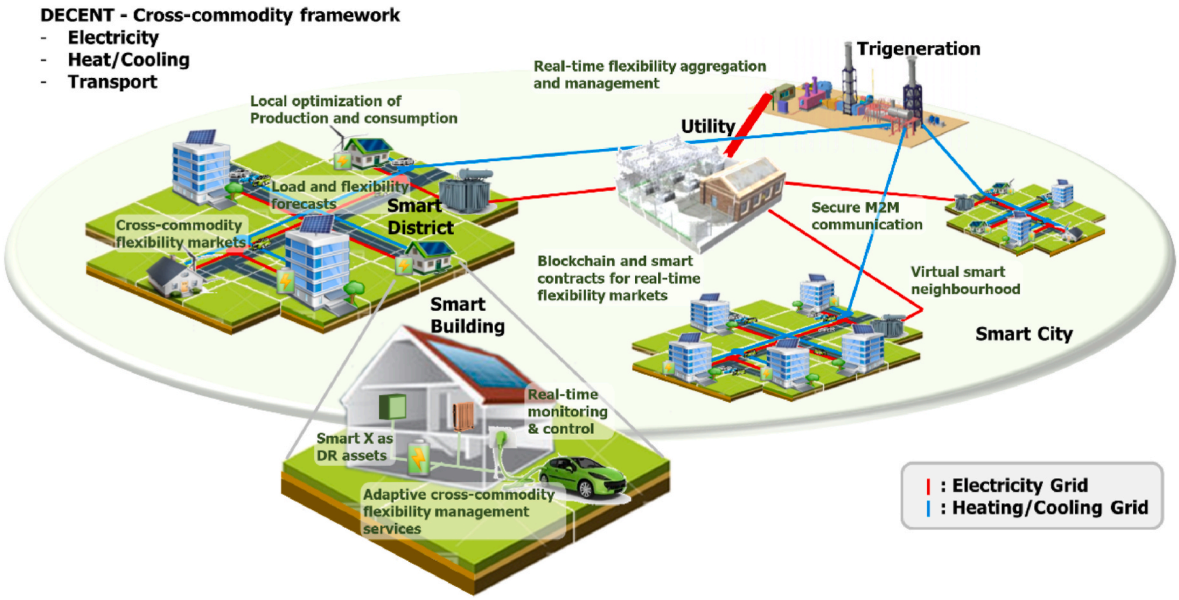

Fig. 1. An indicative image of a cross-commodity energy framework.

services. Another Smart Building uses a fuel-cell to provide heat and electricity, consuming green hydrogen from another local source. Or a Trigeneration unit produces electricity, heat, and cooling at the same time. During the DECENT project, we established a successful prototype of an integrated solution, which is presented in Ref. [39] and will be presented in future work.

In this context, ICT solutions are key to the intended cross-commodity energy sharing. They are needed for distributed, trusted logging of exchanged energy [11,40], self-organizing markets [41–46], and goal-optimizing learning algorithms [47–53]. Bajpai et al. demonstrate how to achieve a higher order of management in cross community energy sharing [39].

From a technical background, local energy exchange necessarily requires Physical Enablers, like pipes or the electricity network. Management and accounting of the energy flows requires remotely controllable valves, counter, and energy system controllers. They are called Cyber-Physical Enablers in our overview (compare Fig. 2).

While the previously described infrastructure is often in-place, an ICT infrastructure on top can bring benefits as this paper shows. Such an infrastructure requires:

- Middleware. It connects the distributed heterogeneous systems. Central challenges here are common semantics [54], and security [55,56].
- Several Core Services. They are detailed in Section 5. It includes different predictions [57–96], secure data exchange between untrusted parties [97–102], and mechanisms for incentivizing investments.
- Business Opportunities. They are required for making systems as efficient as possible based on free market competition [41–46].

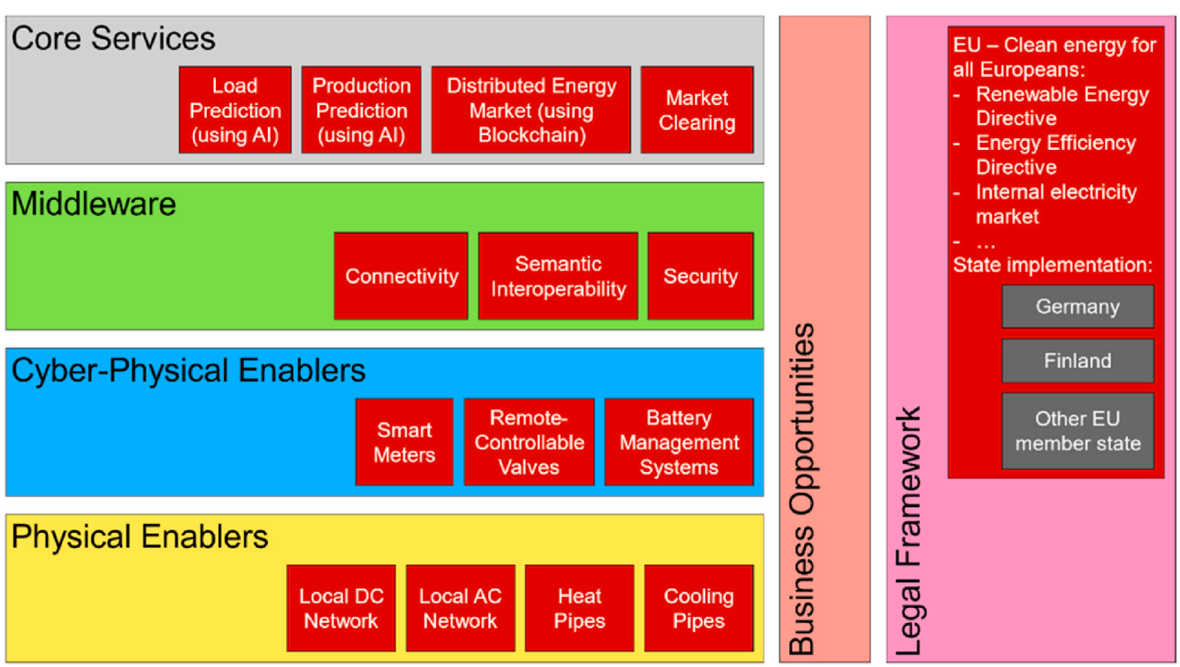

Fig. 2. Cross-commodity energy sharing building blocks.

- A Legal Framework. It defines the possibilities within a country.

Considering this vision, we perform our analysis in three phases (Fig. 3). Firstly, we analyze the existing energy markets in Finland and Germany based on public statistics and other documents. Potential multi-energy markets and trading are analyzed based on literature. Secondly, we compare regulations related to key components of cross-commodity energy systems considering EU and national legislation and initiatives. Thirdly, we review literature on critical ICT enablers.

3. Energy market perspectives in Finland and Germany

Fig. 4 depicts the shares of the main energy-market components (heat, natural gas and electricity) of the end-user energy consumption in Finland and Germany in 2017. The role of gas is small in Finland whereas in Germany it forms the largest share. The heat market is small in Germany compared to the size of markets in general. In Finland, the size of the heating market is about 57 % of the electricity market while in Germany it is only 21 %.

3.1. Electricity markets

In 2018, 46.2 % of the electricity in Finland [104], and 40.6 % of electricity in Germany [105] were produced out of RES. Fig. 5 and Fig. 6 show the development of electricity production between conventional and RES in Finland and in Germany. In Finland, the share of RES has been significant for a long time mainly due to hydropower and wood-based, i.e. biomass fuels (Fig. 5). In Germany, the share of RES has increased steadily, but the burning of brown and hard coal is still extensive (Fig. 6).

In 2018, the Photovoltaic (PV) electricity productions were 0.2 TWh and 46.2 TWh representing 0.23 % and 7.1 % of the total electricity production in Finland and Germany, respectively (Fig. 7, left). Even if the PV production is really small in Finland, it has increased over 32-fold from the year 2010 when it was only 5 GWh [106]. Similarly, wind-electricity production has increased in both countries (Fig. 7, right) being 5.9 TWh (8.4 % of the electricity production) in Finland and 111.6 TWh (17.2 % of the electricity production) in Germany [106,107] in 2018.

Both, the Finnish and the German electricity markets are completely opened/liberalized [109–111]. All electricity users can purchase electricity from any supplier, practice small-scale electricity production, and sell the energy on the market.

Finland is part of the Nordic electricity market [112], covering the Nordic countries and the Baltic states. Germany belongs to Central Western Europe electricity market [113]. Both countries' electricity generation sector is characterized by a relatively large number of actors. A summary of the actors in the overall electricity market structure can be found in Table 1. Note, in some cases companies are active in more than one area of the value chain [114,115], i.e. they are accounted in more than one line of Table 1. That does not contradict unbundling, since it is only mandatory for companies with a certain number of customers.

3.2. Gas markets

German and Finnish gas market structures differ. In Finland, mainly large industry and energy utilities use gas, whereas in Germany, also households burn a greater share of it. In both countries, the markets are open. Table 2 shows the main figures of the gas markets in both countries.

Even though, import dependencies are high already, they might still increase in both countries. In Finland, developments are going on to enable new alternative sources [117]. However, the gas network can also be used to distribute locally produced biogas, the share of which is likely to increase in Finland. In Germany, gas will necessarily substitute energy from nuclear and coal power plants phasing out over the next years. Projects like the pipeline Nord Stream II should ensure the natural gas-supply security therefore by bypassing politically unstable transit regions [118]. On the other hand, Liquefied Natural Gas (LNG) could also become more important. As LNG is transported via ship, it is less dependent on the geopolitical situation [119].

A recent study [120] shows that if renewable gases, like green hydrogen, are supposed to account for a significant share of gas consumed in Germany they either need to be funded substantially or market conditions have to change. The International Energy Agency (IEA) claims in their technical report for the G20 meeting in 2019 that regulations are a main challenge for hydrogen industry too [121]. Lately, EU targets this issue with the hydrogen strategy for a climate-neutral Europe [122]. High production cost and slow development of hydrogen infrastructure are other obstacles for the increasing usage of green hydrogen. If these boundaries will fall, IEA sees high potential in a variety of applications, like use for road freight, aviation, electricity storage, and fuel-cells for distributed generation [121]. Latter is essential for the use of hydrogen in cross-commodity sharing on a local level. A recent study from Potsdam Institute for Climate Impact Research gives a pessimistic prognose for hydrogen. They argue that bad efficiencies of hydrogen and e-fuels lead to 2 to 14 times higher needs of renewable energy for electrification of traffic compared to EV. Even worse, they see a lock-in of fossil-fuel when betting on hydrogen and e-fuels availability. And yet they see potential for selected applications such as chemicals, iron and steel and aviation [123].

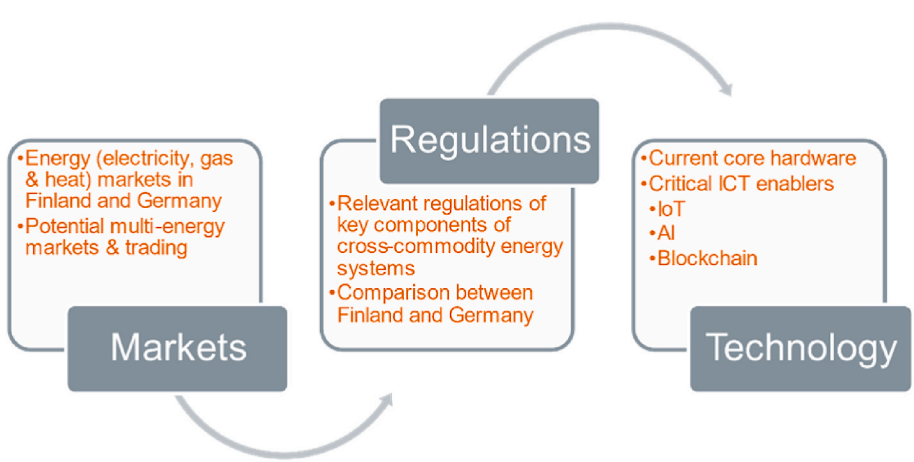

Fig. 3. Principles of the work.

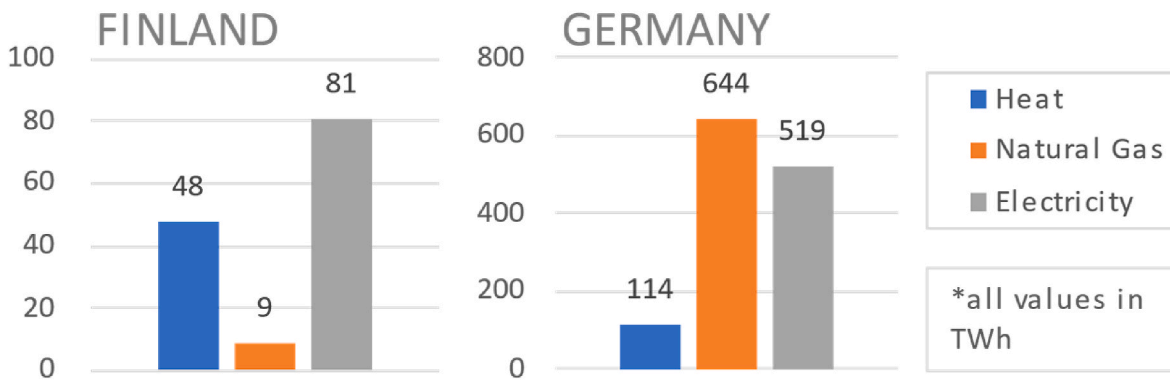

Fig. 4. Main market components from total end-user consumption in 2017 [103].

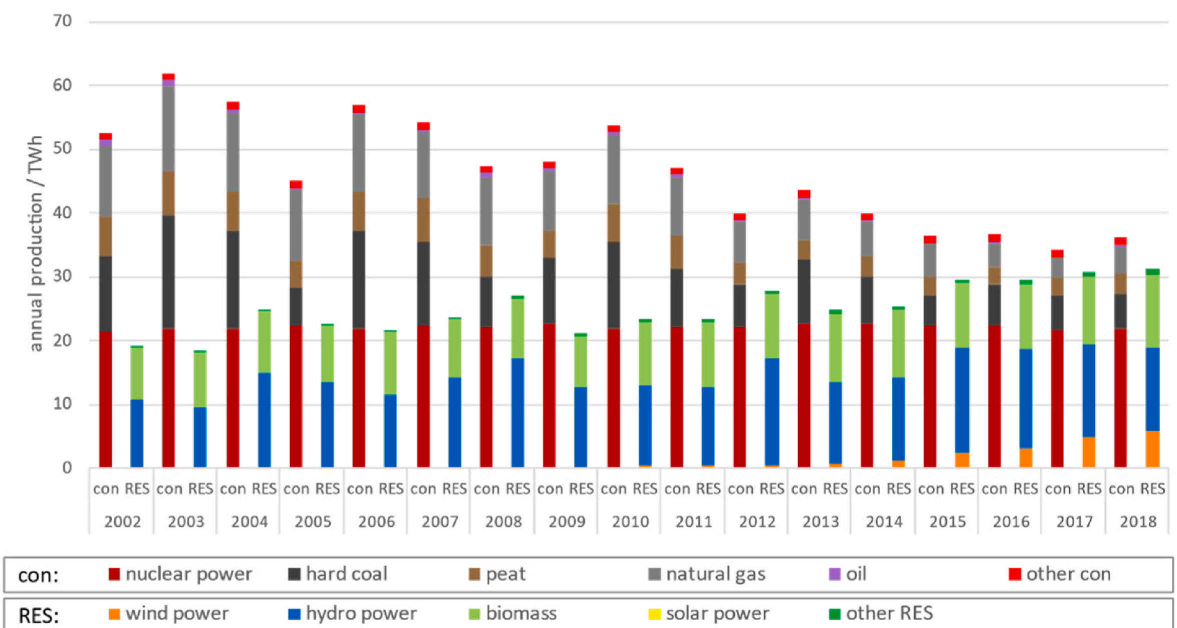

Fig. 5. *Development of conventional (con) and RES in Finnish electricity production. The data is retrieved from* Ref. [104].

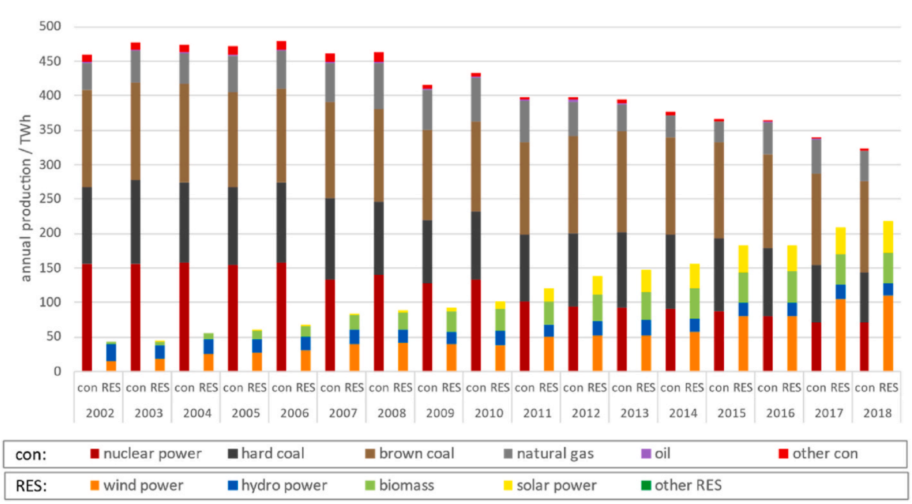

Fig. 6. *Development of conventional (con) and RES in German electricity production. The data is retrieved from* Ref. [105].

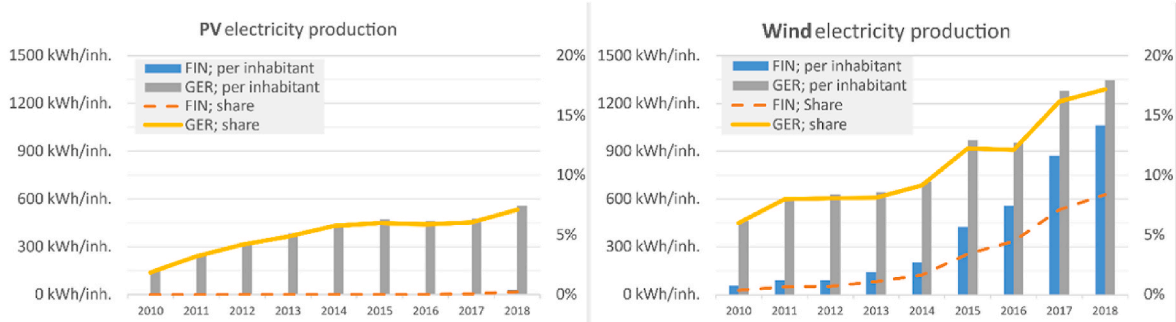

Fig. 7. *Annual electricity production from PV (left) and wind (right) in Finland and Germany. "Per Inhabitant/inh.": power normalised by the total number of inhabitants* [108]. *"share": share of the total electricity production. Electricity data retrieved from* Refs. [106,107].

Table 1
Stakeholders in the electricity markets of Finland [114] *and Germany* [116].

	Finland	Germany	Comment
Producers	150	90	Those two values are comparable to a limited extent. For Finland, every registered company is counted, while for Germany only producers >100 MW are counted. Anyway, the number of producers is increasing in both countries, which is mainly driven by energy transition: Lots of producers having small plants, such as wind turbines, PV, or biomass plants
DSO	77	907	At Distribution System Operators (DSOs) both countries have a comparable structure. Since Germany also has approximately 15-times more inhabitants, it is not surprising to have nearly 15-times more DSOs
TSO	1	4	In Finland, there is one single, state owned Transmission System Operator (TSO), whereas in Germany that task is fulfilled by several private owned companies
Retailers	72	1353	Despite the numbers looks very different, there are the same number of retailers in Germany and Finland in terms of population (16.3 per one million inhabitants)

Table 2
Comparison of Finnish and German gas markets [114,124–126].

	Finland	Germany
Final usage	24.7 TWh (in 2018)	982 TWh (in 2019)
Production	Mainly imported, some own biogas production	Mainly imported
Number of TSOs	1	16
Number of DSOs	24	718
End-users	- large industrial end-users 58 % - energy and power companies in Combined Heat and Power (CHP) production 34 %	- industry 39 % - households 29 % - business, commerce, and services 12 % - heat and cooling production 7 %
Market	opened	opened and unbundled

3.3. Heat markets

Unlike electricity and gas markets, District Heat (DH) market is unregulated in both Finland and Germany. For Germany [115] concludes that liberalization and revenue ceiling for grid operation (as for electricity and gas market) are not necessary, because there is a competition with other heat "fuels" (e.g. natural gas) to limit prices anyway. Furthermore, grid operators are main heat supplier/distributor anyway. Table 3 gives a short overview about the situations.

Table 3
Comparison of Finnish and German DH markets [115,127,128].

	Finland	Germany
Grid	15,140 km	26,400 km
Final usage	33.5 TWh	124 TWh
Production (in 2018)	64 % CHP 36 % DH plants	2/3 CHP
Fuels (in 2018)	53.3 % fossil fuels and peat 36.7 % renewable fuels 10 % other energy sources	>40 % gas >30 % coal increasing but still small shares of waste and biomass
End users	~50 % residential buildings	40 % industry 40 % residential buildings 20 % business, commerce & services
Market	unregulated	unregulated

3.4. Potential multi-energy markets and trading

In this section, we review the latest findings about potential functioning of multi-energy markets. Van Stiphout et al. [41] envision three distinct cases of market design for sharing between different energy commodities. The first, conventional "reference" option is the use of separate markets for different commodities. There, a market participant must sequentially decide what kind of offers to place on the currently open market while forecasting subsequent markets. Another approach is a centrally cleared, integrated wholesale market, where conditional bidding reflects the actual values more accurately. However, the option is not probable or feasible due to practical, regulatory, and historical reasons. .The third "control" option is again a sequential market, where the outcomes from conditional market clearings are used as forecasted values. It served as control scenario for the conditional approach by mitigating forecast errors [41].

Relevant literature suggests several models for centrally cleared markets and linking sequential markets. Van Stiphout et al. [41] organize simultaneously cleared, centralized markets by specifying different order types for the required trade operations. Pekeč et al. [42] prefer more generalized, combinatorial auctions. The auctions could be cleared in a single round or using an iterative auction process. For linking sequential markets, Mitridati et al. [43] consider the effects of the subsequent markets in a bi-level model during the clearing of the initial market. Another model allows conditional bids which depend on the prices of the following markets [44].

The typical time horizon for trading is 1 h in all market simulations of the investigated papers regardless the commodities [41,43–45]. Thinking of different inertias of heat, electricity etc. systems further consideration is necessary, especially on local level. There, with lower number of participants, fluctuation effects exceed statistical means – compare simultaneity factors [129,130]. Additionally, the clearing order of sequential markets deserves investigation. All authors first clear heat, followed by electricity (and then gas) [41,43,44]. Stiphout et al. reason it in lower elasticity of heat demand [41].

For separated single-commodity markets, the markets can be cleared either centrally as a single pool or using centralized or distributed Peet-to-Peer (P2P) mechanisms where product differentiation can be made between preferred trading partners [45,46]. However, the aforementioned solutions do not generally offer the possibility to describe complex valuations that would be required in multi-energy markets.

In most research literature, the aim is to optimize the bidding in the case of separate commodity markets while possibly considering the price uncertainties in the subsequent markets. Multi-Energy Systems' scheduling under known prices has also been optimized considering sources such as PV, battery energy storage systems with inputs for electricity and gas [131]. In addition, storages especially for heat and electricity, heat pumps and boilers have been modelled [132,133]. When uncertainties in coming markets are considered, the Multi-Energy Systems' bidding can be optimized in terms of robustness by e.g. maximizing the worst-case outcome [134], or maximizing robustness while satisfying some specified outcome [135].

Alternatively, a multi-stage model can be specified using a scenario-based approach as a stochastic programming problem, and as a mixed integer linear programming problem [136,137] with relaxing chance constraints [138]. However, bidding strategies in a single multi-commodity market setting have not been actively studied. In addition, the feasibility and practicality of blockchain and smart contracts for complex clearing required in multi-commodity markets is an open topic. Automated trading strategies are required for the trading to be worthwhile on a local scale, considering specificities of a local market, and requirements of end-customer load management. Multi-energy (or more generally multi-product) markets, especially in local contexts with less competition or possibly lack of trust, should provide mechanisms which are incentive compatible and reduce the potential for market abuse and the need for strategic trading. The proposed mechanisms do not always provide such guarantees [41].

4. Regulatory framework

Recently, a comprehensive update of the energy policy framework has been agreed at EU-level including e.g. directives on renewable energy [139], internal electricity markets [140], energy efficiency [141] and energy performance of the buildings [142].

Renewable energy directive [139] promotes increasing the share of RES by setting a binding union target of a share of at least 32 % of RES. The directive includes provisions that aim to accelerate the uptake of RES also in the heating/cooling and transport sector in addition to the electricity sector. New electricity market design aims to make electricity markets more flexible, more market-oriented and enable integration of a greater share of RES. Energy performance of the building's directive aims at promoting smarter buildings and e-mobility in buildings.

Both renewable energy directive and directive on common rules for the internal market for electricity aim to strengthen the role of active consumers and energy communities. The electricity market directive [140] has provisions for active customers and citizen energy communities. Renewable energy directive [139] has provisions for renewable energy communities (article 22) and renewables self-consumers (article 21) e.g.:

Article 22.

- Ensure non-discriminative access to suitable energy markets directly or via aggregators
- Remove unjustified juristic and administrative burdens
- Ensure fair, proportionate, and transparent procedures, including registration and licensing procedures, and cost-reflective network charges, as well as relevant charges, levies, and taxes, ensuring that they contribute, in an adequate, fair and balanced way, to the overall cost sharing of the system in line with a transparent cost-benefit analysis of distributed energy sources developed by the national competent authorities

Article 21.

- Allow individual or aggregated actions
- Ensure production for own consumption, storage and selling of excess production via power purchase agreements with electricity suppliers and peer-to-peer trading arrangements, e.g., without discriminatory or disproportionate (network) charges

In addition to the energy policy framework, there are also other policy domains that are relevant for cross-commodity energy systems e.g., regulatory framework and standardization related to metrology, smart metering systems, energy taxation, data protection and cybersecurity.

Currently, for example, the measuring instrument directive requires measurement instrument displays, which may be unnecessary and expensive as technology evolves [143]. Commission will propose to revise energy taxation directive, which is in its current form not aligned with climate objectives and the required energy transition [144]. Commission has issued recommendations on cybersecurity in the energy sector [145] due to risks that digitalization increasingly exposes the energy system.

The implementation of the EU level energy policy framework is ongoing at national level. In addition, regional or city level framework can be relevant for cross-commodity energy systems as some parts of the systems may be subject e.g. to land use/zoning or permitting requirements. Comparison between Finland and Germany as regards the regulation of some key components of cross-commodity energy systems is included in Table 4.

5. Technical perspective

5.1. Current core hardware

5.1.1. Networks

The current overall trend in energy use is the electrification of many sectors. However, in practice for some cases, other energy carriers such as heat and gas can be useful, either due to technical reasons such as remoteness or for example reuse of excess heat, or alternatively due to network availability for historical reasons. In addition, other commodities such as water is distributed in most places, and its metering data could be utilized in assessing for example domestic hot water or water pumping needs.

Distribution networks are used to transfer the commodities to residential customers. When there is a choice to be made between the commodities, correlation between their demand or possibility for transfer of energy, all the commodities should be considered holistically. Within the specific distribution networks, there can be losses and congestions, which must be considered if optimal use of resources is going to be achieved. In addition, the overall balance of energy generation and demand must be maintained.

5.1.2. Energy metering devices

Energy metering devices are traditionally designed for metering one specific parameter, such as electricity, gas, or heat consumption. Their design has also been influenced by a set of standards such as "Device Language Message Specification", "Companion Specification for Energy Metering", the metering data transfer protocol 62,056 & 61,107 from the International Electrotechnical Commission to name a few of them. These standards are designed for a very specific use defining the consumption values communication protocols between the meter and the data aggregation point. These standards enable vertical integration of operations, which is optimal for traditional utility business today and is effectively locking the consumer with a specific service provider.

Table 4
Overview of the regulation context for cross-commodity markets.

	Finland	Germany	Comparison
Smart metering system	Regulatory requirement to take into use remote meters that register electricity consumption data by the end of 2013. There was almost complete roll-out of remote meters by 2017. Next generation AMR installation is expected during 2020's	Rollout started at the beginning of 2020. Households with distributed generation & high energy consuming customizers first [146]. For participation in cross-commodity markets either smart or Intelligent Metering Systems are mandatory, according to the consumers' annual energy consumption. In theory, this enables market participation via any aggregator/service provider	In overall, smart metering systems enable digitised marketing of (cross-) commodities
Metering data handling	In 2022 centralized information exchange system for the electricity retail market - datahub - will store metering and contract data from 3.7 million electricity accounting points in Finland. This data is currently located in various companies' systems. The aim of the datahub is to speed up, simplify and improve the actions of all parties and enable new services and participation to demand-side management. Similar hub exists for the recently opened gas market [147].	Metering point operator must cover installation, operation, data handling etc. of smart metering installations. The metering point operator can be the DSO, but tasks can be delegated to other companies. In addition, the "Law for digitization of the energy transition" encourages the evolution of a competitive market for Metering point operations and related services. The DSO is the Fallback provider for those who have not opted for a commercial Metering Point Operator [148]. There is no centralized data handling foreseen. The German federal network agency is supervising processes linked to smart meter measuring [146].	In both countries, the flexibility of digitised measuring data supports decentralized market approaches. But still contracts with every single owner of an asset have to be made. On German side this can be overcome by engaging a commercial Metering Point Operator
Control and external connections, like Smart gateway	For electricity, current iteration of smart meters or the coming first version of the centralized datahub do not have standardized control interfaces. For the next generation of meters, the requirement will be to have control interfaces for clients with "substantial loads". However, the interface has not been yet specified but is planned [149]. In addition, a central flexibility resource register is currently being investigated for the purposes of contract and validation information storage [150].	The "Law for the digitization of the Energy Transition" contains a timeline for the obligation to install an Intelligent Metering System (IMS) as well as maximum charges that can be asked. The obligation and timelines are binding for DSO to having installed certified Smart Metering Gateways [151,152] and digital meters connected to those gateways. DSO can subcontract the installation and operation to third parties OR end customer can within the installation period opt for an independent provider and operator of the IMS. DSO in this case is receiving the data required to fulfil regulatory needs from the independent service provider and must pay a regulated fee for this data delivery. In addition, Assets "behind the meter" can be connected and controlled through the SMGW. This can build the foundation to monetize on direct contributions of Assets to the Power Quality (DSO side) and on the Security of Supply (TSO side). TSO and external market player directly receive data from the IMS without having the data passed through a central data hub.	Finland is building a central data hub focusing on meter data and asset resource register while Germany is creating a fully decentralized intelligent metering system with an independent data access control. This data access control is not limited to the metering data but can be extended via a so-called Home interface to assets operated in the building (Home Area Network)
Active customer/ Renewable self-consumers	In 2015, a legislative change easing the taxation of small-scale electricity production entered into force. Small-scale electricity production plants were relieved of the obligation to pay electricity tax. These producers may themselves use at the site tax-free the electricity they have generated. The DSO collects electricity tax from the end-consumers inside the DSO's network Ongoing studies and work with a view to implement Electricity market and Renewable energy directives.	In 2004 PV-energy production was supported by a fixed price of 57,4 ct/kWh, which was steadily decreased to less than 10 ct/kWh in nowadays [153]. This enforces PV owners to use produced energy on themselves, since the overall electricity price (especially with tax included) is higher. The subvention is funded by the German RES Act reallocation-charge [154]. Greater PV-plants must be controllable (shut-down/power limitation in case of too high production) due to German RES act. This mechanism can also be used for direct marketing. (if connected) PV and other RES as well as storage Installations >7 kW fall under the control of the Intelligent Metering System and can become part of any eligible program.	Germany has supported this also directly and Finland mainly through tax relief. Share of PV electricity is much higher in Germany.
Renewable/Citizen energy communities	Government decree on determination of electricity supply and metering was amended to enable better sharing of self-produced electricity in neighbourhood (within the same property) [155]. The amendment was adopted December 22, 2020 and entered into force January 1, 2021. Also, provisions related to local energy communities and active customers have been added to the decree.	Tenant Current Model funds local used power generation in building(s) that belong together by tax incentives. This will be supported furthermore [156]. Besides, people can invest in RES by participating in citizen energy community [154]. They foster the acceptance by creating awareness for RES and thus increase growth rates of RES [157]	Tenant Current Model are applicated rarely; regulation wants to incentivise this more; Tenant Current Model would fit for cross-commodity sharing in the immediate vicinity
Energy taxation at energy storages	Electricity storages do not need to pay double tax for charging and discharging.	Storages don't need to pay all fees twice for charging and discharging, respectively (e.g. German RES Act & CHP reallocation fee only at discharging) [158]	This point is similar in both countries and supports usage of storages. Anyway, in general, storages are mostly too expensive for single-use use cases at the moment.

These standards do not consider the physical communication media, which allows different methods of connectivity, such as Power Line Communication, 802.15.4 family (short range communication) systems or proprietary communication systems in 863–874.4 MHz and 2.4 GHz unlicensed bands or cellular connections.

5.2. Critical ICT enablers

5.2.1. Internet of Things

The Internet of Things (IoT) is an umbrella definition of connecting things to the Internet, but at the same time it does not provide enough context in the scope of our studies. We explore a bit further the critical issues related to wireless technologies, their limitations and how the spectrum regulation within Europe is impacting the wireless communication technology choices.

5.2.1.1. Radio spectrum availability in Europe. How and by whom the radio spectrum can be used is a very fundamental question when considering the use case in the scope of this paper. Radio spectrum is a scarce resource and therefore highly regulated commodity. Globally, most of the radio spectrum is not free to use, but is licensed or assigned for a dedicated purpose, such as mobile communication, satellite use, military and so forth. Globally radio spectrum use is defined in International Telecommunication Union where Europe is part of region 1 countries. The next level of decisions in Europe are based on the European Commission's decision, followed by more detailed technical regulations done by the European Conference of Postal and Telecommunications Administrations. European frequency allocations are defined in European Radiocommunications Committee (ERC) Report 25 [159] which defines the spectrum allocation and intended use.

In short, one may operate either in licensed spectrum, which in our case is the Mobile Network Operator (MNO) exclusive use only band. In Europe the harmonized spectrum allocation for mobile networks is up to 1 GHz, varying between member states [160]. The other alternative is to use licenced exempt bands, which anyone can use, but one must follow the dedicated spectrum use regulations for given band(s) defined in ERC recommendation 70–03 "Relating to the use of Short Range Devices (SRD)" [161]. With licensed spectrum operation the available technologies are 2G General Packet Radio Service (GPRS; phasing out) and 4G Long Term Evolution (LTE) based LTE-M and Narrowband-IoT (NB-IoT). In Europe, the relevant bands for SRD operation for this type of application are:

- 862–869.65 MHz and 870–874,4 MHz and 915–919.5 MHz below 1 GHz frequencies
- 1880–1900 MHz, 2400–2483.5 MHz and 5725–5875 MHz above 1 GHz bands.

We note that even though the operation below 1 GHz bands would bring benefits in communication link distances, the transmitter operational time is limited up to max 10 % activity over a period of 1 h. This sets limitations on what type of applications one may operate in these bands. The Long Range (LoRa) in combination with LoRa Wide Area Network (LoRaWAN) is a commonly known technology that operates on this range [162].

1880–1900 MHz band is allocated for digital enhanced cordless telephone technology. European Telecommunications Standards Institute (ETSI) has published new specifications for Digital Enhanced Cordless Telecommunications (DECT)-2020 technology [163] recently, which provides a substantial performance updated this spectrum.

2400–2483.5 MHz band is probably the most used spectrum globally which most of short-range devices use. The main reason for this is relaxed regulation and no limitations of transmitter activity if one accesses spectrum politely, i.e. does not transmit over other users which are using the spectrum. Wireless technologies such as Bluetooth® [164], 802.11 [165], 802.15.4 [166], ZigBee [167], Thread [168], Wireless Highway Addressable Remote Transducer (HART) [169], to name the most used technologies are using this frequency band.

5725–5875 MHz band is intended for wide band operation for industrial application and vehicle-to-vehicle communication use, but other user scenarios are emerging. The maximum allowed transmitter powers are at the same level as in 2400 MHz band. Because higher operating frequencies are more limiting the communication range, this band is less affordable for the use cases of cross-commodity energy systems.

Forward looking statement: Future cross-commodity energy systems' wireless information transfer would be greatly beneficial for operating environments, where radio spectrum access rules allow anyone to join the system and contribute to it by providing energy consumption information and/or producing energy for community needs. The local energy production and consumption principle influences the radio solutions which should be designed for optimizing the local consumption and production information sharing. The availability of radio spectrum viable for wireless local community energy systems is a critical asset to foster energy system innovation. In addition, the open access to use for such spectrum would be a great enable for innovation.

5.2.1.2. Critical wireless technology enablers. The radio spectrum policies have a strong influence on which radio technology/technologies enable(s) the most suitable application characteristics. The main division between technologies can be drawn whether they can operate in licensed bands or unlicensed bands:

1) The licensed band operation means in practice that the connectivity is managed by a Mobile Network Operator (MNO) and the coverage is determined by the his network. Cellular technologies have been introduced in several books and research papers such as [170,171]. These cellular systems are all based on the existence of network infrastructure, determining the area or service availability.
2) Technologies operating in unlicensed bands provide more variety. Open access to spectrums enables competitive radio technologies operation within them and independent local communication networks use anywhere it is needed. This leads to designing wireless communication which follows the same distributed system functionality principles as the cross-commodity concept.

One of the most recent studies of different technologies operating in 2400–2483.5 MHz frequencies is underway in ETSI - Electromagnetic compatibility and Radio spectrum Matters – Task Group 11 (ETSI ERM TG11 group), responsible to develop technical radio compliance requirements for wideband systems operating in this band. The report title "System Reference document (SRdoc); Data Transmission Systems using Wide Band technologies in the 2.4 GHz band" [172] is still under work, but it contains already a very comprehensive summary of technologies. From this report we summarize the relevant capabilities to Table 5.

Some of the technical parameters equal due to radio regulation in the EU. However, some of the technologies are not designed for large scale systems. The common denominator for standards-based technologies is that they were designed with the idea that someone manages and maintains connectivity. This is a limiting factor to scale wireless systems into massively de-centralized use cases where equipment quantities are counted in millions, like a cross-commodity energy production and consumption will be. Managed systems' complexity is limiting how large systems can be deployed and maintained. The challenge is how solve the limitation of the size of local community driven wireless local networks with minimal maintenance effort and cost.

5.2.1.3. Discussion on wireless communication challenges in cross-commodity system.

1. Cross-commodity energy systems may grow locally quite large, and the number of entities sending and receiving data will demand capacity for data transfer. The communication challenges are related to: how dynamically scale the communication system size and required communication capacity while keeping the cost of communication in a fraction of the cost of energy asset traded in each event?

2. Another dimension of the communication challenge is related to communication system federation: how to prevent the creation of monopolies (around connectivity) and enable an open ecosystem benefitting all participants?

3. The interworking layer for different equipment is an important question. So far, the stable interworking layer for communication has been the Internet Protocol (IP)-layer. Below this layer, we have various communication technologies, which are not compatible to each other, but still may co-exist. The never-ending technological evolution in wireless communication introduces more capable solutions for lower cost. This is contradicting the lifetime expectations of energy systems, which usually happens to be decades. Wireless technologies evolution is unavoidable and therefore it is unpractical to assume that equipment would be able to communicate between different generations at very low level over multiple decades.

4. Similarly, the application data, datagrams and ontologies of data sets completely new requirements for effective data processing systems. One aspect is to create a sensible interpretation of various datagrams (data format conversions), i.e. enable solutions (and regulation) which allow to provide SW upgrades to equipment enabling new capabilities to operate with different datagrams.

5. Together with the previous point, it is important to have a correct understanding of what the data means, i.e. the context where the energy consumption or room temperature is measured.

6. For cybersecurity, challenges are: What is the security and equipment identity root or origin of technologies? This is essential to verify that the identities of each party in automated energy markets. Secondly, how to ensure tamper proof delivery of data between parties in the system. There are numerous technologies to solve these abovementioned problems. The main challenge is to solve them in cost effective manner in relatively simple equipment's which are involved in the system. Encryption of data at move should use well-known encryption technologies such as Advanced Encryption Standard (AES) 128 today or 256 in next 3–5 years. Also, support in relatively simple chip set with novel encryption mask update sequences to prevent or complicate the man in the middle opportunities is mandatory to maintain trust in the transactions.

7. EU Parliament has approved a new cybersecurity act in 2019 [97]. The main objective for this legislation is to improve the cybersecurity capabilities in all ICT equipment sold in the EU. Main new requirements are related to:
   a. Unified cybersecurity requirements in the EU for given application to foster a common EU market.
   b. no default passwords allowed to be used in any equipment.
   c. software update possibility is highly encouraged.

The actual security requirements for different applications are underway in respective standards bodies since e.g. finance, healthcare or energy domains do have different requirements and standards.

5.2.1.4. Discussion about IoT related opportunities. The IoT plays a central role in the success of the envisioned energy-sharing infrastructure. It enables the collection and sharing of data, e.g. metering energy usages and transfers. It also enables controlling devices remotely including the switching of energy producers or state changes in storages and energy consumers.

At the moment, there is no standardized communication between IoT devices, resulting in a lack of interoperability of devices between different vendors. However, the holistic approach we envision would need such interoperability as it works across commodities and vendors. Today, in many cases only devices from the same vendor are capable of

Table 5
Radio characteristics summary from report [173]*, extended by DECT* -2020 NR [163] *and LoRa/LoRaWAN* [162,174].

	Bluetooth® Low Energy	IEEE 802.11 WLAN	802.15.4 ZigBee	802.15.4 Thread	802.15.4 Wireless HART	Wirepas mesh	DECT-2020 New Radio	LoRa/LoRaWAN
Operating band	2400–2483.5 MHz	2400–2483.5 MHz	2400–2483.5 MHz	2400–2483.5 MHz	2400–2483.5 MHz	2400–2483.5 MHz	1880–1900 MHz	867–869 MHz
Transmission (TX) power	10 dBm	20 dBm	13 dBm	10 dBm	10 dBm	10 dBm	23 dBm	14 dBm
Network size	32,767		Up to 65,000 nodes		Hundreds of nodes	Millions of nodes	Million of nodes	
Network management	fixed	Fixed	Fixed roles	Fixed	Autonomous	Autonomous	Autonomous	Fixed roles
Transmission lengths	1 ms	2,08 to 4096 ms				1.2 ms	208/416 μs	
Radio Access type	***TDMA/FDMA	Multiple	*DSSS	*DSSS	*DSSS and **FHSS	***TDMA/FDMA	***TDMA/FDMA	Chirp modulation Spread Spectrum
Maximum activity	<14%	LBT No duty cycle limitation	<66 %	<66 %	<20%	<34 %	LBT No duty cycle limitation	<10 %
Bitrates	1 Ms/s		250 kb/s	250 kb/s	250 kb/s	1 Ms/s	****2,2 Mbit/s	Up to 50 kb/s
# Channel	40	11 (3 non-overlapping channels)	16	16	15	40	11	10
Channel bandwidths	1 MHz	20/40 MHz	2 MHz	2 MHz	2.5 MHz	1 MHz	1728 MHz	125/250 kHz (up) + 125 kHz
Channel spacing	2 MHz		5 MHz	5 MHz	5 MHz	2 MHz	1728 MHz	200 kHz

*DSSS: Direct Sequence Spread Spectrum.
**FHSS: Frequency Hopping Spread Spectrum.
***TDMA/FDMA: Time or Frequency Multiple Access.
**** With 16 Quadrature Amplitude Modulation (QAM) single slot (416 μs) transmission user plane speed. Higher data rates are supported with multi slot transmissions.

communicating, hence reducing the number of possible participants in such a market or imposing restrictions on the consumers choice by forcing them to by devices of a certain vendor.

A solution is the use of middleware since it can provide a unified interface layer to heterogeneous devices [175]. By offering a standardized interface that integrates devices of multiple vendors, a middleware removes the hurdle of non-interoperability and simplifies usability. On the application layer, middleware simplifies the access to data of connected devices. It makes it easier to control devices of different vendors through a standardized interface [98]. In our concrete case, it significantly facilitates the development and deployment of portable, so context-independent, energy-management applications [176].

Overall, a middleware makes it easier to integrate devices from different vendors into a single system and for applications to make use of the present devices through a standardized interface for the collection and exchange of data, as well as, issuing commands. Due to the described advantages, the use of a middleware for the IoT has been recognized in the research community, resulting in several promising approaches with varying adaptation [98–100].

With its intermediary role, middleware can enforce security mechanisms, making a system secure by design [177]. This includes the authentication of devices, access control and encrypted data transmission between the devices and introduce isolation for information on need basis by having different security domains e.g. isolating communication layers and application layers from each other. A middleware could example provide simple mechanisms for authenticity, e.g. a public key infrastructure for all IoT devices [55]. Further, by wrapping the original information in standardized packets it is also possible to provide a unified mechanism for data encryption and integrity protection. This solves the problem of incompatible mechanisms due to different manufacturers that use different security mechanisms. Thus, a middleware also enhances the security of the underlying system.

5.3. Communication protocols in IoT

IoT covers use-cases that have highly different requirements. Several communication protocols emerged that fits the diversity in the use-cases. Lightweight protocols are favourable in embedded devices and microcontrollers due to their low resource usages such as processing power and bandwidth consumption. Message Queuing Telemetry Transport (MQTT) and Constrained Application Protocol (CoAP) are the two most common lightweight protocols used in IoT. MQTT is a lightweight publish-subscribe protocol. It has the advantage of decoupling of synchronization, space, and time. Thus, the two endpoints, subscribers and publishers are connected via a broker. On the other hand, CoAP is a request/response protocol. It is like Hypertext Transfer Protocol (HTTP) that makes it possible to integrate these protocols easily. Both, CoAP and MQTT, consume low bandwidth and low processing power, and thus make them popular in IoT.

Extensible Messaging and Presence Protocol (XMPP) is a message-oriented middleware based on Extensible Markup Language (XML). It has near-real-time structured and extensible data exchange between network entities. Since the message-oriented middleware is an actively researched field, it is crucial to deploy the frameworks that have active development. Furthermore, popular solutions can be prioritized to take advantage of their broad community support.

OPC Unified Architecture (UA) is another dominant protocol mostly used in machine-to-machine communication. It offers rich features of services, addressing capabilities and security. It is a platform-independent service-oriented architecture. With platform independence, it has a vast array of use-cases across hardware platforms such as personal computers, cloud-based servers, programmable logic controllers, micro-controllers, and operating systems such as Microsoft Windows, Apple OSX, Android, or any distribution of Linux. OPC UA works in the client-server network architecture. Address Space Model and the Services are at the core of the protocol. Address Space defines a standard way to represent objects between servers and clients. Services are the standard operations offered to the clients by the servers. OPC UA has implementations in different languages both commercial and open-source [101,102].

5.3.1. Artificial Intelligence

Artificial Intelligence refers to intelligence demonstrated by machines. It is also a scientific field within computer science focusing on the study of intelligent agents, i.e., devices or software processes that take actions that maximize its change of successfully achieving its goals [178]. In recent years, the most successful approach for realizing AI has been Machine Learning (ML). In ML, the goal is to make computer systems able to learn from experience, enabling them to perform tasks without explicitly programmed to do so. There has been a huge buzz around AI and ML during the last years due to various breakthroughs in the fields of perception, natural language processing and game playing, to name a few [179–183]. Naturally, these advancements have encouraged research and development to apply AI-technologies in a wide variety of industries and domains ranging from healthcare to autonomous cars and smart grids. AI technologies are already used in power grid and energy system management, but they will become even more important in decentralized and cross-commodity energy management, because of the increased complexity and challenges in managing such infrastructures.

The solutions provided by AI-technologies for decentralized and cross-commodity energy management can be divided into two main categories. First, AI technologies, in particular machine and deep learning, provide advanced methods for data-based modelling of complex energy systems. This includes modelling and forecasting of demand-side resources such as Heating, Ventilation, and Air-Conditioning (HVAC), as well as RES such as PV and windmills. Second, AI technologies provide means for automating and optimizing energy management, empowering consumers and prosumers to become central actors in the local energy systems. Depending on the market structures and incentive mechanisms, the automated energy management performed by AI-enabled intelligent agents can range from intelligent control of flexible resources, to active participation in the (local) energy markets through automated trading of energy and flexibility.

5.3.1.1. Machine learning for distributed energy system modelling. Machine and deep learning provide advanced means for modelling complex processes and systems. It is therefore natural to apply them for learning the dynamics of distributed energy systems. We focus on Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) and classify existing work on following categories: type of the energy system, temporal granularity of the energy data, and type of ML modelling approach. Fig. 8 illustrates the distribution of the related works with respect to these categories.

From decentralized energy management point of view, energy systems can be divided into three main categories: inflexible loads, flexible loads and local generation. The challenge for AI-based modelling and control is to match local generation and consumption by intelligent control of flexible loads. To this end, there is a need for modelling and forecasting the inflexible consumption, local generation and flexibility.

When considering the current infrastructure, buildings constitute majority of the electricity consumption in local neighbourhoods. In the future, Electric Vehicles (EVs) are most likely to be also a major consumer, as well as source for flexibility within local communities. Modelling and forecasting buildings energy consumption with Artificial Neural Networks or Support Vector Machines has been an active research topic with 50 papers. Most of these papers (27 in total) focus on modelling total energy load of buildings [57–73,80,91–96]. Almost a large portion (17) of papers have on focused on forecasting flexible loads such as HVAC [74–79,81–90]. The inflexible load portion can be natural calculated by reducing the flexible loads from the total loads. A smaller amount (6) deals with energy generation forecasting mostly focusing on PV generation.

In principle, buildings contain a wide variety of controllable loads that could be used for flexibility management. In practice, the most potential flexibility source of buildings is the HVAC due to the fact that thermal mass of the buildings acts as a natural energy storage. HVAC systems are also interesting from cross-commodity energy management point of view as heat and cool can be generated with different energy vectors (e.g. combination of DH and RES powered heat pumps). This is also shown in the research works as almost all papers on forecasting building's flexible resources have focused on HVAC systems. The main shortcoming in existing research is that while relatively large focus has been given on forecasting flexible consumption none of the works forecast actual response of demand response or flexibility management control.

Primary RES in local neighbourhoods are solar and wind power. Forecasting local renewable power is essentially weather forecasting. After solar irradiance or wind speed is known, predicting the energy output is straightforward. The main challenge is that unlike in typical weather forecasting, the spatial accuracy of the forecast plays a much bigger role. For example, it is generally not sufficient to use solar irradiance forecast for the whole city to forecast building-level solar generation. In addition, a considerable random element has to be taken into account, for example, microclimate events such as wind gusts and small clouds blocking the sun are commonplace.

Most of the energy markets currently operate at an hourly time granularity and energy data is also typically collected at this frequency. It is therefore natural that most of the research (39 papers) on load and generation forecasting is done at hourly resolution [57–61,67–69,74–77,81–87,92,93,95,96,184–196]. Moreover, in generation forecasting, even larger time granularity such as a day or even a month is common [197–201]. With increasing amounts of volatile RES, the markets are moving towards finer time granularities. This is also important for local cross-commodity energy management with large share of volatile RES. In the current literature twelve papers have used 15-min or 10-min data granularity [62–65,71,79,202–207]. Only three studies have been done with 1-min or finer data resolution [73,94,186].

ANN [208] and Support Vector Machines (SVMs) (or Support Vector Regression) [209,210] are two most popular and best performing model families for load and generation forecasting. ANNs are decentralized and layered computing systems inspired by biological neural networks. There are a wide variety of different type of ANN architecture styles, including Feed-Forward ANN, Convolutional ANN, Recurrent ANN, Long Short-Term Memory and Gated Recurrent Units. Also there are several different ways for training ANNs with backpropagation being the most popular [211]. The Feed-Forward ANNs (with single hidden layer) have been the most popular ANN architecture style for energy system modelling with a total 44 works on building loads, flexibility and local generation forecasting. Another popular ML technology for building load and RES generation forecasting (33 papers) is Support Vector Machines (or more precisely its regression variant called Support Vector Regression). In addition to standard Feed-Forward ANNs, more advanced ANNs for load forecasting have been studied in five papers [58,73,185,186,195].

5.3.1.2. Automated and optimal decision making for distributed energy systems. Over the past decades, there has been a steady interest in intelligent control of distributed energy systems utilizing a cavalcade of different control strategies, as shown in Fig. 9. The more primitive control techniques are utilizing on-off scheduling in order to capture cycles in electricity price or in ambient temperature, for example. Proportional-Integral-Derivative (PID) controllers are simple feedback controllers that aim to minimize tracking error, i.e. the difference between measured and controlled variable. They can be used for example to keep temperature or power consumption constant.

Model-based control techniques rely on a *dynamics model*, i.e., a representation of the system dynamics known to the controller. In current research, most model-based strategies employ Model Predictive Control (MPC) approach, which uses the model to predict future behaviour of the system and plan controlling of the system accordingly, as depicted in Fig. 10. With MPC, the dynamics model can be equations describing the dynamics [212–214] or learned from historical data using various ML techniques [215–217]. Provided that the system dynamics and cost function are differentiable, convex optimization algorithms such as quadratic programming can be used [47–50] in planning. Otherwise, more general trajectory-space search algorithms such as Monte Carlo Tree Search, Particle Swarm Optimization or Genetic algorithms are used [51–53]. MPC systems are generally robust and data-efficient, though they may suffer from performance issues depending on the model used.

On the contrary, in recent years, with the rise of volatile RES and the subsequent need for distributed energy management, the demand for more complex and more intelligent control systems has emerged. Fortunately, the recent developments in AI, and more specifically in Reinforcement Learning (RL), have provided means for accomplishing just that. Reinforcement Learning is a machine-learning paradigm that learns to control through interaction with the environment, bearing similarities with human learning [218]. It has the obvious advantage of not needing any labelled training data to learn from, although it is a good practice to first train the RL algorithm in a safe setting before deploying it to the real world. In addition, learning through interaction also means that no dynamics model is required, classifying most RL as

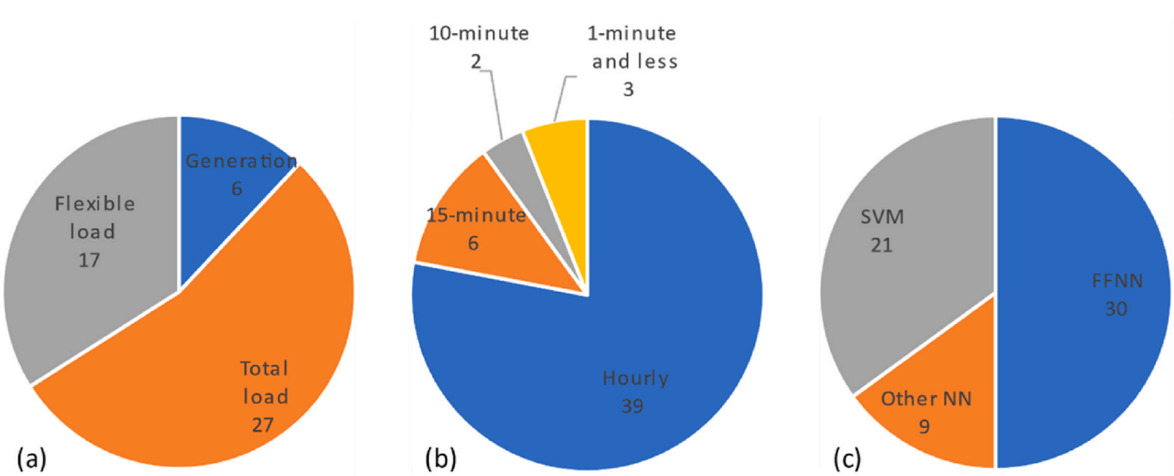

Fig. 8. Distribution of related works with respect to (a) type of energy system, (b) temporal granularity of the data, and type of (c) ML models.

Model-Free approach. Model-Free algorithms aim to learn an optimal control policy through trial and error with the system. Not needing a model is a large benefit, as implementing one requires a lot of data or person-hours (or both). The downside is that the control policy is largely unknown, thus usually a backup controller is used to override any adverse controls the policy might suggest, as in Fig. 11. Most commonly used RL algorithm for energy system control is Q-learning [218] and it has been battle-tested in multiple scenarios [219–228], capable of incorporating RES as well. In Q-learning, the agent learns an approximation Q of the optimal action-value function, that gives the quality of an action A performed in state S [218]. Given this function, we can find the optimal policy to maximize the expected future rewards. Q-learning was first introduced in 1989 [229]. It has since risen to prominence as it is easy to implement and understand, while also being a very effective algorithm. Over the years, it has also seen improvements and additions such as Deep Q-learning [182].

5.3.2. Blockchain

Blockchain is a distributed ledger technology that contains a record of transactions that are stored in a distributed manner. The idea of blockchains was first introduced by Satoshi Nakamoto where a P2P electronic cash system i.e. bitcoin was proposed [230]. Thereafter, blockchains are used extensively as an underlying technology for cryptocurrencies that aim to move from centralized systems to decentralized systems. Centralized models rely on a single node for computing and storage resources, to achieve control and authority over processes. Decentralized models share these resources among geographically distributed and heterogeneous nodes in a network [40]. It introduces transparency, immutability and trust in the system. Every node in the network maintains a local copy of an immutable record of transactions. Furthermore, smart contracts are deployed in the blockchain in order to provide self-executing autonomous programs. They are used to model terms and agreements between different parties. A custom business logic for any application can be built and deployed on the blockchain using smart contracts. Due to these properties blockchain is used in various sectors ranging from finance, healthcare, supply-chain, etc.

5.3.2.1. Blockchain in energy domain. Blockchain is applied extensively in the energy sector as it promises automation, disintermediation, decentralization, transparency and audit trails. Decentralization in energy systems bridges the gap between energy producers and energy consumers. There are a variety of use cases possible in the energy domain. There are different industry and academic projects in the direction of use of blockchains in the energy sector. Brilliantova et al. [231] discuss the role of blockchain as shown in current energy market transformation. The work provides insights into the future of energy systems in context of blockchain. Andoni et al. [11] conducted an extensive literature survey on the use of blockchains in the energy domain by studying around 140 initiatives. The paper discusses the use of blockchains in different areas in energy ranging from metering, billing, certificates, grid management and security to energy trading. The authors classified different projects based on the blockchain technology and the consensus algorithms used for the development of the platform. They concluded that the research is still in an early development phase and a lot of work is focusing on improvement areas such as security, scalability, privacy, etc. in such systems. A recent work by Silvestre et al. [232] reviews the use of blockchains in power systems by studying the current applications including electrical energy trading and renewable energy certification and demand response tracing. The authors also argue on the applicability of blockchain for different power system use cases by identifying the scenarios and determining if blockchain implementation is required or it can be avoided. Furthermore, the study examines the features of different blockchain technologies such as Ethereum, Hyperledger, Tendermint and Multichain and proposes the use of suitable technology based on the requirements.

5.3.2.2. Blockchain based energy markets. Peet-to-Peer energy trading makes the energy market more competitive. It gives the consumers the flexibility of deciding the energy provider besides the main grid. The consumer can have preferences such as buying energy locally, favoring RES, etc. Blockchain helps in achieving P2P energy trading through decentralization. It makes the system transparent by providing the audit trails. Moreover, smart contracts can be used to automate the transactions in a publicly verifiable manner. An early report by PWC throws light on the use cases of blockchains in the energy domain while taking the legal framework in consideration based on German market [233].

The earliest adoption of the blockchain based energy market dates to 2014. NRGCoin [234] introduced a virtual currency to enable energy trading. There is no energy market or matching of orders. SolarCoin [235] is also an early adopter which incentivizes solar energy producers. It uses a custom blockchain platform based on Proof-of-Stake Time algorithm. A review by Zhang et al. discusses the outcome of the early projects. The authors emphasized the importance of the communication and control network design along with the business models. These studies show the potential of blockchains in energy markets. In contrast to earlier findings, however, Buth et al. [236] conducted a study on the role of actor configurations and concluded that the impact of blockchain in P2P trading can be significant but may not be as disruptive as expected.

The major energy market projects can be categorized broadly in three categories. Projects such as Solarcoin [235], EnergiToken [237], GrünStromJeton [238], NRG-X-Change [239], Climatecoin [240],

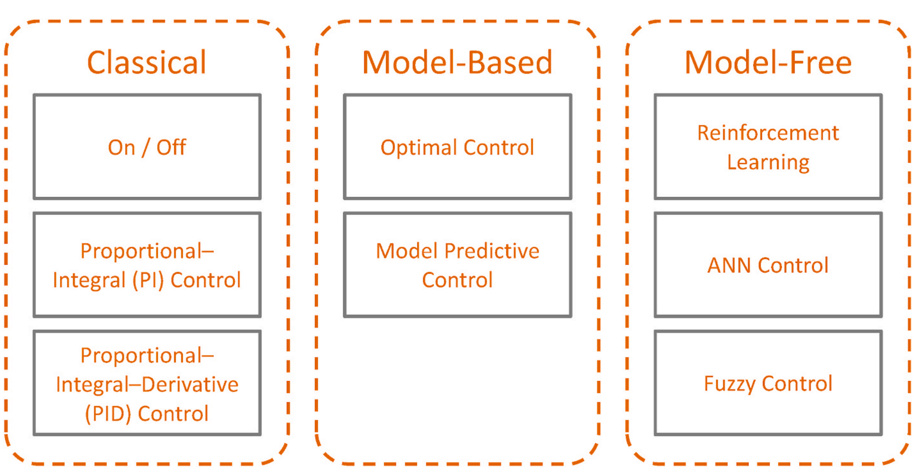

Fig. 9. Classification of most commonly used control techniques in intelligent energy systems.

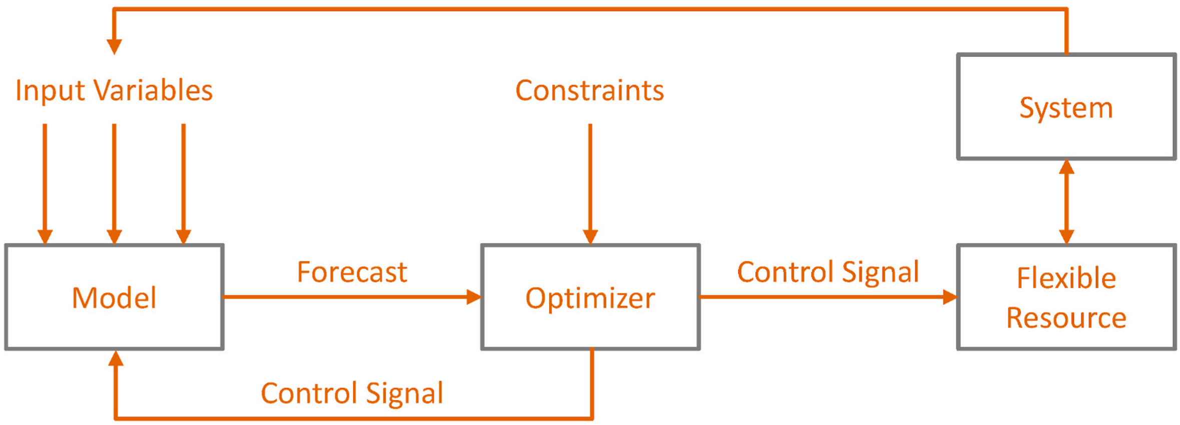

Fig. 10. A simplified view of the classical MPC control algorithm deployment in energy system setting.

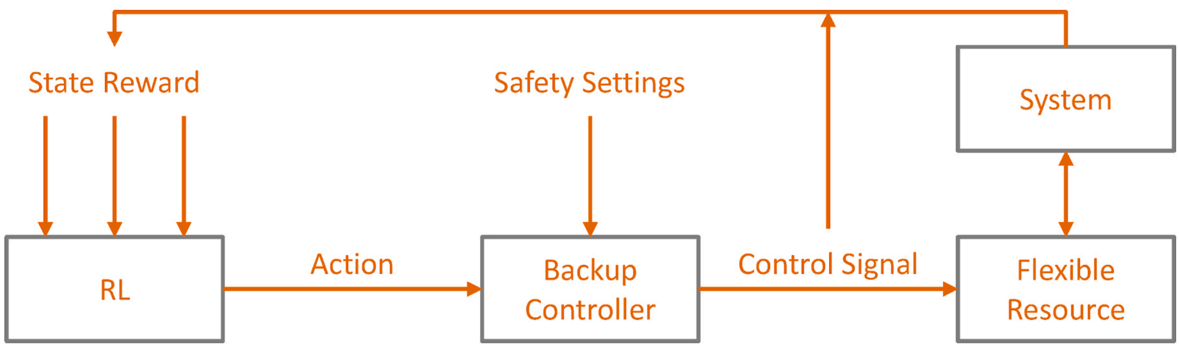

Fig. 11. An example of RL based model-free control algorithm in energy system setting.

WePower [241] focus on incentivizing environmentally sound behavior through assets or tokens. On the other hand, projects like Power Ledger [242], Grid+ [243], BrooklynMicrogrid [244] enables the direct trading of energy (P2P trading) between prosumers. There are also blockchain platforms that are specifically designed to cater energy applications such as Energy Web Foundation. Energy Web Foundation [245] is based on top of Ethereum and provides an energy web chain that uses proof of authority as a consensus algorithm. We only focus on the second category (P2P trading) in this paper.

5.3.2.3. Design aspects of P2P energy systems. A considerable amount of literature has been published on P2P energy trading addressing design aspects. These studies can be broadly categorized in decentralized economic models and decentralized grid control. The economic models mainly focus on market mechanisms and implementing the buyer-seller agreements in the smart contract. They also focus on other aspects such as fairness, privacy, security, scalability, availability etc. Leeuwen et al. [45] proposed an integrated blockchain-based energy management platform with bilateral trading for microgrid communities. Trading mechanism is combined with the physical microgrid constrains for formulation of the optimization problem. A real dataset from a community in Amsterdam is considered for the simulation. The simulation results show that the peak energy is reduced by 50 %. Han et al. [246] presented a framework for blockchain platform to enable P2P energy trading using private Ethereum blockchain. The study proposed a double auction trading mechanism and also considered security and fairness parameters. Another work by Li et al. [247] considered design aspects of distributed energy systems and proposed a framework for demand side management by enabling P2P energy exchange. A case study was conducted to show that the proposed model helps in flattening the energy consumption schedule from external grid. Furthermore, the use of blockchain helped in achieving better security and transparency. In contrast, the increasing number of participants could pose scalability issues that requires further research.

The authors in Ref. [248] address the privacy and security issues in blockchain based decentralized energy trading systems. Furthermore, a blockchain-based solution is introduced to provide transactional security and privacy in decentralized energy systems. A token based secure energy trading system is implemented that enables peers to anonymously trade energy within themselves. Previous research findings into privacy issues have been consistent in Ref. [249] where a consortium blockchain was presented to deal with privacy issues during energy trading. A method is proposed to overcome linking attacks, an attack where data mining algorithms are used to obtain information by linking public blockchain information with the existing datasets. These data sources can come from an electric company. There are other works that focus on privacy and security issues by considering transaction in IoT based energy systems [250,251].

The scalability issues can be handled either by adapting the market clearing process or by relying on underlying technology. To deal with the scalability issues, Khorasany et al. [252] followed the former approach and proposed an adaptive segmentation method for market clearing mechanism. Segments are formed using clustering algorithm based on the similarity between players considering amount and price as features. In the next step, distributed method is applied to clear the market thereby enhancing scalability by reducing communication overheads.

There are various technical challenges that can occur in the integration of blockchain in energy systems and a broad analysis of these challenges is required for the adoption of blockchain in energy domain. The most important finding to emerge in the work by Ahl Et al [253]. is that the challenges are not limited to technology but can also appear in the form of economic, society, institutional and environmental challenges. However, discussion on that is beyond the scope of this paper.

5.3.2.4. Regulatory aspects of blockchains. In general, there are a number of legal and regulatory requirements that blockchain projects and their application in the energy domain must comply with [233]. The law on the EU level provides the general right to be supplied with electricity and legal provisions must ensure the protection of "vulnerable customers". With regard to customer protection, also the European General Data Protection Regulation applies as well as the economic consumer protection through unbundling. Furthermore, various national regulations must be taken into account as, for example, contracts for energy supply need to include among others the contracts term, price variations, termination deadlines as well as methods of payment, supplier switching or how information about tariffs can be obtained. The implementation of Blockchain would affect the current market roles, with the changes to be reflected in the regulations. This will also lead to changes in the defined areas of responsibility of the currently existing roles. Who transmits the measured values to the distribution network operator? Who prepares planning and forecasts for the transmission system operator? Who is the current contract partner or balancing group manager? These tasks, which are defined in the various regulations, must be taken into account and agreed upon in a decentralized system.

In summary, many of the regulations and frameworks are tailored to a centralized energy system and, when taken into account, weaken the advantages of a decentralized energy market. In the transformation from a centralized system with a clear assignment of organizational and legal responsibility, to decentralized blockchain-based concepts, roles and responsibilities need to be assigned and defined.

6. Discussion

In electricity markets, there is an increasing need for flexibility also from the distributed resources located on the demand side. The flexibility could be used for arbitrage in energy markets or for congestion management, i.e. balancing the grid. In places where also other commodities (e.g. heat or gas) are used as energy carriers, the correlation between changes in demand (or generation) could be significant and holistic energy management solutions are required, which need to be incentivised by government or the grid operators.

There are centralized market mechanisms in place for trading commodities, which vary according to region and commodity type. For optimal trading and final use of resources, trading in these markets and potentially the interaction of the specific commodity markets in their timing, bidding structures and clearing is beneficial. Smaller localized markets could also fill a niche for enabling small-scale resources to participate in markets, share energy and resources and aid in the management of the local distribution network.

There is a need to take a broad look at the regulatory framework when discussing what supports and what restricts cross-commodity energy systems. The framework should consist of several pieces of regulation at different levels (EU, national and regional) for various policy domains (RES, energy-efficiency, buildings, electricity markets, heating and cooling, metrology and smart metering systems, ICT and data, data protection and cybersecurity, taxation etc.). Various pieces of regulation have different objectives and they may thus on their own or in combinations support or restrict cross-commodity energy systems.

Considering future middleware functionalities and design, it is important to promote software upgrades for all devices since its essential capability to maintain and introduce features for the devices in the field. With software updates, it is also possible to update datagrams (such as ProtoBuf [254]) and/or conversion protocols in each equipment. This can even be considered being more important than trying to find a one common application language for these systems in the future. With sufficient software upgrading, one can modify and adapt devices in the field and foster innovation.

Artificial Intelligence technologies have been studied extensively for modelling and controlling energy consumption and generation. However, most of the work has focused on hourly data and more work is needed to be done for 15 min and finer granularities. This is important to be able to manage energy systems in more distributed manner. Another significant limitation in the existing research is that, although there are many studies forecasting flexible building loads such as HVAC, there is a lack of studies modelling flexibility of buildings with data from actual controls. This would give a realistic idea on the actual thermal performance of buildings and the response caused by flexibility management. This is also partly visible in the automated control studies that mainly focus on simulated environments.

From methodology point of view interesting direction for future work include hybrid models that combine deep learning models with physics-based models in order to achieve high representation capacity in data-efficient manner. ML-based approaches are also based on the i. i.d. assumption, which is not realistic in real-life buildings since the data distribution change due to many reasons (e.g. changes in the control logic of HVAC, new appliances, new inhabitants). To this end, more work such as in Ref. [255] are needed to make the ML approaches such as deep neural networks able to handle changing data distributions, e.g., by utilizing information on the errors made by the model in the recent past.

The relevance of the integration of blockchain with energy systems is clearly supported by the current findings. Therefore, it can be concluded that blockchain can form an important part in energy transition, especially in P2P energy trading by providing transparency, supporting audit trails and allowing decentralized autonomous computations. However, the integration also introduces several challenges. These challenges are not limited to technical front but also in terms of legal and regulatory parameters. If the challenges are addressed appropriately, then blockchain can prove to be disruptive in the energy domain.

Throughout this article, we have considered 'cross-commodity energy'. In fact, our thinking is supporting energy system integration, the term of which could also have been used. EU Strategy for Energy System Integration [122] discusses the pathway towards an effective, affordable and deep decarbonisation of the European economy. According to the strategy, the Clean Energy Package provides a basis for better integration across infrastructure, energy carriers and sectors. There are, however, still regulatory and practical barriers. It its stated that *"without robust policy action, the energy system of 2030 will be more akin to that of 2020 than a reflection of what is needed to achieve climate neutrality by 2050"*. The strategy includes several proposals that will be prepared during 2021 to advance energy system integration.

7. Conclusions and recommendations

This paper dealt with foreseen views to realize cross-commodity energy systems when considering trends in energy transition, supporting regulations of key components and core technical enablers. Considering our research questions, we conclude the following.

The energy markets both in Finland and in Germany are in a transition process. Phasing out coal will need all available means including new market mechanisms. Several options for organizing markets for distributed multi-energy systems have been recently proposed but practical applications and supporting forecasting, planning, and trading systems are not established. In addition, bidding strategies in a multi-commodity market setting have not been actively studied. Automated trading strategies are required for the trading to be worthwhile on a local scale, which consider the specificities of the local market and requirements of the end-customer load management.

Clean Energy Package includes several pieces of legislation that are at the general level supportive towards the broad aims of the cross-commodity energy sharing solutions discussed in this article. The EU Strategy for Energy System Integration states that Clean Energy Package provides a basis for better integration across infrastructure, energy carriers and sectors and recognises need for additional policy action to enable effective, affordable, and deep decarbonisation. A Hydrogen strategy [256] for a climate-neutral Europe elaborates in more detail on the opportunities and necessary measures to scale up the uptake of hydrogen in the context of an integrated energy system. In designing further steps at the EU level, it is important to pay attention to linkages between energy policy and other policy domains and lessons learned in various national contexts when implementing EU policies. Finland and Germany are both implementing measures that can pave the way for cross-commodity energy sharing solutions (e.g., smart metering and data handling, active customers, and renewable self-consumption). There are, however, differences between approaches.

The article provided state-of-the-art review on IoT, AI and blockchain with a viewpoint on how these technologies can support decentralized and cross-sector energy systems. Key components of IoT are wireless communication and interoperability middleware. Wireless communication technologies are needed for monitoring and control of distributed energy resources and flexibility assets, as well as, to support P2P communication in local energy markets. However, the development should have more focus towards local network deployments from the nationwide and MNO driven business model. This development should be backed by EU level spectrum policy support for local spectrum access. Locally available spectrum and communication capacity will be critical assets to support local and decentralized energy management and trading. Middleware provides the connecting glue between the required heterogeneous distributed entities for measuring and control. The state-of-the-art solutions presented in this paper address the central challenges of integration, security, scalability, and robustness. However, having a set of common interoperability standard(s) is still to be established.

AI provides key technologies for modelling and optimization of sector-integrated and distributed energy systems. There has been a vast amount of research and good results on machine learning methods especially for load and generation forecasting. AI-based automated control and optimization methods have been also heavily studied and shown to improve traditional control methods. However, most of the studies have been executed in simulation environments and the Technology Readiness Levels need to be increased to support adoption of AI methods also in automated decision-making.

Similarly, to AI, many blockchain based solutions for decentralized energy systems have been proposed in the literature. However, there are still many technical challenges, and it would be beneficial to further analyze the challenges to support the adoption of blockchains in energy domain. Moreover, existing regulations and frameworks are designed for centralized energy system and organizational and legal responsibilities need to be clarified to support the adoption of blockchains in decentralized energy systems.

Based on our work, we give the following recommendations for future research directions, which also presents limitations of our proposal:

- It would be useful to continue and broaden comparative research on impacts of EU-level and national policies for advancing cross-commodity energy sharing solutions to facilitate learning between policy makers at various levels and those developing new concepts. The outcome should be new, or refined concepts to incentivise cross-commodity energy sharing.
- Future energy solutions require combining novel communication and security technologies that are designed for decentralized operation. This also requires rethinking at policy level to support technologies that are can be used on a local level instead of requiring nation-wide deployments.
- Security-by-design is a central challenge for the discussed ICT solutions. Central challenges are the vertical integration of different technologies, including their complexity.
- Standardized interfaces are required to combine the necessary building blocks for the envisioned ICT solution.
- The research on AI methods should focus on practical implementations with real buildings instead of simulation environments. To support this, research is needed to enable more data-efficient, robust, and adaptive methods both for supervised and reinforcement learning.
- As the regulation and technical framework is evolving very fast. New business opportunities should be scouted frequently.

Declaration of competing interest

The authors hereby confirm that they do not have any known conflicts of interest.

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