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Review

Digital Twins for the Future Power System: An Overview and a Future Perspective

Zhao Song [1], Christoph M. Hackl [1,*], Abhinav Anand [2], Andre Thommessen [1], Jonas Petzschmann [3], Omar Kamel [2,4], Robert Braunbehrens [2], Anton Kaifel [3], Christian Roos [4] and Stefan Hauptmann [4]

1 Laboratory for Mechatronic and Renewable Energy Systems (LMRES), Munich University of Applied Sciences (HM), 80335 Munich, Germany
2 Wind Energy Institute, Technical University of Munich (TUM), 85748 Garching, Germany
3 Center for Solar Energy and Hydrogen Research Baden-Württemberg (ZSW), 70563 Stuttgart, Germany
4 MesH Engineering GmbH (MesH), 70563 Stuttgart, Germany
* Correspondence: christoph.hackl@hm.edu

Abstract: The inevitable transition of the power system toward a sustainable and renewable-energy centered power system is accompanied by huge versatility and significant challenges. A corresponding shift in operation strategies, embracing more intelligence and digitization, e.g., a Cyber-Physical System (CPS), is needed to achieve an optimal, reliable and secure operation across all system levels (components, units, plants, grids) and by the use of big data. Digital twins (DTs) are a promising approach to realize CPS. In this paper, their applications in power systems are reviewed comprehensively. The review reveals that there exists a gap between available DT definitions and the requirements for DTs utilized in future power systems. Therefore, by adapting the current definitions to these requirements, a generic definition of a "Digital Twin System (DTS)" is introduced which finally allows proposing a multi-level and arbitrarily extendable "System of Digital Twin Systems (SDTSs)" idea. The SDTSs can be realized with an open-source framework that serves as a central data and communication interface between different DTSs which can interact by "Reporting Modules" and are regulated by "Control Modules" (CMs). Exemplary application scenarios involving multiple system levels are discussed to illustrate the capabilities of the proposed SDTS concept.

Keywords: digital twins; power systems; multi-level systems; framework

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1. Introduction

The increasingly problematic challenges due to climate change and the growing energy demands imply that the current energy system has to transition rapidly. The transition must address the urgent need for sustainability while ensuring that social development is not compromised. Consequently, changes are required on all levels of the system, such as generation, conversion, storage, and consumption. Academia, industry, governments, and society must pave the way with sustainable innovations, products, policies, and acceptance. In addition to economic feasibility, the key technical challenges are the efficiency and stability of the future decentralized energy system whose backbone will be the electrical power grid. The following aspects must be considered during its design, implementation, and operation: (1) more renewable energy resources will be integrated, leading to a distributed and decentralized generation [1]; (2) correspondingly, the fraction of conventional centralized power plants in the power system will keep declining [2]; (3) the installation of energy storage systems will provide more flexibility in generation, conversion, and consumption [3]; (4) the electrification of more and more prosumers will significantly change the load profiles and challenge power grid capacity and stability [4]; (5) the capability of back-feeding from prosumers to the power grid will and already increases the complexity of the power flow [5,6]; and (6) the electricity markets will drastically evolve according to the changing roles of consumers and prosumers in order to unleash emerging financial opportunities [7]. These trends will result in a versatile and dynamic power system in the future, which requires high intelligence and digitization based on the huge amounts of data to achieve proper, safe, and secure operation [8]. Emerging technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Cloud Computing are driving the wave of Industry 4.0, creating vast opportunities and allowing for a paradigm shift in control and operational approaches in the energy sector [9,10]. Building upon these technologies, digital twins (DTs) are gaining momentum as a promising tool for realizing intelligent power systems. Initiated by aerospace and manufacturing applications, the digital twinning technology finds its place where integrating services based on observations and predictions of the real-world system is needed. For example, General Electric is implementing DTs to monitor and predict asset performance so that operation and maintenance costs can be lowered [11]. Siemens is also reducing energy consumption by the use of DTs to predict the battery capacity as frequency containment reserve for transmission operators [12]. Nevertheless, DTs in the power system are not mature and are in their early stages of development, as most solutions or approaches are only given conceptually; e.g., in [13], a possible modular design of a DT is proposed to combine multiple applications-specific models for powers systems; while in [14], the concept of a DT for microgrids is introduced. Although there already exist a few literature reviews of DTs in power systems, a synthesis, concerning the structural and operational characteristics of the future power system and the respective requirements of DTs used in such a power system, is missing [15,16].

1.1. Motivation: Why Should We Apply DTs to the Future Power System?

Due to the increasing penetration of distributed renewable energy resources and active prosumers, the future power system must and will undergo a drastic transition in its operational strategy. On one hand, the uncertainty of the renewable energy availability and the installation of power electronic converters as grid-tied interfaces will inject not only stochastic but also deterministic disturbances into the grid [17,18]. Furthermore, due to the growing drop-out of conventional synchronous generators, the available inertia in the system will drastically reduce, which threatens grid stability as intrinsic power reserves vanish. On the other hand, a significant optimization potential emerges in efficiency and economic benefit as the distributed power converters allow for increased flexibility, fast dynamic response, and the optimal (local) management of generation and consumption [19]. The generation will consist of multiple renewable energy sources and storage systems, whereas the consumption will accommodate the local and individual needs by, e.g., economic dispatch [20] and peak shaving [21]. To tackle the challenges arising from this transition and embrace the disruptive opportunities, environmental, economical, and functional information of the interconnected system and its agents in real time is essential. The concept of Cyber-Physical Systems (CPSs) has been gaining prominence in the last decade. Its core idea is to integrate computational and physical components into the virtual world to implement optimized processes in the real world and to transform and equip energy systems at all levels with intelligence, reliability, and security [22]. The integration relies on modern modeling methods and the systematic investigation of the interaction between physical and cyber system [23]. In this regard, digital twins (DTs), based on models of the physical systems and equipped with communication and computing technologies, are a popular and meaningful approach to realizing CPS [24–26]. The ability to capture, predict, and visualize either virtual or real states for human–system interaction and to provide services for autonomous operation makes DT a key enabling tool for establishing cyber-physical power systems.

1.2. Problem Statement: What Are the Challenges of Applying DT to the Future Power System?

Unlike conventional models for a single component or an asset, a DT in the context of a power system distinguishes itself by diversity in composition and complexity in operation. Continuous live data are usually required for a proper state observation and/or prediction of the system. Moreover, due to the heterogeneity and distributed characteristics of the future power system, the data flow between subsystems and the sharing of expertise among different stakeholders or fields are prerequisites for a seamless holistic system optimization [9]. The operation of such a complex system comprises, e.g., the switching of power electronic devices on the component level, maximum power point tracking on the unit level, optimal wind park control on the plant level, and frequency and voltage stability on the grid level. The goal is to enable flexible but stable operation of the overall system and also to allow for distributed and optimal energy management of the local subsystems. Depending on operation targets, communication and interaction can be required across component, unit, plant, and grid (system) levels involving timescales from microseconds to days [27,28]. A holistic framework offering this communication and interaction to orchestrate data flow, storage, exchange, and analysis and to coordinate all subsystems in a standardized and generic way allowing for various data sources, protocols, and communication channels must be developed. Moreover, the capability of (pre-/post-)processing of massive amounts of data with small latencies must also be addressed while specifying such a framework architecture [29]. In addition to these requirements, the modular nature of power systems due to several hundreds to thousands of individual units should be captured by its virtual representation as well. The modular design must not only provide the potential for "plug-and-play" functionality in physical systems but also minimize the adaption cost for system extensions by including more and more DTs [13]. Based on modularity, large-scale power systems are expected to exhibit hierarchical structures, whose real-time control is usually performed on a multi-level basis [30,31]. It is therefore mandatory that multiple control layers from the component, unit, plant and system level must be feasible within the DT framework. In brief, referring to DT design according to the addressed power system requirements, the following must be investigated and addressed by a holistic framework:

- Availability and integration of live data from physical systems;
- Flexibility in distributed definition and operation of applications and services;
- Generic capabilities for communication and coordination;
- Modularity and extensibility.

However, as the literature review in the following section will reveal, most discussions on DT technologies limit themselves either to application-oriented models for small-scale objects or lack generality when implemented in the context of the overall power systems. A DT solution, which covers all of the above-described requirements for power systems, is still not available and remains an unanswered research question.

1.3. Proposed Solution and Vision

In this paper, we bring up the idea of a "System of Digital Twin Systems" (SDTS), which is composed of modular Digital Twin Systems (DTSs) and, based on a holistic framework architecture, allows for an arbitrary extension to an ultra-large-scale SDTS. The proposed SDTS and its corresponding framework are generic in design, enabling services defined and provided by multiple stakeholders. Moreover, the proposed concept is not limited to power systems, although this is our focus in this paper. The hierarchical and coordinated structure guarantees that each individual DTS can operate independently at their own relevant level (such as component, unit, plant, or system level). Meanwhile, data flow, communication channels, and computation/analysis can be orchestrated among these DTSs.

The rest of this paper is organized as follows. Section 2 reviews the state of the art of DTs including common definitions, concepts and implementations, and the underlying enabling technologies. In Section 3, the definition of a general Digital Twin System (DTS) is refined and sharpened in order to introduce the key module of the overall concept of the System of Digital Twin Systems (SDTS). Possible applications considering multiple levels of the future power system are discussed and illustrated. Finally, Section 4 summarizes and concludes this paper.

2. Review

Although it has been almost two decades since the introduction of the term "digital twin", its definitions, its characteristics, and its implementations remain very use-case-dependent. In this paper, we firstly collect and summarize the most fundamental definitions of DTs in order to highlight commonalities and distinctions. After that, the essential enabling technologies behind DTs are introduced to give ideas on how a DT is or can be realized. In the end, we focus on applications of DTs to the power system, ranging from basic modeling approaches to complex realizations such as smart energy management systems. The considered system aspects expand from mechanical and electrical component to unit, plant, and system levels. Based on the requirements raised in Section 1.2, a comprehensive evaluation is given as to whether existing DTs can fulfill the needs of the future power system and which gaps still do exist.

2.1. Existing Definitions of Digital Twins

Since the term "digital twin" was firstly coined in the year 2002 [32], the idea has been applied to a wide range of industries under various interpretations. Applications in manufacturing, aviation, medicine, and the energy industry have led to different conceptual understandings of what a DT actually is and what it can be used for [33]. Despite the differences in details, the most common consensus about the DT concept, as shown in Figure 1, consists of three core elements: A DT is thereby generally defined as a co-existing *Virtual Representation* of a *Physical Asset* and their bidirectional *Communication* (defined as "two-way data flow" in [34]). Building upon this essential idea, definitions diverge into two directions: Either there are narrower definitions focusing on only partial elements of Figure 1, or there are broader interpretations which cover all necessary application-dependent subsystems to provide the required DT functionalities.

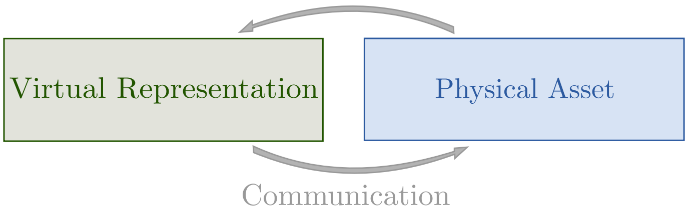

Figure 1. Core concept of a digital twin: A virtual representation, co-existing along with the physical asset in combination with bidirectional communication between them.

Some authors regard DTs only specifically related to the considered applications. In [35–39], a DT is characterized as an ultra-high-fidelity representation of the corresponding physical asset that can be integrated into the software. Data and communication in these cases are regarded as peripherals of DTs whose functions were provided externally by the software environment. The models are developed using either a multi-physics-based approach, a data-driven probabilistic approach, or a combination of both [40,41]. However, these proposals focus more on modeling structures for system representation. The modeling perspective is extended in [42,43], where the data transmission and exchange between the models and their corresponding physical assets are considered in real time. However, these formulations still lack the presentation of how such data exchange can contribute to real-time control operations. It should be noted that if a virtual representation is used only to represent the physical asset without influencing the real world, such a "one-way data flow" model is usually called a "Digital Shadow" instead of a DT [44].

Others have broadened the definitions and considered the DT in a more systematic way. Based on the standard three-elements architecture [45] (recall Figure 1), a more elaborated view on the DT was proposed in [46] by carving out *five* essential components: *Real System*, *Virtual Model*, *Services*, *Data* and *Connections*. This definition fuses *Data* from the physical–virtual interaction for information capture. It also encapsulates functions of the DT (e.g., detection, judgment, and prediction) in the *Services* component for unified management and on-demand usage. Extending from a single DT, a concept of networks of DTs was proposed in [47], where a superordinate unit named Digital Twin System was raised to coordinate centralized communication among individual subordinate DTs. However, the question of how the DTs under different superordinate units communicate with each other was not discussed. Moreover, the interactions between the virtual and physical worlds were not described.

Although these existing definitions of the DT concept convey almost fully the basic underlying essence, a clear demarcation between the essential inherent capabilities of the DT and those derived externally is lacking. A generic, configurable, and extendable Digital Twin System (DTS), that fully covers all DT features internally and externally, needs to be defined. Furthermore, a holistic representation of a complex, hierarchical real system where several DTS constitute a System of Digital Twin Systems (SDTS) has not yet been discussed. This can also be seen in [48], where a sustainable energy management system has been developed to be used in a DT framework for a smart city. Although the authors have considered the power system holistically, the work did not take into account the explicit hierarchies in the power system. Additionally, capturing the underlying interactions within such an SDTS is of paramount importance.

In this paper, we recognize the five-element definition in [46] as the key basis of a single DTS, which will be sharpened and extended to a multi-level structure in Section 3.

2.2. Enabling Technologies of Digital Twins

The birth and evolution of DT can be rooted back to the development of its enabling technologies, which support the functionalities of a DT. Requirements on synchronized measurements, accurate models, real-time communication, and the processing of tremendous amounts of data among services are fulfilled by them. In this section, enabling technologies are presented in accordance with the following aspects: data acquisition, modeling, communication, computing, and data analysis.

2.2.1. Data Acquisition

As a bridge between the digital and physical world, measurement and sensing devices feed the functionalities of a DT with live data. The interfaces for data acquisition need to be consistent and the used protocols need to provide the necessary transmission rates such that the DTs stay synchronized; in particular, as different types of applications have different requirements regarding transmission latency.

SCADA/PMU: The Supervisory Control And Data Acquisition (SCADA) system provides conventionally the data exchange between a control/monitoring unit and the associated devices. With technology advancements, SCADA systems are able to work with microprocessors in a wireless way, gathering measurements from remote units or controllers; however, this takes place at a low update rate and lacks a time stamp [49]. Phasor Measurement Units (PMUs), as a multifunctional signal acquisition system with a much larger sample rate compared to SCADA, are increasingly utilized in power system control centers for real-time identification and monitoring, improving condition monitoring and the fault detection and diagnosis of power systems [50]. Based on the Global Positioning System (GPS), PMUs can provide locally synchronized phasors of phase voltages and currents over a wide geographical area, making it advantageous for detecting transient events in large-scale power systems, especially for stability-related issues, where instant decisions are crucial to avoid further fault propagation [51]. Although the optimal placement of PMUs as a compromise between full estimation capability and hardware investment costs still remains an open research question [52], the combination of SCADA and PMU in DT is a promising basis for an intelligent and automated control system for power systems [53]. Condition monitoring estimates the state of the asset over a long period of time. The usual update rate of SCADA systems is in the order of minutes and is sufficient for such slow tasks [54]. For other DT applications, such as asset optimization algorithms, much lower latency and much faster computational execution are crucial. Data acquisition should be implemented through a PMU system.

In the future, open questions about data availability need to be addressed. Often, data are proprietary and protected by data security regulations. This limits the available test cases for digital twin development. Recently, more and more data sets are being published as open source (e.g., wind farm operational data). This will help to spread and validate DT implementations [55].

2.2.2. Modeling Technologies

As the essential element of a DT, an accurate virtual representation that is able to deliver real-time simulation results, or predictions, is the key challenge of the modeling problem. Although being a classical and developed research topic, how to model complex, large-scale power systems with desired cost and accuracy remains to be addressed, for which system identification and model reduction are most relevant in adopting the DT technology.

System identification: To represent the physical system with high accuracy and in real time, it is required that the models are updated to reflect changes or degradation due, e.g., to aging. System identification is the process that updates the parameters of the mathematical description of the dynamical system from measured input–output data [56]. Depending on the understanding of the system and its specific applications, the applied model present in a DT can be classified into three types: white box, gray box, and black box, where the a priori knowledge of the physical system structure decreases but the data reliability increases. Difficulties can occur at the interactions between submodels, where model assumptions and simplifications can lead to deteriorated overall model behavior even though the individual submodels are identified with satisfying accuracy and performance.

Model reduction: As the system complexity grows, the number of model states increases, and the simulation requires more computational effort. Model reduction is a technology for DTs of large-scale power systems to speed up the simulation while preserving the expected fidelity [57]. The exclusion or simplification of physical processes or components leads to a reasonable model order reduction if the effect on the considered system is negligible. Thus, for every model, a trade-off between modeling depth and simplicity as well as between simulation accuracy and speed has to be found. Well-established mathematical order reduction methods exist such as balanced truncation and Krylov subspace methods for linear systems, singular value decomposition and orthogonal decomposition for nonlinear systems [58]. A reduced-order model of the full system may lead to significantly larger simulation errors especially under disturbances [59]. To improve the performance, switching to full models from reduced models in a faulty occasion can be a meaningful solution [60]. In addition, model partitioning before order reduction is also a way to increase the simulation speed, as already applied in DTs for power electronic devices [61].

2.2.3. Communication Technologies

To unleash the full potential of the locally measured and acquired data, communication technologies should enable higher-level or global data access. For instance, this is key for data-based holistic system modeling and identification technologies. The significant increase in the amount of data exchanged in DT, either from local to cloud or between locally neighboring DTs, challenges communication capacity and the speed of conventional tools [62]. The need for high throughput and reliable communication with low latency can be regarded as one of the bottlenecks for realizing DT [63]. The demand of realizing large-scale DT systems without geographical limits and the trend of cloud-platforms lead to the idea of utilizing wireless communication in DT.

5G/6G: With transmission delay being as slight as milliseconds and bandwidth up to 20 GB/s, the 5G technology standard meets the stringent requirements for DT communication. The integration of data-intensive applications, such as machine-learning processes, can be contributed by 5G [64]. On top of this, the 6G network further strengths the communication ability with peak throughput improved to 1 TB/s, enabling distributed DTs over the cloud and at the edge [65]. Alternatively, the resilience of communication networks benefit from applying DTs in combination with AI improving monitoring and analyzing the performance of the network [66].

Offering a high data rate is essential for DT applications, but future communication technologies should also take the energy consumption footprint into account. For instance, the widely adopted Passive Optical Network (PON) technology causes a high energy consumption footprint [67]. In [67], the operation strategy to control the PON infrastructure is adapted online in order to minimize the energy consumption while meeting the required transmission and data quality. This is based on a DT-assisted framework to track the PON performance in real time. Thus, the trend toward the communication of big data comes along with an intelligent (and possibly DT-based) use of infrastructure.

2.2.4. Computing Technologies

The actual deployment of large-scale DTs requires flexible and distributed hardware, while in the scope of power systems, the combination of cloud computing and edge computing matches the need for grid control systems and local distributors.

Cloud computing: Cloud computing offers computing services and resources to users without sufficient access and availability of their own hardware and software. The pure provision of resources such as computing power or storage capacities is known as Infrastructure-as-a-Service (IaaS). Platform-as-a-Service (PaaS) additionally hands over programming or run-time environments to the user of the service. In contrast to IaaS and PaaS, Software-as-a-Service (SaaS) also provides access to application software and algorithms. Cloud computing aims at cost reductions through outsourcing and on-demand use of hardware and software to a centralized system. The cloud computing provider benefits from high-capacity utilization of the hardware and software.

Edge computing: As introduced in [68,69], edge computing is the paradigm of distributed computing. Contrary to cloud computing, the computation and data storage capabilities are brought closer to the end user. This reduces latency in time-critical processes as decisions are made close to the physical location of the asset, which suits local controllers in power systems. Furthermore, bandwidth can be saved by pre-processing data before sending it to a cloud server. On the downside, having more devices on the edge of the network raises security concerns as the number of targets increases.

2.2.5. Data Analysis

Closely linked to and driven by cloud/edge computing technologies, data-based analysis such as Machine Learning stands for one of the intelligent engines for DTs.

Machine learning: Advanced data science techniques are suitable for analytics as well as model calibration and adaption [52,70,71]. Classification and regression models are two main areas where supervised learning algorithms are useful. Here, a large amount of labeled training data is used to analyze a process and learn the underlying physics. Afterward, the learning accuracy is evaluated over test data. Depending on the accuracy level, the algorithm is modified or rerun to re-learn and to improve the accuracy [72]. In unsupervised learning, the algorithms attempt to categorize and highlight patterns and structures within data and thus do not necessarily require labeled data [73]. Deep learning refers to using neural networks that have more than one hidden layer [72]. These learning algorithms can be effectively implemented for both black-box and gray-box modeling approaches [71]. Model accuracy can further be improved by using standard verification, validation, and accreditation technologies employing static and dynamic methods [74].

In addition to mathematical models for real-world replication, data analysis plays an important role in realizing DT applications: With data sets either from models or from measurements, online monitoring strategies can be implemented and allow identifying abnormal conditions or faults by integrating Machine Learning algorithms [75]. Predictive operation and maintenance can also be achieved with data-driven forecasting [76]. By performing online training with measured data, data-driven models and services inside DTs can adapt to changes in the real world.

2.3. Digital Twin Applications in the Power System: A Review

Accompanied by the boom in enabling technologies, a significant development of DT applications has been witnessed in the last few years, spanning from concept descriptions to practical implementations. In this paper, we consider and categorize DT applications in the scope of power system applications. An exhaustive spectrum, ranging from low-level issues such as converter model parameters to high-level coordination, such as power distribution among microgrids, is considered in the literature. In correspondence to the consistency of future power systems with high renewable energy penetration, topics spanned across DT applications in wind energy, solar energy, power electronics as the future interfacing devices, microgrids, and the overall power grid. Starting with pre-digital twins, the literature review is arranged and evaluated with respect to the maturity of the DT technologies and their applicability to future power systems.

2.3.1. Pre-Digital Twins

Although not labeled as DTs, the essential idea of DTs can be glimpsed already from many technologies before the term was born. In some definitions, this is already considered as so-called pre-digital twins (pre-DTs) [40]. Comparing to the very primitive concept of DTs as shown in Figure 1, model-based adaptive control, for example, can be regarded as one of the embryos of the DT technology since they share the following in common:

1. A model is available, either physics-based or input–output-based—similar to the digital representation of a DT;
2. Controllers are designed based on the model and interact and affect the physical system operation—similar to the data flow-based action sent bidirectionally between the DT and the physical system;
3. Disturbances of the environment and changes of the physical systems are fed back to the model [77]—similar to the live data flow from the physical system to the DT.

Similar analogies are present for model-based state observers, which allows for reducing the number of measurement devices to design more sophisticated controllers (e.g., with full state feedback). By its ability to follow and mirror the dynamics of the physical asset virtually by feeding back measurements [78], observers can be regarded as another pre-DT. In addition to model-based methods, data-driven analysis, which is also a hallmark of DTs, has been widely applied to predict operation states and detect anomalies. Thus, typical functions of DTs, such as condition monitoring and fault detection, were realized without claiming the concept of DT, and they can be fairly regarded as a pre-stage of DTs [79–83]. However, although these pre-DTs can realize some applications that are now considered as DTs, they show limitations in data integration, computing power and flexibility in providing novel services. Moreover, a pre-DT usually works locally for small-scale systems with no or only a few communication capabilities.

2.3.2. Digital Twins

Ever since its invention, new applications gathered under the term "digital twins" keep emerging both in academia and industry. However, the integration degree of DT technologies varies a lot. To find out whether there is a DT concept already suitable for the future power system, the review results are categorized and evaluated based on four questions (Q1)–(Q4). These four questions are raised in line with the requirements raised in Section 1.2 and cover four perspectives: data integration, application flexibility, framework implementation, and hierarchical structure. By these four questions and perspectives, the technological maturity of available DT approaches shall be investigated and compared.

- **Q1: Are live data considered or integrated?** Although emphasized in many definitions that one of the DT's key aspects is the existence of a real-world physical device/asset living alongside the digital replica, we found out that this was ignored in many implementations. Several researchers actually limit their contributions to computationally fast models or methods that are identified and validated with historical data. In [84], the authors proposed a transformer DT model using measurements from the low-voltage side in order to estimate waveforms of the medium-voltage side instead of direct measurements. The DT model was validated with historical field data and was meant to be used for real-time (condition) monitoring. In [85], an analytical model based on an equivalent circuit was used in order to estimate the behavior of an induction machine. The analytical model was validated with a finite element model at steady state, which itself was validated with laboratory measurements. In order to estimate the states of a power converter, the authors of [86] used a neural network as a DT model, for which the training data were generated from simulations and the model was validated both in the time domain as well as in the frequency domain. An estimation method for wind turbine gearbox loads based on a linearized high-fidelity drivetrain model was proposed in [87]. The method with the purpose of estimating online fatigue damage was validated by simulations and measurements. Instead of a single component, Song et al. focused on the state estimation of inverter-dominated grids [88]. To do so, a neural network was trained with data obtained from traditional dynamic state equations of inverters and power grids. The model can be used in order to estimate actual or possible future states in the power grid. A similar approach of detecting grid anomalies with the help of a neural network was proposed in [75]. However, in contrast to [88], the grid anomalies detection method was presented as a module of a DT framework which has been proposed by the same authors in an earlier work [43]. In all of these papers, live data are not acquired online and have no impact on the virtual models or methods. Further steps to implement them as real-world applications are needed.
- **Q2: Are multiple applications or services possible?** In comparison to those contributions above, some authors include in their discussions the physical systems along with the virtual models aiming at different applications with integrated live data. In [36], a fault diagnosis method for photovoltaic systems was proposed based on the comparison between real and virtual measurements. Another fault diagnosis method which is based on deep transfer learning is proposed in [89], where the continuously measured data are used to update the DT model, and the simulation data compensates for the data unavailability problem for some fault conditions. Making effective use of data fusion and interaction between a physical asset and the respective digital representation, a DT-driven prognostics was applied to wind turbines (WTs) for health management in [90]. Combining a mechanical model and a set of measurements, ref. [91] estimates the loads on WT towers for real-time monitoring of fatigue. A dynamic load DT of power distribution grids which updates its parameters with online measurements was proposed in [92]. In [61,93], DTs were embedded in the FPGA of power electronic components for real-time monitoring and diagnostics, where measurements from physical counterparts are integrated online to generate scenario identification vectors or diagnostic thresholds (residuals). While in these cases, DTs are designed mainly and specifically for a certain application, this is neither realistic nor efficient for seamless and holistic control. In power systems, where multiple optimization tasks across different stakeholders and subsystems exist, it is desirable—instead of designing a corresponding DT for each desired application—to allow for generic information exchange among the stakeholders and to increase system redundancy. Thus, the flexibility of defining applications within an interconnected DT system despite the various service formulations is of uttermost importance. Such a collection of multiple DT applications is currently still and mainly found in the conception stage. In [94], a generic approach for fault detection and lifetime estimation of large generators based

on a multi-domain physical model is presented only theoretically. In [95], possible applications of DTs in the electric railway power system, such as energy management and power flow analysis, were discussed (without experimental validation). As shown in both references, the ability to implement multiple applications has the prerequisite that interactions among multi-physics models or subsystems are available, and communication channels to ensure the data exchange are available as well. However, generality is missing.

- **Q3: Is there a generic DT framework considered?** Multiple applications and arbitrary data flow imply that there could exist various digital models or servers within an interconnected system. This leads to the need for a generic framework or platform that is able to coordinate this data flow and process sources from several stakeholders. The role and importance of an encompassing framework are highlighted throughout the reviewed literature, but the discussions vary in detail and extent. The comprehensive overview study in [33] does not specifically analyze the usage of the underlying software platform. However, it is mentioned in the outlook that an open software platform would reduce the cost of DT development significantly. Some researchers propose theoretical DT frameworks that can map the requirements of particular use cases to modeling methods. However, the proposed concepts are only roughly described or not fully implemented. In [96], a possible DT framework that connects local energy communities and the electricity grid was designed. The possibility of modeling of different system levels and the resulting different timescales were briefly discussed. A concept that uses distributed networks to spread out computing and data among multiple agents was described in [97], aiming at alleviating the burden of a single master station in a large power distribution system. In [43], the so-called Automatic Network Guardian for Electrical systems (ANGEL) DT framework was introduced. It allows for real-time microgrid data visualization and detection of three-phase faults in a 39-bus benchmark configuration. Other authors include a detailed description of their software implementation but without claiming generality. In [25], a new data processing and computation architecture was proposed, supporting both fast data-driven security assessment and the conventional model-driven online analysis of power grids. Ref. [98] provided a detailed description of the necessary interfaces and communication protocols for a control architecture applied in distribution systems; all aspects are considered for a specific software platform only. To collect and fuse data streams from all connected assets, ref. [99] defines semantic objects and analysis algorithms based on the "semantic neighborhood relation", which is applied to a concrete use case in wind farms. Some contributions focus specifically on possible software architectures and guidelines in the design of DTs but without validation by practical implementations [39,100]. Although differing in their implementation methodology, most of the proposed frameworks share the idea of cloud-based data centers using IoT standards under the CPS environment [24]. While in [101], the data management, modeling and simulation module are incorporated together on one platform, ref. [29] propose a data-centric middleware-based platform that consists of distributed heterogeneous DTs in a standardized way, which is more suitable for applications in large-scale power systems. Due to its autonomy, fault-tolerance and consistency, ref. [102] brought the multi-agent system idea to the DT system structure for control and management in power substations, where data are shared among agents on a central database. Finally, ref. [103] specifies a generic software solution that implements the data structures as "things", which is a concept also followed in this study.
- **Q4: Is there a hierarchical DT structure considered?** A key question that comes along with the introduction of a DT framework is whether the framework itself is expandable and scalable to a hierarchical structure, as how it is expected to be necessary for power systems. With the increasing need of realizing coordinated applications or services across all system levels of the future power systems, a hierarchical structure

or organization of DTs is crucial, but this is usually not considered, and therefore, it is limited to very few cases in energy management. The first challenge to be faced is the modeling, since multi-physical domains with dynamics at different timescales are to be considered [95]. Another challenge is the interconnection among subsystems, where large latency and bad synchronization can deteriorate operation and performance. An IoT-based multi-agent CPS for energy systems, which combines low- and high-bandwidth physical models was introduced in [103], showing the potential of sharing power among interconnected microgrids to support the voltage at the point of common coupling (PCC) in a sequential control algorithm. However, the DT is not scalable and not independently operational, since all virtual models are bundled and run on one cloud service. A distributed implementation is missing. Similar to this, a DT for a national distribution feeder was proposed in [98] to optimize the reactive power set-points for multiple energy resources and to improve PCC voltage stability. To do so, state estimators based on data from multiple grid buses are utilized to reconstruct higher-level system states, but both levels discussed (plant and grid level) have the same timescales (seconds). In addition to optimized operation management, a real-time system reliability pre-assessment tool for the integration of distributed energy resources was proposed in [104] and covers both low and high system levels. The dilemma between the precision and physical limitations of large-scale systems was also addressed. In [48], an additional coordination layer was applied for several independent and modular subsystems to achieve optimal energy management under higher-level constraints. However, the results are again restricted to similar timescales. All these examples showed the trend of considering multi-level DT structures for the future power system, where multiple generation and consumption units are involved and a coordinated optimization must be performed. However, none of these contributions gave an explicit definition of a hierarchical DT structure that demonstrates modularity, scalability, extendability, and the interaction across all system levels with all timescales.

To conclude, despite the increasing interest in and works on DTs, most of them are application-specific and are solely implemented in this regard. Table 1 collects and summarizes the results of the literature review and categorizes them with respect to the four evaluation questions (Q1)–(Q4). Different DT applications are categorized based on their majurity level ranging from simple DT models mostly with “one-way data flow” (known as “Digital Shadows”) over more specific services or even conceptual DT architectures and complete frameworks.

Table 1. Literature review results according to the stated requirements of DTs for the future power system (✓, ✗ and ❍ indicate that requirements were “met”, “not met” and “partially met”, respectively).

Reference	Q1	Q2	Q3	Q4	Remarks
[84]	✗	✗	✗	✗	Static transformer model for online monitoring of the medium-voltage side from measurements at the low-voltage side (one-way data flow; Digital Shadow).
[85]	✗	✗	✗	✗	Analytical model of induction machine with static parametrization identified from finite element analysis (one-way data flow; Digital Shadow).
[86]	✗	✗	✗	✗	Converter models based on dynamic neural networks, trained offline with data sets from simulations (one-way data flow; Digital Shadow).
[87]	✗	✗	✗	✗	Static model for continuous estimation of wind turbine gearbox loads with online measurements (one-way data flow; Digital Shadow).

Table 1. *Cont.*

Reference	Q1	Q2	Q3	Q4	Remarks
[90]	✓	✗	✗	✗	Conceptual prognostics and health management based on the DT model, suggested action carried out both on virtual and physical assets (Digital Twin).
[88]	✗	✗	✗	✗	Inverter models based on neutral networks for grid state estimation, trained with simulation data from analytical models and fixed control algorithm (one-way data flow; Digital Shadow).
[75]	✗	✗	❍	✗	Detection of grid faults using neural networks trained with deep learning, data sets acquired from offline simulations, real-time critical due to small timescales (one-way data flow; Digital Shadow).
[36]	✓	✗	✗	✗	Real-time fault diagnosis for PV panels based on error residuals between DT simulations and measurements, implemented on FPGA with pre-defined fault signatures (Digital Twin).
[91]	✓	✗	✗	✗	Adaptive DT model based on Kalman filter to estimate loads on a wind turbine, accuracy depends on measurements and model (Digital Twin).
[92]	✓	✗	✗	✗	Statistic and dynamic grid load models online identified with Bayesian inference (Digital Twin).
[93]	✓	✗	✗	✗	Real-time model implemented on FPGA for monitoring and fault diagnosis of power electronics transformers, algorithms based on pre-defined error thresholds (Digital Twin).
[61]	✓	✗	✗	❍	Real-time and probabilistic model of converters implemented on FPGA, models partitioned to reduce computational load (rudimentary Pre-Digital Twin System).
[94]	✓	✓	✗	❍	Concept of a multi-domain physical simulation platform with multi-level control algorithms for large generators, centralized DT implementation (rudimentary Pre-System of Digital Twin Systems).
[95]	✓	✓	✗	✗	Conceptual modeling structure of electric railway power systems with communication between submodels, multiple applications possible (Pre-Digital Twin System).
[96]	✓	✓	❍	✓	DT platform/framework for local energy communities, applications run in different timescales but defined centrally (Pre-System of Digital Twin Systems).
[97]	✓	✓	❍	✗	Conceptual DT architecture using distributed networks to alleviate the pressure of master station, specified for smart power distribution (rudimentary Pre-System of Digital Twin Systems).
[43]	✓	✓	❍	✗	Conceptual DT framework for cyber defense with real-time and physics-based models, specified for microgrids (rudimentary Pre-System of Digital Twin Systems).
[25]	✓	✓	❍	❍	Event-driven DT framework for online analysis of distributed data grid, specified for power grids (Pre-System of Digital Twin Systems).

Table 1. *Cont.*

Reference	Q1	Q2	Q3	Q4	Remarks
[98]	✓	✓	❍	✓	DT framework for optimized voltage regulation with state estimation among multiple distributed energy resources, no generic implementation (Pre-System of Digital Twin Systems).
[99]	✓	✗	❍	✗	Conceptual cloud-based DT framework for wind farm monitoring, data transported in the form of semantic objects (one-way data flow; Digital Shadow).
[39]	✗	✗	✓	✗	Generic DT architecture describing the interactions within the CPS, limited to single-DT cases (Pre-System of Digital Twin Systems).
[100]	✓	✓	✓	❍	Generic DT architecture based on the 5-dimensional DT, coordination among multiple DTs, modularity not shown (rudimentary Pre-System of Digital Twin Systems).
[101]	✓	✓	❍	❍	Cloud computing-based DT platform specified for distributed and centralized integrated energy systems, modules are implemented centrally (rudimentary Pre-System of Digital Twin Systems).
[102]	✓	✓	✓	❍	Multi-agent construction of power substation DTs, agents are defined within a single DT as different executors, no communication among DTs (Pre-System of Digital Twin Systems).
[103]	✓	✓	❍	✓	DT-based procedure for assessing the impact of integrating renewable energy, both locally and globally by centralized DT implementations (Digital Twin System).
[104]	✓	✓	✗	✓	An IoT-based DT of connected microgrid systems with communication between "things" and "things" in the cloud, distributed controllers but centralized DT models and services (Pre-System of Digital Twin Systems).
[48]	✓	✓	❍	✓	DT framework for optimal energy management across multiple energy sectors, cross-level services possible, services and models implemented centrally in cloud (Pre-System of Digital Twin Systems).
This paper	✓	✓	✓	✓	Generic DT framework for modular extension across multiple levels, distributed and coordinated services possible (System of Digital Twin Systems).

The main outcome of the review is that a generalized hierarchical structure of a holistic DT system, with arbitrary interconnections between all modular components on all system levels in one framework allowing for distributed implementation, has not yet been proposed and introduced. The vision of such a holistic "Digital Twin System (DTS)" and, more important, a generic "System of Digital Twin Systems (SDTS)" is the main contribution of this work. Figure 2 illustrates the conceptual framework of this paper: from review to vision. The upper block in Figure 2 illustrates the idea of the "Review": After tracking the evolution of enabling technologies and various DT definitions and evaluating the DT applications, we found out that there is a need to extend the DT definition based on the available five-element structure to fulfill the needs and requirements imposed by the future power grid for the implementation of digital twins. This extension, its realization, and its potential applications are depicted in the lower part of Figure 2 in the "Vision" block. The individual blocks and sub-blocks in Figure 2 are linked with each other to illustrate (i) how DT applications rely on (enabling) technologies, (ii) how various DT definitions lead to the extended DT definitions and (iii) how the proposed SDTS concept emerged and should work: The framework is based on the enabling technologies (data acquisition, modeling, data analysis, computing, communication). It coordinates the data flow and exchange between the individual DTSs and allows a central or distributed data storage. By that, it enables the interoperability across different system levels and with external stakeholders (e.g., electricity markets). The interconnected DTSs provide services and cooperate with each other to achieve a holistic power system optimization taking economical aspects, efficiency, reliability and security into account.

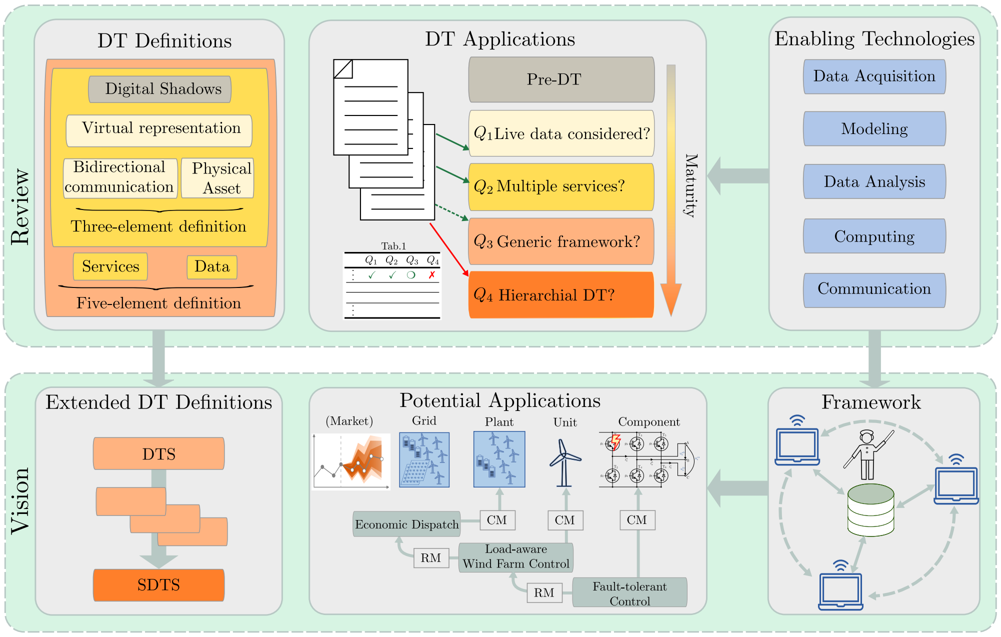

Figure 2. The conceptual framework of this paper: From review to vision.

3. Vision

As mentioned in Section 2.1, prior research has presented diverse definitions for DTs. However, a generic definition that can not only demonstrate the functionality and working principle of a single DT but also the co-working structure and interactions for multiple DTs is lacking. This gap is closed with our proposed definition. The definition is presented in two steps. Firstly, the existing definition of a DTS from [90] is refined and sharpened for a single-level structure. Afterwards, the single-level definition is generalized and extended modularly to the multi-level structure to introduce the concept of "System of Digital Twin Systems (SDTS)". A framework that covers the need of the defined SDTS will be introduced as well. In the end, three possible application scenarios of the SDTS for the future power system based on the proposed framework will be discussed.

3.1. Digital Twin System: Definition & Concept

For this paper, we propose the following definition (as illustrated also in Figure 3).

Definition 1 (Digital Twin System (DTS))**.** *A digital twin system consists of a digital twin and its corresponding physical asset. The digital twin digitally runs alongside the physical asset. The digital twin is structured into three interconnected parts: Virtual Model, Data and Services. The physical asset and the parts of the digital twin are interconnected via Connections. The digital twin system can adapt and reconfigure itself to mirror the actual state of the physical asset during its life cycle and offers services to improve/extend the performance and capabilities of the physical asset. These functionalities can be availed using the reporting modules (RM) and the control modules (CM) of the digital twin.*

Figure 3 shows the single-level representation of the proposed DTS. Uni- or bidirectional connections are represented by uni- or bidirectional gray arrows. Extending the proposal from [90], the service dimension is additionally split into two categories, i.e., the *intrinsic* and the *extrinsic services*. Intrinsic services are indispensable for the configuration of the DT that support the basic operation of a DT. In contrast, extrinsic services are optional services that provide further in-depth knowledge of the DT and its interconnected dimensions and/or the physical asset. Extrinsic services can be defined and modified according to the application scenarios of the DT.

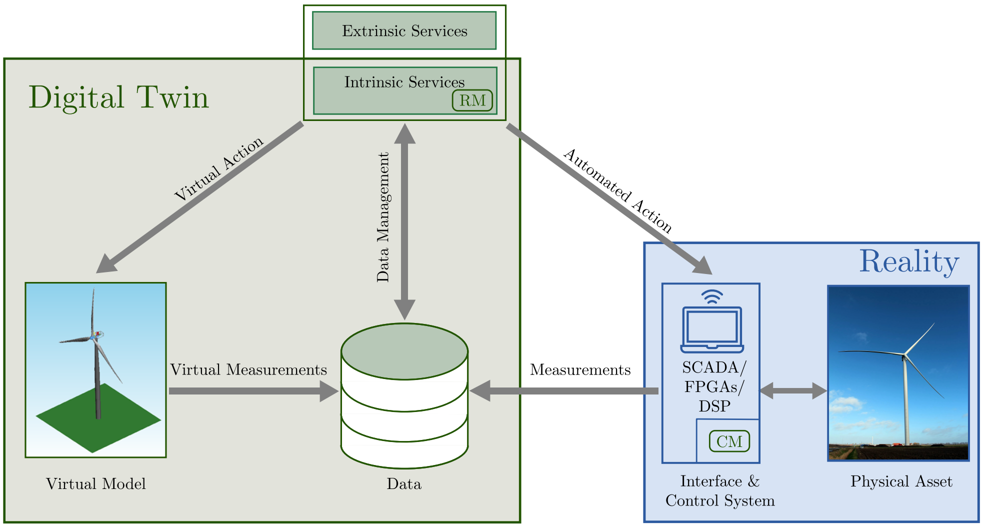

Figure 3. Digital Twin System (DTS) that consists of the digital twin and its corresponding physical asset. The green box represents the boundary for the digital twin, which consists of a virtual model of its physical counterpart, data (storage), and services.

The following bullet points describe the five pillars of a DTS in detail:

1. **Physical Asset** is the physical counterpart of a DT. In the proposed formulation, a physical asset also includes the corresponding standard control and the SCADA/FPGA/DSP system which can provide an interface for connections to the DT. The physical asset can be a component (e.g., IGBT-module, drivetrain), a generation unit (e.g., wind turbine) as well as a power plant (e.g., wind farm), or even the grid itself. FPGA/DSP systems are more frequently applied on the component level, whereas SCADA (or in combination with PMUs) is applied on the system level. By sending *(real) measurements* to the DT and receiving *automated actions* (commands) from DT services, the DT influences the physical asset operation via the *control module (CM)* that is contained in the control system. In essence, a CM could run on the cloud or could be part of the local (sub)system, either on a separate hardware or integrated in the existing SCADA/FPGA/DSP system. Moreover, CMs can have dedicated buses or utilize the same data bus as the associated control system. The physical asset together with its corresponding control interface system is illustrated as *Reality* in Figure 3.
2. **Virtual Model** is a physics- and/or data-based model of the physical counterpart which usually runs digitally alongside the physical asset and generates *virtual measurements*. These virtual measurements can either be representations of current states or their predictions. The potentials of, e.g., reducing sensors, detecting irregularities or faults, and optimization can be unfolded based on such virtual measurements. The virtual model receives *virtual actions* from the running services that determine which and how the model should be applied and adapted.

3. **Data** represent the stored version of (real) measurements from the physical asset and virtual measurements from the virtual model. The data can represent actual and/or historical measurements or predictions of events yet to come. Furthermore, data are exchanged with the services through the *data management*.
4. **Services** provide the functionalities that add benefits and intelligence to the whole DTS. Services are divided into intrinsic and extrinsic services.
    - **Intrinsic services** are essential elements of the architecture of DTs and ensure realizations of functionalities of DTs. They include data coordination between different dimensions of the DT, providing calibration and adaptation of the virtual models to improve the reflection of the actual state of the physical asset and to ensure synchronization between different system clocks. The behavior of DTs can also be interfaced with an external system using *reporting modules* (RM). Such information can be used for the performance evaluation of DTs, long-term analysis, or to provide input to a separate application running on an external system.
    - **Extrinsic services** establish additional functionalities that DTs can provide to the physical asset. For example, extrinsic services such as condition monitoring enable the user to take strategic decisions (e.g., predictive maintenance). Another example can be an advanced control task such as the coordination of generation units at the plant level for a more economic dispatch. Multiple and different extrinsic services can be added (and removed) to the overall service portfolio according to the demands of the stakeholders. They are therefore an add-on, not critical for establishing or running a DT and, therefore, are placed outside the boundary of the DT in Figure 3.
5. **Connections** stand for communication channels that are established and maintained between physical assets, data, virtual models and services. As shown in Figure 3, the connections are the embodiment of interactions between the DT elements and allow for data exchange of (i) real and virtual measurements, (ii) automated and virtual actions, and (iii) data management commands from services to the data center. They enable the exchange and synchronization of information.

3.2. System of Digital Twin Systems: Definition & Concept

As Figure 3 only shows a representation of a DTS for a single physical asset, it is not sufficient to capture the interconnected and cascaded nature of the power system today and in the future. For this purpose, we propose a generic *System of Digital Twin Systems (SDTS)* as well as a possible software framework. The proposed SDTS is illustrated in Figure 4. In a similar manner as a power system, it consists of different physical assets and associated DTs on four system levels (please note that the power system architecture is used here as an example to explain the idea of the proposed SDTS; the idea itself is generic to all multi-level systems) which are *Component*, *Unit*, *Plant* and *Grid (System) Level*. On the one hand, horizontal physical and virtual interconnections between different subsystems at a particular system level are crucial. On the other hand, *vertical interconnections* with different timescales of the subsystems capture hierarchical dependencies, where functionalities of the upper-level system depend on lower-level system states, and the operation of lower-level systems should follow higher-level constraints. As a result, a horizontally and vertically interconnected SDTS is established, with single DTSs as the basic modules. This idea is summarized in the following definition.

Definition 2 (System of Digital Twin Systems (SDTS))**.** *A system of digital twin systems consists of horizontally and vertically interconnected digital twin systems on all system levels such as component, unit, plant, and grid (system) level.*

The building block of the SDTS is the already introduced DTS corresponding to a single physical asset including the asset itself, the virtual model, data, services and internal connections, as shown in Figure 3. The physical asset interacts with the external world through SCADA systems or FPGAs/DSPs, depending on its vertical level. The bidirectional connections and resulting interactions between the physical asset and a SCADA system block represent the flow of control and data acquisition commands between both of them.

The horizontal bidirectional interconnection between the block "Reality" (blue box) and the corresponding block "Digital Twin" (green box) in Figure 4 represents the flow of real measurements from the physical asset to the digital twin, and the automated control action commands from the digital twin to the physical asset. The vertical interconnection between two subsequent levels on the "Reality" side connects lower and higher-level physical assets and highlights the possible bidirectional information exchange (blue tube). On the "Digital Twin" side, the vertical interconnection (green tube) represents the (possibly bidirectional) information exchange between the corresponding DTs on different system levels. Moreover, on each system level (as shown for the "Unit Level" as transparent blocks), the different DTs of one component, unit, or plant can also be interconnected to the DTs of one or more components, units or plants.

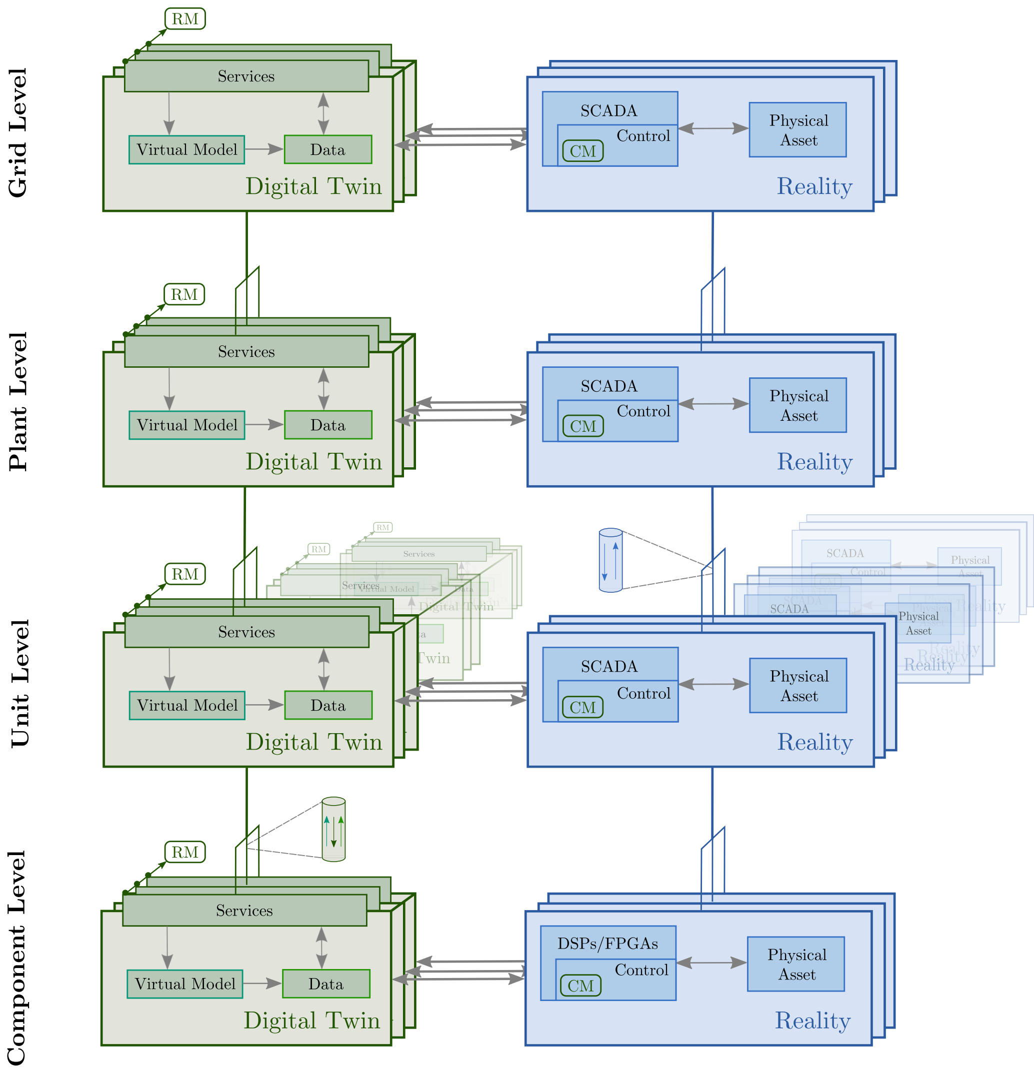

Figure 4. Visualization of a System of Digital Twin Systems (SDTS). The horizontal and vertical interconnections between different levels (Grid, Plant, Unit, Component) and entities ("Reality" shown in blue and "Digital Twin" shown in green). On each level (as shown for the unit level as transparent blocks), the different DTs can also be interconnected.

A physical asset at the upper level (e.g., a wind farm) is usually composed of multiple, lower-level physical assets (e.g., wind turbines). These are therefore represented by multiple, stacked "Reality" blocks. This cascaded nature runs from the topmost level (the grid level in our case) down to the smallest considered physical asset level (the component level in our case).

On the "Reality" side, the SCADA system of the physical asset at the higher level can gather status/data from the physical assets it is composed of and issues operational control commands to them. These two exchanges are explicitly highlighted in the snapshot of the interconnecting bus represented using two arrows in the blue tube. Similarly, on the "Digital Twin" side, the possible communication between the digital twins from two levels has been shown using arrows inside the green tube:

- The virtual model at a higher level could be composed of virtual models from the DTs at lower levels, either directly or possibly with reduced-order modeling. This requires model information flow between the hierarchies.
- The collected data can be sent to the higher level when needed; this could refer to the operational history data, time series of measurements, or current system constraints that could help in coordinating decisions made by the higher level services, etc.
- The lower level obtains the coordination commands from a higher level, which will be processed in the services block, and in the end, sent to CM implemented in the SCADA or DSP/FPGA systems.

In addition to the information flow through horizontal and vertical interconnections, DTs at a particular level are also capable of communicating with each other directly, irrespective of whether they belong to the same upper-level asset or not. This communication is indicated by the connection between the transparent blocks at the unit level as an example. Such a distributed communication feature can help to reduce latencies and offers additional possibilities for applications that require swift information exchange between the entities. Since the whole system is built upon each individual DTS, the extension to the SDTS can be realized in a modular way without significant adaptation work.

3.3. System of Digital Twin Systems: Framework and Implementation

To realize the SDTS as described in the previous section, a generic software framework for the creation and implementation of DTs and their orchestration is proposed. As shown in Figure 4, the central pillar of such a system architecture is to enable seamless data handling between multiple clients, where the "client" can either be understood as a physical asset, a virtual model, a service or the local data set that requires data exchange. Concerning this characteristic and the requirements raised for the future power system, the following functionalities should be fulfilled by the framework:

- Data exchange: Data exchange between a DT and its corresponding physical asset is necessary. In addition, communication between different parts of the DTs, i.e., the virtual models, services and data storage is useful. Data exchange between different DTSs should also be enabled. These requirements lead to the demand for a central communication hub.
- Data persistence: A client may require the data of other clients that are updated in different timescales, even when the clients themselves are not connected to the central communication hub. Therefore, at least, the last updated status of all clients must be stored persistently and accessible for other clients. In addition, for certain applications, time-series data need to be provided.
- Data compatibility: Due to the very different types of devices connected to the framework, abstract access options to the data, independent of the hardware itself, are necessary. The integration of already existing systems into the network should be possible with as little effort as possible.
- Cloud-based access: As the physical asset and its digital twin are not necessarily located at the same location, cloud-based access to the data is necessary as well.

- Data authorization: Since the software platform is running for multiple stakeholders, authorized access to specific data is necessary. In addition, the possibility of implementing different types of access, e.g., write or read-only access, is required.
- Data aggregation: The construction of higher-level virtual models and services involving cross-level coordination might require the aggregation of data from different sources.

Thus, the essential idea of the framework is a cloud-based platform, whose fundamental task is to provide a database for DTs and their physical assets that are connected to it and plays the role of a central communication hub. As a starting point to meet these intended functionalities, the open-source software Eclipse Ditto is considered, which is already used for IoT projects to manage classical DTs [105]. Eclipse Ditto, in the current version 3.0.0, provides standardized Application Programming Interfaces (APIs) on a database via multiple protocols such as HTTP, WebSocket, AMQP 0.9.1, AMQP 1.0, Kafka 2.x, MQTT 3.1.1, and MQTT 5. These protocols are commonly used in the IoT. Ditto features a database that stores data in nested key-value structures called *Things*. Things are generic entities and are mostly used as a "handle" for features defined under it. Things can contain data on the current states of connected assets, either physically or virtually measured. Things can also carry automated commands, e.g., setting reference points given by services. Communications are made in the framework by defining, writing, and reading Things that are accessible to dedicated users/clients. Subscribed clients are informed about changes made to data stored in the Things. Interaction between the connected clients is also possible by exchanging messages, which are distributed to all Things. For models in digital space, suitable libraries for connection via the given protocols are already available in common programming languages such as Python, MATLAB, or Java, or they can be easily implemented. Depending on the service needed, the communication can happen periodically or by event-based triggers.

In addition to the integrated functionalities of Eclipse Ditto, there are more features necessary to meet the requirement of the software platform, which are not provided by Eclipse Ditto itself. Nevertheless, it is to be noted that the described SDTS can be integrated into the network as easily as possible. While Eclipse Ditto provides the connections for DTs, data from physical assets should also be available in the framework. Such a connection can, for example, be implemented with the Eclipse Kura software, which is an open-source IoT Edge Framework. Eclipse Kura offers API access to the hardware interfaces of IoT Gateways (serial ports, GPS, watchdog, GPIOs, I2C, etc.) or field protocols (including Modbus, OPC-UA, S7), which are commonly used in state-of-the-art SCADA systems. In addition to these connections, to exchange virtual dynamic models across different software platforms and enable co-simulations among stakeholders, a standard called functional mock-up interface (FMI) has been described by the Modelica Association. To allow for an easy exchange of dynamical models for digital twins, an interface between Eclipse Ditto and FMI-based models has to be developed.

Based on the above discussions, the overall structure of the software platform is shown in Figure 5, where a single DTS is connected to it as an example showing the interactions, communication, and data flow. The platform provides several intrinsic services:

- The history service allows the connected clients to store data on cloud computing and access it with the native Ditto functionalities. In addition to the application within RMs, such processing of time historic data is essential for DTs that make use of iterations or services involving different timescales, e.g., DTs that are based on neural networks and apply real-time updates.
- The aggregation service allows aggregations between different data sets such as copying or calculations to be performed automatically by the framework. This is especially useful to group information from lower levels to a correspondingly higher level, i.e., collecting wind turbine data (unit level) and providing it to a wind park (plant level).

Interactions, such as data exchange or the configuration of a service, are performed via the same entry point and the same APIs for each connected client. DT functionalities, such as Machine Learning or uncertainty quantification, can be implemented accessibly for IoT devices by each client locally in the form of external services. Already existing functions can be integrated using the provided common protocols of the IoT. The concept of connecting all functionalities via cloud-based protocols allows the adaption to different requirements with regard to scalability, multi-fidelity, location independence, and modularization. As shown, the cloud-based framework itself works as the communication hub with data integration, while the computing tasks involved in services are run and completed locally at each client itself, thus making full use of distributed (edge) computing capacity to save data transmission bandwidth.

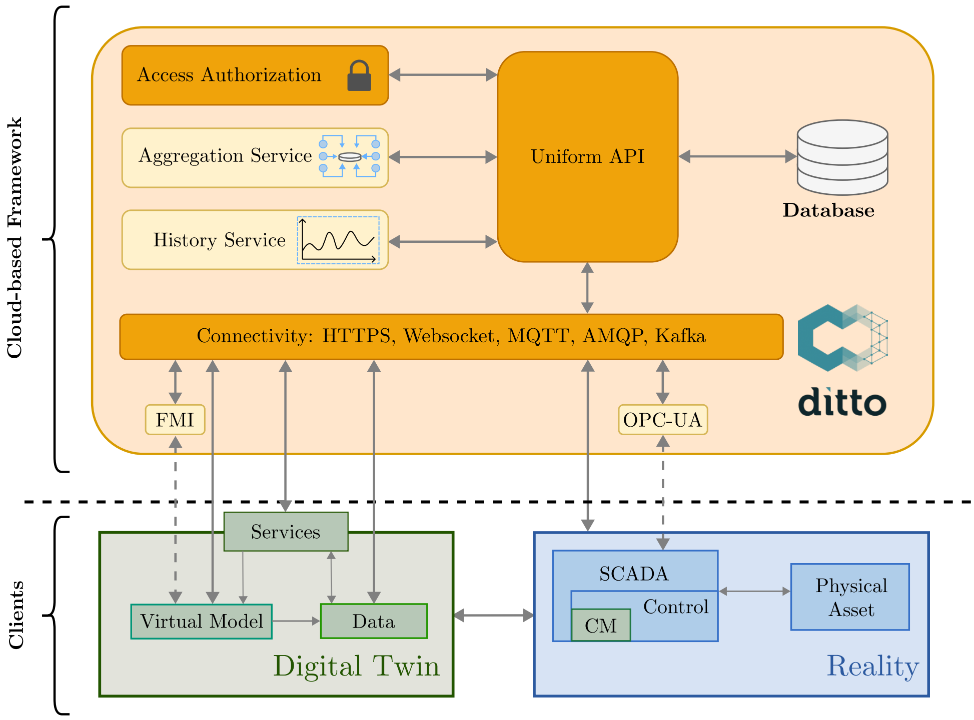

Figure 5. The cloud-based framework architecture connected to a single DTS.

3.4. Selected Application Scenarios for the Future Power System

The future power system faces several already described challenges which shall be handled and solved in a holistic manner that considers all system levels. In the following, three application scenarios incorporating different system levels are discussed. It will be shown that with the proposed SDTS and framework, a systematic optimization, exploiting the benefits of the DT technology, is feasible.

3.4.1. Economic Dispatch

In order to guarantee a stable frequency, the electrical grid needs to be in equilibrium between power injection and consumption at all times. Thus, market and physical processes need to be coordinated and aligned in a scheduling process before the time of delivery. This is achieved by dividing the system into balancing groups. Every injection or consumption into or from the electrical grid needs to be assigned to one balancing group. The balancing group manager is the responsible party to maintain the balancing group equilibrium within defined time intervals (normally 15 min). Due to forecast errors, this goal can only be achieved up to a certain extent. However, the remaining deviations between planned and real power production and consumption within the balancing group lead to costs as the transmission system operator charges for the resulting frequency regulation services in the form of balancing energy. These deviations can be avoided through pooled biddings on energy markets and plant adjustments through the balancing group manager [106–108].

Optimal economic dispatch within the balancing group management can be efficiently realized with the proposed SDTS on the grid and plant level as shown in Figure 6. On the plant level, probabilistic forecasting is realized so that uncertainty is taken into account during the bidding process from the overall optimizer on the grid level. The power forecast can be augmented with live data from the physical device, as this information improves the accuracy, especially of short-term forecasts. The forecast as well as the actual states of plants are communicated through the RM to the economic dispatch service. Based on this information, the economic dispatch service takes into account different market options and places bids for the aggregation of all plants. During the operation phase, the aggregated bids are matched by controlling the individual power plants of the respective balancing group. The calculated set points drop down from the grid level to the plant level where they are distributed to individual units of the power plant through the CMs.

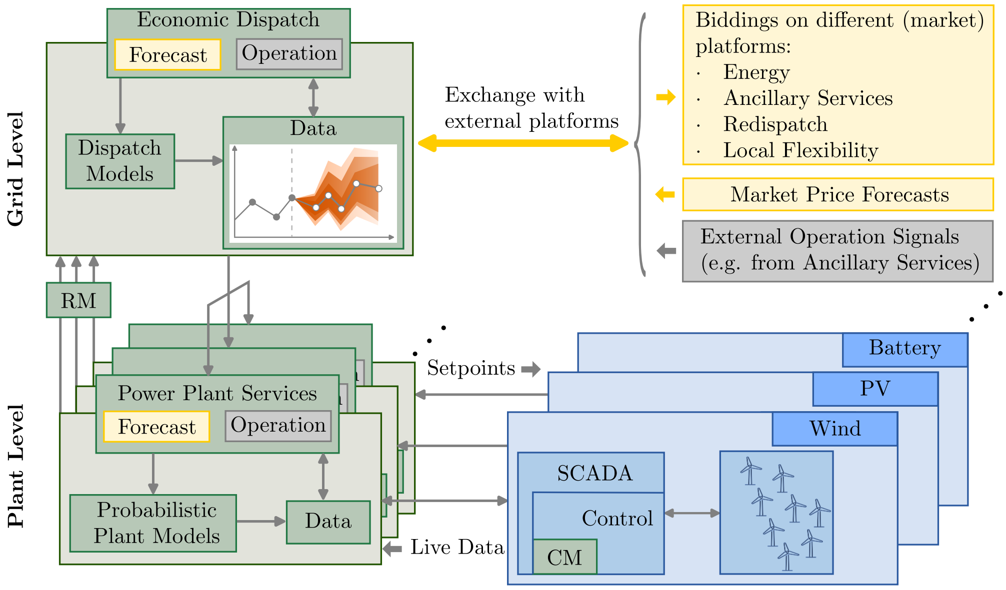

Figure 6. Exemplary scenario for grid and plant level: Economic dispatch based on probabilistic power forecast.

3.4.2. Load-Aware Wind Farm Control

Another possible application aims at exploiting the potential of the proposed SDTS in going beyond the conventional wind farm operation strategy toward economic wind farm operation. In the conventional approach, commonly known as the greedy control strategy, each turbine maximizes its individual power production. However, this neglects the costs caused by mechanical loads due to intra-plant flow effects such as wakes [109,110]. In case a battery unit is being used, a greedy operation further disregards the degradation and permanent loss in the charge capacity of the storage unit. With the proposed multi-level SDTS approach, this strategy could be replaced with an advanced economic operation where the revenue is maximized by considering resulting wake effects within the farm and mechanical loading of the individual units [111,112].

The scenario is visualized in Figure 7. First, the physical entities at the unit level (wind turbines, batteries) are connected to a super controller at the plant level. Its task is to determine the overarching control strategy for the entire plant. This is implemented in the form of an extrinsic service, which passes optimal set points down to the individual units. The goal is to consider the turbine loading in the set-point calculation. This quantity and the resulting fatigue damage accumulation depend highly on the ambient wind conditions. Consequently, there is room for optimization in situations with high loading but expendable power production. Two virtual models are necessary: first, a wind farm flow model, that mirrors the states of all relevant flow quantities, such as turbulence intensity, in the farm; second, a damage model of the turbines that predicts the instantaneous loading of each turbine under the current inflow conditions. However, the remaining lifetime of each individual turbine has to be computed at the unit level. Both are combined in an optimization algorithm to find the optimal set point.

At the unit level, the DTs of the individual units record the total damage and the remaining useful lifetimes for wind turbines, battery units, and others. The damage-tracking task is implemented as an extrinsic service, and the reported damage is communicated to the extrinsic service application running at the plant level. It should be noted that for accurate damage tracking of individual units, the corresponding DT shall utilize live measurements obtained from the SCADA unit of the respective physical entity.

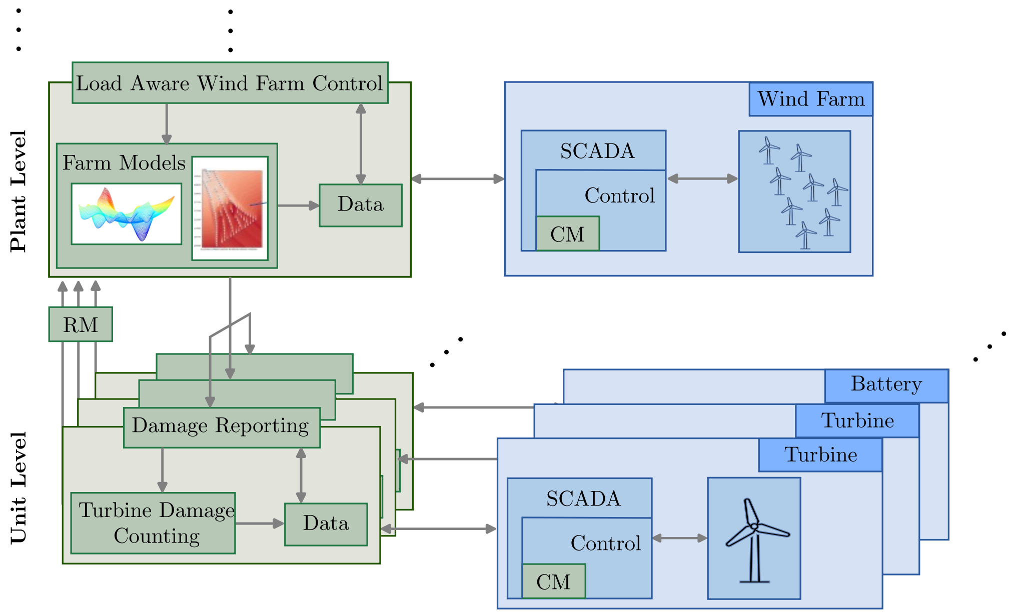

Figure 7. Exemplary scenario for plant and unit level: Farm control with revenue maximization by considering wake effects and mechanical loading.

3.4.3. Fault-Tolerant Control

In wind energy conversion systems, converter faults are one of the most frequent faults at the component level, which degrade the system performance [113]. A short-circuit fault is easy to detect and directly triggers a system shutdown. In contrast, an open-switch fault requires enhanced fault detection methods [113]. The latter fault degrades the system performance drastically or even causes secondary faults in other components if no proper counteractions are taken timely [114]. Thus, the generator is usually shut down after fault detection, producing no electricity at all and leading to generation losses. Instead, with the SDTS enabling online fault detection and diagnosis of the faulty switch, the CM switches to fault-tolerant control in that case, as shown in Figure 8.

More precisely, the virtual inverter models, running in parallel to the physical hardware, replicate the real inverter behaviors in normal operation. The fault detection and diagnosis are based on the comparison between virtual and real measurements, as unexpected fault leads to abnormal deviations. Finally, evaluating these deviations—e.g., by checking if characteristic thresholds are exceeded—triggers the CM to immediately switch from normal to fault-tolerant control. A possible fault-tolerant control is introduced in [114], where the injection of an optimal d-axis current for the machine-side inverter of type 4 wind turbines is presented with minor performance degradation. In addition, the fault diagnosis service in Figure 8 identifies the faulty switch and communicates with the upper unit level via the RM. The interconnections between different CMs shall work in collaboration to improve the operation of the whole unit.

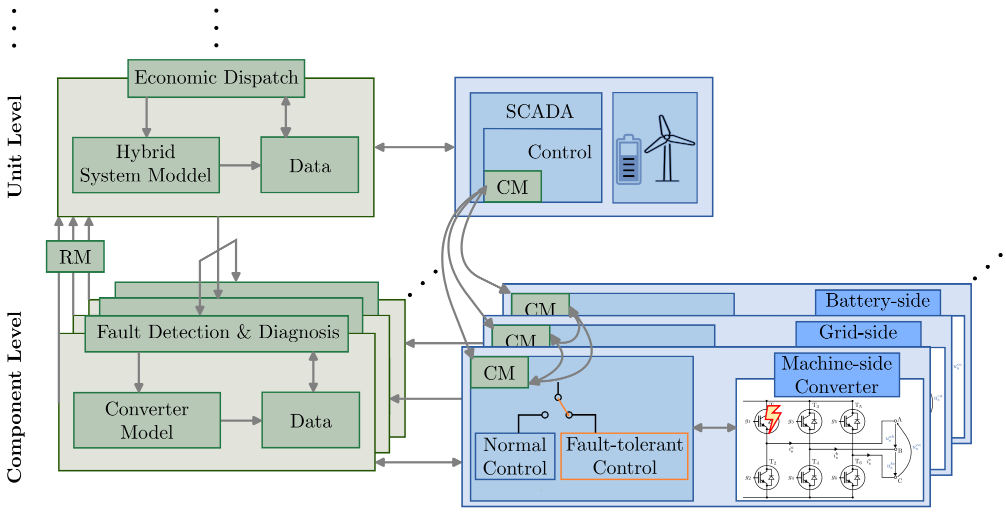

Figure 8. Exemplary scenario for unit and component level: machine control under open-switch converter faults.

In vertical communication between the unit and component level, the upper-level CM is aware of the fault and adapts the operation strategy of the economic control service, re-coordinates the generation of set points, and adjusts parameter tuning to achieve global optimization on the unit level; by, e.g., taking into account (slightly) increased losses and torque ripples during the active fault-tolerant control mode. For horizontal communication at the component level, considering a WT configuration with battery and assuming that the machine-, battery- and grid-side inverter share a common DC-link, a simple way of CM communication can be realized by modifying the DC-link voltage. For instance, if the machine-side converter feeds in less power to the DC-link after a fault, the DC-link voltage decreases. However, the battery-side converter recognizes the voltage drop, and its droop control automatically increases the power output in order to keep the DC-link voltage constant, or at least in a predefined range. As long as enough battery energy is left, the grid-side converter is able to provide the same services as in normal (fault-free) mode. Similarly, assuming a grid-side instead of a machine-side inverter fault, the battery can absorb extra energy to compensate for the reduced capability of feeding power to the grid. This allows the operation of the machine-side inverter and the wind turbine at the maximum power point as in normal mode as long as the battery is not fully charged. In summary, increased generation reliability is achieved by the proposed multi-hierarchical SDTS.

4. Conclusions

In this paper, a comprehensive literature review of digital twin (DT) applications with a focus on electrical power systems is given. The review assesses the existing DT definitions and evaluates their features with respect to the requirements imposed by the future power system and potentially needed DT capabilities. The review shows that there is a significant gap between definitions and features necessary for a generic utilization of DTs in future power systems. Therefore, an extended DT definition is needed to close this gap and to cover the wide range of implementations and applications of DTs. To this extent, a refinement of the existing definition is proposed to introduce a modular "Digital Twin System (DTS)", where the concept of intrinsic and external services is established, allowing to distinguish between the essential operational functionalities of a DT framework from additional stakeholder-defined applications. The idea of a "System of Digital Twin Systems (SDTS)" is introduced based on the refined DTS definition, where vertical and horizontal data exchange allows to (inter)connect DTS at the component, unit, plant, and grid (system) level, leading to a holistic cyber-physical power system with the potential of global system optimization. Afterward, a software framework for the proposed SDTS concept is proposed and implemented using and extending open-source software platforms. With a central database and distributed clients, the framework acts as a central communication hub for low-latency communication and provides flexibility in service definition and distribution. The modular architecture ensures an easy extension, and the generic data structure "Thing" makes the framework applicable to a universal use cases. Finally, three exemplary application scenarios that involve multiple system levels are discussed to illustrate the capabilities of the proposed SDTS concept to improve the operation of the future power system, taking into account economic and functional aspects. Currently, the practical realization and implementation of the proposed cross-level and cross-platform framework is under investigation. Although the general SDTS framework is already running on Eclipse Ditto, the implementation of, e.g., services becomes tricky as synchronization among different DTSs and non-deterministic communication latencies (over TCP/IP) must be taken into account. In conclusion, the proposed framework and the idea of SDTS allow for a generic implementation and application to future power systems; however, several technical issues must still be solved in the future.

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