Digital Twin Techniques for Power Electronics Based Energy Conversion Systems: A Survey of Concepts, Application Scenarios, Future Challenges, and Trends

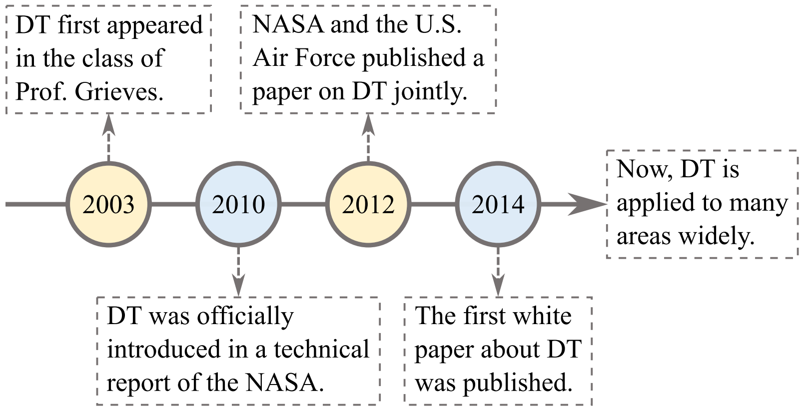
Haoyu Chen, *Student Member, IEEE*, Zhenbin Zhang, *Senior Member, IEEE*,
Petros Karamanakos, *Senior Member, IEEE*, and Jose Rodriguez, *Life Fellow, IEEE*

Abstract

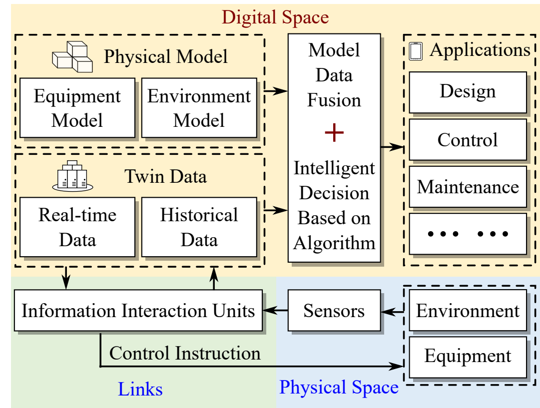
The steady increase in energy demands has led to an ever-increasing "energy generation". This, coupled with the need for higher efficiency, flexibility, and reliability, has boosted the use of power electronics in power and energy systems. Therefore, power electronics based energy conversion systems have become prominent in power generation, power transmission, and end-user applications. Given the relevance of such systems, and by considering their trend of digitalization, it is crucial to establish digital and intelligent power electronics based energy conversion systems. To this end, digital twin can be adopted as it integrates many cutting-edge information techniques to realize the life-cycle management of complex systems by constructing real-time mapping of them. In this paper, existing digital twin techniques for power electronics based energy conversion systems are reviewed. The concept, system layers, and key technologies of digital twin are described first. Some application cases of digital twin are then elaborated. Finally, future trends and challenges of digital twin are discussed to provide a valuable reference for subsequent research.

I. Introduction

In the new era of energy transformation, to cope with the existing power supply and environmental problems, distributed renewable energy generation systems (such as wind, wave, solar energy, etc.) have already been utilized on a large scale. In doing so, power and energy systems are rapidly developing towards a more power-electronics-based paradigm [1]. In addition, today's market trends—such as electrification, renewable power generation—combined with technology trends—such as higher power electronics system efficiency—enabled power electronics based energy conversion systems (PEECS) to become a major part



(a) Development history of DT.



(b) Structure diagram of DT.

Fig. 1. Basic information and introduction of DT.

of the modern power and energy systems [2]. Therefore, maintenance, particularly the so-called complete life-cycle management of PEECS, has become an important and relevant research topic.

To meet the requirements of the complete life-cycle management for PEECS, such as an accurate description of the system model and plenitude of supporting data, digital twin (DT) has attracted significant attention from many experts and scholars [3]. The DT of a system can accurately reflect the appearance and all the operating states as well as internal mechanisms of an entity in real-time. In addition to real-time capability and fidelity, DT also has strong scalability. DT can be easily combined with artificial intelligence (AI) and other advanced techniques, and it can successfully cover the whole process of product design, control, and maintenance [4].

TABLE I

EXPLANATIONS SOME TERMS RELATED TO DT

Terms	**Exlanations**
Physical entity	An discrete, identifiable, and observable object in the physical world.
Twin body	A digital model reflecting an entity from appearance and internal mechanism.
Physical space	A set of physical entities.
Digital space	A set of digital or virtual bodies.
Data	A standardized representation of the entity state.
Link	A tool that enables parts to communicate with each other.

Fig. 1(a) summarizes the development history of DT. The first appearance of DT dates to 2003 when Professor Grieves introduced the concept in his course on “product life-cycle management”. Therein, a three-dimensional model, including the physical entity, virtual body, and their connections, was proposed [5]. In 2010, the term “Digital Twin” was officially introduced in a technical report of the National

Aeronautics and Space Administration (NASA) [6]. In 2012, NASA and the US Air Force jointly published a paper on DT, identifying it as one of the key technologies driving the development of future aircraft [7]. In 2014, the first white paper about DT was published, implying that the concept of DT was gradually standardized [8].

For a better understanding of the concept of DT, Table I gives the explanations of some common terms in DT. Although many articles have been published to explain this novel concept, there is no unified definition of DT. Some researchers consider it in terms of the model level and believe that DT is a living, intelligent, and evolving model [9, 10]. Some hold that DT may be a part of the "Cyber-Physical System" or the link between virtual space and the real world [11, 12]. As briefly reported in Table II, the definitions of DT are mostly described from three dimensions, namely model, data [13, 14], and links. However, these might be partial understandings of the novel concept. On the basis of the three-dimensional model, [15] proposed a five-dimensional model for DT that includes the physical entity, twin body, connection, data, and service. Thanks to its comprehensiveness, the five-dimensional model has been widely recognized by academia and industry. Based on this understanding, DT is defined as a technique that maps the physical entity into a virtual body. In doing so, it aims to manage the complete life-cycle process of the entity by means of historical and real-time data as well as intelligent algorithms [16].

TABLE II

DIFFERENT DEFINITIONS OF DT

Dimensions	**Definitions**	**References**
Model	A model of a physical device or system that represents all functional features with the working elements.	[4]
	Computer-based models that are simulating, emulating, or mirroring the life of a physical entity.	[9]
	Copies of the physical asset which need not necessarily run in real-time.	[10]
Data	A digital replica of the physical environment along with abundant data and the operator.	[13], [14]
Links	Connections of data and informationthat ties the virtual and the real product together.	[8]
	A part of a cyber-physical system where physical entities interact with virtual spaces through networks.	[11]
	Virtual counterparts for real-world entities.	[12]
Integration	A technique that maps the physical entity into a virtual body, which aims to manage the complete life-cycle process of the entity through historical and real-time data as well as intelligent algorithms.	[15], [16]

Fig. 1(b) shows the structure diagram of DT. As can be seen, twin bodies are typically deployed in the digital space. For the implementation of DT, data, model, and algorithm are three essential elements. Among them, data is the basis, rooted on which physical entities and twin bodies can interact with each other. Model is the core. Mechanism model will run through the complete life-cycle of devices. Algorithm is the carrier. Model and data are fused by algorithm, and then a series of intelligent decisions can be made.

The following is the workflow of DT. First, a (digital) model of the (physical) system is constructed in the digital space. Then, as links between the physical and digital spaces, information interaction units are responsible for the interaction of the operation data collected by sensors. Based on the data interaction and fusion, the model can be corrected, adjusted, and updated in real-time. Generally, the units are controllers and other communication equipment, which also need to send control signals to the physical entities to guarantee their stable operation.

Owing to the advantages mentioned above of DT, it has until now been applied in many industries, including but not limited to electrical, construction, and manufacturing, see [17]. Nevertheless, due to the large amount of operation data and complex model of PEECS, research and applications of DT in the said field are still in infancy. In recent years, however, Internet of Things (IoT), cloud computing, AI [18], and other information techniques have been effectively applied to PEECS, thus laying a solid foundation for the realization of DT in PEECS.

In this direction, there have been some cases of DT in PEECS. For example, DT has been applied for grid analysis, converter maintenance, motor control, battery management, etc. [19]. In [20], an online real-time grid analysis software based on DT is developed, which has a second response speed. In [21], an approach is proposed for the online diagnostic analysis of power converters utilizing probabilistic DT. With this approach, probabilistic simulation models of power converters are established using generalized polynomial chaos expansion to reflect the running status of a physical entity in real-time. In [22], a DT model of photovoltaic devices is constructed, which can realize real-time fault diagnosis. A health indicator estimation method based on the DT concept is proposed in [23] to improve the reliability of capacitance and switching tubes in a Buck converter. In [24], a new method using DT-driven prognostic and health management (PHM) for wind turbines is proposed, thus making effective use of the interaction mechanism and fused data of DT. Based on IoT, the DT of a battery management system is implemented in [25], where the degradation, as well as the remaining useful life (RUL) of batteries can be evaluated.

Regardless of the above-mentioned paradigms, there is a lack of a comprehensive review of DT in PEECS and its future outlook and possible trends. Motivated by this, this paper presents the function layers and key technologies of DT in PEECS, aiming to form the basic theoretical framework. Furthermore, the complete life-cycle management (i.e., design, control, and maintenance) of PEECS is discussed. In parallel to that, relevant applications are presented along with the development trends in each case. With the above, the main contributions of this article are listed below.

1) A comprehensive summary of applications of DT in PEECS to engage practitioners in the topic of interest and serve as a reference for subsequent research.

2) A systematic investigation of DT in PEECS from a complete life-cycle perspective to provide sufficient insight into DT and demonstrate its potential benefits.

3) A detailed discussion of future development trends and challenges of DT in PEECS to initiate and motivate future research.

The remainder of this article is organized as follows. Section II discusses the function layers and key technologies of DT in PEECS. Following, the applications of DT in the design, control, and maintenance of PEECS are presented in Section III. Then, Section IV provides a case study of the implementation of DT for a power converter. The outlook of DT for PEECS is put forward in Section V. Finally, Section VI concludes this article.

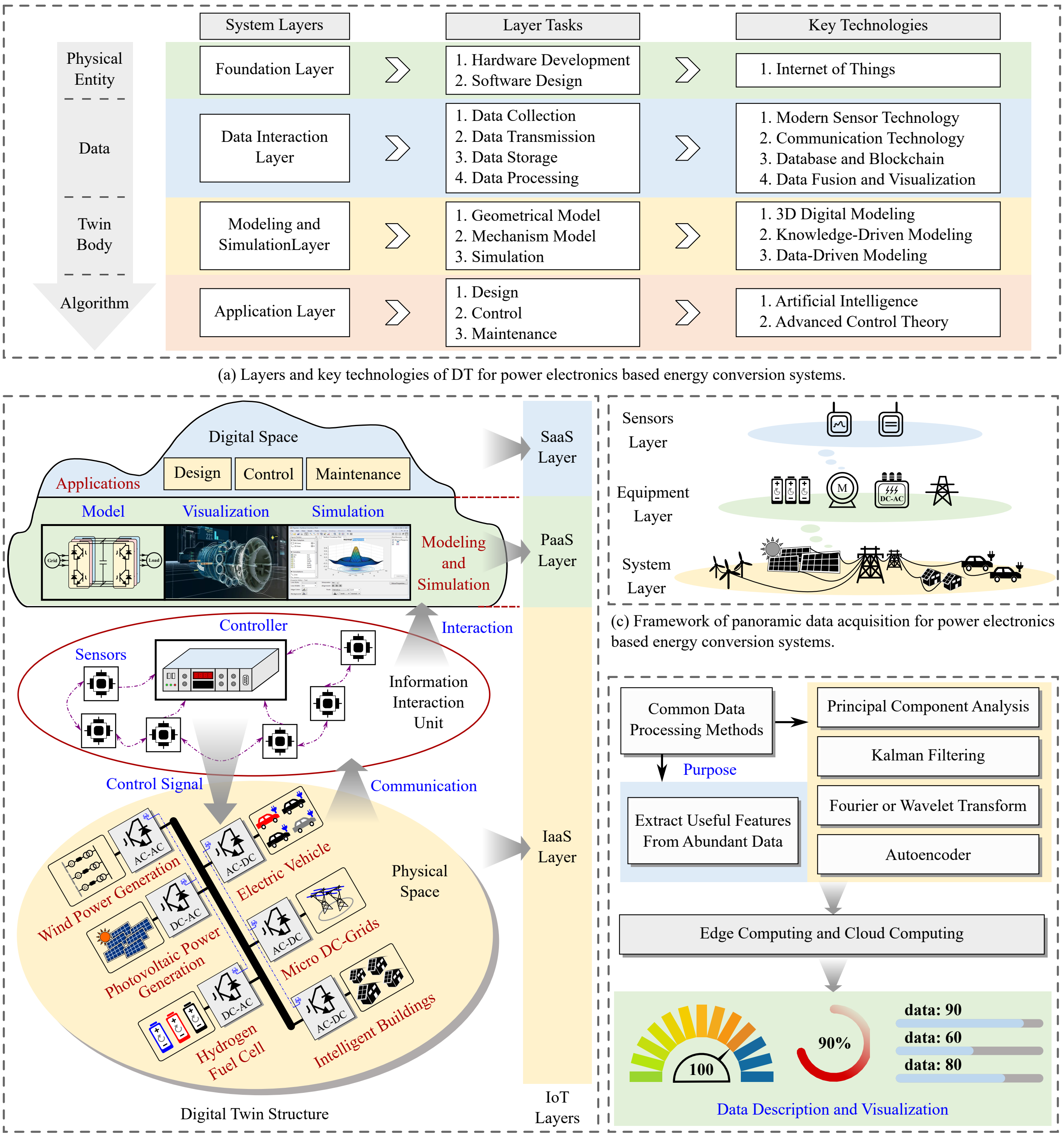
II. Layers and Key Technologies of Digital Twin

Fig. 2(a) summarizes the function layers and key technologies of DT for PEECS, including the foundation, the data interaction, the modeling and simulation, and the application layer. Each layer has its own key technologies, which are discussed in the sequel of this section.

A. Foundation Layer

The foundation layer includes hardware and software platforms. For PEECS, the hardware platform refers to the power equipment or systems represented by power converters. Power converters are core devices in PEECS, such as renewable energy power generation systems, energy storage systems, micro-grids, and variable speed drive systems [26], etc. As a result, the implementation of DT in such systems should start with the power converters and be subsequently extended to other parts of the systems, such as motors, grids, and loads. In addition, controllers, sensors, and other communication equipment are crucial.

The IoT platform is the key carrier of the function realization and landing applications for DT [19]. IoT refers to a platform that collects multi-dimensional information through various sensors and then connects them to various accessible networks to realize real-time perception, monitoring, and management. As for the architecture of IoT, most commonly, a three-layer architecture is used that consists of the infrastructure layer (IaaS), platform layer (PaaS), and software layer (SaaS) [27]. As the framework of DT is very similar to that of IoT, the latter is considered to be the most suitable structure paradigm for the implementation of the former. As different software platforms are needed to realize the functions of DT at different levels, the paradigm of the IoT can serve as the basic architecture to realize the information interaction and resource sharing among these software platforms. Each software platform plays its role in the IoT environment to



(a) Layers and key technologies of DT for power electronics based energy conversion systems.

(b) Relationships between IoT platform and DT.

(c) Framework of panoramic data acquisition for power electronics based energy conversion systems.

(d) Flow chart of data processing.

Fig. 2. Key techniques in the layers of DT for PEECS.

facilitate the realization of DT systems. Specifically, mainstream DT software like “Ansys–Twin Builder” and “Matlab–Simulink” are frequently-used simulation software with DT modeling modules, and “Unity–Unity Pro” focuses on the geometrical models and 3D visualization [19].

Fig. 2(b) shows the relationships between the IoT platform and the DT framework. As can be seen, the

IaaS layer includes hardware equipment that DT needs and collects, stores, and manages massive amounts of data, providing reliable data sources for DT. It serves as physical entities and links in DT. The PaaS layer deploys a series of tools for DT model construction, simulation, and visualization, corresponding to the model block in Fig. 1(b). As the interaction units in DT, controllers not only process the collected data and send them to the PaaS layer, but also transmit the control signals to physical entities based on the updated models. The DT application platform is further established in the SaaS layer to serve the design, control, maintenance, and the complete life-cycle process of the equipment, through AI and other algorithms [28]. As a whole, the implementation process of DT is similar to the workflow of IoT. While DT is more focused on constructing dynamic models to track physical entities in real-time, and then manages the complete life-cycle process. Compared to IoT, the functions of DT are more targeted. As a relevant example, an IoT-based DT of the cyber-physical system that interacts with the control system is proposed to resist cyber-attacks in [29].

B. Data Interaction Layer

It is worth noting that the data size of DT for PEECS is enormous due to the real-time reflection of the physical entity. As a result, the data interaction layer is established to provide data support for the DT of the whole system. This layer mainly involves four tasks, namely data collection, transmission, storage, and processing, as discussed in the following.

1) Data Collection: With the wide application of new measurement materials and the rapid development of advanced intelligent sensing techniques, the breadth and depth of operation data collection for PEECS can fully support the massive operation data demand of DT. For PEECS, electrical parameters, such as current and voltage, are the most significant operating state data. Moreover, environmental characteristics, such as temperature, humidity, and pressure, are also significant for DT. The framework of panoramic data acquisition for typical PEECS is shown in Fig. 2(c). With the hardware support from the sensors layer, operating state and environment characteristic data can be easily obtained from the equipment layer and system layer, respectively. As a result, the DT model can be modified continuously and gradually, fully imitating the physical entity.

2) Data Transmission: Data transmission is the key process to realize real-time information interaction between physical entities and DT. This implies that communication is vital in this task. Communication technologies usually depend on communication protocols, access methods, channel multiplex modulation, and coding technologies [16]. For the DT of PEECS, high-quality and flexible communication technologies are required. In this direction, 5G architecture is expected to accommodate these use cases, especially in terms of latency, resilience, coverage, and bandwidth [30].

3) Data Storage: The responsibility of data storage is to store the collected data for further processing, analysis, and application. It is inseparable from database technologies [31]. Nevertheless, due to the increase in data quantity and heterogeneity in DT, distributed control methods are widely applied to PEECS, which can inadvertently lead to severe data security problems for classical databases. Blockchain is expected to solve the problem.The reason for this is that even though blockchain is known as a computing paradigm based on distributed architecture, it stores various data through the block and chain data structure, and utilizes the knowledge of cryptography to ensure the security of data transmission and storage. Hence, it has many features such as decentralization, secure encryption, and transparency [32]. In [33], to cope with the problems of unreliable communication channels and storage environment caused by the distributed DT paradigm, a blockchain-empowered federated learning framework is proposed. Furthermore, to enhance the security and reliability of DT from untrusted end users, the DT data are stored in the blockchain and they are updated as the state of the corresponding user changes. Similar examples can be found in [34].

4) Data Processing: Data processing techniques generally include data compression, fusion, transformation, discretization, etc., intending to extract these data with useful features [19]. Specifically, principal component analysis and autoencoders are the mian tools for data compression. Kalman filtering, essentially belonging to data fusion techniques, aims to minimize the interference of redundant information and get the most relevant information by fusing the prediction data from system models and the sampled data from sensors [35]. Furthermore, Fourier and Wavelet transforms are used to transform the signal between the time-domain and the frequency-domain to obtain insightful and useful information. Fig. 2(d) gives the flowchart of data processing. As can be seen, the introduction of cloud and edge computing provides powerful and reliable analysis capabilities for the big data needed for DT. Consequently, this can solve the problems of data redundancy and delay in the realization of DT [36]. Subsequently, useful data information can be vividly presented through data visualization.

C. Modeling and Simulation Layer

As previously mentioned, the model is the core of DT. The construction of a DT model should be in the following order, namely geometrical, physical, behavior, and mechanism modeling [37]. The first two mainly focus on describing the shape of a physical object using geometric concepts, and see e.g., [10]. Correspondingly, the last two relate to the operation law and mechanism of the physical system, see [21, 35]. Therefore, as shown in Fig. 2(a), the models can be generally divided into geometrical and

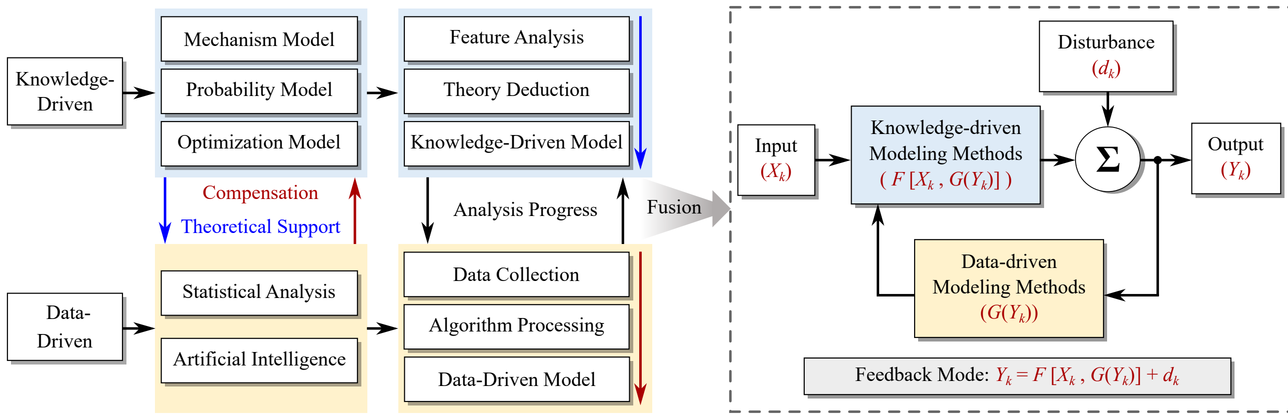


Fig. 3. Comparison between knowledge-driven and data-driven methods.

performance models. However, the geometric model is not further considered in this work because research in PEECS is more focused on the performance model.

Knowledge-driven and data-driven methods are the two frequently-used modeling methods for the performance model [38]. A knowledge-driven method obtains the characteristics of research objects by analyzing the mechanisms. Subsequently, it describes the relationship between variables with mathematical expressions. The main tools of such a method include mechanism modeling, probability modeling, and optimization modeling [39]. Correspondingly, data-driven methods are based on a large number of tests and data. Through different data processing algorithms, the empirical model is generated. Data-driven methods rely on statistical analysis, AI, and other tools to build models.

To break through the limitations of single knowledge or data dependency that classical methods are suffering from, the knowledge-data fusion methods are now widely used. The difference and relationship between the two methods are shown in Fig. 3. Among many knowledge-data fusion methods, the feedback mode modeling method, shown in Fig. 3, is the most common in PEECS. The feedback mode modifies or compensates for the relevant modules or parameters of the knowledge model through a data-driven method. As an example, the ultra-local model of modular multilevel converters (MMCs) is established in [40], and a neural network (NN) observer is designed to observe the system disturbances and compensate for parameter deviations. In doing so, the accuracy and robustness of the whole system are greatly improved.

D. Application Layer

DT can run through the complete life-cycle of PEECS, which usually includes design, control, and maintenance. The design part typically takes very little time, while most functions of DT need to be invested in the control and maintenance parts of PEECS [41]. In addition, the design works can often be carried out offline and dispensed with real-time interaction. However, control and maintenance works need to be done online, which requires the IoT platform and related hardware to collect data and update models. Advanced control theories and AI methods are used to complete these tasks. More details of DT applications in these three parts are provided in the next section.

III. Applications of Digital Twin for Power Electronics Based Energy Conversion Systems

This section discusses the applications of DT in the design, control, and maintenance of PEECS. Moreover, some typical cases are given to demonstrate the advantages of DT.

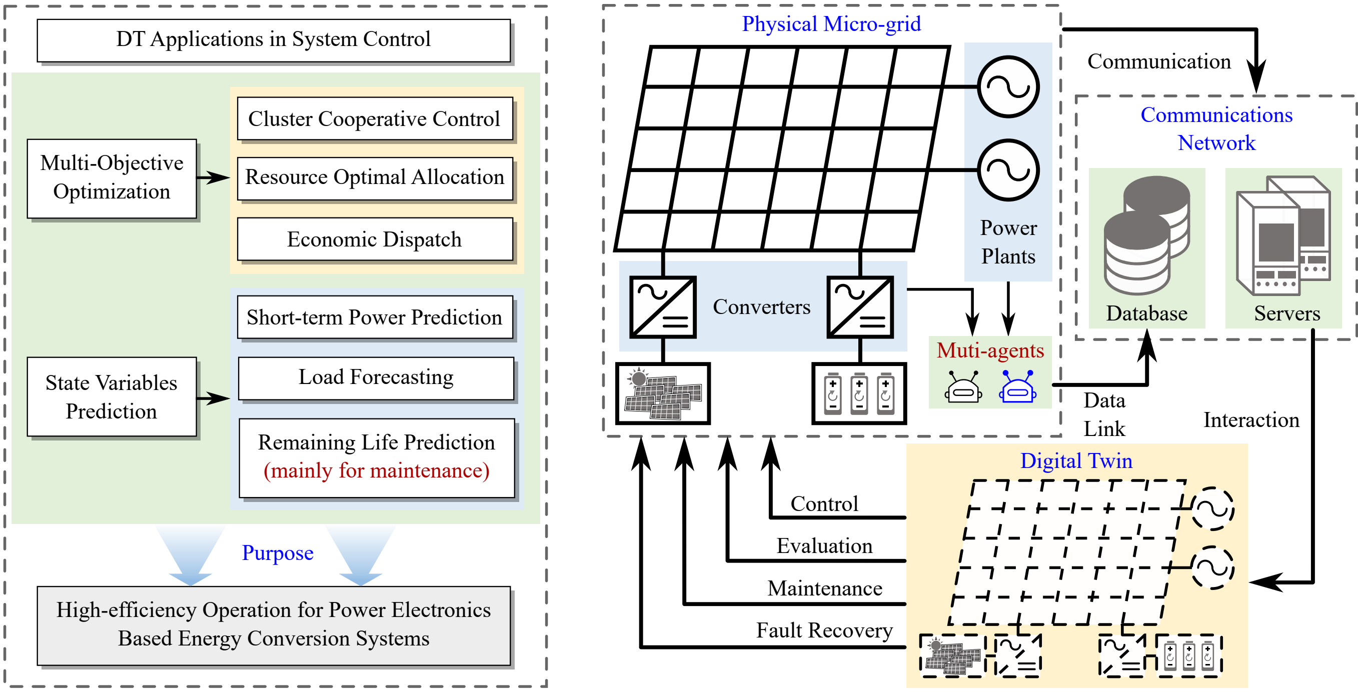
A. Design

The design in PEECS includes the requirements of topology, component size and weight, reliability, etc., as defined by the IEEE standards for the design of power electronics equipment [42]. The design work of PEECS can be divided into three steps, namely objective formulation, scheme selection, and effectiveness verification [18]. In the process of the objective formulation, the desired goal(s) should be first quantified by a function, and supplemented with (equality and/or inequality) constraints. Then, the optimal solution is found by solving the formulated optimization problem, implying that this process is in essence an optimization task. Following, the candidate schemes are verified by simulation and experimental tests. Finally, the final design scheme is selected and applied to the physical system.

Nevertheless, classical design methods in PEECS are time-consuming as they need multiple iterations to conclude the desired design due to the high complexity and uncertainty of the systems in consideration [43]. However, DT can avoid such problems. DT provides a precise and real-time simulation platform as well as sufficient data for designing, testing, and assessing PEECS. Moreover, various operating conditions of the equipment can be simulated by DT to improve the design efficiency and equipment reliability.

As an example of the effectiveness of the above DT-based design procedure, the DT of battery emulator and tester systems are designed in [44]. Specifically, the power converters and motors are validated and tested by building the DT of batteries to simulate the behavior of real batteries. At the same time, a battery tester is developed in a hardware-in-the-loop (HiL) environment for the design and test of battery packs, ultracapacitors, etc. As it is shown in that work, the three-day testing required for the real-world system can be cut down to merely four hours in the Hil DT environment. Similar examples can be found in [45] for more information.

In [46], the design work for the microgrid digital twin (MGDT) is discussed from a structure aspect. In this process, the capacity of the system equipment, application environment, and the uncertainty resulting from the wind speed, solar radiation, as well as ambient temperature should be considered. Then, the



(a) DT applications in system control.

(b) DT-based multi-agent control architecture of a microgrid.

Fig. 4. DT applications in the control of PEECS.

virtual models of the MGDT can be first developed and even delivered in advance to validate these candidate design schemes.

Another application of a DT-based design is presented in [47], where DT is employed to increase the reliability of a photovoltaic (PV) power station. To do so, the real-world PV power station is mapped into a virtual one. Specifically, three-dimensional scene models of the solar PV panels are built using the Unity3D virtual reality engine. Following, a back-propagation neural network (BPNN) and a particle swarm optimization algorithm (PSO) are applied to process the collected data and realize fault diagnosis.

B. Control

Due to the ability to accurately reflect the operating state of the physical entity in real time, DT can contribute to the performance assessment of PEECS, and make fast decisions in response to changes in parameters and operating conditions. Generally, the applications of DT in the control of PEECS relate to two aspects, they are multi-objective optimization, and prediction of key state variables (see Fig. 4(a)).

Specifically, intelligent algorithms are usually adopted to realize multi-objective optimization problems, thus ensuring that the system tracks the reference fast and accurately. In this context, DT techniques can further improve the accuracy of the system representation and give more accurate control signals. Furthermore, DT models of the PEECS cover different information about multiple physical fields and can accurately reflect any changes in physical entities. Based on this, DT techniques can be used to realize real-time and accurate prediction of system state variables, and enhance its anti-interference ability.

Regarding the former aspect, i.e., multi-objective optimization, a DT-based multi-agent coordination control strategy for microgrids is proposed in [48]. Firstly, the DT and multi-agent control architecture of the microgrid is designed, see the schematic diagram in Fig. 4(b). Following, according to the tasks in the complete life-cycle process, the microgrid is divided into different agents, and the DT model of each agent is constructed. Power prediction and multi-objective optimization can be made with the assistance of PSO. Finally, the DT model of the microgrid is built on an Opal-RT simulation platform for verification, and its hardware architecture is similar to the "physical space" in Fig. 2(b). Simulation results demonstrate that the application of DT can effectively improve the self-sensing, self-prediction, and self-adaptation capabilities of the microgrid. Moreover, similar examples can be found in [49, 50].

As for predicting some state quantities, NNs are usually used in PEECS. In [51], a DT model based on long- and short-term memory network (LTSM) is used to predict the power of a PV system. In virtue of transfer learning, this model can be employed to predict the power of other PV systems with short operation time and insufficient data. Furthermore, this method can also facilitate and improve the reliability of PV systems. Similar examples of prediction based on DT can be found in [52, 53].

C. Maintenance

Reliability and safety of PEECS are paramount [54]. Hence, maintenance is crucial, particularly in the complete life-cycle. Roughly, the failures in the systems can be separated into two categories, i.e., short- and long-term faults. Short-term faults relate to sudden and abrupt faults due to overstress conditions and may cause catastrophic effects. Long-term faults refer to the wearing out and degradation of the hardware due to long-term operation [18]. Fig. 5(a) shows the maintenance strategies for the two kinds of faults. For long-term faults, condition monitoring and prediction of the RUL of key components—such as switching tubes, capacitors, etc.—are generally adopted to avoid faults [55]. For the same aim, the reliability of the plant can be systematically tested in the design process. While, for short-term faults, fast, accurate diagnosis and fault-tolerant strategies should be adopted to ensure the stable operation of systems [56]. Due to the nature of this type of fault, this research dimension focuses on the system level.

Considering the different types of faults, it can be inferred that their time scale can be very different and vary a lot. The same applies to the complexity of the faults. Therefore, combining maintenance strategies to implement the most effective one to avoid possible faults in PEECS is a nontrivial task. Thanks to its attributes, DT can tellingly address this issue [57]. To do so, sensing devices as well as historical

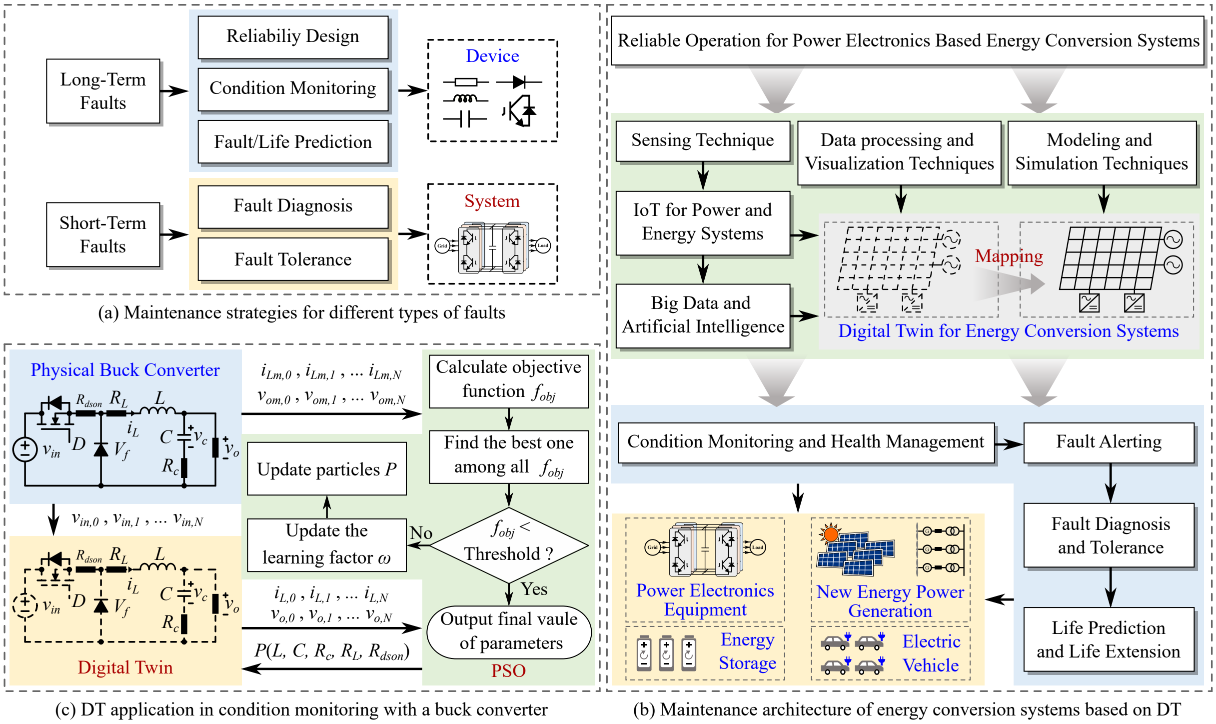


Fig. 5. DT applications in the maintenance of PEECS.

and current data are used to make state monitoring and life prediction of the devices more accurate [58]. Furthermore, AI and advanced control algorithms can be employed for fault feature extraction and fault-tolerant strategy formulation [59].

As an example of the benefits that DT can bring in the maintenance of PEECS, [22] presents a DT method for fault diagnosis in a PV energy conversion unit. This is done by estimating the characteristic outputs of the system. As shown, DT can compute a residual error vector required for fault detection in real-time. By doing so, higher fault sensitivity can be achieved. Similarly, a real-time field-programmable gate array-digital twin (FPGA-DT) technique is proposed in [60] to realize the fault diagnosis for transformers used in power electronics applications. The physical entity and the twin body operate with the actual conditions and expected conditions, respectively. With the faults injection, operation data of the physical entity and the expected data of the twin body can be obtained. Then, the fault diagnosis module realizes fault identification and location by comparing the differences between operation and expected data. Furthermore, a method is developed within the DT framework in [61] that predicts the RUL of an offshore wind turbine power converter by estimating the IGBT and diode junction temperatures.

In [23], a DT-based health estimation method is proposed for a buck converter. The state-space description of a buck converter is established, and the fourth-order Runge-Kutta method is used to construct the discrete-time equivalent model. Due to its effectiveness with multi-objective optimization problems, a PSO algorithm is applied to monitor and correct the numerous parameters of the converter in real-time. The schematic diagram of this method is shown in Fig. 5(c). The presented experimental results clearly show the ability of the DT-based method to accurately estimate the parameters of the real-world system during both steady-state and transient operating conditions. To avoid modeling errors caused by linearization, in [62], a new digital-twin-based condition monitoring method is proposed. Compared with the method in [23], the parameters of the replica buck converter in [62] can be calculated and updated in Matlab/Simulink through an automatic process, which could further reduce estimation errors. Similar examples can be found in [63, 64].

D. Summary of DT Applications in Design, Control and Maintenance

In summary, Table. III presents the classified applications of DT in design, control, and maintenance for PEECS. It is clear that most of the applications (about 50 %) are for the maintenance phase, around 35 % of applications belong to the control phase, and only a few applications (15 %) focus on the design phase. During the maintenance process, DT techniques are primarily applied for the online condition monitoring of PEECS, including degradation parameter identification and state-of-health estimation, etc. It indicates that the long-term condition monitoring for complex systems fits best with the original purpose of the DT concept and maximizes its advantages. Nevertheless, Table. III also summarizes the main tasks and benefits of DT in other processes. In the future, as DT techniques become more and more mature, their application scope will be extended and even cover the equipment recycle [16].

TABLE III

OVERVIEW OF DT APPLICATIONS IN PEECS

Applications	**Advantages of DT Applications**	**Main Tasks**	**References**
Design	Cost-effective; High design efficiency; High design security and reliability.	Structure Design	[46]
		Simulation Platform Design	[43], [44], [45], [65]
		Reliability Design	[47]
Control	Coordinate multiple control objectives flexibly; Accurate predictions with abundant data; Strong adaptability in various conditions.	Multi-objective Optimization	[30], [48], [49], [50], [66]
		State Variables Prediction	[51], [52], [53], [67]
		Other Control Tasks	[20], [38], [68]
Maintenance	Real-time perception of states; Accurate predictions with knowledge-data fusion; Fast diagnosis and robust fault tolerance.	Condition Monitoring	[23], [24], [35], [57], [62], [63], [64], [69]
		Remaining Useful Life Prediction	[25], [58], [61], [70]
		Fault Diagnosis and Tolerance	[21], [22], [29], [60]

IV. Implementation of Digital Twin For A Power Converter

DT can serve the needs of collaborative design, intelligent control, and predictive maintenance for PEECS. Meanwhile, the implementation of DT in PEECS also faces lots of challenges, and is in urgent need of research. As mentioned above, model, data, and algorithm are the three elements of DT. Therefore, the implementation of DT should be carried out from these three aspects. In this section, a case study of an AC-DC rectifier is given to elaborate on the implementation method of DT from the following steps, namely DT model construction, DT platform development, as well as HiL experimental results analysis.

A. DT model construction

To build an accurate dynamic twin body that can be updated in real time, the knowledge-data fusion modeling method should be adopted [68]. As shown in Fig. 6(a), the input and output signals of the circuit collected by sensors, are used to identify model parameters with intelligent algorithms. Further, we can modify the mechanism model in real time and obtain better control performance with new parameters.

Fig. 6(a) depicts the circuit topology of a three-phase AC-DC rectifier, which is connected to the AC grid via three grid-side filter inductors L_{g} and resistors R_{g}. Furthermore, it also contains six switching tubes (G_{a1} to G_{c2}), six antiparallel diodes, a dc-link capacitor (C), and the load (equivalent resistance R_{L}). According to the rectifier model, the output voltage can be represented as

$$v_x = e_x - L_{\mathrm{g}}\frac{di_x}{dt} - R_{\mathrm{g}} i_x, \tag{1}$$

where e_x is the grid voltage, v_x is the output voltage of the rectifier ($x \in \{a, b, c\}$).

To achieve decoupling of the current components, the Park transformation is needed to obtain equations in the dq frame. The discrete-time model in the dq frame, using the forward Euler approximation, is given as

$$\vec{i}_{\mathrm{dq}}(k+1) = \begin{bmatrix} 1-\frac{T_{\mathrm{s}}R_{\mathrm{g}}}{L_{\mathrm{g}}} & T_{\mathrm{s}}\omega_{\mathrm{g}} \\ -T_{\mathrm{s}}\omega_{\mathrm{g}} & 1-\frac{T_{\mathrm{s}}R_{\mathrm{g}}}{L_{\mathrm{g}}} \end{bmatrix} \vec{i}_{\mathrm{dq}}(k) + \frac{T_{\mathrm{s}}}{L_{\mathrm{g}}}[(\vec{e}_{\mathrm{dq}}(k) - \vec{v}_{\mathrm{dq}}(k)], \tag{2}$$

where T_{s} denotes the sampling interval, ω_{g} is the frequency of the grid voltage.

Equation (2) is the knowledge model of the rectifier that we want to obtain. Based on this, we use NN predictor to estimate parameters in the knowledge model in real time [40], so that we can get a more accurate and dynamic model of the rectifier (see Fig. 6(a)). Specifically, we take $\vec{i}_{\mathrm{dq}}(k-1)$, $\vec{e}_{\mathrm{dq}}(k-1)$, and $\vec{v}_{\mathrm{dq}}(k-1)$ as the input variables of the NN. Correspondingly, $\hat{\vec{i}}_{\mathrm{dq}}(k)$ is the output variable of the

NN, where $\hat{x}$ represents the estimated value of variable x. The parameters in (2) can be expressed as the weighting factor ω_i of the NN. Hence, the fusion model of the rectifier is described as

$$\hat{\vec{i}}_{\mathrm{dq}}(k) = \begin{bmatrix} \omega_1(k-1) & \omega_3(k-1) \\ -\omega_3(k-1) & \omega_1(k-1) \end{bmatrix} \vec{i}_{\mathrm{dq}}(k-1) + \omega_2(k-1)(\vec{e}_{\mathrm{dq}}(k-1) - \vec{v}_{\mathrm{dq}}(k-1)), \tag{3}$$

The NN representing the system model is trained online through the gradient descent algorithm. The main objective of the training procedure is to reduce the prediction error between the real and estimated states ($\vec{i}_{\mathrm{dq}}$ and $\hat{\vec{i}}_{\mathrm{dq}}$) and then identify the real parameters [66]. Therefore, we should formulate an objective function which is given as follows.

$$F = \frac{1}{2}[(\hat{i}_{\mathrm{d}}(k) - i_{\mathrm{d}}(k))^2 + ((\hat{i}_{\mathrm{q}}(k) - i_{\mathrm{q}}(k))^2]. \tag{4}$$

Then, the gradient descent training algorithm is defined as

$$\begin{cases} \dfrac{\partial F}{\partial \omega_1} = (\hat{i}_d(k) - i_d(k)) i_d(k-1) + (\hat{i}_q(k) - i_q(k)) i_q(k-1), \\ \dfrac{\partial F}{\partial \omega_2} = (\hat{i}_d(k) - i_d(k)) \left(e_{\mathrm{d}}(k-1) - v_{\mathrm{d}}(k-1)\right) + (\hat{i}_q(k) - i_q(k)) \left(e_{\mathrm{q}}(k-1) - v_{\mathrm{q}}(k-1)\right), \\ \dfrac{\partial F}{\partial \omega_3} = (\hat{i}_d(k) - i_d(k)) i_q(k-1) - (\hat{i}_q(k) - i_q(k)) i_d(k-1), \\ \omega_i(k) = \omega_i(k-1) - \alpha_i \dfrac{\partial F}{\partial \omega_i(k)}, \quad (i = 1, 2, 3), \end{cases} \tag{5}$$

where α_1, α_2 and α_3 are the learning rates of the algorithm.

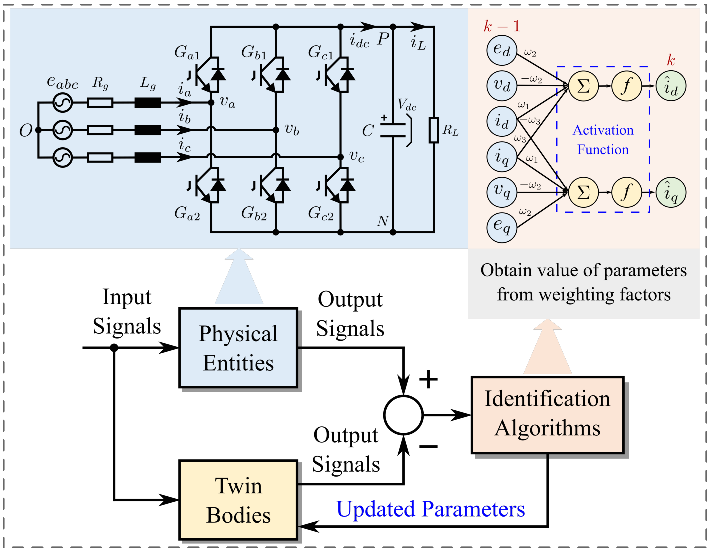
Through the updated weighting factors, we can easily obtain the real parameters of the model at each sampling interval. The specific expressions are given as

$$\begin{cases} R_{\mathrm{g}}(k) = \dfrac{1 - \omega_1(k)}{\omega_2(k)}, \\ L_{\mathrm{g}}(k) = \dfrac{T_{\mathrm{s}}}{\omega_2(k)}. \end{cases} \tag{6}$$

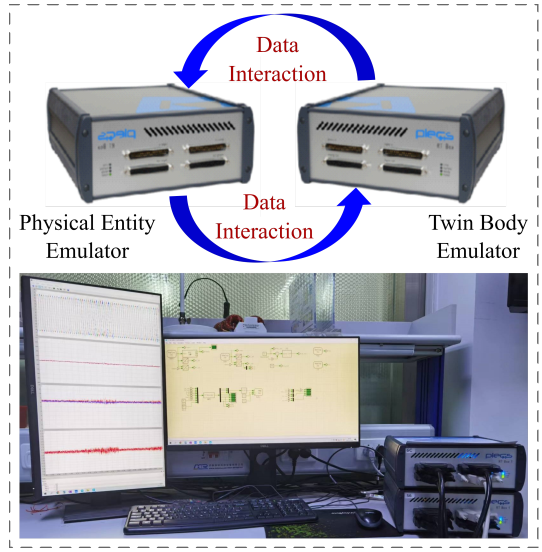
With the data transmission step, the twin body of the rectifier can be updated in real time through the obtained real parameters. Then, a list of control and maintenance tasks can be completed.

B. DT platform development

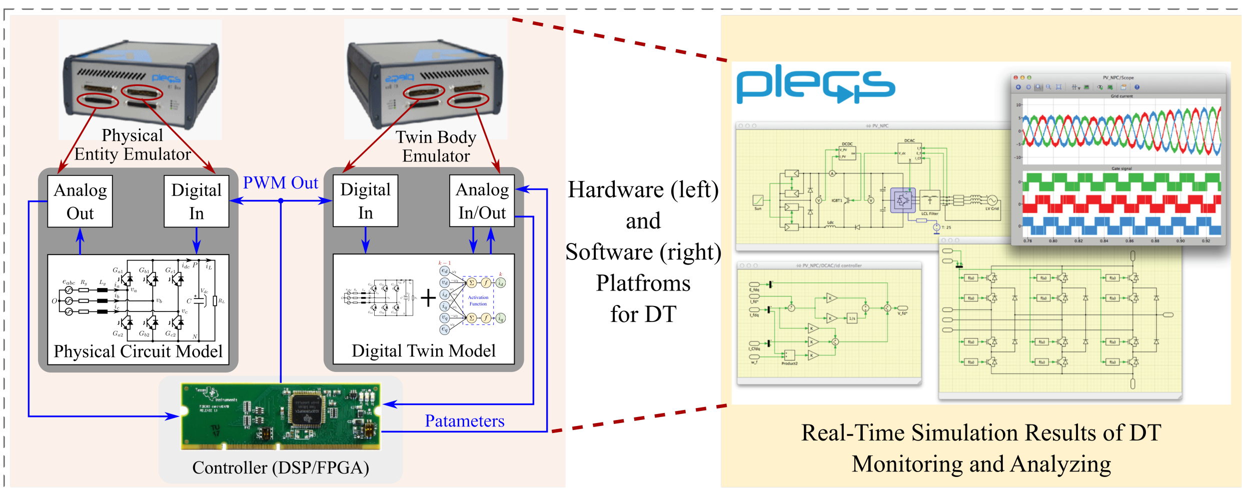
Ensuring high fidelity of real-time simulations is the most prominent requirement for the hardware and software platforms of DT. Specifically, switching signals of power electronics devices are needed to be captured in the range of several nanoseconds. In doing so, the information collected from the real-time simulator can be as close as possible to the response of the physical entity. Therefore, the HiL platform should have sufficient computational power to provide the means for the implementation of DT. Through



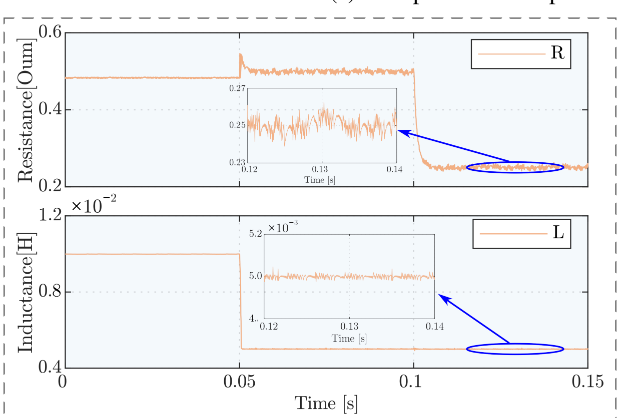
(a) Schematic diagram of the implementation of DT for an AC-DC rectifier.



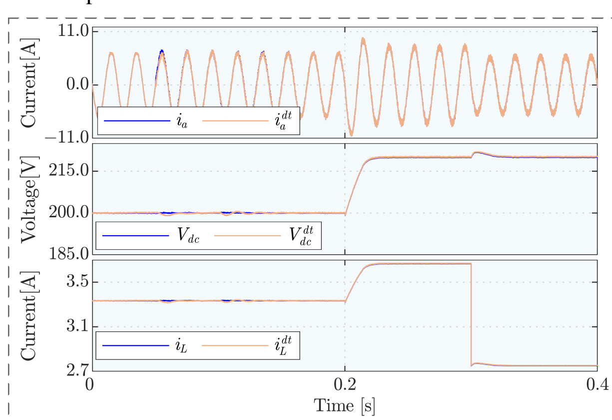
(b) Hardware tools for the implementation of DT.



(c) Component development for the implementation of DT.



(d) Parameter (R_g and L_g) identification results.



(e) Physical rectifier state tracking results of the twin body.

Fig. 6. Implementation of DT for a power converter.

suitable interfaces, real-time simulators are connected with the dedicated controller, which provides the opportunity to realize the interaction between twin bodies and the real power equipment [65].

Fig. 6(b) shows the RT-Boxes for the implementation of DT for the chosen case study. One box emulates the physical rectifier and another one is used to deploy the DT model. Each box integrates multiple CPU cores, and one of them performs communication with the user while the remaining cores are used for the real-time simulation. During the operation, the two boxes communicate with each other in real time and the operating data are transmitted with ADCs in the box which features 16-bit resolution with simultaneous sample and update. Specific development processes of the components are shown in Fig. 6(c). It is clear that the controller obtains and processes the analog signals like currents and voltages from the boxes, and then, provides PWM signals to the emulators. To ensure that the communication is synchronized, I/O delay is set for each box. Furthermore, system models in the physical entity emulator are built through specific modules and the ones in the twin body emulator are devleped through compatible programming languages. Same sample intervals are set for the two emulators, which is one-tenth of the control period.

In this case study, we use the "PLECS" simulation software to validate the performance of the DT for the rectifier. The software can provide models of multiple physical fields, such as electric, magnetic, thermal, and mechanical models, as well as their control parts, and emulate the actual physical system to the maximum extent. In doing so, models can be built based on the functional modules of the software and integrated with the collected data. Therewith, with the data visualization interface of the software, each state of the physical entity and the twin body can be monitored and analyzed (see Fig. 6(c)). As for the implementation of a single power converter, thanks to its small data size, several functions of DT can be realized based on a simple software. However, for a complex system such as microgrids, advanced tools like IoT and more powerful controllers are required [67]. Additional details about tools of the implementation for DT are specified in [69, 71].

C. HiL Experimental Results analysis

In this step, the integration of model, data, and algorithm is completed based on a series of deployments on the RT-box, and the DT of the rectifier is finally implemented. Furthermore, the "PLECS" platform is used for real-time display and analysis of the HiL results. The accuracy of parameter identification and the entity tracking ability of the twin body are mainly validated in this part. The HiL experimental results are shown in Fig. 6(d) and Fig. 6(e) with the experimental parameters in Table. IV.

Considering the extreme situation that the values of parameters drop abruptly, we set the values of R_g and L_g to half of their initial values to emulate the degradation process. At $t = 0.05s$, a step of the value

TABLE IV

PARAMETERS OF THE RECTIFIER

Parameter	Symbol	Value	Parameter	Symbol	Value
Gird voltage	e_{abc}	70V	DC-link voltage	V_{dc}	200V
Frequency	w_g	50Hz	DC-link capacitance	C	1.1mF
Resistance	R_g	0.5Ω	Load Resistance	R_L	60Ω
Inductance	L_g	10mH	Sampling frequency	f_s	20kHz

of L_g from 10mH to 5mH happens. Similarly, at $t = 0.05s$, the value of R_g drop to 0.25Ω. The parameter identification results are shown in Fig. 6(d). It is clear that these parameters (R_g and L_g) converge to a stable value in a short period of time. Furthermore, the identification accuracy of the value of L_g is quite high, and the relative error is within 2%. As for the identification accuracy of R_g, it is also acceptable and the relative error is within 5%. With these estimated parameters, the twin body can be updated and track the state of the physical power converter in real time.

The comparisons of the operating state between the DT and the physical rectifier are shown in Fig. 6(e). The waveforms from top to bottom are the current of phase A (phase B and C are the same as phase A), dc-link voltage, and load current respectively. At $t = 0.2s$, the dc-link voltage changes from 200V to 220V in a step-wise manner, and then at $t = 0.3s$, the load resistance changes to 80Ω from 60Ω (parametric variations are consistent with those described in the preceding paragraph). It can be seen that the waveforms almost overlap with each other in both dynamic and static responses, which indicates that the estimated parameters are very close to the real ones and the twin body can fit the physical entity accurately.

V. OUTLOOK ON DIGITAL TWIN FOR POWER ELECTRONICS BASED ENERGY CONVERSION SYSTEMS

The previous section presents a comprehensive introduction to the implementation method of DT techniques in an AC-DC power converter. Based on the implementation in a single converter, DT techniques can be further in complex energy conversion systems. As shown in Table. V, DT techniques are summarized from the perspective of application context and objects, and the role of DT in these application scenarios is also attached. It is clear that, currently, in PEECS, new energy power generation systems and microgrids are the two fields in which DT techniques are developed most maturely and more than half of the studies have focused on them. It is because of the enormous scale and investment of these systems that DT can maximize its superiority and run through the complete life-cycle. Furthermore, as emerging research topics, energy storage systems [70] and electric vehicles [72] are in infancy as well as DT. But in the future, all of these systems are embedded in our lives as part of the micro-energy conversion system and DT techniques will help us manage and maintain these systems more intelligently and securely [41].

TABLE V

OVERVIEW OF VARIOUS APPLICATION SCENARIOS OF DT IN PEECS

Application Scenarios	Concrete Objects	Role of DT Techniques	References
Power Converters and Other Equipment	DC-DC Converters	Online parameters identification, health monitoring and fault diagnosis	[21], [23], [62], [63]
	DC-AC Inverters	Parameter identification and fault diagnosis	[60], [64]
	MMCs	Small-scale real-time simulator design	[65]
	Power Transformers	Real-Time monitoring of medium voltage	[69]
Microgrids	Microgrids	Optimal allocation and scheduling	[20], [30], [48], [49]
		Structure design for DT of microgrids	[46]
		DT for microgrids against cyber attacks	[29]
Electric Vehicles and Drive Systems	Motors	State and health monitoring of motors	[35], [38], [58]
	Electric Vehicles	Open the avenues for cost-effective and efficient development of electric vehicles	[72]
Energy Storage Systems	Batteries	Battery simulation platform design	[44], [45]
		Frequency regulation of batteries	[68]
		Battery management and health estimation	[25], [70]
Renewable Energy Power Generation Systems	Photovoltaic Systems	Photovoltaic power prediction	[51], [53]
		Fault diagnosis and reliability design	[22], [47]
	Wind Power Generation Systems	Wind power prediction	[52]
		Online monitoring and health management	[24], [39], [57], [61]
	Renewable Energies	Improve efficiency for energy usage, enable effective decarbonisation and low costs	[41]

At the moment, the advanced theories and methods proposed by various researchers have been monumental in establishing the foundation of DT technologies in PEECS. However, this is merely the tip of the iceberg for the potential of DT. As a result, in this section, we aim to bring into consideration these pertinent opportunities and challenges that will govern the objectives of future research in this domain.

A. Challenges and limitations

In terms of the challenges, the most striking is the modeling of extremely intricate and interconnected systems. When building a DT model for a complex system, each part of the system is first modeled as a standalone entity, and in a second step, they are combined together. Considering PEECS, this means that the electrical, mechanical, thermal, and other parts need to be modeled separately from each other. Due to different time scales and modeling software for the different parts, their compatibility is a relevant problem that needs to be solved [73].

As far as the data aspect is concerned, data integrity and fidelity can be facilitated by DT. As mentioned in Section II, existing data interaction techniques are mature enough to support the realization of DT in PEECS. However, there are still some problems that need to be tackled. On the one hand, it is difficult to achieve consistency in multi-dimensional and multi-scale data acquisition. On the other hand, multi-source heterogeneous data types are hard to merge and fuse, especially when data are sampled at different rates.

DT ties closely to IoT, making it extremely versatile and flexible. However, due to the high-security data sharing and immature opening mechanisms, the inclusion of IoT will lead to numerous risks to data security. For instance, data sharing is vulnerable to cyber attacks [74], which may result in data missing or leakage. For PEECS, which is closely interlinked to energy security of a whole region, cyber attacks can be potentially fatal and must be carefully examined when constructing DT.

Another interesting point that requires further investigation relates to the connection of the link of the complete life-cycle (design, control, and maintenance) of PEECS. Specifically, as DT is independently designed for and applied to each link of the complete life-cycle of PEECS, the correlation between them needs to be improved such that the benefits of DT are fully harvested.

B. Future trends and solutions

There are many challenges faced by the DT applications in PEECS, however, in the future, the role of DT may be expanded and become more and more prominent in PEECS. DT framework can be customized to any topology of power converters and is capable to model hundreds of them within seconds once the initial architecture is set up. DT techniques also poses the capacity to streamline the study and testing of modern energy conversion systems. This will be the catalyst for the interaction between virtual and physical energy conversion systems. As a whole, DT has immense potential in PEECS. Some solutions aiming at the aforementioned issues are explored as follows.

1) Universal Modeling Platform: Given the compatibility of the models, a modeling and design platform for DT should be developed on which all types of models can run. This should be followed by the design of specification programs to describe the different components, their interactions, and simulate various environmental conditions they would operate. For instance, the platform should take the coupling characteristics of mechanical, electrical, and thermal fields of PEECS into account, and then standardize the interface design.

2) Multilevel Data and Model Fusion: For a specific energy conversion system, various kinds of information and knowledge are generally available. For this purpose, the knowledge-data fusion driven advantages need to be exploited for better accuracy and robustness of the system models. Digging into the available data helps to study the parts hard to describe in the complex system. Meanwhile, the maximum utilization of classical knowledge can reduce the burden of numerous data collection and transmission.

3) Powerful Real-Time Computational Unit: Although AI and other advanced techniques can provide superior performance for DT, it is computationally intensive in the case of PEECS. As a result, controllers and other computational units should possess the capability of fast computation and data processing. Moreover, due to the nanosecond-level operation time step required by power electronics switching devices, real-time and high-performance solvers are extremely essential for DT in modern PEECS.

4) Data Privacy and Security: Research is needed to discuss which kind of data is vulnerable to intrusion and can be monitored. Accordingly, it will mitigate the threat by using encrypted protocols or other active defense methods. Additionally, a multi-layered defense mechanism is indispensable. It allows the first defense layer to be penetrated to trigger a response and stop the attack in subsequent layers [41].

5) Predictive Control and Maintenance: At the present stage, model predictive control (MPC) combines the advantages of prediction and optimization [75], implying that its combination with DT can bring significant benefits. Furthermore, PHM is crucial for complex systems operating in a harsh environment. This kind of predictive maintenance will gradually replace existing "post-fault maintenance" by means of DT [24]. Under this tendency, design, control and maintenance will be in closer contact with each other. This will be more conducive to the application of DT in the complete life-cycle management of PEECS.

VI. Conclusion

With the development of digital transformation and more power-electronics-based paradigms in energy and power systems, the application of DT to PEECS has become a relevant research topic. As a result, existing DT techniques in PEECS are reviewed in this paper. The basic hierarchical structure and key technologies of DT for PEECS are emphasized. In particular, DT for PEECS is systematically investigated from a complete life-cycle perspective, i.e., design, control, and maintenance. In doing so, application cases of DT in each process are presented to provide more insight into the benefits of the discussed method. Moreover, future trends and problems of DT for PEECS are discussed in detail. The current investigation results show that the application of DT to PEECS can effectively improve the design efficiency of power electronics equipment, enhance the control performance, realize the maintenance of the system more flexibly and conveniently, and ensure the high quality and reliable operation of the whole system.

VII. Acknowledgments

The corresponding author of this work is Prof. Zhenbin Zhang. This work is financially supported in part by the National Distinguished Expert (Youth Talent) Program of China (31390089963058), in part by the General Program of National Natural Science Foundation of China (51977124), in part by the National Natural Science Foundation of China (52007107), in part by the National Natural Science Foundation of China (52277191), in part by the National Natural Science Foundation of China (52277192).

References

[1] Z. Zhang, "On control of grid-tied back-to-back power converters and permanent magnet synchronous generator wind turbine systems," *Technical University of Munich*, 2016.

[2] Q. C. Zhong, "Power-Electronics-Enabled Autonomous Power Systems: Architecture and Technical Routes," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 7, pp. 5907–5918, 2017.

[3] Y. Wu, K. Zhang, and Y. Zhang, "Digital twin networks: A survey," *IEEE Internet of Things Journal*, vol. 8, no. 18, pp. 13 789–13 804, 2021.

[4] A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital Twin: Enabling Technologies, Challenges and Open Research," *IEEE Access*, vol. 8, pp. 108 952–108 971, 2020.

[5] M. W. Grieves, "Plm–beyond lean manufacturing," *Manufacturing Engineering*, vol. 130, no. 3, pp. 23–23, 2003.

[6] R. F. O. R. The, "Modeling, Simulation, Information Technology and Processing Roadmap," vol. 29, no. 3, pp. 525–557, 2005.

[7] E. H. Glaessgen and D. S. Stargel, "The digital twin paradigm for future NASA and U.S. Air force vehicles," *Collection of Technical Papers - AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference*, no. April, 2012.

[8] M. Grieves, "Digital Twin : Manufacturing Excellence through Virtual Factory Replication - A Whitepaper by Dr . Michael Grieves," *White Paper*, no. March, pp. 1–7, 2014.

[9] B. R. Barricelli, E. Casiraghi, and D. Fogli, "A survey on digital twin: Definitions, characteristics, applications, and design implications," *IEEE Access*, vol. 7, pp. 167 653–167 671, 2019.

[10] A. Rasheed, O. San, and T. Kvamsdal, "Digital twin: Values, challenges and enablers from a modeling perspective," *IEEE Access*, vol. 8, pp. 21 980–22 012, 2020.

[11] K. M. Alam and A. El Saddik, "C2ps: A digital twin architecture reference model for the cloud-based cyber-physical systems," *IEEE Access*, vol. 5, pp. 2050–2062, 2017.

[12] J. Autiosalo, J. Siegel, and K. Tammi, "Twinbase: Open-source server software for the digital twin web," *IEEE Access*, vol. 9, pp. 140 779–140 798, 2021.

[13] N. Nikolakis, K. Alexopoulos, E. Xanthakis, and G. Chryssolouris, "The digital twin implementation for linking the virtual representation of human-based production tasks to their physical counterpart in the factory-floor," *International Journal of Computer Integrated Manufacturing*, pp. 1–12, 2018.

[14] C. Semeraro, M. Lezoche, H. Panetto, and M. Dassisti, "Digital twin paradigm: A systematic literature review," *Computers in Industry*, vol. 130, 2021.

[15] F. Tao and M. Zhang, "Digital twin shop-floor: a new shop-floor paradigm towards smart manufacturing," *Ieee Access*, vol. 5, pp. 20 418–20 427, 2017.

[16] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, L. Wang, and A. Nee, "Enabling technologies and tools for digital twin," *Journal of Manufacturing Systems*, vol. 58, pp. 3–21, 2021.

[17] F. Tao, H. Zhang, A. Liu, and A. Y. Nee, "Digital Twin in Industry: State-of-the-Art," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2405–2415, 2019.

[18] S. Zhao, F. Blaabjerg, and H. Wang, "An overview of artificial intelligence applications for power electronics," *IEEE Transactions on Power Electronics*, vol. 36, no. 4, pp. 4633–4658, 2021.

[19] F. Yang, T. Wu, R. Liao, J. Jiang, T. Chen, and B. Gao, "Application and Implementation Method of Digital Twin in Electric Equipment," *High Voltage Engineering*, vol. 47, no. 5, pp. 1505–1521, 2021.

[20] M. Zhou, J. Yan, and D. Feng, "Digital twin framework and its application to power grid online analysis," *CSEE Journal of Power and Energy Systems*, vol. 5, no. 3, pp. 391–398, 2019.

[21] M. Milton, C. De La O, H. L. Ginn, and A. Benigni, "Controller-embeddable probabilistic real-time digital twins for power electronic converter diagnostics," *IEEE Transactions on Power Electronics*, vol. 35, no. 9, pp. 9850–9864, 2020.

[22] P. Jain, J. Poon, J. P. Singh, C. Spanos, S. R. Sanders, and S. K. Panda, "A digital twin approach for fault diagnosis in distributed photovoltaic systems," *IEEE Transactions on Power Electronics*, vol. 35, no. 1, pp. 940–956, 2019.

[23] Y. Peng, S. Zhao, and H. Wang, "A digital twin based estimation method for health indicators of dc–dc converters," *IEEE Transactions on Power Electronics*, vol. 36, no. 2, pp. 2105–2118, 2020.

[24] F. Tao, M. Zhang, Y. Liu, and A. Y. Nee, "Digital twin driven prognostics and health management

for complex equipment," *CIRP Annals*, vol. 67, no. 1, pp. 169–172, 2018. [Online]. Available: https://doi.org/10.1016/j.cirp.2018.04.055

[25] W. Li, M. Rentemeister, J. Badeda, D. Jöst, D. Schulte, and D. U. Sauer, "Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation," *Journal of Energy Storage*, vol. 30, no. April, p. 101557, 2020. [Online]. Available: https://doi.org/10.1016/j.est.2020.101557

[26] Y. Li, Z. Zhang, T. Dragicevic, and J. Rodriguez, "A Unified Distributed Cooperative Control of DC Microgrids Using Consensus Protocol," *IEEE Transactions on Smart Grid*, vol. 12, no. 3, pp. 1880–1892, 2021.

[27] M. Wollschlaeger, T. Sauter, and J. Jasperneite, "The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0," *IEEE Industrial Electronics Magazine*, vol. 11, no. 1, pp. 17–27, 2017.

[28] P. Jia, X. Wang, and X. Shen, "Digital-twin-enabled intelligent distributed clock synchronization in industrial iot systems," *IEEE Internet of Things Journal*, vol. 8, no. 6, pp. 4548–4559, 2020.

[29] A. Saad, S. Faddel, T. Youssef, and O. A. Mohammed, "On the implementation of iot-based digital twin for networked microgrids resiliency against cyber attacks," *IEEE transactions on smart grid*, vol. 11, no. 6, pp. 5138–5150, 2020.

[30] Z. Zhou, Z. Jia, H. Liao, W. Lu, S. Mumtaz, M. Guizani, and M. Tariq, "Secure and latency-aware digital twin assisted resource scheduling for 5g edge computing-empowered distribution grids," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 7, pp. 4933–4943, 2022.

[31] D. Geng, C. Zhang, C. Xia, X. Xia, Q. Liu, and X. Fu, "Big data-based improved data acquisition and storage system for designing industrial data platform," *IEEE Access*, vol. 7, pp. 44 574–44 582, 2019.

[32] X. Yu, C. Tang, P. Palensky, and A. W. Colombo, "Blockchain: What does it mean to industrial electronics?: Technologies, challenges, and opportunities," *IEEE Industrial Electronics Magazine*, vol. 16, no. 2, pp. 4–14, 2022.

[33] S. Son, D. Kwon, J. Lee, S. Yu, N.-S. Jho, and Y. Park, "On the design of a privacy-preserving communication scheme for cloud-based digital twin environments using blockchain," *IEEE Access*, vol. 10, pp. 75 365–75 375, 2022.

[34] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Low-latency federated learning and blockchain for edge association in digital twin empowered 6g networks," *IEEE Transactions on*

Industrial Informatics, vol. 17, no. 7, pp. 5098–5107, 2021.

[35] B. Rodríguez, E. Sanjurjo, M. Tranchero, C. Romano, and F. González, “Thermal parameter and state estimation for digital twins of e-powertrain components,” *IEEE Access*, vol. 9, pp. 97 384–97 400, 2021.

[36] W. Dai, H. Nishi, V. Vyatkin, V. Huang, Y. Shi, and X. Guan, “Industrial Edge Computing: Enabling Embedded Intelligence,” *IEEE Industrial Electronics Magazine*, vol. 13, no. 4, pp. 48–56, 2019.

[37] G. N. Schroeder, C. Steinmetz, R. N. Rodrigues, R. V. B. Henriques, A. Rettberg, and C. E. Pereira, “A methodology for digital twin modeling and deployment for industry 4.0,” *Proceedings of the IEEE*, vol. 109, no. 4, pp. 556–567, 2021.

[38] A. Rassõlkin, V. Rjabtšikov, V. Kuts, T. Vaimann, A. Kallaste, B. Asad, and A. Partyshev, “Interface development for digital twin of an electric motor based on empirical performance model,” *IEEE Access*, vol. 10, pp. 15 635–15 643, 2022.

[39] J. Yi, W. Lin, J. Hu, J. Dai, X. Zhou, and Y. Tang, “An integrated model-driven and data-driven method for on-line prediction of transient stability of power system with wind power generation,” *IEEE Access*, vol. 8, pp. 83 472–83 482, 2020.

[40] X. Liu, L. Qiu, W. Wu, J. Ma, Y. Fang, Z. Peng, and D. Wang, “Predictor-based neural network finite-set predictive control for modular multilevel converter,” *IEEE Transactions on Industrial Electronics*, vol. 68, no. 11, pp. 11 621–11 627, 2021.

[41] W. Yu, P. Patros, B. Young, E. Klinac, and T. G. Walmsley, “Energy digital twin technology for industrial energy management: Classification, challenges and future,” *Renewable and Sustainable Energy Reviews*, vol. 161, pp. 112 407–, 2022.

[42] “Ieee recommended practice for the design and application of power electronics in electrical power systems,” *IEEE Std 1662-2016 (Revision of IEEE Std 1662-2008)*, pp. 1–68, 2017.

[43] F. Arrano-Vargas and G. Konstantinou, “Modular design and real-time simulators toward power system digital twins implementation,” *IEEE Transactions on Industrial Informatics*, pp. 1–1, 2022.

[44] S. Deda, A. Eder, V. Mhetre, A. Kuchling, R. Greul, and O. Koenig, “Designing a battery emulator/tester from scratch to prototyping to automated testing within a hil digital twin environment,” in *PCIM Europe digital days 2020; International Exhibition and Conference for Power Electronics, Intelligent Motion, Renewable Energy and Energy Management*, 2020, pp. 1–8.

[45] E. Söderäng, S. Hautala, M. Mikulski, X. Storm, and S. Niemi, “Development of a digital twin for real-time simulation of a combustion engine-based power plant with battery storage and grid

coupling," *Energy Conversion and Management*, vol. 266, p. 115793, 2022.

[46] N. Bazmohammadi, A. Madary, J. C. Vasquez, H. B. Mohammadi, B. Khan, Y. Wu, and J. M. Guerrero, "Microgrid digital twins: Concepts, applications, and future trends," *IEEE Access*, vol. 10, pp. 2284–2302, 2022.

[47] J. Liu, X. Lu, Y. Zhou, J. Cui, S. Wang, and Z. Zhao, "Design of photovoltaic power station intelligent operation and maintenance system based on digital twin," in *2021 6th International Conference on Robotics and Automation Engineering (ICRAE)*, 2021, pp. 206–211.

[48] Y. Gao, X. He, and Q. Ai, "Digital twin based multi-agent coordination and optimization control strategy for smart microgrid," *Power System Technology*, vol. 45, no. 7, p. 9, 2021.

[49] H.-A. Park, G. Byeon, W. Son, H.-C. Jo, J. Kim, and S. Kim, "Digital twin for operation of microgrid: Optimal scheduling in virtual space of digital twin," *Energies*, vol. 13, no. 20, p. 5504, 2020.

[50] Y. Cui, F. Xiao, W. Wang, X. He, C. Zhang, and Y. Zhang, "Digital twin for power system steady-state modelling, simulation, and analysis," in *2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2)*, 2020, pp. 1233–1238.

[51] K. Shi, D. Zhang, X. Han, and Z. Xie, "Lstm and transfer learning based digital twin model for photovoltaic power prediction," *Power System Technology*, pp. 1–11, 2021.

[52] M. Fahim, V. Sharma, T.-V. Cao, B. Canberk, and T. Q. Duong, "Machine learning-based digital twin for predictive modeling in wind turbines," *IEEE Access*, vol. 10, pp. 14 184–14 194, 2022.

[53] D. E. Guzman Razo, B. Müller, H. Madsen, and C. Wittwer, "A genetic algorithm approach as a self-learning and optimization tool for pv power simulation and digital twinning," *Energies*, vol. 13, no. 24, p. 6712, 2020.

[54] J. Falck, C. Felgemacher, A. Rojko, M. Liserre, and P. Zacharias, "Reliability of power electronic systems: An industry perspective," *IEEE Industrial Electronics Magazine*, vol. 12, no. 2, pp. 24–35, 2018.

[55] S. A. Rizzo, G. Susinni, and F. Iannuzzo, "Intrusiveness of power device condition monitoring methods: Introducing figures of merit for condition monitoring," *IEEE Industrial Electronics Magazine*, vol. 16, no. 1, pp. 60–69, 2022.

[56] X. Hu, K. Zhang, K. Liu, X. Lin, S. Dey, and S. Onori, "Advanced fault diagnosis for lithium-ion battery systems: A review of fault mechanisms, fault features, and diagnosis procedures," *IEEE Industrial Electronics Magazine*, vol. 14, no. 3, pp. 65–91, 2020.

[57] F. K. Moghadam and A. R. Nejad, "Online condition monitoring of floating wind turbines drivetrain

by means of digital twin," *Mechanical Systems and Signal Processing*, vol. 162, no. 5, p. 108087, 2022.

[58] S. Venkatesan, K. Manickavasagam, N. Tengenkai, and N. Vijayalakshmi, "Health monitoring and prognosis of electric vehicle motor using intelligent-digital twin," *IET Electric Power Applications*, vol. 13, no. 9, pp. 1328–1335, 2019.

[59] W. Booyse, D. N. Wilke, and S. Heyns, "Deep digital twins for detection, diagnostics and prognostics," *Mechanical systems and signal processing*, vol. 140, no. Jun., pp. 106 612.1–106 612.25, 2020.

[60] J. Xiong, H. Ye, W. Pei, L. Kong, Q. Huo, and Y. Han, "A monitoring and diagnostics method based on FPGA-digital twin for power electronic transformer," *Electric Power Systems Research*, vol. 210, no. 6, p. 108111, 2022. [Online]. Available: https://doi.org/10.1016/j.epsr.2022.108111

[61] K. Sivalingam, M. Sepulveda, M. Spring, and P. Davies, "A review and methodology development for remaining useful life prediction of offshore fixed and floating wind turbine power converter with digital twin technology perspective," in *2018 2nd International Conference on Green Energy and Applications (ICGEA)*, 2018, pp. 197–204.

[62] Y. Liu, G. Chen, Y. Liu, L. Mo, and X. Qing, "Condition monitoring of power electronics converters based on digital twin," in *2021 IEEE 3rd International Conference on Circuits and Systems (ICCS)*, 2021, pp. 190–195.

[63] S. Chen, S. Wang, P. Wen, and S. Zhao, "Digital twin for degradation parameters identification of dc-dc converters based on bayesian optimization," in *2021 IEEE International Conference on Prognostics and Health Management (ICPHM)*, 2021, pp. 1–9.

[64] Q. Wu, W. Wang, Q. Wang, L. Xiao, and B. Hu, "Digital twin approach for degradation parameters identification of a single-phase dc-ac inverter," in *2022 IEEE Applied Power Electronics Conference and Exposition (APEC)*, 2022, pp. 1725–1730.

[65] S. Milovanovic, I. Polanco, M. Utvic, and D. Dujic, "Flexible and efficient mmc digital twin realized with small-scale real-time simulators," *IEEE Power Electronics Magazine*, vol. 8, no. 2, pp. 24–33, 2021.

[66] X. Song, T. Jiang, S. Schlegel, and D. Westermann, "Parameter tuning for dynamic digital twins in inverter-dominated distribution grid," *IET Renewable Power Generation*, vol. 14, no. 5, pp. 811–821, 2020.

[67] X. Xie, A. K. Parlikad, and R. S. Puri, "A neural ordinary differential equations based approach

for demand forecasting within power grid digital twins," in *2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*. IEEE, 2019, pp. 1–6.

[68] N. Kharlamova, C. Træholt, and S. Hashemi, "A digital twin of battery energy storage systems providing frequency regulation," in *2022 IEEE International Systems Conference (SysCon)*. IEEE, 2022, pp. 1–7.

[69] P. Moutis and O. Alizadeh-Mousavi, "Digital twin of distribution power transformer for real-time monitoring of medium voltage from low voltage measurements," *IEEE Transactions on Power Delivery*, vol. 36, no. 4, pp. 1952–1963, 2021.

[70] Y. Wang, R. Xu, C. Zhou, X. Kang, and Z. Chen, "Digital twin and cloud-side-end collaboration for intelligent battery management system," *Journal of Manufacturing Systems*, vol. 62, pp. 124–134, 2022.

[71] M. M. Rathore, S. A. Shah, D. Shukla, E. Bentafat, and S. Bakiras, "The role of ai, machine learning, and big data in digital twinning: A systematic literature review, challenges, and opportunities," *IEEE Access*, vol. 9, pp. 32 030–32 052, 2021.

[72] G. Bhatti, H. Mohan, and R. R. Singh, "Towards the future of smart electric vehicles: Digital twin technology," *Renewable and Sustainable Energy Reviews*, vol. 141, p. 110801, 2021.

[73] F. Tao and Q. Qi, "Make more digital twins," *Nature*, vol. 573, no. 7775, pp. 490–491, 2019.

[74] S. Tan, P. Xie, J. M. Guerrero, J. C. Vasquez, and R. Han, "Cyberattack detection for converter-based distributed dc microgrids: Observer-based approaches," *IEEE Industrial Electronics Magazine*, pp. 2–12, 2021.

[75] M. Novak, U. M. Nyman, T. Dragicevic, and F. Blaabjerg, "Statistical model checking for finite-set model predictive control converters: A tutorial on modeling and performance verification," *IEEE Industrial Electronics Magazine*, vol. 13, no. 3, pp. 6–15, 2019.

Biographies

Haoyu Chen (haoyu.chen@mail.sdu.edu.cn) was born in Jiangsu, China. He received the B.Eng. degree from the School of Control Science and Engineering, Shandong University, China, in 2021. He is currently working toward the Ph.D. degree at the Lab of More Power Electronics Energy Systems, School of Electrical Engineering, Shandong University, China. His research interests include digital twin for power electronics, sustainable energy systems and their reliability. He is a Student Member of IEEE.

Zhenbin Zhang (zbz@sdu.edu.cn) was born in Shandong, China, in 1984. He received the Ph.D. degree (summa cum laude) from the Institute for Electrical Drive Systems and Power Electronics (EAL), Technical University of Munich (TUM), Munich, Germany, in 2016. From 2016 to 2017, he was a Research Fellow and the Group Leader of the Modern Control Strategies for Electrical Drives Group, EAL, TUM. Since 2017, he has been a Full Professor and the Lab Director with Shandong University, Jinan, China. His research interests include digital twin and advanced control for power electronics, sustainable energy systems, and micro-grids. He is a Senior Member of IEEE.

Petros Karamanakos (p.karamanakos@ieee.org) received the Diploma and Ph.D. degrees in electrical and computer engineering from the National Technical University of Athens, Greece, in 2007, and 2013. From 2010 to 2011, he was with the ABB Corporate Research Center. From 2013 to 2016, he was a PostDoc Research Associate in the Chair of Electrical Drive Systems and Power Electronics, Technische Universität München. Since 2016, he has been with the Faculty of Information Technology and Communication Sciences, Tampere University, Tampere, Finland, where he is currently an Associate Professor. His research interests lie at the intersection of optimal control, mathematical programming, and power electronics. He is a Senior Member of IEEE.

Jose Rodriguez (jose.rodriguez@unab.cl) received the engineering degree in electrical engineering from the Universidad Tecnica Federico Santa Maria, in 1977, and the Dr.- Ing. degree in electrical engineering from the University of Erlangen, Erlangen, in 1985. He has been with the Department of Electronics Engineering, Universidad Tecnica Federico Santa Maria, since 1977, where he was a Full Professor and the President. From 2015 to 2019, he was the President of Universidad Andres Bello. Since 2022, he has been the President of Universidad San Sebastian. His main research interests include multilevel inverters, control of power converters, and adjustable-speed drives. He is Life Fellow of IEEE.