An Overview of Digital Twin Technology for Power Electronics: State-of-the-Art and Future Trends

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***Abstract*—Power electronic systems (PESs) are pivotal in power generation, transmission, and diverse industrial applications. With the increasing shift toward digitalization, digital twin (DT) technology has emerged as a transformative enabler, enhancing the informatization and intelligence of PESs. This article offers a comprehensive overview of DT applications for PESs, highlighting core features of real-time synchronization, accurate mapping, seamless data interaction, and high-fidelity modeling. Four prevalent DT modeling approaches are reviewed, with a detailed discussion of their respective strengths and challenges in the context of PESs. This article further examines the role of DT across three critical lifecycle phases—design, control, and maintenance—illustrating how DT optimizes and drives innovation at each phase. By reviewing more than 170 publications, this study identifies key trends, implementation challenges, and research gaps, offering valuable insights into the state-of-the-art and future directions for DT in PESs. This work aims to serve as a foundational reference for researchers and practitioners, fostering a deep understanding of the potential of DT and providing a comprehensive grasp of the application in academics and the industry.**

***Index Terms*—Design, digital twin (DT), operation control, power electronic systems (PESS), predictive maintenance, prognostics and health management (PHM).**

I. Introduction

NOWADAYS, digital twin (DT) technology is developing and expanding rapidly, remaining one of the most salient research areas during the past decades [1], [2].

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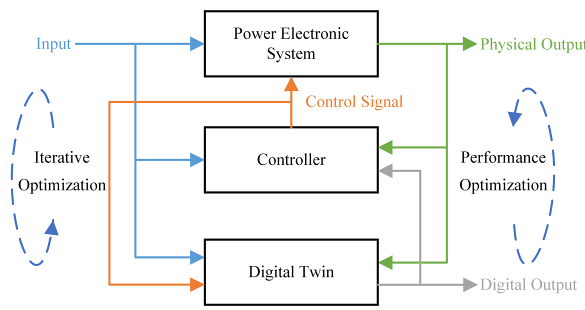

Fig. 1. DT structure for PESs (bidirectional interaction between the physical and digital systems).

DT enables the mapping from the virtual space to the physical space and reflects the whole life cycle process of the corresponding physical object [3]. DT technology has been successfully applied in numerous industrial fields, including intelligent manufacturing, electric vehicles, energy conversion, aerospace missions, etc. With the consideration of achieved effects and further potentials, power electronics benefit from the development of DT. There are various applications, including modeling of power electronic converters [4], parameter estimation of ac–dc converters [5], control for dc–dc converters [6], fault diagnosis in grid-connected inverters [7], life prediction of dc–ac Inverter [8], etc. Through the implementation and integration of DT, power electronic system (PESs) are empowered with capabilities of digitalized modeling, characteristic service, in-depth observability, global prediction, etc.

With the rapid development of artificial intelligence (AI) [9], [10], virtual reality (VR), the Internet of Things (IoT) [11], edge computing [12], and big data analytics [13], new concepts are being introduced to power electronic systems (PESs) across different phases. The emerging technologies and application demonstrations provide immense opportunities and lay a solid foundation for DT in power electronics. DT can establish a simultaneous operational digital system to improve comprehensive performance by system modeling, control optimization, parameter identification, etc. As a consequence, research in power electronics can be conducted through the DT framework, especially in complex and challenging cases.

The typical DT structure for PES is demonstrated in Fig. 1. The DT system is established through the input, output, and control information to realize real-time mapping. The output error between the physical and digital systems is overcome

TABLE I
SUMMARY OF EXISTING REVIEW FOR DT IN PESs

Ref.	Main focus	Methodology	Purpose
[14]	DT modeling methods	DT modeling, Physical-to-virtual, Virtual-to-physical flow	Reveal the relationship between physical and virtual system
[15]	DT uncertainty quantification, optimization methods, datasets and tools	DT uncertainty quantification and optimization methods	Improve accuracy, reduce uncertainty, and improve the usefulness of DT model.
[16]	DT of power systems	DT MSA for the steady-state of power systems	Revisit of steady-state analysis of smart grid
[17]	DT for PV installations	DT enables more informed decision-making in the solar energy sector.	Improve energy efficiency, energy prediction, and the reduction of operation and maintenance costs
[18]	DT for power electronics-based energy conversion systems	DT application throughout the lifecycle management of complex systems	Digitalization and informatization
[19]	DT in various energy supply sector	DT technology within the energy industry	Analyze myriad applications, benefits, and impediments associated with DT technology
[20]	DT in electrical machine control and predictive maintenance	Categorization of framework with DM, DS, and DT	Redefine the next-generation-DT concept
[21]	DT for microgrid	DT modeling methods and applications in microgrids	Assist design, operation management, and maintenance of microgrid
[22]	DT-based predictive maintenance	DT enabling predictive maintenance from a software engineering perspective	Provide reference architecture for predictive maintenance using DT
[23]	DT for offshore wind turbine power converter	DT methodology for RUL prediction of wind turbine power converter	Improve diagnostic and prognostic health monitoring for offshore operating environment
[162]	DT-based health monitoring of DC/DC converter	DT concept in health monitoring of DC/DC converter	Present the design and methodology of the DT modeling methods

and thus guarantees high fidelity. DT interacts the controller and the controller will dynamically regulate the PES to realize performance optimization.

The specific challenges and unique characteristics of power electronic systems (PESs) primarily include high tuning speed in control, strong coupling in health monitoring, limited data availability data in predictive maintenance, etc. Thus, the application of DT in power electronics is quite different from other engineering areas, e.g., smart city, manufacturing, and medical treatment. It is necessary and important to conduct an overview of DT in power electronics to expedite cooperative research and interdisciplinary applications. Based on the literature reviews, the applications of DT in power electronics are categorized into three aspects, i.e., *design*, *control*, *and maintenance*.

Several reviews related to this topic already exist in the literature. In [14] and [15], a comprehensive review of DT, including modeling, enabling technologies, uncertainty quantification, and optimization, is presented. In [16], DT-based steady-state modeling, simulation, and analysis (MSA) for power systems are presented, which only focuses on the steady-state analysis of power systems. In [17], a review of DT and its application in the modeling of photovoltaic (PV) installations is presented, which mainly focuses on energy prediction and maintenance costs. In [18], a survey of DT techniques for power electronics-based energy conversion systems is presented. This article elaborates on a few application cases of DT-based power electronics in power and energy systems.

Design, control, health monitoring, and predictive maintenance in power electronics are always the enduring research hotspot. In [19], a comprehensive review of the dynamic applications of DT technology across diverse energy sectors is presented. Nevertheless, the desirable details of illustrative examples and comparisons are not available. In [20], state-of-the-art of DTs in electrical machine control and predictive maintenance are summarized. This article mainly focuses on the benefits and future work prospects of enabling predictive maintenance in AI techniques. In [21], concepts, applications, and future trends of microgrid DTs are presented to explore different applications of DTs in microgrids. In [22], a systematic literature review of predictive maintenance using DTs is presented. This article points out that the computational burden, data variety, and complexity of models, assets, or components are the key challenges. In [23], a review and methodology development for remaining useful lifetime (RUL) prediction of wind turbine power converter with DT is presented. In [162], several key aspects of health monitoring for dc/dc converters using various approaches based on the DT concept are covered. Table I summarizes the existing review papers, including the main focus, methodology, and purpose.

Previous reviews have focused on the general framework and specific application of DT without a more concentrated and detailed examination of DT modeling methods and typical applications. Therefore, this article predominantly focuses on the general meaning, applicable framework, and typical application of DT in power electronics, providing a thorough survey of theoretical foundations and practical methodologies.

DT technology creates high-fidelity digital replicas of physical systems to accelerate the development process, verify control strategies, and promote maintenance performance, which is critical in power electronics. From the perspective of function, this article endeavors to address the gap and provide a thorough overview of the published research employing DT on power electronics techniques under a systematic consolidation. The significant contributions of this article are highlighted in the following aspects:

1) The relevant DT modeling methods are classified into mechanism, simulation, multiphysics, and data models. The DT techniques in power electronics are investigated systematically from the perspective of enabling functions.
2) The advantages and limitations of DT techniques are comprehensively investigated throughout the lifecycle.

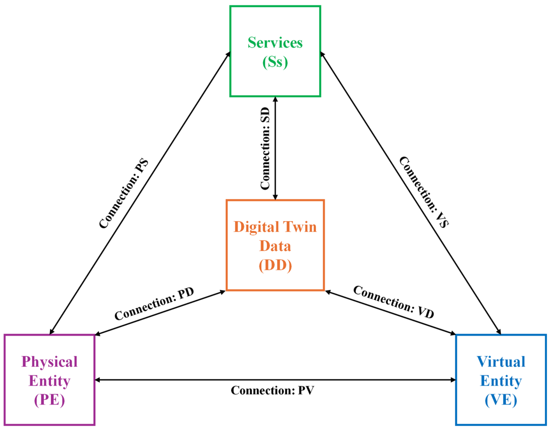

Fig. 2. 5-D DT model [1].

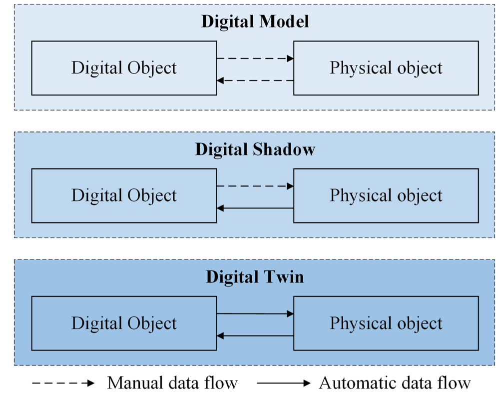

Fig. 3. Data flow in DT at different subcategories.

Exemplary applications for DT in different enabling functions and application scenarios are fully discussed and demonstrated.

3) The challenges and future research directions in the next stage are prospected, especially the digital triplet (DTri). The novel definition can enable high fidelity, local digitization, improved monitorability, superior scalability, and independent controllability.

The rest of this article is organized as follows. Section II discusses the DT concept, framework, and DT for PESs. Section III presents the commonly utilized four DT models in power electronics, including a comprehensive comparison. Sections IV–VI discuss the DT applications throughout the design, control, and maintenance of PESs, respectively. Section VII looks forward to the further prospects of the DT applications, especially the various expansions of DT and novel DTri concept and framework. Finally, Section VIII concludes and summarizes this article.

II. DT Concept and Framework

A. DT Concept

The DT concept was first proposed by Professor Grieves in the course of product lifecycle management in 2003 at the University of Michigan. The initial DT concept was represented as a 3-D model, which includes physical entity, virtual entity, and connection. However, with the continuous expansion of relevant theoretical technologies and the continuous upgrading of applications, the development of DTs presents new trends.

In 2012, the National Aeronautics and Space Administration revisited the concept of DTs, defining them as multiphysics, multiscale, probabilistic, and ultra-fidelity simulations that accurately reflect the state of a corresponding physical twin. This reflection is achieved in a timely manner using historical data, real-time sensor data, and physical models [7].Tao [1] creatively proposed the 5-D DT model, including five dimensions: physical entity, virtual entity, services for both physical and virtual entity, data, and the connection of different parts, which has been widely applied and adopted in industry. The structure of the 5-D DT model is shown in Fig. 2.

In the 5-D DT model, the physical part is the basis of building the virtual part, which supports the simulation, decision making, and control of the physical part. The virtual part characterizes and describes a physical part from multiple dimensions, multiple spatial scales, and multiple time scales. Data lie in the center because of the precondition for creating new knowledge. Services can enhance the convenience, reliability, and productivity of systems. Connection can achieve interconnection between the physical entity, virtual entity, services, and DT data.

Due to the various existing solutions and interpretations of DT across industries, the concept is often understood in diverse and sometimes incomplete ways. Based on various definitions of DT across different contexts, a common and generalized understanding emerges: *DTs serve as digital replicas of physical objects*. This definition of DT is widely approved and is discussed throughout the manuscript.

B. DT Framework

Within the various DT definitions and applications in different domains, some terms are often used indiscriminately, such as digital model (DM), digital shadow (DS), and DT. However, this is a confusion of DT concept and framework aroused by the form of data integration and information interaction. The DT framework can be classified into three subcategories according to the level of data integration [3], which is shown in Fig. 3.

DM is a virtual representation of an existing or planned physical object without automated data exchange between the physical and digital entities. If there is an automated one-way data flow from the physical to digital object, then this combination can be referred to as DS. If data flow between an existing physical and digital object is fully integrated in both directions, then it is referred to as DT. Automatic data flow enables dynamic optimization of the digital object based on physical data, as well as performance enhancement of physical objects through simulation-based insights. The DT framework fosters the interaction and integration of empirical knowledge with data.

Based on the generalized DT framework, the specific DT structure of PES is illustrated in Fig. 1, where data flow in both directions to achieve interaction between virtual and real. The information from PES establishes the DT, while DT reversely optimizes the PES through the feedback to the controller.

C. DT Data

As shown in Fig. 2, the DT data drive the operation of DT, which includes physical entity, virtual entity, service system related data, and fusion data. The integration of physical and digital data can provide more real-time and accurate application services.

In PESs, various sensors embedded within the physical system collect real-time data, including temperature, voltage, current, and other operational parameters. DT data are systematically collected, processed, and utilized to promote design [97], intelligent control [102], [170], operation and maintenance [25], [28], simulation, and optimization [43], [171].

The continuous feedback loop established through ongoing data collection and processing allows the DT to evolve with the physical entity, maintaining high levels of accuracy and fidelity. Advanced analytics, including machine learning (ML)algorithms [81], [41] and statistical [98] methods, are employed to analyze the data, identify patterns, and further aid decision making. During the design phase, DT data help refine system components [66], ultimately improving efficiency and performance [97], [98]. In addition, processed data facilitate real-time monitoring [28] and control [6], enabling the DT to dynamically adjust operating conditions and proactively address potential failures through predictive maintenance [22].

Thus, DT data not only provide actionable insights for decision-makers but also enhance the reliability and overall effectiveness of PESs.

D. DT Modeling for Power Electronics

In the field of power electronics, DT modeling for PECs may just satisfy the partial combinations of the characteristics in multiphysics, multiscale, probabilistic, and ultra-fidelity simulations. In some cases, depending on specific requirements in power electronics, none of these characteristics may be strictly necessary.

The DT model of PES is initially constructed in the digital space based on the modeling complexity and required fidelity. Through data interaction and information fusion, the DT model can be iteratively optimized in real time as the physical system operates. Digital system will also transfer digital output and control signals to the physical system, guaranteeing stable operation and optimizing overall performance. Here is a common guidance for DT modeling in power electronics.

1) Requirement Definition: Clearly define the requirements of the PESs, such as improving design efficiency, promoting control performances, and realizing predictive maintenance. Identify both explicit (e.g., voltage, current) and implicit (e.g., static/dynamic stress) parameters, which further serve as physical inputs.

2) Model Development: According to the specific requirements and modeling feasibility (mechanism complexity, simulation necessity, multiphysics coupling, data accessibility, etc.). Choose and establish the virtual model to accurately replicate the system behavior.

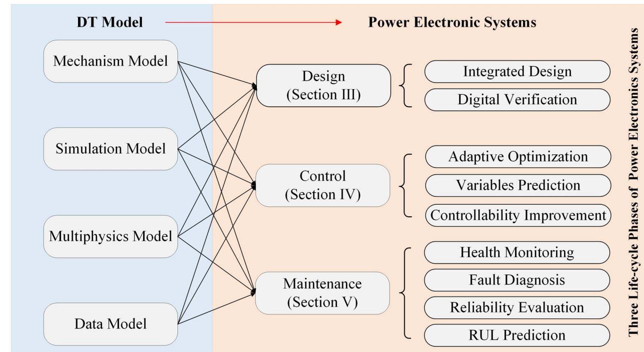

Fig. 4. Four general DT models throughout the design, control, and maintenance lifecycle of PESs.

3) Real-Time Simulation: Continuously collect data from the physical system, such as voltage, current, temperature, and stress levels. Connect the virtual model to real-time operational data, and the DT model should continuously update based on physical inputs, reflecting the current state of the physical system.

4) Fidelity Verification: Evaluate the consistency between the output of DT model and the physical object under the same conditions. To guarantee both availability and reliability, the fidelity of the DT model could be validated at the component level and system level.

5) Model Refinement: Refine the DT model based on feedback from physical experimental results. Test the DT model across different operating scenarios, environmental conditions, and component configurations to ensure overall adaptability and generalization to various use cases.

While real-time synchronization is often considered as a defining feature of DT technology, it is not a strict requirement for all applications in power electronics. DTs can encompass a spectrum of implementations, ranging from fully synchronized, real-time systems to high-fidelity, quasi-static simulations. With the consideration of computational power, advanced sensors, high-speed communication, etc., the implementation of DT depends on the application's specific goals and constraints, keeping a balance between resource requirements and actionable insights.

DT of PES can accurately reflect the real-time operating states, internal mechanisms, possible degradation trends, etc. Furthermore, DT offers real-time capability, high fidelity, and strong scalability, which can be integrated with other advanced techniques, encompassing the entire process of design, control, and maintenance lifecycle for PESs.

III. DT Models for PESs

DT technology has been applied widely throughout the lifecycle of PESs, including design, control, and maintenance. Fig. 4 gives a summary of the models and applications of DT for power electronics. It can be seen that DT has been extensively applied to the three distinctive lifecycle phases of PESs, including design (integrated design and digital verification), control (adaptive optimization, variables prediction, and controllability improvement), and maintenance (condition monitoring, fault diagnosis, reliability evaluation, and RUL prediction).

The construction of a DT model should follow the geometrical, physical, behavior, and mechanism modeling. From the perspective of the object, the DT virtual models can be generally categorized into mechanism, simulation, multiphysics, and data models. The DT models and application stage will be detailed subsequently. Note that a comprehensive but still not exhaustive investigation is conducted. Only the relevant DT methods widely applied are considered in this article.

A. Mechanism Model

Mechanism models, also known as physics-based models, are developed based on the fundamental principles governing the physical system's behavior. These models rely on equations and laws of physics (e.g., Kirchhoff's laws) to represent the system dynamics. Mechanism models directly describe the system characteristics with distinct physical meanings and good interpretability [172]. The mechanism model is also the most commonly utilized DT model, and it has been widely implemented in various PESs [166].

The mechanism model of PES is commonly constructed based on the energy storage devices, such as the voltage and current of inductors and capacitors. Through average modeling and equivalent approximation, the state space can be achieved. In control theory, the state space can reveal the internal relations of the system, the input causes the change of state, and the change of state determines the output [25]. Once the structure and parameters of the PES are determined, the system state can be established, expressing the relationships between internal state variables, inputs, and outputs of the system [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40]. The general expression of the state space equation is as follows:

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du \end{cases} \tag{1}$$

where x is the state vector, u is the input vector, A is the state matrix, B is the input matrix, C is the output matrix, and D is the transfer matrix.

It is also notable that the state-space model is valid for different operation modes [discontinuous conduction mode (DCM) and continuous conduction mode (CCM)] through the combination of switching components. Two ways can be applied to solve (1) and achieve a state vector. One is calculating the eigenvector and eigenvalue of differential equations and constructing the general solution. Based on the initial value of the state vector, the specific solution of these differential equations can be thus calculated. This method requires quite a heavy computation burden in the calculation of eigenvector and eigenvalue.

The other one is through the linearization of (1) with acceptable accuracy. This method has better application and prospects. The output of the system can be described with a discrete time step as

$$y_{n+1} = Cx_{n+1} \tag{2}$$

where the nth time step is defined as the present time interval, and the $(n+1)$th time step represents the next one.

In most applications, forward Euler (FE), backward Euler (BE), Tustin, and Runge–Kutta (RK) methods are selected to linearize the differential equations with the consideration of computing resources, stability, and accuracy. In [30], these four solving algorithms are comprehensively compared. The calculation amount of the FE method is the smallest. The calculation amount of the RK method is approximately four times that of the FE method. The BE and Tustin methods solve the inverse matrix, which means a large amount of calculation.

The RK method is used to linearize the differential equations due to the acceptable error it may cause and the lower simulation time steps [24], [28], [29], [32], [33], [39], [42]. Euler backward is used for larger time steps where numerical stability and accuracy are of greater concern than reduced computation cost and time [27]. Discretized equations are built in a laboratory virtual instrumentation engineering workbench [31] and implemented on the field programmable gate array (FPGA) [34].

The outstanding advantage of mechanism-based DT models is that the complexity of equation expression and analysis will not increase when the number of state variables, inputs, and outputs increases. Meanwhile, the state space analysis method is a kind of matrix operation in the time domain, which is especially suitable for computer operation.

B. Simulation Model

Simulation models are virtual representations of physical systems that replicate their behavior under various conditions. Simulation models enable the virtual testing of scenarios that would be difficult or costly to implement in the real world. Simulation models also ensure stability, improve power quality, optimize dynamic performance, and handle fault situations, especially in the early stages of development and before hardware testing.

Simulation models for power electronics are commonly established in MATLAB/Simulink, which is suitable for complex digital control [51], [52], [57], [59], implementation of intelligent algorithms [45], [46], [47], [48], [54], [58], [63], [64], cooperation with other mathematical analysis tools [50], [53], [60], [135] in MATLAB, and the cosimulation with external real systems [55].

Based on the Simulink controlled object model, hardware-in-the-loop (HIL) is used to develop and test controllers [43], the physical part of which is replaced by an emulator. HIL systems have become widely adopted for the commissioning and testing of control software, such as dSPACE, Speedgoat, RT-LAB, Typhoon, NI VeriStand, and eMEGAsim [44], [133], [140], [141]. The characteristics of HIL are determined by the model fidelity. The real-time nature and I/O capabilities of HIL enable the connection to external equipment for closed-loop testing [49], [56]. The HIL communicates with the hardware-measured values via voltage and current sensors [61], [62], [63], [65].

The simulation-based DT model is a simulated system of the physical PES, the fidelity of which depends on the model accuracy, including the parasitic parameters, switching loss, and electrical stress. Through MATLAB/Simulink, the DT model can be

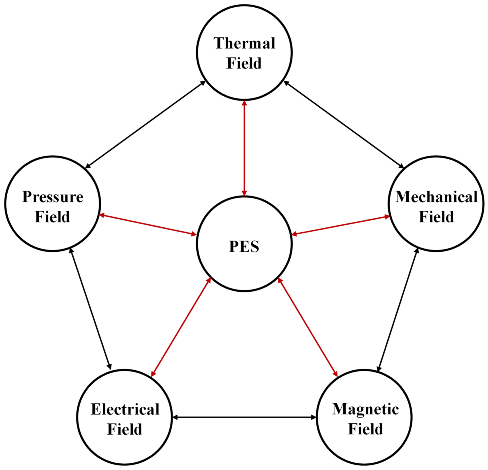

Fig. 5. Effect of multiphysics field (electrical, magnetic, thermal, mechanical, and pressure) of PES.

rapidly established and constructed. Furthermore, through the HIL simulation platform, instantaneous time domain simulations can run in real time using purpose-built high performance, multicore, multiprocessor computing platforms with real-time input/output interface capabilities. HIL simulation is also the further development and extension trend of DT for power electronics.

C. Multiphysics Model

Multiphysics models integrate multiple physical domains, including electrical, magnetic, thermal, mechanical, and pressure, into a unified framework. This DT modeling approach can accurately reflect and represent the interactions between different physical phenomena in PESs. Multiphysics models are crucial for applications requiring high-fidelity analysis, such as reliability assessment and lifetime prediction.

PESs operate in multiple physical fields; this means that the electrical, mechanical, magnetic, thermal, and other parts also need to be modeled from one another. Electromagnetic fields can affect the voltage, current distribution, and electromagnetic interference characteristics. Thermal field can affect the electrical performance of the device, such as ON-resistance and breakdown voltage. Components in PESs are also vulnerable to mechanical stress and strain.

The time scale of physical processes in power electronics covers the range from submicroseconds to years. The system is subjected to various stresses throughout its full lifetime, which will eventually fail and lose function. As shown in Fig. 5, a coupling effect exists between electromagnetic [66], thermal [67], [68], [69], [71], [73], [72], [73], mechanical [70], and pressure [139] fields. In particular, it is difficult for manufacturers of key components to provide safe operation and reliable data under conditions of high-frequency switching.

The behavior and performance of PESs under different working conditions can be understood more comprehensively through the multiphysics model, improving the design efficiency and reliability. DT can comprehensively deal with the coupling problems between multiple physical fields and the interaction effects of multiple time scales.

The electromagnetic model includes PCB layout and packages for power semiconductor devices, which enable the normal operation of PES in the expected electromagnetic environment, without performance degradation or failure. The reliability of electronic components decreases obviously with the increase in ambient temperature. Thus, the thermal model is important for the implementation of measures for reliability improvement and active thermal control. Two common thermal network models include the Cauer model [67], [68], [71], [73] and the Foster model [69], [72]. Stress influences the conversion efficiency and operational reliability of power electronics systems in the subsea environment [139]. The electromagnetic model is important to consider space harmonics, magnetic imbalance, and fault conditions in power electronics [144]. The mechanical model (2-D or 3-D) [85] can quickly locate different loops and information of the PES, bringing great convenience to the operation and maintenance [70].

Finite element analysis (FEA) is a commonly used numerical calculation method for solving multiphysics problems, which decomposes the complex physical field into finite small elements and approximates the distribution of the physical field by numerical solution. FEA has been widely applied in PESs, offering detailed insights and simulations that enhance the performance [144] and predictive maintenance of PESs [85], [142], [143].

The real-time DT model focuses on operational control, monitoring, and maintenance. In some scenarios, understanding detailed physical behaviors, such as thermal dynamics, electromagnetic effects, or mechanical stress, is more critical than synchronization. FEA-based DTs provide insights by offering high-resolution, physics-based simulations, exploring and reflecting complex, nonlinear physical phenomenon.

To meet the challenge of computational power, model reduction techniques can be employed to simplify the model complexity. Moore reduction and balanced truncation methods are widely used to achieve reduced-order models [169]. These approaches involve identifying and preserving the most significant variables while eliminating those with negligible contributions to the overall behavior. For instance, in DT applications, reduced-order multiphysics models can provide near-instantaneous feedback while maintaining high fidelity.

Integrating FEA within a DT framework enables comprehensive monitoring, predictive maintenance, and optimization, contributing to the overall advancement of power electronics technology. Multiphysics simulation software and platforms include COMSOL Multiphysics, ANSYS Multiphysics, Simcenter STAR-CCM+, Altair HyperWorks, Cosim, MpCCI, etc. Note that the multiphysics model plays a critical role in the DT enabling technology, which can be combined and integrated to construct a more complete and synthetical DT system. The multiphysics DT model allows for detailed and comprehensive simulations of multiple interacting physical domains, providing valuable insights that enhance the design, control, and maintenance of PESs.

TABLE II
APPLICATIONS OF DATA MODELS IN DT FOR PESs

Method	Advantages and limitations	Complexity	Exemplary Applications
ANN	- The network structure is simple and the training process is rapid - The optimization algorithm influences the network fitting performance - The overfitting problem remains not solved	+	Maintenance [77], [41], [82], [85], [159]
NARX-ANN	- Memory blocks enable the replication of the nonlinear state equations - High fidelity in both time and frequency domain - More hyperparameters to select	++	Monitoring [74], [78] Maintenance [78]
ELMAN-ANN	- The generalization and adaptability can avoid falling into local optimization - The empirical models of capacitor, resistor, MOSFET, and diode are necessary	++	Maintenance [79]
GRUNN	- Memory of mechanical, electrical, and excitation characteristics - High accuracy in representing the non linear parts for dynamic equivalencing - Simplify structure, improve operation efficiency, and reduce parameters	+++	Maintenance [75]
DNN	- Optimization of learning rates, number, and size of the hidden layers or training batch size - Accuracy enhancement over time and high confidence in DT decisions	++	Maintenance [76], [80], [81]
RF	- Extremely accurate and efficient to run on large data sets - When the number of decision trees is large, the space and time will increase	+	Maintenance [83]
ANFIS	- Robust and adaptive, strong generalization ability, low model complexity - High training cost, difficult to obtain the global optimal solution	++	Maintenance [86]
LSTM	- Handle long sequence dependency and gradient disappearance problems - Long training time and many training parameters	++	Maintenance [103], [109], [114]
CNN	- Excavate the deep multidimensional correlation features of the mapping data - High computational resources required	++	Maintenance [145]
Recurrent NN	- Capture long-term dependencies in time series - Low calculation efficiency and exists the problem of gradient explosion	++	Maintenance [154]

Superior: +++, intermediate: ++, inferior: +.

D. Data Model

Data models are based on empirical data and prior knowledge rather than physical laws, leveraging techniques from AI, statistical analysis, and data mining to identify patterns and relationships within large datasets. The accuracy and reliability of data models mainly depend on the quality and quantity of the available data, which always have certain requirements for the intelligent algorithm, computing power, and communication capabilities. In addition, data models may struggle to extrapolate beyond the range of observed data or to explain the underlying causes of observed data [164].

Data models aim to establish the mapping and functional relationships between the inputs and outputs information of PESs implicitly. The data-dependent characteristics are especially useful when the mechanism model or system expression of a PES is challenging to formulate and achieve. ML has developed rapidly and provides large amounts of data. This growing volume of data lays a solid foundation for data modeling in different DT applications.

Table II summarizes the data models of DT for PESs, in terms of the advantages, limitations, complexity, and exemplary applications. Generally, data models are established through connectionism, such as neural network (NN). Through NN, knowledge is learned from the training dataset, which will decide and influence the connection weights and structure characteristics of the network. Numerous corresponding kinds of research have enhanced the performances of NN-based data models for DT modeling. ANN has achieved good fidelity for DT modeling of PESs [77], [41], [82], [85].

Some further researches deal with enabling the uncertainty capability in handling the noisy signal of ANN to improve the robustness and fidelity of DT. This feature is facilitated by integrating the fuzzy logic into the ANN [e.g., adaptive network-based fuzzy inference (ANFIS)] [86], the auto regressive into the ANN [e.g., nonlinear auto regressive model with exogenous inputs-artificial neural network (NARX-ANN)] [74], [78], and the memory structure into the ANN (e.g., ELMAN-ANN) [79],

Compared with the conventional NN, the dynamic performance of the NN can be improved to tackle time-series dataset cases and enhance dynamic performances. This feature is facilitated by introducing the recurrent structure into NN [e.g., gated recurrent unit neural network (GRUNN)] [75], and the deep learning (DL) techniques explore and deepen the structure of NN [e.g., deep neural network (DNN)] [76], [80], [81]. long short-term memory network (LSTM) NN is used to diagnose the multiple faults in a modular multilevel converter (MMC), which has better robustness and accuracy [103], [109], [114]. A convolutional neural network (CNN)-based DT model with topology information extraction layers and key equipment parameter adaptive perception layers is built to measure the loss in ultra-high voltage direct current systems [145].

E. Discussion

In DT modeling methods, the mechanism model and multiphysics model mainly depend on theoretical knowledge, the simulation model depends on computational power, and the data model depends on data quality and quantity. The mechanism model can help with the interpretation of physical entities, and predicting system behavior and performance. The simulation model can observe and optimize the operation of the system, helping with decision support and risk assessment. The multiphysics model emphasizes multiphysics coupling analysis for

TABLE III
COMPARISON OF FOUR DT MODELS FOR PESS

DT model	Advantages	Disadvantages	Computational Cost	Scalability	Ease of Integration	Suitable Applications
Mechanism Model	**Understandability:** easier to interpret since well-known physical principles. **Accuracy and Predictability:** ensure high confidence in predictions and, critical for reliability **Deterministic Nature:** offers consistent and predictable outcomes	**Model Complexity:** quite complex when interacting components **Limited Flexibility:** difficult to adapt to changes or to incorporate new phenomena not initially considered	**Low:** relies on physical laws and equations	**High:** easily adapts to larger systems.	**High:** integrates with straightforward models and physical interpretations	**System Design:** simulating of inverters, converters, electrical drive systems, etc. **Stability Analysis**: realizes the system stability analysis and compensation **Mathematical Model**: iterable, portable and embeddable
Simulation Model	**Flexibility**: complex and nonlinear systems modeling, which are difficult to solve analytically. **Scenario Analysis:** multiple scenarios to evaluate different operating conditions	**Model Accuracy**: depends on the accuracy of the underlying model and metamodel **Computational Resources:** resource-intensive to guarantee high-fidelity simulation	**Moderate:** requires numerical solvers and simulations,	**Moderate:** depends on the model complexity and simulation resources	**Moderate:** depends on compatibility with simulation platform	**Preliminary Design**: structure, typology, and parameters selection **Control Strategies**: evaluating and optimizing control algorithms **Reliability Testing**: simulates long-term operation effects and improves reliability
Multiphysics Model	**Interdisciplinary Applications**: understands interactions between different physics fields **High Fidelity**: high-fidelity system considering interdependencies	**High Complexity**: complex to develop and validate due to multiple physical domains **Resource Intensive**: requires computational power and expertise	**High:** requires solving complex coupled equations across multiple domains	**Low to moderate:** difficult to scale of the integrated physical domains	**Low:** dependencies on specialized software	**Multiphysics Coupling**: the interplay between multiphysics performance in PESs **Failure Analysis**: the effects of combined stressors on reliability
Data Model	**Data Mining**: discovers hidden patterns, and relationships in large amounts of data **Scalability**: easily scalable to large and complex datasets	**Data Dependency**: heavily relies on data quality and quantity **Interpretability**: less interpretable due to the algorithm complexity **Model Training**: significant effort to train models	**High:** large datasets and complex algorithms	**High:** easily scalable with TL	**High:** easily integrates with AI/ML frameworks	**Predictive Maintenance**: predict failures and schedule maintenance **Performance Optimization**: real-time monitoring and optimization **Fault Detection**: identifies anomalies and faults

both power electronic components and systems. The data model relies on data analysis techniques to solve prediction, classification, and optimization problems, extracting patterns and patterns from the historical dataset.

With the consideration of real requirements and characteristics, different modeling methods can be selected to construct the DT model. In the design phase, mechanism and multiphysics models can contribute to the rapid principal proof and effective initial design. In the control phase, the simulation model is suitable to verify control strategy, system stability and robustness with the advantage of continuous testing and validation. In the maintenance phase, large amounts of operational data emerge within the long operation period, which has the potential to leverage data to promote maintenance performances.

Table III tabulates a comprehensive comparison of four DT models for PESs, expressing respective advantages, disadvantages, and applicable scenes. By leveraging the strengths of each method, more accurate, comprehensive, and insightful DT models can be established and tailored to particular needs in power electronics.

In future research, different DT modeling methods will evolve into a more diversified and comprehensive stage. DT models can be integrated to create a more comprehensive DT system. For example, the mechanism model can serve as the foundation for the simulation model, with the simulation results used to train the data model. In addition, the multiphysics model can enhance the realism and accuracy of the PES.

The edge-cloud deployment of different DT models places computational and storage resources either at the edge (closer to the physical system) or in the cloud (centralized and remote servers), which always needs to balance performance, cost, and flexibility. Edge-cloud deployment strategies are critical for the real-time control, monitoring, and maintenance of DT in power electronics systems.

The technical tradeoffs include latency versus computational power, scalability versus localized control, data security versus centralized analytics, cost versus performance, etc. The implementation strategies for edge-cloud deployment also balance performance, flexibility, and cost in diverse power electronics applications. Tasks partitioned with real-time, high-priority functions (e.g., fault detection and predictive control) are executed on edge devices to minimize latency, while resource-intensive tasks (e.g., long-term monitoring and large-scale simulations) are processed in the cloud. An optimal balance between edge and cloud resources, informed by system-specific requirements, is critical to achieving high reliability and performance in modern power electronics applications.

The following three sections will thoroughly describe and discuss research on the previously introduced DT modeling methods for typical PESs, covering the entire lifecycle of design, control, and maintenance. In addition, several typical application cases are available to illustrate the characteristics of DT.

IV. Design

The design process of a PES mainly includes the topology selection, component sizing, circuit synthesis, reliability evaluation, and so on, which can be referred to by IEEE standards for the design of power electronics equipment [87]. The design of a power electronics system is essentially a single or multiple objective optimization process. A typical design procedure can be divided into four steps, namely, objective formulation, constraint space, solution exploration, and performance verification [88].

Objective functions are the design goals to be either maximized or minimized. In general, the design goals of power electronics mainly include component parameters, weight, volume, cost, power loss, etc. Then, the feasible space, boundary, and limitation of the objective function are defined as constraint space (linear or nonlinear equalities and inequalities). Different optimization algorithms can be used to adjust the decision variables in the constraint spaces to find the optimal solution. Finally, the candidate schemes can be testified and simulated through simulation, HIL testing, prototype experiments, etc. until the finalization of the design scheme.

The traditional design methods of PESs are quite time consuming and involve too many repetitive and cyclic iteration processes, e.g., objectives adjustment, constraint space modification, optimization algorithm selection, etc. However, DT can solve the aforementioned problems by realizing integrated design and rapid simulation. In the DT-based design process, the design efficiency, simulation modeling, and system reliability can be improved.

During the design period in power electronics, DTs mainly focus on the subcategory of DM. The input of DTs consists of design objectives and constraints, parameter selection, and design solution to be proven, etc. DT will output the optimized design plan through iterative optimization and digital verification, improving design efficiency. The connection between the physical and virtual systems is mainly executed in a manual way to exchange data.

A. Integrated Design

The DM in the objective formulation can effectively reduce the computational effort. The DM yields both dynamic and static behavior to the physical entity, which is challenging to formulate or requires computational efforts to characterize. In the iterative design process, DT provides an integrated platform that can reduce the computational effort [94].

DT integrates diverse disciplines, physical phenomena, scales, and probabilities simulation processes through the physical models and sensors. It achieves comprehensive mapping in virtual space, mirroring the entire lifecycle of corresponding entities. This integration facilitates optimization in power grid design [89], simulation of grid faults [90], development of virtual power plants, intelligent equipment monitoring [21], and provision of related services. In [21], the design process for a DT microgrid system is examined from a structural perspective, considering the capacity of the system equipment, application environment, and uncertainties stemming from factors, such as wind speed, solar radiation, and ambient temperature. Subsequently, virtual DT models can be initially developed and provided to validate the design schemes.

An intelligent operation and maintenance system for PV power stations leverages DT technology. The system design was accomplished using the Unity3-D VR engine, while solar PV panels were modeled using the 3-D modeling software 3dsMAX. In addition, two AI algorithms aimed at achieving real-time power prediction and fault diagnosis within the DT system [92]. DT is utilized to design thermal power plant cooling systems using the fuzzy system [93]. This DT model will function as an automated decision support tool grounded in logical reasoning, aimed at integrating enhancements in energy efficiency.

DT has also been applied to the parameter design and optimization of power converters [66], [97], [98], electrical drive systems [96], and electrical networks [99].

In [66], a DT of the switching cells containing discrete silicon carbide (SiC) power devices was developed and verified through double-pulse experiments. The developed DT is capable of simulating the influences of parasitic capacitances in SiC power MOSFETs, which can also optimize the distribution of the signals and the thickness of the PCB layers to reduce power losses. In [96], the framework and technical route of building DT models for permanent magnet synchronous motor (PMSM) drive systems are fully discussed. In [97], a DT of a phase-shifted full-bridge converter can realize precise calculations of effective and circulation intervals. In addition, the DT facilitated the parameter optimization of magnetic components to minimize operational losses across diverse application scenarios. In [98], a DT application focuses on an active neutral point clamped (ANPC) inverter integrating a controller. The controller simulates ANPC responses to validate the design-for-trust attributes, thereby incorporating preemptive protective measures.

B. Digital Verification

In the early development and modeling stages for PESs, DT can promote the stage of digital verification. DT can eliminate the necessity for physical prototypes, reduce design time, and improve quality by combining multiphysics simulation, data analytics, and ML to demonstrate the impact of design changes, application scenarios, environmental conditions, and other variables. Therefore, the DT model is also very useful for testing, validating, and integrating complex PESs, which are hard to verify on real systems. The dynamic analysis of the system under various operating conditions is also available through DT-based digital verifications.

With the combination of HIL and rapid control prototyping, the DT model with HIL capability is more compatible with model-based design, promoting real-time connection, bidirectional mapping, rapid simulation, dynamic interaction, and feedback control.

A robust adaptive back-stepping control approach for MMC is verified through DT simulator. Compared with the traditional proportional–integral control method, the proposed method is more robust in tracking the reference signal quickly and accurately [108]. The capability of DT real-time simulators is fully described to highlight the interfaces with other software tools and system controllers for the HIL test of onboard power systems, demonstrating the DT model-based design engineering methodology with real-time controllers in [43].

Moreover, HIL can validate and test the batteries, power converters, and motors, enabling simulation of real behavior. A significant reduction in the testing time of power plants with battery storage and grid coupling is achieved from a three-day testing period in the real-world system to just 4 h within the HIL DT environment [95]. HIL environment is built to bring considerable improvements in the development process of DT-based battery emulators. The congruence of the HIL system and model-based controller parameter tuning is also proved [91]. A DT-based framework is used to simulate higher-fidelity battery systems in real real-time environment. The proposed DT model is split into multiple cores to achieve faster and more accurate HIL simulations, which is useful for developing more robust control systems and satisfying real-time requirements [140].

In [141], a comprehensive analysis of the field-oriented control algorithm for a PMSM is achieved by developing an analytical DT model and a structural model using Typhoon HIL. The digital verification results demonstrate the accuracy of the DT approaches, providing a simulation tool capable of estimating the behavior of real PESs.

C. Discussion

During the design phase, DT can enhance designs through optimization and simulation based on high-fidelity DMs. Various design schemes can be tested in a virtual environment to evaluate overall performance and select the optimal solution. This approach shortens the design cycle and reduces development costs. Moreover, the data and insights generated by DT during the design stage can also contribute to improving the overall performance of the PES during the further control and maintenance phases.

V. Control

DT is capable of accurately reflecting and sensing the real-time operating state of physical entities, which can contribute to the performance evaluation of PESs and thus make rapid decisions in response to changes in parameters and operating conditions. Fundamentally, control applications with DT methods in PESs can be categorized into the following three aspects: adaptive optimization, variable prediction, and controllability improvement.

Similar to the optimization process during the design phase, intelligent algorithms are usually adopted to realize multiobjective optimization problems. The DT can track the reference fat accurately, ensuring a detailed perception of the physical system. Furthermore, DT techniques can improve the accuracy of system representation and provide more accurate control signals.

DT system can combine different data and knowledge in multiple physical fields, keeping a high fidelity with the physical entity from several dimensions. Therefore, DT techniques can be applied to realize the real time and accurate prediction of state variables in PESs. Through the prediction of critical variables, the anti-interference ability can thus be improved and enhanced.

The controllability of a system mainly reflects the ability of a system to keep control performances under the disturbance of external uncertainty. DT contains its own digital controller, which keeps synchronous operation with the physical controller. Thus, DT can improve the control robustness, detect the failure of the physical controller, and further replace it in real time.

During the control period in power electronics, DTs mainly focus on the subcategory of DS. The input of DTs is the real-time operational data and control requirements of the physical system and the output is the control strategy, operation plan, predicted variables, etc. The data automatically flow from the physical to the digital system and builds a one-direction connection to exchange data.

A. Adaptive Optimization

DT technology provides a feasible technical path for the complexity and flexibility of smart microgrid operation [100], [102], [105], analysis [90], and control systems [100]. Compared with the conventional model-based counterpart of smart microgrids, DT-based MSA for the steady-state control method is more adaptive and effective [90]. The DT-based decision-making methodology, along with clustering techniques, has been leveraged to identify the most effective microgrid operating strategy. This approach provides swift solutions while ensuring adherence to constraints, thus mitigating computational burdens in optimizing microgrid performances [105].

In [100], a DT model was proposed to establish a daily energy storage system (ESS) charging/discharging schedule for microgrid operation. Through the DT, the variation of microgrid configuration and different operating algorithms were applied to the virtual space to solve the difficulties during the operation of the microgrid and improve overall operational efficiency. The suitability of the DT model was evaluated through comparative analysis with the optimization-based ESS charging/discharging scheduling pattern.

In [102], DT agent model components were constructed to realize the multiagent control of smart microgrids based on multiobjective decision analysis. The Opal-RT digital simulator built a semiphysical simulation platform for verification experiments. The results validated that the data-driven operation of various agents under the guidance of DT can improve the self-sensing, self-predicting, and adaptive capabilities of smart microgrids.

In [101], a genetic algorithm (GA) approach was introduced within the DT framework to learn and optimize seven parameters of a PV system or subsystem of unknown characteristics. Significant reduction in deviation from ideal PV parametrization is achievable tailored to a specific PV system, along with access to extensive training datasets. A real-time DT-based power HIL test bed for reliable PESs has been discussed with examples of fault-tolerant converters, power electronic interfaces, all-electric ships, and multiterminal dc systems protection [56].

The DT approach is applied to the adaptive control of a switching converter in the power distribution system of an all-electric

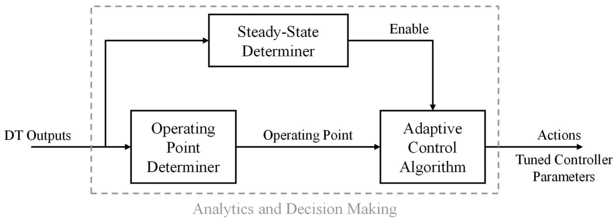

Fig. 6. Analytics and decision-making DT function block for adaptive control algorithm in tuning controller parameters of power converters [37].

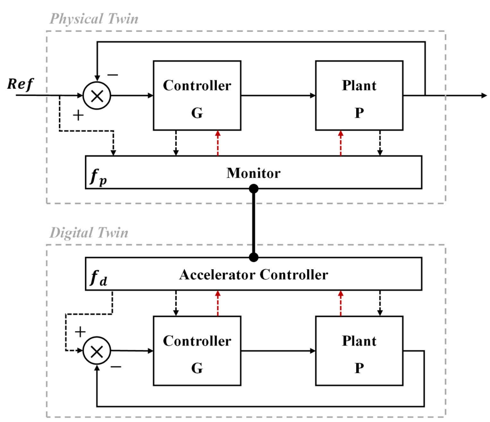

Fig. 7. DT-based state prediction accelerator controller and the close loop control of physical twin for DAB converter [40].

ship [37]. The DT model of a boost converter runs in real time or faster than real time (FTRT) for look-ahead simulations. As shown in Fig. 6, the operating point determination block finds the converter operating point, the steady state detector block enables the adaptive control algorithm block. In simulation verification, when the reference voltage increases to 120, 150, 200, and 250 V, the DT-based adaptive controller can effectively eliminate voltage oscillations during the transients. After steady state is detected for the boost converter, the values of adaptive controller change accordingly to obtain a certain bandwidth. Thus, the DT model was able to adaptively tune the outer voltage loop controller for a specific bandwidth to maintain stability and performance at a wide voltage range.

B. Variables Prediction

DT model of a PES is characterized by an acceleration process [40], FTRT [75], model accuracy [104], and future prediction [103], [109]. In [40], a prediction accelerator DT model is established for a dual activate bridge (DAB) converter, which feeds back the predicted system state to the controller. This method can recover from faults, such as load and input voltage variations, in real-time and can integrate with HIL for future applications.

Fig. 7 shows the structure of the accelerator scheme, the accelerator operates the simulation model with a faster operating clock and makes predictions operating trend of the physical twin. The predicted future time size depends on the ratio of the accelerator operating frequency f_d to the physical operating or sampling frequency f_p.

After the prediction, a matrix containing the controller state and output error will be captured for each predicted time step. The data will then be transferred to the accelerator controller, which will calculate the effective controller state for the physical twin controller. DT accelerator is verified to achieve better control performances than feedback control, output-current-feedforward control, sliding-mode control, and moving discretized control set model predictive control.

In [75], an FTRT DT method is introduced for energy control centers, integrating ML-based models for synchronous generator (SGM) and dynamic equivalent (DEM). The proposed models are implemented on FPGAs to emulate real power system dynamics. Leveraging the GRUNN, the SGM, and DEM are trained using datasets derived from offline simulation tools, ensuring an accurate representation of system behavior.

DT model for PV power generation prediction based on LSTM and transfer learning (TL) is established [103]. The proposed DT model realizes the synchronous and real-time updating of the PV systems, thus obtaining more accurate prediction results. The knowledge learned from PV systems with sufficient historical data is used to assist PV systems with limited historical data to establish a DT model of power generation prediction and save the model's training time [109].

In [104], the output voltage of multilevel boost converters is stabilized through the combination of nonlinear terminal sliding mode control technique and deep reinforcement learning. The DT model of the controller is established to improve the accuracy of the model implemented on a digital signal processor (DSP). The results showed that the proposed methodology can effectively tune the feedback control coefficients. A stability analysis method employing the DT approach is proposed to determine the closed-loop impedance of three-phase ac systems. DT can offer insights into its dynamic response and identify potential instability issues [158].

C. Controllability Improvement

To address the challenges in modeling, designing, and developing proportional–integral–derivative feedforward algorithms for the control of PESs, researchers have identified the DT method for implementation on resource-constrained FPGAs [105]. This methodology involves several steps: digital hardware design of a discretized PID controller, determination of PID gains using MATLAB/Simulink, and integration of the digital design into a DT environment for software-in-loop tuning and validation. The outcomes highlight the effectiveness of this approach in crafting high-performance and dependable controls, while also reducing control development time.

Large-scale simulators, such as RTDS, Opal RT, and dSPACE, which are commonly utilized in the power systems domain [43], [107], and smaller-scale counterparts are typically designed for power electronics applications [44]. In [107], a novel overcurrent protection scheme based on DT for a distribution network with distributed energy resources is proposed. The power HIL scheme is designed and three-phase short circuits are simulated in the

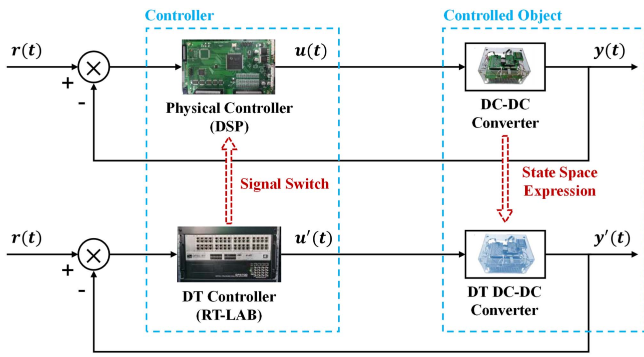

Fig. 8. Control architecture of the DT-based Buck converter system based on state space expression (DT controller controls the physical converter through signal switch) [6].

network at three points to validate the fault clearance times and selectivity of the relays. In [44], the DT of the MMC is realized using the small-scale HIL units. Seven RT box units were employed to run the MMC model. The developed DT-based HIL platform was verified against an industrial ABB PEC800 controller under different modes, including MMC charging, no load operation, full load, and voltage reference change.

In [6], a DT-based buck converter system is explored for simplicity without loss of generality from the perspective of control adaptability. Fig. 8 illustrates the control architecture of the physical-DT buck converter control system, including both the hardware (physical part) and the DT system (digital part), running in RT-LAB. In Fig. 8, $r(t)$ represents the input, $u(t)$ and $u'(t)$ represent the control signal from the physical and digital controller, $y(t)$ and $y'(t)$ represent the output of the physical part and digital part, respectively.

The proposed DT system is validated to be effective for different cases, including reference value tuning, system model variation, and the switching of the physical controller. In [6], once the control input $u(t) = 0$ is detected, which means the physical controller of the physical buck converter system fails. The DT controller can be regarded as a redundant system to improve the reliability and stability of the physical system. Both simulations and experimental verification are conducted, showing that the DT can dynamically track the physical dc–dc converter, detect the failure of the physical controller, and replace it in real time. During the switching process, the physical system can quickly adapt to the DT controller, the transition time is about 500 ms and the aroused overshooting keeps under 1.0 V (48 V output), which ensures a smooth transition and maintaining good control performance.

The DT model is updated in real time based on the physical system, and the DT controller can be used to control the physical system if physical controller failure occurs, which can comprehensively improve the overall control performance.

D. Discussions

The complexity of control algorithms and the computational burden are major challenges in control applications. However, with real-time feedback and synchronization of virtual models, DT allows PESs to adaptively adjust control strategies in response to external changes and system dynamics. A DT-based control structure can predict the system state, optimizing the control process and overall control performance. To further enhance the controllability of power electronics systems, the interaction and collaboration between the DT controller and the physical controller present promising opportunities.

VI. Maintenance

While reliability characteristics have been thoroughly deliberated throughout both design and control processes, PESs continue to face diverse risks and occasional catastrophic failures attributable to complex and harsh operating environments [6], [28], [110]. The long-time and high reliability of power electronic components, converters, subsystems, and systems hold paramount significance in various practical field applications.

Various maintenance policies for PESs have been implemented, including corrective maintenance, scheduled maintenance, condition-based maintenance (CBM), and predictive maintenance. Predictive maintenance has gradually become a research hotspot with the advantages of high reliability and low cost throughout the whole life cycle [20], [86].

Predictive maintenance puts more emphasis on the utilization of the system's future state, dealing with the knowledge mining of all kinds of Big Data and reducing the influence of information uncertainty on the prediction model. DT can contribute to mechanism-driven and data-driven learning in predictive maintenance, which can accurately predict the possible failure probability and the remaining service life of PESs [20], [22].

During the predictive maintenance period, preventive measures, such as condition monitoring, fault diagnosis, reliability evaluation, and RUL prediction, play pivotal roles in improving reliability. These activities adhere to the IEEE standard framework of prognostics and health management (PHM) for electronic systems [111]. Fig. 9 illustrates a systematic flowchart detailing maintenance activities within PESs. Generally, it consists of the following three parts. The characteristics and advantages of DT-empowered maintenance activities are obvious and prominent.

1) *DT informed learning:* This part integrates both physical and digital PESs. The physical system contributes to prior degradation, historical failure, and failure effects, and nondestructive testing can energize the physical system. The digital system energizes expert knowledge, mechanism analysis, multiphysics simulation, and multiscale deduction. Through the combination and formalization of physical and digital information, the DT informed learning is executed and achieved, including processing methods (data cleaning, data correction, data fusion, data mining, feature extraction, knowledge reasoning, etc.) and learning methods (parameter identification, state estimation, expert system, statistical modeling, signal analysis, NN, etc.).
2) *Monitoring and predicting*: This part enables the information selection, learning methods switching, and parameter tuning. Based on DT-informed information, different

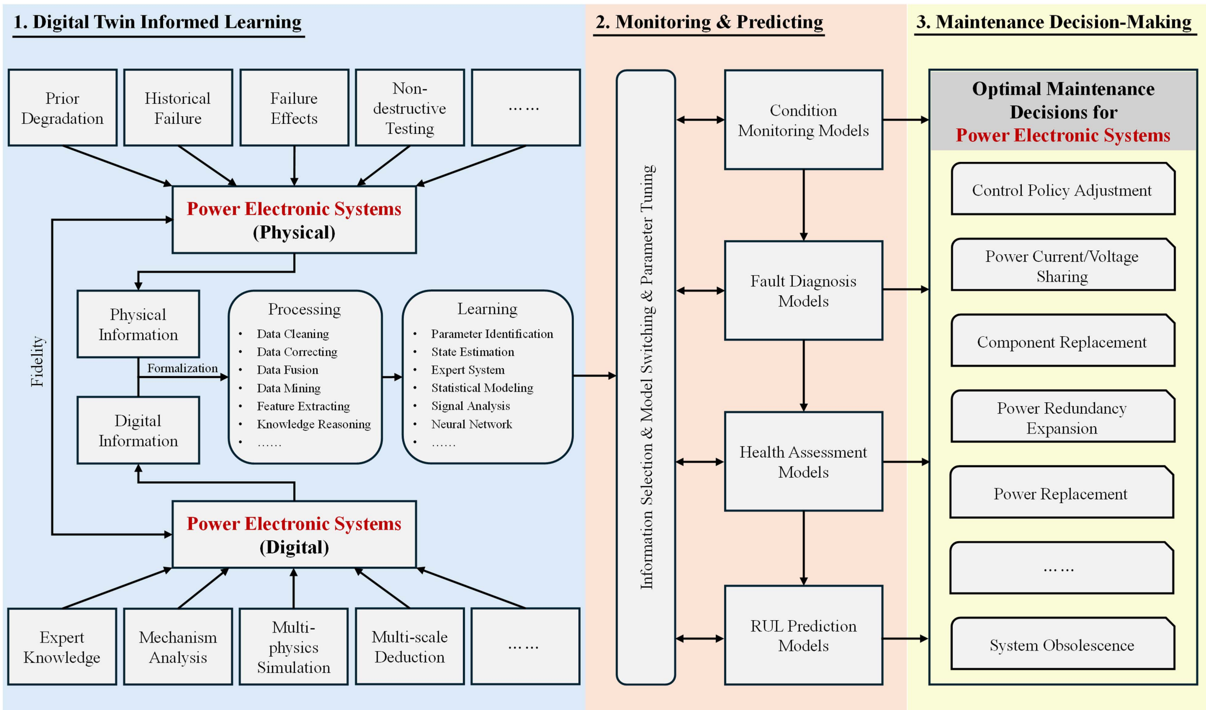

Fig. 9. Systematic flowchart of maintenance in power electronics, including DT informed learning, monitoring and predicting, and maintenance decision making.

learning methods are switched to establish appropriate condition monitoring, fault diagnosis, health evaluation, and RUL prediction models to realize different functions. Moreover, the model parameters are customized and individualized to suit the real operational environment and enduring stress through the model parameter tuning and updating. Therefore, DT-informed knowledge can be extracted from the continuous condition monitoring information, thus guiding and promoting maintenance decision making.

3) *Maintenance decision making*: In this part, the DT supportive knowledge from the monitoring and predicting part is feedback to optimize the maintenance decision-making process, including control strategy adjustment, power sharing, component replacement, system redundancy expansion, system replacement, and system obsolescence. The DT can continuously facilitate and promote the condition-based and predictive maintenance of PESs.

Traditional maintenance has various limitations, such as difficulty in obtaining data due to harsh environments, understandability, and explainability of ML algorithms. However, maintenance based on DT models is a highly customized, high-fidelity, real-time operable process that can evaluate the current condition and further predict future development trends of PESs [124].

During the maintenance period in power electronics, DTs mainly focus on the subcategory of DT. The input of DTs is the real-time observational data of the physical system. Through the data analysis and algorithm process, DT will output estimated conditions, possible faults, assessed reliability, and predicted life of the physical system. The data circularly flow between the physical and digital system, dynamically keeping the high-fidelity mapping and bidirectional connection. A comprehensive discussion on the pertinent applications of DT in maintenance will be presented, focusing on the following three aspects.

A. Condition Monitoring

Condition monitoring technology enables predictive maintenance by monitoring changes in system characteristics and predicting the maintenance requirements before serious deterioration or failure occurs [24], [28]. Real-time monitoring of voltage, current, temperature, vibration, and other parameters, combined with data analysis and processing management are used to determine the condition of the power electronics system [46], [54]. The selected characteristic parameters can evaluate the real-time condition more accurately. Through parameter monitoring, possible faults or degradation conditions can be promptly located, improving the reliability of the system [112].

Compared with the conventional condition monitoring method, the DT technique can observe and cover more hidden and informative insights, including a higher precision of parameter identification and a deeper degree of data mining. Sufficient and comprehensive condition monitoring for PESs serves as a basis for the subsequent PHM applications. Table IV compares DT-based parameter identification methods in PESs.

1) Parameter Identification: According to the former research [119], the main reasons for failure in PESs are capacitors, inductors, semiconductors, etc. The characteristic parameters of these components can be directly measured and sampled through the development of specific hardware. However, the

TABLE IV
COMPARISON OF DT-BASED PARAMETER IDENTIFICATION METHODS IN PESS

Method	Power electronics system	Characteristics parameters	Accuracy	Advantages and limitations	Reference
PSO	Matrix converter	Capacitor and inductor	>95%	- Stability analysis is conducted [30] - Cluster-data based method is used [25], [28] - Noninvasive, calibration-free, and without additional hardware circuits [25], [28], [32], [47], [51], [54] - Considering the power loss of self-heating components [33] - No need of tedious mathematical modeling and linearization steps [46], [39] - Parasitic components in the gate loop circuit are considered [55] - Solving time within 1μs [58] - Cross-coupling effects between self-heating and all cross-coupled heating is considered [67] - Expansion verification of multi working conditions [152]	[30]
	Buck converter	Capacitor and MOSFET	N/A		[25], [28]
	Buck–boost converter		>85%		[32]
	Boost converter	Inductor, capacitor, and MOSFET	>95%		[31], [34] [168]
	Buck converter	Capacitor, diode, and MOSFET	>94%		[33]
	Multiphase Boost Converter	Inductor, capacitor, and MOSFET	> 95.3%		[39]
	Buck converter		N/A		[46]
	Single-Phase PWM Rectifiers		>92.5%		[51]
	DC–AC Inverter	Inductor, capacitor, IGBT, and load	N/A		[47]
	MMC		>95.24%		[54]
	Single-phase full bridge	MOSFET	>97%		[55]
	AC–DC Boost rectifier converter	Inductor, capacitor, and IGBT	>93.5%		[58]
	Buck converter	IGBT	N/A		[67]
	3L-ANPC inverter	Capacitor, IGBT	>95%		[152], [167]
Chaos particle swarm optimization (CPSO)	PMSM	Stator inductances, stator resistance; flux linkage.	>90%	- Without signal injection or additional sensor and measuring equipment	[42]
Constriction particle swarm optimization (CPSO)	Five-level active neutral point clamped (5L-ANPC) inverter	Semiconductor switches	>92.5%	- Simplicity and effectiveness in high-dimensional search spaces - Dependence on the resolution and precision of the sensory data	[64]
PSO and DEKF	Power semiconductors in converter	Thermal resistance and junction temperature	N/A	- Fast convergence speed - Robustness is unverified	[73]
PSO and GA	Two-phase interleaved boost converter	Inductor, capacitor, and MOSFET	>95%	-Verified in both balancing and unbalancing situations - More influencing factors need to be considered	[29]
	Buck converter		>93.5%		[153]
	AC–DC three-phase boost rectifier converter	Inductor and capacitor	N/A		[63]
AOA	Buck converter	Inductor, capacitor, and MOSFET	>92%	- Efficient global search and fast convergence	[48]
BO	Boost converter and buck converter	Inductor, capacitor, and MOSFET	>90%	- Achievement of similar optimization results as PSO with less iteration steps	[45]
GA	Buck converter	Capacitor	>95.58%	- Considering the electrothermal coupling effect	[69]
RLSs	/	Capacitor	>90.5%	- Characteristic parameters of capacitors can be monitored simultaneously with the operating temperature	[71]
Interior Point Method (IPM)	Two-level bidirectional DC/DC converter	Inductor, capacitor, MOSFET	>99%	- Fast convergence, high precision, consistency in producing repeatable results	[161]

accuracy of parameter identification depends on the performance of hardware equipment, which limits its applicability.

Considering the features of tight space layout, rapid switching frequency, coupling between parasitic parameters, and long-term influences of ambient stress, the indirect noninvasive method without any extra hardware implementation is sensorless and cost-efficient [88]. The internal parameters can be estimated or inferred through the available physical signals, which mainly include input and output information, and some signals are easy to measure.

In this way, the parameter identification task can be transferred into the exploration of optimal parameters and constructing the digital PES. Metaheuristic methods are flexible and gradient-blind approaches to solving global optimization problems, which require less expert experience and are efficient for various optimization tasks. Thus, various metaheuristic methods are widely applied to solve this kind of optimization problem, such as particle swarm optimization (PSO) [28], [30], [39], [46], [51], arithmetic optimization algorithm (AOA) [31], [34], [48], GA [69], recursive least squares (RLSs) [71], Kalman filter [73], Bayesian optimization (BO) [45], etc., or their integrated methods.

PSO has the advantages of fast convergence speed, few parameters, a simple algorithm, and easy implementation [119]. In [25] and [28], the DT of a buck converter is established through a mechanism model, which includes the power stage, sampling circuit, and closed-loop controller, as shown in Fig. 10. PSO is applied to estimate the critical parameters of interest based on the incoming data from both the DT and the physical prototype. The monitoring accuracy during the degradation process of the

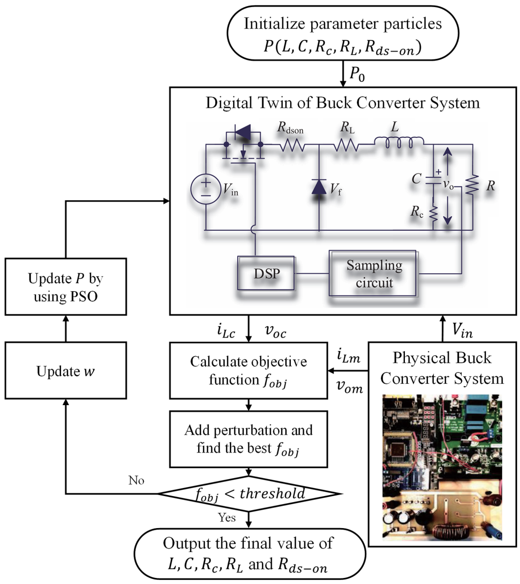

Fig. 10. DT-based parameter identification of buck converter through PSO algorithm [25], [28].

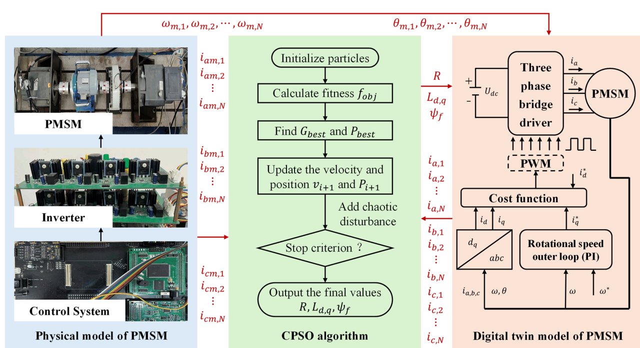

Fig. 11. DT-based parameter identification process of PMSM through CPSO algorithm [42].

key components, including the capacitor and MOSFET, is verified experimentally.

Similarly, the health status of some internal passive components and semiconductors in a boost converter is monitored through the application and iteration of PSO, including the input inductance and the output capacitance and their parasitic equivalent series resistances and the MOSFET ON-state resistance in [31] and [34].

In [42], the DT model of a PMSM system is established, which includes the inverter-driven power stage and the closed-loop controller. A chaos particle swarm optimization algorithm (CPSO) is applied to optimize the DT model and obtain the parameters in the PMSM (e.g., stator resistance, stator inductance, and flux linkage), as shown in Fig. 11.

In [29], the DT of a two-phase interleaved boost converter with a reverse-coupled inductor is established based on an HIL platform. GA is utilized in the parameter identification process, which mainly leverages the concepts of chromosomal crossover and mutation to reach an optimal solution [120]. Compared with PSO, GA boasts superior accuracy, reduced dispersion, and faster execution.

In [48], AOA is adopted to identify parameters of the buck converter, which can realize fast convergence and effective global search. The experimental results prove that the AOA-based DT reflects the dynamic characteristics with efficient global search and faster convergence than PSO [121].

In [73], the dual extended Kalman filter (DEKF) is used to estimate the unknown states and parameters of thermal DT in insulated gate bipolar transistor (IGBT). The repetitious cycle of prediction and correction of DEKF guarantees the convergence of thermal model parameters, which can achieve an optimal representation of the physical thermal behavior [122]. Through the comparison, the convergence speed of DEKF-based thermal DT is 1000 times higher than the synchronous execution of the PSO.

DT is integrated with multiphysics simulation and finite element method to monitor power electronic components. A fast, lightweight, and physics-based DT is established to estimate the real-time junction, case, and heat sink temperatures of the switching device in a PV boost converter. The finite element simulation is performed to extract the thermal resistances of the MOSFET [68]. A DT model for the inverter of an electric drive system is constructed by merging the electrical model and the thermal network model. The finite element simulation model of the SiC power module (CAB011M12FM3) is established to realize a rapid and accurate estimation of the junction temperature [143].

2) Data Regression: With the development of AI techniques, the monitored parameters in power electronics systems can be estimated or mapped through the relationship between the inputs and outputs. The data regression performance mainly depends on the algorithm ability, data amount, training hyperparameters, etc.

Artificial neural network (ANN) is applied to identify the parameters in the buck converter [41] and boost converter [77], achieving noninvasive, cost-effective, high accuracy. The inductor current and output voltage of the buck converter construct the input information. The electrothermal model of the boost converter is used to train and generate the ANN, estimating the ON-state resistance of MOSFET as well as the capacitance and equivalent series resistance of the capacitor [41]. Similarly, it is demonstrated that the capacitance, inductance, and parasitic resistances of the capacitor, inductor, and MOSFET are estimated by the ANN [77].

To improve the generalization ability and solve the overfitting problem, different variants of ANN have been proposed and applied to the parameter identification. NARX-ANN containing memory blocks enables the replication ability of differential equations.

In [74], the boost converter model contains only one delay in both input and output. Furthermore, the control-to-output voltage frequency response of DT also shows a high fidelity to the analytically predicted response. In [78], the test case considers the different behavior in DCM and CCM of the buck converter.

Compared with traditional ANN, DNN has obvious advantages in training accuracy, speed, and hardware requirements, better capturing the complex features of the data. In [80], DNN

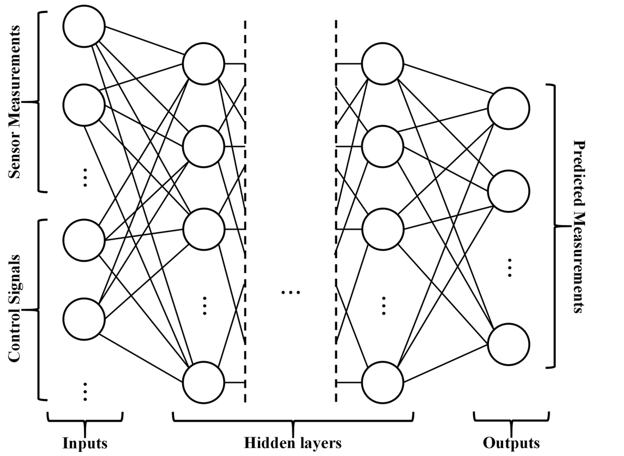

Fig. 12. Generic DNN of DT model, where the number of inputs, outputs, hidden layers, and the number of neurons per layer vary based on the application [80].

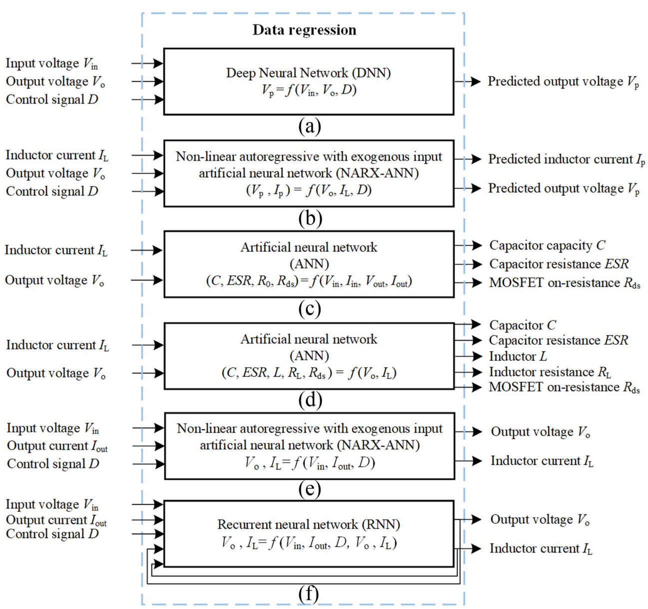

Fig. 13. Examples of DT-based data regression in PESs. (a) Output voltage of converter [80]. (b) Output voltage and inductor current of converter [78]. (c) Capacitor, MOSFET, and load in converter [41]. (d) Capacitor, inductor, and MOSFET in converter [77]. (e) Output voltage and inductor current of converter [74]. (f) Output voltage and inductor current of converter [154].

models are trained and evaluated with data gathered from a T-type three-level rectifier. The network inputs include sensor measurements and control signals, and outputs are the predicted measurements. The identification error, time complexity, and hyperparameters of DNN are analyzed and discussed in detail. The proposed DNN structure is demonstrated in Fig. 12.

DT enables the same dynamics as the real system through the updating of parameters in the PES. A summary of the DT-based data regression methods is given in Fig. 13, where $f(\cdot)$ represents the nonlinear mapping tool between the designed input signals and the monitored parameters.

B. Fault Diagnosis

Fault diagnosis is the prerequisite for implementing predictive maintenance, the reliability and timeliness of which are directly related to the effectiveness of maintenance for PESs. Realizing diagnosis for explicit and implicit faults and adopting appropriate maintenance strategies are effective ways to improve the reliability of PESs.

Research shows that PESs, power devices, and driving circuits are vulnerable to functional failure [7], [35], [113]. Fault diagnosis methods mainly include signal processing-based [114], data mining-based [76], [165], and analytical model-based methods [115], [135]. Although the application of analytical models is an effective method to achieve rapid fault diagnosis, traditional mechanism modeling methods cannot accurately reveal the condition characteristics of the system and are not suitable for fault analysis and diagnosis. However, the DT model can solve this problem and show further potential with high fidelity [134].

In [50], DT is used to detect and identify faults of over voltage, over current, and high temperature in a buck converter, operating in continuous conduction mode. In each scenario, alert flags will activate the LEDs of the utilized DSP, which would detect instances of failure. It was observed that during peak voltage, all flags were activated, indicating the presence of the three potential faults.

In [76], a DT-based framework for fault diagnosis in grid-connected inverters is proposed by expanding the search space through the incorporation of online data using a Bayesian approach. In order to evaluate the fault classification performance, different fault cases in virtual SG controlled grid-forming converters have been considered, including line-to-line faults, sensor faults, single-phase voltage sag, and three-phase faults.

In [26], DT is used for fault diagnosis on the basis of measurable characteristic outputs of a PV energy conversion unit. DT serves as a digital emulation of a physical system, enabling real-time analytical computation of measurable characteristic outputs. An error residual vector is generated by comparing the outputs of the DT and the physical twin, which is used for fault detection and identification.

DT is widely utilized to detect and diagnose faults in electrical drive systems [83], [155], [156], [167]. A DT-based and improved sparrow search algorithm optimized random forest (RF) fault diagnosis method for PMSM is proposed, where RF is utilized as a classifier containing multiple decision trees [83]. The early interturn short-circuit diagnosis of the PMSM is realized through the analysis of the residual current between the DT model and the motor [156]. Ramanujan DT architecture is proposed to deal with the preset parameter dependence, which is robustness to strong noise interference, and switching working condition problems in the health monitoring and fault detection of induction motor (IM) [157].

With the combination of multiphysics simulation, different fault diagnosis methods for PESs have been developed. The 3-D finite element model of the IM is combined with ANN to improve fault diagnosis algorithms. DT can provide substantial data gains in the training of networks and identify the fault signatures of broken rotor bars in the stator current signal [85]. FEA is applied for the computational development of an IM DT system, which considers a strong numerical coupling thermomagnetic simulation. The thermomagnetic behavior of the motor, including temperature distribution, torque profile, resistive losses, and stator copper conductivity, can be achieved in a noninvasive way, providing useful information for potential failures [142].

An FPGA-based DT implementation is employed in the controller optimization of a flyback converter system. The order reduction of the DT model is realized through the translation from MATLAB/Simulink into the hardware description language code. The order-reduced DT enables various ML methods to predict converter load conditions and fault diagnosis [135].

DT is utilized to minimize degradation in the nanogrid caused by communication loss under electrical fault conditions. By providing physics-based insights into its physical counterpart, the DT generates an error vector that serves as a feature for detecting and identifying electrical faults in the nanogrid [163].

Noteworthy, DT plays a crucial role in minimizing the necessity for destructive testing, which is important in data support during the maintenance process. The destructive testing is especially difficult to replicate in laboratory settings [123]. The economic benefits and overall impact of DT implementation are particularly observable in the fault diagnosis for PESs.

C. Reliability Evaluation

The reliability and safety of PESs are crucial throughout the full lifecycle. Although the reliability characteristics have been fully considered in design and control, PESs still face various risks and potentially catastrophic failures due to complex and harsh operating environments [116], [118], [84]. The reliability evaluation process during the maintenance stage is long-endurance and high-complexity.

DT contributes to the reliability evaluation of PESs by enabling real-time monitoring, predictive maintenance, multiphysics simulation, etc. DT offers a virtual environment to simulate various operational conditions, including extreme scenarios, which can assess how PESs would perform under different stresses [84]. Therefore, DT can realize accurate reliability evaluation and ensure the long-term stability and performance of PESs.

In [146], a reliability evaluation method for the distribution network is established based on the DT and hologram technology. The DT technology realizes the real-time calculation, rapid identification, and accurate prediction of the distribution network reliability. Furthermore, a case study of a high-reliability demonstration area is utilized to verify the effectiveness of the proposed method.

In [147], the DT technique is used for the reliability assessment of superbuck converter. The Markov model of superbuck converter is established with the consideration of critical components and the possible cases of short-circuit and break faults. The high-fidelity DT model is used to obtain critical component currents and voltages, assessing the physical reliability of the superbuck converter.

In [148], a digital reliability twin of power converter is learned from past operations under different operating conditions to optimize maintenance for scenarios with new operating conditions, thus improving operational reliability. Based on failure mechanism understanding and inference strategies from accelerated life testing, system failure behavior can also be quantified through DT.

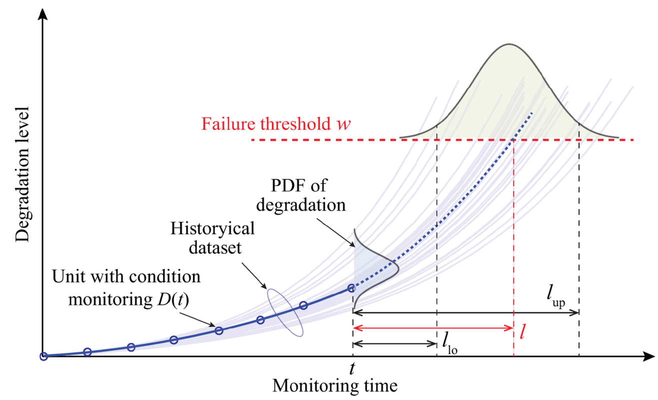

Fig. 14. Process for RUL prediction in PESs, where PDF: probability density function [88].

D. RUL Prediction

Remaining useful lifetime (RUL) prediction can help device manufacturers design products with longer service life and help users reduce the corresponding maintenance costs. Based on the condition monitoring information and fault diagnosis results, the residual lifetime of an individual component in service can be thus predicted. However, various uncertainties are associated with lifetime prediction, such as model calibration errors, manufacturing tolerances, operational environment variations, and workload fluctuations. [116]. These uncertainties often lead to inaccurate reliability estimation or misjudgment of failure [117], [160].

The application of DT technologies in RUL prediction of PESs can enable the maintenance stage to better responsiveness, predictability, and adaptability [125]. Employing DT-based RUL prediction serves as an additional tool to mitigate these uncertainties, especially in reliability-critical, safety-critical, or availability-critical applications of PESs. The process for RUL prediction in power electronics systems is depicted in Fig. 14.

As shown in Fig. 14, PES operates properly at monitoring time t and the historical dataset has been constructed. The RUL of PES l is defined as the residual lifetime when the degradation process $D(t)$ exceeds the failure threshold w

$$l = \inf \{l : D(t+l) \geq \omega | D(t) < \omega, D_{1:j}\} \tag{3}$$

where $\boldsymbol{D}_{1:j}$ represents the cumulative data till t.

Considering RUL is a random variable, the uncertainty metrics with the lower and upper confidence intervals (l_{lo}, l_{up}) are also critical.

In [49], an electrothermal DT model is combined with the power grid data to predict the loss, junction temperature, and service life for IGBT in an MMC. The DT model is simplified through the real-time subperiod averaged equivalent modeling

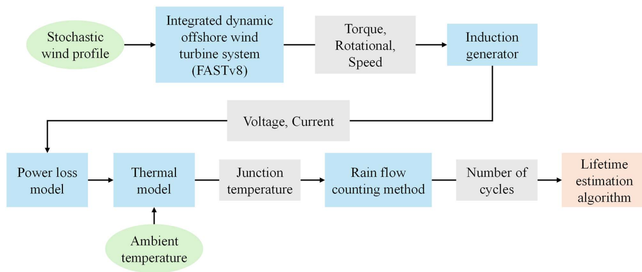

Fig. 15. Flow diagram for both damage accumulation and RUL prediction of power converter [128].

method to ensure real-time operation efficiency. A virtual submodule DT model of MMC is established simultaneously for heat loss calculation and obtaining the junction temperature. In the controller HIL simulation, the DT method can provide a decision-making basis for estimating the life of the module and making maintenance plans for MMC with the combination of the manufacturer's life model.

In [128], the DT approach is used to model a physics-based RUL prediction model for an offshore wind turbine power converter. With the combination of the *Supervisory Control and Data Acquisition* system from Lloyd's register, the DT model can enable the prediction method with more data availability and prediction accuracy. Fig. 15 demonstrates the flow diagram for both damage accumulation and RUL prediction, which is designed to solve changes in medium and short-term thermal cyclic loads on the power converter.

The transformer is a crucial component in the PES, which plays a pivotal role in determining health conditions and informing various operational decisions [126], [127]. The transformer DT model is established with multiphysics field coupling simulations under various working conditions to construct the DT temperature database. Then, the extreme learning machine algorithm [138], a kind of single-hidden-layer feedforward network with good generalization performance and extremely fast learning ability, is utilized in the NN to learn the data-based information and actively predict the transformer temperature [126].

The DT-based RUL prediction method is integrated with multiphysics coupling to calculate the change law of the winding hot spot temperature parameters under different working conditions. In the verification experiments of an SZ10-50000/110 oil-immersed power transformer (S represents three-phase, Z represents on-load voltage regulation, 10 represents the performance level code, 50 000 VA represents the rated capacity, and 110 V represents the voltage level), the RUL prediction accuracy achieves about 95% [127].

In the review of DT-based predictive maintenance for electrical machines [20] and PV installations [17], various possibilities of CBM and RUL prediction models are discussed in detail.

E. Discussion

The DT-related research mainly emphasizes the maintenance of PESs. The DT system can be viewed as the synchronous or semisynchronous mirror system of a physical system, which presents more internal observability for parameter identification, data availability for fault diagnosis, and model reliability for RUL prediction. Thus, DT-based maintenance methods can promote predictive maintenance to avoid system failures and reduce downtime.

Actually, not all DT implementations achieve real-time synchronization, some DT-based applications may focus on providing high-fidelity simulations and predictive analyses without continuous real-time updates. In particular, physics-based DTs put more emphasis on the stress, strain, thermal, and multiphysics behavior of power electronic components under various conditions.

Condition monitoring, fault diagnosis, reliability evaluation, and RUL prediction pass throughout all stages of predictive maintenance. With the deep integration of the DT framework, the joint research of these four parts also shows important application value in promoting predictive maintenance. Through the comprehensive validation of the DT system under different operation conditions, the system security and reliability can be guaranteed, the maintenance plan can be optimized, and maximize the service life of the PES.

In future research, DT can customize individualized maintenance strategies based on the specific characteristics and operating conditions of different PESs. By analyzing data and leveraging knowledge, DT is capable of self-updating and evolving, thereby optimizing maintenance strategies and enhancing system reliability and maintainability.

VII. Prospect on DT for PESs

A. Opportunities and Challenges

DT holds tremendous potential in PESs. Numerous opportunities and challenges still exist to be explored, as outlined below.

1) General DT Modeling Platform: One of the primary challenges in implementing DT for power electronics is establishing high-fidelity models that accurately represent the system behavior. A deep understanding of the underlying physics can help to capture the nonlinearities, switching operations, and interactions between multiphysics fields of power electronics systems. The connection, convergence, and integration between different DT models can further improve the comprehensiveness and overall performance. The advantages of different DT models can be combined, such as the interpretability of mechanism models, physical property of multiphysics models, scalability of simulation models, and fitting ability of data models. Considering the compatibility of different DT models, a comprehensive DT modeling platform for PESs should be developed that supports the effective synergy of various DT models.

Future research should focus on enhancing the fidelity of DT model, addressing the challenges posed by the complexity of physical mechanisms, multiphysics coupling effects, and data inaccuracies. Developing advanced DT modeling techniques will be critical to achieving higher accuracy and reliability.

2) Interwoven DT Implementations Through Lifecycle: The comprehensive integration across the entire lifecycle of PESs spans design, control, and maintenance, which presents multifaceted challenges. As the physical system upgrades, modifications, or expansions, the DT should scale with the increasing complexity and size of the power electronics system throughout the full lifecycle. Implementing DT in different phases can enable more flexible and diverse functional interactions, which contributes to overall performance optimization and simplifies procedures. For example, RUL prediction, fault diagnosis, and parameter identification results achieved from the DT can be flexibly incorporated into the DT-based predictive control and controllability improvement. The adaptive optimization and variables prediction outcome obtained from DT can be timely feedback to the DT-based intelligent design, reducing the development cycle and cost of verification. Design, control, and maintenance of PESs will thus be more closely integrated. Therefore, more attention should be given to the interwoven interactions powered by DT.

3) Power Electronics Data and Knowledge: The integration and management of data from diverse sources, such as sensors, controllers, and external databases, should ensure synchronization, consistency, and accuracy. However, data integration can be complicated by sensor noise, communication delays, and discrepancies between different data formats. Low-latency communication networks, such as 5G or time-sensitive networking, can effectively minimize delays in data transmission. Through the fusion of both data and knowledge, the accuracy and robustness of DT models can be improved. Exploring the available data aids in understanding mechanisms that are challenging to describe in PESs. Taking full advantage of classical knowledge can reduce the burden of data collection and guide long-time and high-reliability operations. Thus, these DT datasets and knowledgebase are essential for accelerating DT application development, benefiting the global power electronics communities in both academia and industry.

4) Real-Time Computational Unit: As PESs become more complex, the computational burden on the real-time unit increases. Scaling the computational resources to handle more complicated models and larger systems without compromising real-time performance is a significant challenge. Although AI and other advanced techniques can provide superior performance for DT, the computational cost in PESs is highly intensive. Consequently, controllers and other computational units should be capable of rapid computation and data processing. The power electronics system covers a wide range of multiple time scales from the nanosecond-level of switching devices to the second-level of control period, and year-level of maintenance plan. The cost-effective edge-computing framework is a potential solution, which integrates the core capabilities of network, computing, storage, and application to provide the nearest service [136].

The integration of edge computing with cloud platforms for DTs is an exciting area of future research, which enables real-time data processing at the edge while leveraging cloud resources for more complex analytics. Exploring the tradeoffs and synergies between edge-cloud deployments is essential for optimizing DT performance in power electronics.

5) Data Privacy and Security: The DT relies on continuous data exchange between the physical system and the DM, which is vulnerable to cyberattacks. Protecting sensitive data and ensuring the integrity of the DT are crucial for preventing unauthorized access, data breaches, and potential disruptions to the physical system. Throughout the full lifecycle of a PES, these kinds of data are vulnerable to intrusion and can be monitored should be strictly discussed and classified. Implementing multifactor authentication and intrusion detection systems can enhance overall security. Encrypted protocols and other active defense methods can mitigate threats of DT-based systems. The defense mechanism and level during the phase of design, control, and maintenance of the PESs should be customized to adapt to different industrial scenarios and improve safety performance. Furthermore, large language models are the potential solution to preserve data security and privacy in different datasets [137].

6) Integration With Emerging Technologies: The advent of emerging technologies, such as AI, IoT, VR, and cloud computing, is revolutionizing the landscape for the development and application of DT technology in power electronics. AI enhances the capabilities of data analytics, predictive modeling, and autonomous decision making. IoT plays a critical role in real-time data collection, monitoring, and control. VR introduces immersive visualization and interaction capabilities. Cloud computing provides the infrastructure for the storage, processing, and sharing of generated data, supporting large-scale DT implementations. By combining these technologies, DT can offer more comprehensive and robust solutions. For instance, AI can analyze data collected by IoT devices, while VR provides an immersive interface, all supported by the accessibility of cloud computing. The ongoing evolution of these technologies will further enhance DT applications in power electronics, leading to more autonomous, intelligent, and interactive systems.

7) Industrial Integration Development: Developing a DT that can be modularly integrated into different parts of an industrial process without disrupting operations is difficult, requiring a deep understanding of the industrial process and a high degree of customization. Although there is increasing research on DT for PESs in the literature, the practical implementations in the industry are still limited. DT-enabling PES can play their role in all aspects of energy production and consumption through integration and development with smart manufacturing, smart transportation, smart cities, and other fields, thereby realizing the promotion of DT in various industries. Therefore, the concept of integrated development of DT and other fields should continue to be strengthened to promote data interoperability and information sharing between different industrial fields.

B. Further Research Insights

1) Best Practices and Common Pitfalls: Through the review of the manuscript, some best practices and common pitfalls of developing and implementing DTs in power electronics can be summarized and concluded.

The best practices of DT in power electronics are the realization of simulating, controlling, monitoring, diagnosing, and predicting the process and behavior of the physical system in the real environment. Especially in the maintenance stage, the health status, remaining life, and fault information of the physical prototype are fully sensed through the high-fidelity, real-time updated DT models. More advanced AI and ML algorithms could be integrated with DT models to improve fault prediction accuracy and system reliability, particularly in high-stakes environments.

The common pitfalls mainly include a lack of DT fidelity and DT technology maturity and standardization. The complexity of the physical mechanism, coupling effects of multiphysics fields, performance limitation of simulation, and the inaccuracy of data will result in a decrease in DT fidelity. At present, the application of DT technology in power electronics is still in the development stage, and the degree of technical maturity and standardization is relatively low. This may also lead to poor interoperability between different PESs, affecting the effectiveness of DTs.

As DT technology develops, establishing industry-wide standards will be essential. Future work should focus on developing universal standards for DT frameworks that can ensure interoperability across different PESs, which promotes broader adoption and more effective integration of DTs in practical applications.

2) DT Expansion: Current research extends classical DT models and their adaptive variants, introducing some new and emerging DT concepts. The conceptual diversity converges to form a comprehensive DT family, including "cognitive DT," "hybrid DT," and "experimentable DT."

Cognitive DT combines knowledge engineering and focuses on developing cognitive capabilities, which can perform human-like intelligent activities, such as perception, comprehension, reasoning, and decision making [149]. Hybrid DT integrates physical information with DT models and employs learning models to enhance predictive performance. [150]. Experimentable DT focuses on enhancing simulation capabilities within the physical environment, creating an efficient transformation engine between system models and simulation models [151].

More members of the DT family will emerge in the future, each exploring distinct characteristics, thus increasing the conceptual diversity of DT.

3) Digital Triplet: Recently, the DT concept, framework, and model have been extended into DTri in different industrial applications [129], [130], [131], [132]. The characteristics of DTri also show great potential and prospects for application in PESs.

In [131], a surrogate system is redefined to reduce data imbalance effects and fill knowledge gaps in the production system. The discussed surrogate system mainly utilizes knowledge from the physical system to guide data generation for minority classes in the application of condition monitoring and fault diagnosis. The flow, information, and relationship between data and knowledge in the DTri system is illustrated with the example of a bearing system, applying TL and DL. The data generated in the surrogate system, based on the physical system knowledge, provide the means to generate health information for maintenance decisions.

In [132], the concept and 6-D model of DTri is raised with the extension of parallel triplet, which constructs a critical system between the physical and digital system, as shown in Fig. 16. The parallel system consists of parallel triplet and parallel controller, which enables high fidelity, local digitization, improved monitorability, superior scalability, and independent controllability.

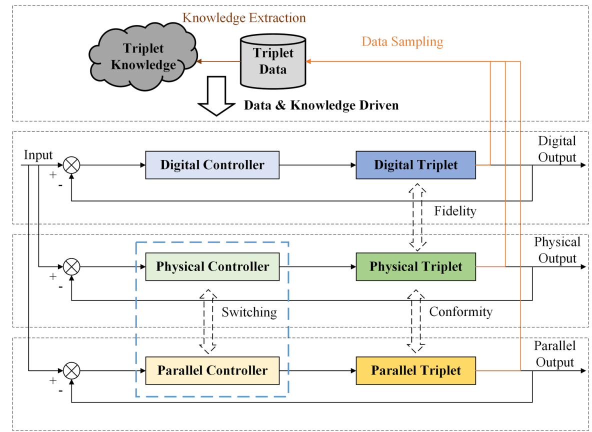

Fig. 16. DTri structure with the combination of digital, physical, parallel systems, data, and knowledge [132].

A military aircraft horizontal tail control system is illustrated as a DTri case to demonstrate completeness and superiority.

When the physical controller fails, the parallel controller can replace the physical controller to ensure normal operation. The parallel triplet can reduce the data imbalance effects of predictive maintenance. The verification of the maintenance strategy can also be passed through the parallel triplet to ensure effectiveness. With further development and exploration, the interaction between digital, parallel, and physical triplets will be the future research focus, providing merit for application ideas and schemes in PESs.

Finally, further research should explore methods for making DT technology more scalable and cost-effective. As DTs become more widespread in power electronics, the ability to deploy these models across large, complex systems without prohibitive costs will be crucial.

VIII. Conclusion

This article provides a comprehensive review of existing DT methods applied in PESs. The investigation results show that the application of DTs can improve design efficiency, enhance control performance, promote predictive maintenance, and ensure the high-quality and reliable operation of the system. The new findings and contributions of this article are summarized as follows:

1) From the perspective of model establishment, the DT models employed in PESs can be classified into mechanism, simulation, multiphysics, and data models. The features, applicability, and practicality of each model type are thoroughly described and analyzed. In addition, a comprehensive comparison of these DT modeling methods is provided, clearly illustrating their respective advantages, disadvantages, computational cost, scalability, ease of integration, and suitable application scenarios.
2) From the perspective of lifecycle application, the DT concept and framework applied in PESs are categorized into design, control, and maintenance. Each phase is examined in detail, with a comprehensive discussion of unique characteristics, advantages, and specific requirements of DT. The analysis highlights the distinct contributions of

DT to each lifecycle phase, enabling a more informed comparison and understanding.

3) For each lifecycle phase, illustrative examples and detailed explanations are demonstrated, encompassing a range of applications, such as power converter systems, electrical drive systems, PV systems, and power battery systems. In addition, the possible opportunities and challenges associated with DT are also identified and discussed, offering further research insights.

This comprehensive overview underscores the evolving role of DT in achieving a higher level control, monitoring, and maintenance performance in power electronics.

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