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A survey of Digital Twin techniques in smart manufacturing and management of energy applications

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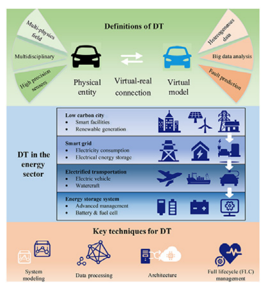
HIGHLIGHTS

- A systematically review of digital twin technique and its applications is presented.
- The definitions, classifications, main features, and case studies of digital twin is presented.
- The key technologies of digital twin are present.
- The future directions and challenges of digital twin in energy fields are foreseen.

GRAPHICAL ABSTRACT



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ABSTRACT

With the continuous advancement and exploration of science and technology, the future trend of energy technology will be the deep integration of digitization, networking, intelligence with energy applications. The increasing maturity of digital technologies, such as the Internet of Things, big data, and cloud computing, has given rise to the creation and use of a potential technology – Digital Twin. Currently, research on Digital Twin has produced many concepts and outcomes that have been applied in many fields. In the energy sector, while some relevant ideas and case studies of Digital Twin have been generated, there are still many gaps to be explored. As a potential technology with advantages in many aspects, Digital Twin is bound to generate more promotion and applications in the energy fields. This paper systematically reviews the existing Digital Twin approaches and their possible applications in the energy fields. In addition, this paper attempts to analyze Digital Twin from different perspectives, such as definitions, classifications, main features, case studies and key technologies. Finally, the directions and challenges of possible future applications of Digital Twin in the energy fields have been presented.

1. Introduction

With the rapid development of social economy, energy crisis and the environment pollution have become important issues facing the world. The modern green energy system offers a systematic solution to achieve emissions peak and carbon neutrality. An important characteristic of the modern digital green energy systems is their interconnection with the internet, which advances the overall intelligence process [1]. The Digital Twin (DT) has been investigated in recent years, which is seen as a key technology for the intelligence process, along with the Internet of Things (IoT) and artificial intelligence (AI).

DT is a commonly adapted technology concept that has been proposed and rapidly developed in recent years, and has already been used in many areas. In manufacturing, shop floor manufacturing design,

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production processes are more closely integrated with the DT [2]. A good example is the information-physical production system, which is the precondition and core of smart manufacturing [3,4]. Some smart manufacturing technologies such as manufacturing key features and production framework optimization are also supported by the use of the DT [5–7]. Secondly, fault prediction and health management [8] can be driven by DT to form a new model of device health management. This model is based on simultaneous mapping and real-time interaction between physical and virtual devices, enabling rapid capture of fault phenomena. This allows rational design and validation of maintenance strategies. In addition to the above-mentioned areas of interest and application, DTs have also been used in power, healthcare, urban management, environmental protection, automotive, and construction, which have shown great potential for application. In addition, DT technology has enriched research and applications in power and industrial systems. Many features of the DT can be combined with various aspects of the energy sector to improve and optimize related problems, such as modeling [5], simulation [6], human–computer interaction [9], product lifecycle [10], physical network link [11] etc.

This paper focuses on the energy aspect, grouping together an analysis of the application of DT in the energy sector. DT applications involving, but not limited to, urban, transport, automotive and energy storage applications are summarized in terms of the degree of integration. For example, for model of urban energy systems, energy forecasting in smart grids and smart buildings, intelligent synergy between vehicle and grid, or the corresponding DT of a complete vehicle and its components. For smaller systems, it is possible to step down to the catalyst layer inside the fuel cell as well as the conductive film layer at the cell bank level, including modeling and analysis.

The rest of the paper is organized as follows. Section 2 presents a brief description of definitions and classifications of DT. Section 3 analyzes the state-of-the-art of DT in the energy sector. Section 4 reviews the key techniques for DT. Some discussions and future work are given in Section 5. Finally, the conclusions are drawn in Section 6.

2. Definitions and classifications of Digital Twin

2.1. Definitions of Digital Twin

In 2003, Grieves proposed the Mirrored Spaced Model (MSM), which can be seen as a prototype for the conceptual idea of the DT. This concept consists of a digital model, a physical entity and a link between them [12]. In 2011, NASA first gave the specific DT concept, and applied it to the health maintenance and protection of future Spacecraft [13]. Specifically, a model was created in digital space. Then, sensors were used to achieve complete synchronization with the real state of the aircraft, and historical data was analyzed to assess maintenance requirement. With the proliferation of the industrial IoT, DT technology has gained widespread importance. The DT is not only limited to the aerospace, but also extends to other areas such as manufacture design and line design [14], DT shop floors [15], production process optimization [16], Industrial Internet reference framework [17], prognosis & health management [8], and smart cities [18]. As a result, DTs have more connotation and extension, gradually moving from theory to application.

The general definition of DT is a virtual model of a physical entity created digitally, which uses data to simulate the behaviour of the physical entity in the real environment. It provides feedback and interoperability of physical entities through interactive feedback, data fusion and analysis, and iterative optimization of decisions for optimal control, safety monitoring and data analysis.

Due to the development of technology and the expansion of its applications, there is no common definition of the DT. A major reason for this is the diversity of focus areas within different disciplines. A summary of this work is given by Concetta Semeraro et al. [19]. They categorise their definition of DT into five components: ability of simulation along product life cycle, the synchronization of the cyber system with the physical assets, the integration of real time data, the behavioural modeling of the physical space, the services provided by the virtual system.

2.2. Classifications of DT

The DT as an integrated multi-physical, multi-scale, probabilistic simulation of a complex product system, its classification and analysis is necessarily multifaceted, multidisciplinary and multi-integrated. Different stages of DT present different characteristics, and the understanding of the DT cannot be divorced from specific objects, specific applications and specific needs. Not only that, but as mentioned above, the focus of attention must also be different for different subject areas. Therefore, following is a classification of DT in terms of different dimensional of understanding.

Continuing with the above definition of DT, the following is a classification of DT in terms of the role it plays in applications, including, simulation, virtual-real connectivity, model building and data processing.

After analyzing several papers, it can be concluded that the main role of DT in applications is as a modeling and simulation tool, with less relevant applications using DT as a virtual-real connection method with data processing [3,5,8,9,16].

This approach can be found in Ref. [20], in which Werner Kritzinger et al. proposed a classification of DTs into three subcategories, including digital model, digital shadow and DT. Digital model means that a change in the state of the physical object has no direct effect on the digital object and vice versa. Digital shadow means that a change in the state of the physical object causes a change in the state of the digital object, but not vice versa. DT means that a change in the state of the physical object directly causes a change in the state of the digital object and vice versa. The data flow diagrams for the three subsystems are shown in Fig. 1.

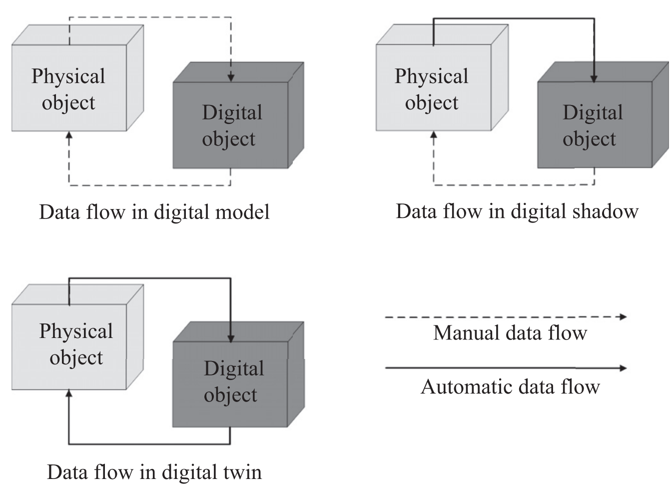

Fig. 1. Data flows in digital model, digital shadow and Digital Twin [20].

However, it is difficult to have a strict synchronization between physical entities and virtual models. Therefore, the mentioned data circulation and updates also need to vary with the size of the system to accommodate the periodic updates and iterations of DT. For example, a city system that collects and processes data in days, then synchronization between physical entities and virtual models needs to be performed at least once a day.

Digital models may include but are not limited to, simulation models of a plant, mathematical models of a new product, or any other model of a physical object. These models are modeled in such a way that the state of the physical object is idealized. The DT is different from other models since it is modeled in a more complex way and requires multiple iterations. Sensing techniques, data analysis, fusion techniques, and model evolution may be key in modeling. High-standard, high-precision virtual models and their operating environments are built in a data-driven manner. This is how data from the physical world and data from the virtual world can be processed simultaneously.

3. DTs in smart energy applications

In energy neighborhood applications, the DT can be divided into different layers depending on the level of integration. On the one hand, this paper summaries the parts of the retrieved literature that are relevant to applications, highlighting the different effects of DT applications at the energy level. On the other hand, the following aspects include some of the DT-based technologies and methods, which are grouped in this article according to possible future application scenarios. Combining these two aspects, DTs in smart energy applications are divided into the following four levels: low carbon city, smart grid, electrified transportation, advanced energy storage system.

The specific application scenarios are shown in Fig. 2. The above classification of DT levels in smart energy applications considers the scale and progressive state of the application domain. From the high-level comprehensive structured level to the bottom-focused detailed level, the sequential levels are the city level, power system level, transportation level, and energy storage monolith level. In addition, each high-level level contains the next bottom level, and only systems related to the smart energy domain are listed in this paper. Looking from the bottom up, subsystems applying DT in multiple domains work together to form systems of higher complexity. The characteristics in the application are gradually changing from refinement and fast synchronization to complexity and strong decision making capabilities. The following section will describe each level in detail and give the integration of it based on personal insights.

3.1. Low carbon city

Cities are the economic hubs of modern society, they are also the focus of carbon emissions [21,22]. From the evaluation of cities by multiple criteria and indicators, it can be concluded that a low carbon city is one that has a lower overall level of carbon emissions than the benchmark when the carbon emissions of each criterion are weighted [23]. Low carbon cities control CO_2 emissions in four areas, including the urban environment, urban transport, urban infrastructure and buildings [24]. Low carbon cities are a response to the growing need to reduce carbon and mitigate climate change in cities [25]. In recent years, an increasing number of cities around the world have launched low carbon initiatives [26].

Low carbon cities, as the largest project in energy management and environmental protection, are the product of a combination of technological tools. The application of DT in this context is often for the modeling of complex systems, a task that corresponds to the advantages of DT in terms of high precision modeling. This also includes many other applications such as urban energy planning [27], smart charging management [28], energy efficiency improvement, etc. Whether it is the production, transmission, distribution or end use of energy, efforts are being made towards decarbonization. Urban energy planning is about planning for future energy production, transmission and distribution through DT's ability to iterate and predict data in order to aspire to an optimal solution.

The goal of the low carbon city is to reduce energy consumption while maintaining or increasing the current level of broadly understood economic activity. In detail, the energy efficiency is the ratio of the obtained value of the utility effect of a given facility, technical device, or installation to the amount of energy consumption by this facility, technical device, or installation, or as a result of the service provided, the process necessary to achieve this effect [29]. Given the huge potential for reducing greenhouse gas emissions and the low cost of improving energy efficiency, many countries see energy efficiency as one of the directions

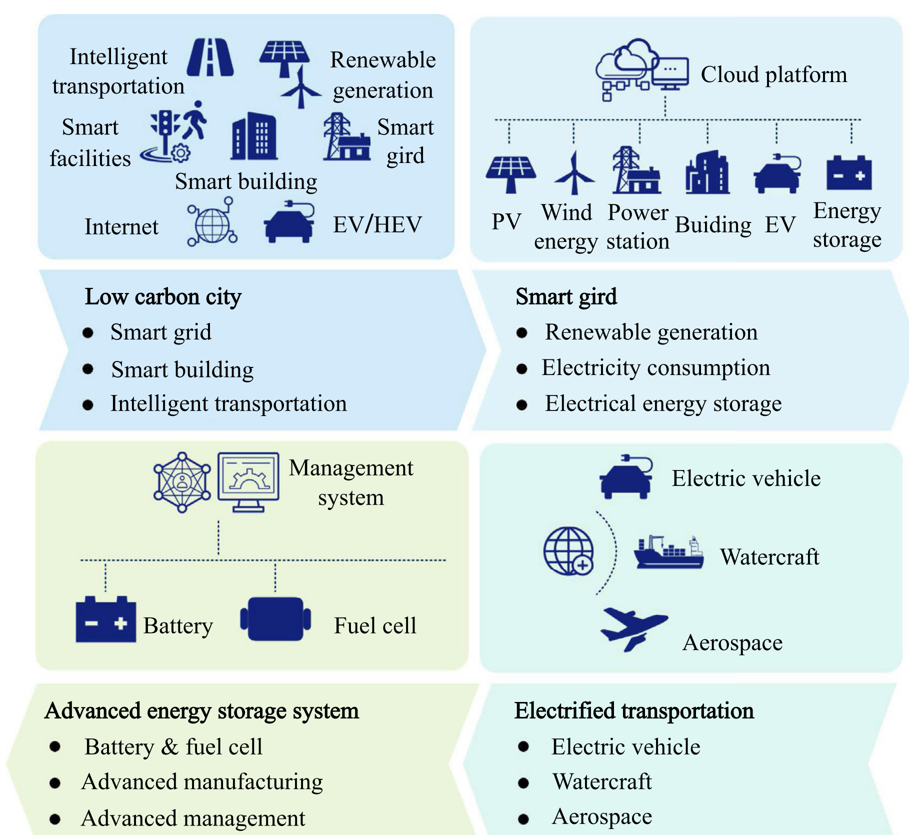

Fig. 2. Smart energy applications.

for decarbonization. In terms of energy efficiency, it is the reduction of energy consumption without reducing the level of economic activity. This requires multiple related systems to increase output efficiency, and for the city as a whole, this can be seen as an iterative optimization of DT at the system level. This can be done by modeling each product or enterprise at a smaller level of DT, simplifying it to focus only on energy consumption and economic levels, and then integrating it. The DT modeling study of the city by Gary White et al. [30] can be used as an example to construct a twin body using multiple information layers overlaid. Data is sent from the digital layer about the mobility, infrastructure, buildings, and terrain in the city. This data is used to conduct simulations in the virtual layer, which can then be passed back as information through the layers of the city. The authors also used Unity3D software to conduct simulations of green spaces, skylines, floods, and crowds. By replacing the simulated objects with energy-related information, this study can be applied to the energy sector and generate smart city energy optimization solutions after data collection.

It can be seen that the advantages of DT and the associated technological innovations applied to low carbon cities can be summarized as:

- Ensuring low carbon production
- Reduce the carbon emissions created by the economy
- Online testing of energy strategies
- Monitoring abnormal energy consumption
- Warning about high emission behavior

Possible weaknesses in the application can be summarized as:

- Complex model building
- Need to filter a large amount of information
- Lack of fine-grained data
- Privacy issues arising from the monitoring of energy consumption
- Slow model updates and poor real-time performance

Fig. 3 provides a solution for managing a smart low-carbon city, which consists of four management platforms. The sensing and identification platform is used for interconnection sensing, data acquisition and data pre-processing. The human–computer interaction platform is used for city governance decision making and bi-directional interaction. The cloud computing platform is used for storing data, background calculation and updating models. The modeling and display platform enables digital modeling and visualization presentation. The whole process can be used as an accurate portrayal of the city and achieve intelligent intervention and early warning of urban carbon emissions.

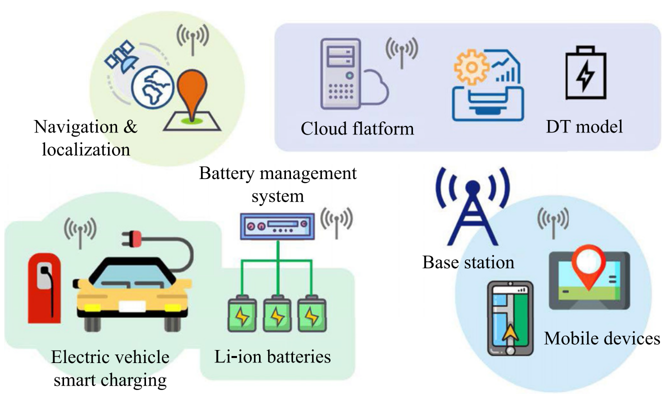

Fig. 3. Electric vehicle infrastructures with cloud.

3.2. Smart grid

A smart grid is a grid that uses computer technology to enhance communication, automation and connectivity between energy networks [31,32]. Technologies such as cloud computing, reinforcement learning and big data processing are already being used in smart grids [33–35]. Smart grids also need to integrate common non-renewable and renewable energy sources, reduce environmental hazards and enhance sustainability [36,37].

DT can be used in many phases of the smart grid because it can follow and reflect the full life cycle (FLC). Some of the following applications are promising for DT to take advantage of its strengths and make a further development. Such as, the modeling of a smart grid architecture model [38], data aggregation in the smart grid [39], design of smart meters [40], data analysis of smart meters [41]. In addition, Feng et al. [42] argued that in an ideal state, a cyber community built with edge computing could develop as a DT system for smart girds in both the power transmission network and the power distribution network. There are also applications relating to smart grids where DT is not directly involved in the application. However, from a long-term perspective, DT is likely to be combined with other related technologies to cope with the future energy supply challenges and to accommodate the institutionalization shift [43].

Papadimitrakis et al. [44] provided an overview of the meta-heuristic search in smart grid. Their focus was on using meta-heuristic search methods to solve smart grid optimization tasks. The proposed optimization tasks can be categorized into three major classes, namely the optimal power flow, scheduling and planning problems. These tasks often behavior undesirable characteristics like non-convexity, mixed types of design variables and multiple - and often conflicting - objectives. This corresponds precisely to the technical characteristics of DT. Therefore replacing meta-heuristic search with DT techniques, or combining them, would be the promising directions for future research. Fan et al. [45] believe that restoration of smart gird has recently received considerable attention. This article suggests that DT technology represent a promising avenue for the development of modeling framework for smart grids. They count smart grids as not only self-sufficient, but also highly interdependent. They also considered that the smart grid could be divided into a grid network (traditional grid) and a communication network (control and communication functions). With a description of the dynamic processes of the power system, knowledge-driven and data-driven DT models can be calibrated based on the data obtained from the sensors. In addition, the DT models also can facilitate the prognosis of the complex dynamic behavior of fault propagation in interdependent networks. The multi-agent system techniques can enable the power system to become smarter, reliable, self-healing, and robust. A Multi-agent System architecture suitable for smart grid applications was proposed by Shobole et al. [46]. In addition, the application of multi-agent systems in smart grid protection was reviewed. Where the smart grid domain model can be built in connection with methods such as DT. Pong et al. [47] reviewed pervasive sensing techniques in power grids that encompass contactless sensing technologies, IoT connectivity, energy harvesting and shielding. They explored how pervasive sensing can contribute to the development road map of autonomous energy grids, where the grid will be making automated operational decisions. It is clear that DT can help to refine this automated operation, by analysing the data acquired by pervasive sensing and making decisions that will further optimise the framework of autonomous energy networks.

The study by Nandha Kumar Kandasamy et al. [48] is a worthy case for analysis in that they provide a set of methods for building a Digital Twin of a smart grid for testing purposes. They focus on the cyber security of the grid and do not consider energy distribution and optimization issues. They build a more comprehensive platform, including a physical lab bench for testing, and a twin model. Various software such as MATLAB-SIMULINK, Node-RED, and others were used to achieve the system's functions. They completed the transfer of physical process data and controller network data, and successfully implemented the testing function of smart grid network security.

It can be seen that the advantages of DT and related technological innovations applied to smart grids can be summarized as:

- Optimization of energy consumption in the grid
- Possibility of modularization of grid functions
- Dynamic scaling up or down of the grid
- Monitoring irregular energy consumption
- Reducing carbon emissions and monitoring them in real-time

Possible weaknesses in the application can be summarized as:

- Model accuracy does not meet the requirements
- Optimization algorithms require large computational resources
- Large scale use of sensors on mobile
- Harmonization of heterogeneous data interfaces

3.3. Electrified transportation

Electric vehicles are generally characterized by their use of an electric traction motor for propulsion of the vehicle [49]. These motors are powered from an efficient energy storage device such as Li-ion batteries or ultra-capacitors, which can be charged by solar energy [50,51]. In addition, in hybrid vehicles, the introduction of batteries and electric motors helps the internal combustion engine to increase efficiency and reduce greenhouse gas emissions [52,53]. The development of these new vehicles and their integration with intelligence can be very effective in decarbonising [54,55].

In short-distance transport, battery-electric vehicles already have a much greater decolonization capacity in light transport than those using biofuels and oil [56]. This also allows DT to be used in a wide range of applications in the rapidly developing electrified transportation.

The applications of DT in electro-powered transport are even more extensive and diverse, and some applications can be interlinked with the smart grid. For example, Kucevic et al. [57] reduced peak loads on the grid by coordinating the control of battery storage systems at electric vehicle charging stations. This can also be considered as an application of low carbon city in terms of smart charging management. In addition, this paper has developed an open source simulation tool that couples models to simulate different operating modes of the distribution gird. The simulation tool in this work is expected to be replaced by DT. In Ref. [58], the authors proposed a simulation platform based on DT modeling for replicating the charging and discharging of large mobile electric vehicles in various scenarios in order to build a time series model of the vehicle network. This allowed the simulation of realistic and reasonable vehicle movement trajectories using DT and then analysed experimental data from simulated mobile phones to assess the efficiency of charging strategies in terms of EVs and charging posts in different scenarios. They also see the possibility of introducing different navigation and charging algorithms into this simulation platform for validation in the future, as a way to carry out validation related to the layout of charging infrastructure and the impact of smart grids. Fig. 3 provides the infrastructures of electric vehicle applications with cloud. The DTs of on-board energy storage systems can be built on cloud platforms to deduce battery aging behavior and predict battery failures.

Bhatti et al. [59] divided intelligent vehicle systems into special domains and discussed each subsystem. This paper further facilitated appreciation of the role of DT technology within each classification from a holistic technical perspective. Rudskoy et al. [60] optimized intelligent transport systems by modeling and using DT and AI, which allows solving the main problems of the transport network. The DT uses mathematical modeling methods in the system to analyse the traffic network and give recommendations for solving problems: optimizing traffic and pedestrian flows, public transport, traffic management, and traffic signals.

The application of DT in watercraft and aerospace technology has also recently been researched accordingly. Yin et al. [61] describe the application of DT in aerospace, showing the advantages over traditional modeling methods. Finally, an outlook on the future development of DT in aerospace is discussed. Kutzke et al. [62] established a generic process for identifying a set of priority-based system components that require DT development for state-based maintenance purposes. They framed the design problem as a multi-objective optimization problem, using data identified in experiments with unmanned underwater vehicle systems to verify generalisability in other systems.

The study by Yang et al. [63] on path planning for autonomous underwater gliders is presented below as a case study. Although underwater traffic is still relatively rare in daily life, the digital modeling approach they used for the environment can be extended to a wider range of traffic scenarios. They use the Digital Twin to map the real marine environment to a virtual digital space, thus providing a comprehensive and reliable environment for path simulation. They use a grid approach to describe the relevant factors and visualize the virtual digital space, including the corresponding currents, topography, and other observational data. This approach, when simplified, can be used for the detection and visualization of roads and vehicles. In practical applications, the virtual digital environment can be updated in real-time based on sensor data. Experiments show that the environment using the DT method have great advantages in terms of representability and reliability compared to traditional path planning methods.

The advantages of DT and related technological innovations applied to electrified transportation are:

- Integration with algorithms for path planning
- Reduced pressure on cloud computing
- Better portability of environment modeling
- Real-time optimization of traffic energy consumption
- Data collection and global optimization as an element of a higher level

Possible weaknesses in the application can be summarized as:

- Lack of uniformity and standardization of models
- Need for good network transmission capabilities
- The construction and opening of the cloud platform
- High cost for large scale use

3.4. Advanced energy storage system

The increasing use of electrified mobile devices is driving the demand for mobile power sources, which is stimulating the development and management of energy storage devices and energy storage systems [64]. Energy storage devices and energy storage systems can in turn be combined with new age smart technologies [65]. Battery energy storage systems are seen as a potential solution to the problem of global warming because of their fast and stable response, adaptability and controllability compared to conventional energy sources [66,67]. DT has more application aspects in advanced energy storage systems, and the application scenarios are different. Examples include FLC management of batteries [68], estimation of the ageing state of batteries [69,70], optimization of catalyst layers in fuel cells [71], or DT modeling of fuel cell [72]. Wu et al. [73] provided a detailed account of models, data and AI in intelligent battery management systems. Li et al. [74] proposed a cloud battery management system to improve computational and data storage capabilities through cloud computing. Using this data, a DT model can be constructed for the battery system. The application of the equivalent circuit model of the battery system was also explored. The application of DT in batteries can be analyzed depending on different types of battery. Commonly used batteries today include lithium-ion batteries [75], all-solid-state battery [76], fuel cells [77], etc. The following are applications related to fuel cells first.

Fuel cells are complex in structure [78] and modeling of fuel cells are difficult. DT is not only better at modeling complex systems, but can also help reflect the internal state of the fuel cell during operation. Meraghni et al. [79] applied data-driven DT to build an integrated remaining life prediction system. They also constructed a deep transfer learning model based on a superimposed denoising auto-encoder for online updating of the DT. The study surfaced that the prediction results can receive less influence even with limited measurement data. Wang et al. [80] proposed an alternative modeling approach by combining a physical model of a three-dimensional proton exchange membrane cell with a data-driven model. The method significantly reduced the computational cost and time without reducing the model accuracy, and the establishment of the multi-physics field model provides a good representation of the distribution characteristics. Through this study, the potential of DT to combine data-driven and integrated physical models for the development of complex systems is demonstrated.

Over the past decade, lithium-ion batteries have taken the lead in the electric vehicle market due to their high performance and low cost. The recycling of lithium-ion batteries has become a necessary part of the whole life cycle [81]. Furthermore, there is considerable interest in the study of batteries after they have aged or after the retirement of electric vehicles. Zhou et al. [82] classified batteries based on battery capacity and internal resistance with segmented linear fitting to put used electric vehicle lithium-ion batteries to the secondary use. And they also incorporated neural networks to predict battery capacity and internal resistance after model training. DT holds potential as an alternative to this technology. Sancarlos et al. [83] developed a numerical and hybrid twin that applied each of the three reduced-order models to a different range of application. Battery design optimization and pack modeling are accomplished while ensuring accuracy and saving computational resources. Finally, the model is self-correcting by extracting online data. Merkle et al. [75] set up a data pipeline and digital battery twin to track the battery state, including state of charge and state of health. Focusing on the e-Golf battery, they used IoT technology to transfer data to a cloud twin system that matched the battery model to the data to infer the individual battery internal resistance. A DT-driven all-solid-state battery with a solid sulfide electrolyte was constructed by Joonam Park et al. [76] The fundamental properties of all-solid-state cells in terms of physical and electrochemical behaviour are investigated. DT also revealed valuable time-resolved and space-resolved information, including dead particles, specific contact areas and charge distribution in the three-dimensional domain.

Batteries can be used as a representative of advanced energy storage systems, and the construction of a cloud-based battery management system by Li et al. [84] can be seen as an exemplar of battery DT. They implemented online state of charge estimation and health estimation for batteries. They build a cloud-based battery management system that includes six subsystems: the battery system can generate data for stationary or mobile batteries. The battery management subsystem enables the monitoring of multiple cells and data sampling. The IoT component enables the communication between the cloud platform and other batteries. The cloud subsystem uses a database for data storage and guarantees data privacy and security. The application programming interface allows the conversion of algorithms and the estimation of battery status in different languages. Finally, a user interface is used to visualize the data and status to improve operator efficiency.

As can be seen, the advantages of DT and related technological innovations applied to advanced energy storage systems can be summarized as:

- Facilitate data collection, storage, and processing of energy storage systems
- Full lifecycle management of the energy storage system
- Facilitate the deployment of cloud-based system management
- Reduces the difficulty of human–computer interaction

Possible weaknesses in the application can be summarized as:

- Inadequate data sharing and opening mechanism
- Lack of standardization of the whole life cycle structure
- Built models can only simulate the system operation mechanism through data

Fig. 4 provides a solution of advanced manufacturing and management of lithium-ion batteries, which consists of four management platforms. The business management platform is used to manage the customer relationship as well as the project and order information. The manufacture management platform is used to manage the production materials and process. The software management platform is used to release and update program, and perform product application tracking. The operation data platform is used for data reception, storage, and analysis in order to provide early alerts. Data from the manufacturing process and service process are stored in different databases for the construction of DT models of the batteries which can be used for state prediction and health prognosis.

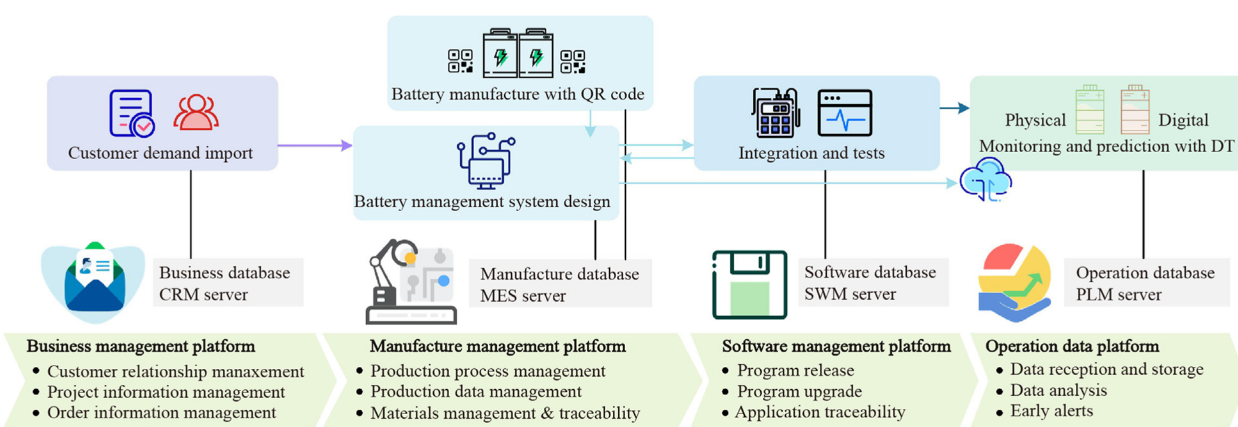

Fig. 4. Advanced manufacturing and management of lithium-ion batteries.

4. Key technologies of DT

The key technologies of DT will be integrated in a complex way with the new generation of information technology. Fig. 5 shows a summary of the key technologies of DT. The specific functions of DT in applications (e.g. modeling, data management, connectivity, etc.) can be summarised. It can be concluded that big data, cloud computing, AI and blockchain can all be used as key technologies for DT [19]. The data generated by DT integrates multiple sources, types and structures of massive data such as physically sensed data, model-generated data and fusion of reality and imaginary data. As a result, big data processing can provide greater computational and storage capacity to extract more valuable information to analyse and plan the outcomes and processes of real-life events. Cloud computing meets DT's larger data computing, storage, and operational needs through the use of a model with distributed sharing. Edge computing is also an important technology that may be combined with DT to speed up network services while also improving the protection of user privacy. AI can automatically perform data analysis and deep knowledge mining of data through the optimization of algorithms to generate various types of service, DT can significantly improve the responsiveness and service accuracy of various services with the help of AI. The independence, immutability, and security of block-chain technology can ensure that data is traceable and traceable, increasing the security of DT and thus encouraging better innovation. It also ensures the security of service transactions and the retention of historical traces, making users more trustful of DT. In addition, knowledge graph can be regarded as a pre-requisite technology for building DT models, which uses visualization and knowledge bases to collect relevant knowledge in multiple domains and at multiple levels for subsequent model building. In the operation phase, the DT model can also be optimized by Bayesian algorithm, machine learning and other data mining algorithms.

After a brief introduction to the key related technologies of DT. In the following, the perspective will be turned to the specific functions of DT in applications, which are presented with the help of literature. The key technologies used in the model building phase, the data acquisition phase, the framework research phase, and the full lifecycle management are described in detail.

4.1. System modeling

The following literature can illustrate that for the construction of DT models, multiple techniques need to be used under a certain architecture in order to keep the virtual model highly consistent with the physical entity. In addition, the knowledge graph can help build a knowledge base related to the model, and machine learning can help the first DT model to be better improved and iterated. Massel et al. [85] took DT as a model for integrating mathematics and information, and discuss scientific tools for building DT and DS. They proposed an improved architecture for multi-agent intelligence environments. They also use a knowledge management language as a tool to support research on energy systems DT. Techniques such as databases, semantic modeling, visual analysis, and ontological knowledge spaces are also used to build DT models in a multi-agent intelligence environment. Leng et al. [86] apply DT to intelligent manufacturing systems and answer some key questions about DT by reviewing the relevant definitions and techniques. They concluded that multi-domain physical-chemical modeling and visualization techniques need to be considered in high assurance modeling. Then, the use of DT models may involve industrial IoT, big data analysis, real-time synchronization, etc.

4.2. Data processing

The following literature can illustrate that data processing techniques and diverse AI techniques are also critical in the process of DT implementation. For data transmission, 5G can be seen as a very promising method. In addition, the advantages of cloud computing in data processing are more obvious, the processing in the cloud server can greatly

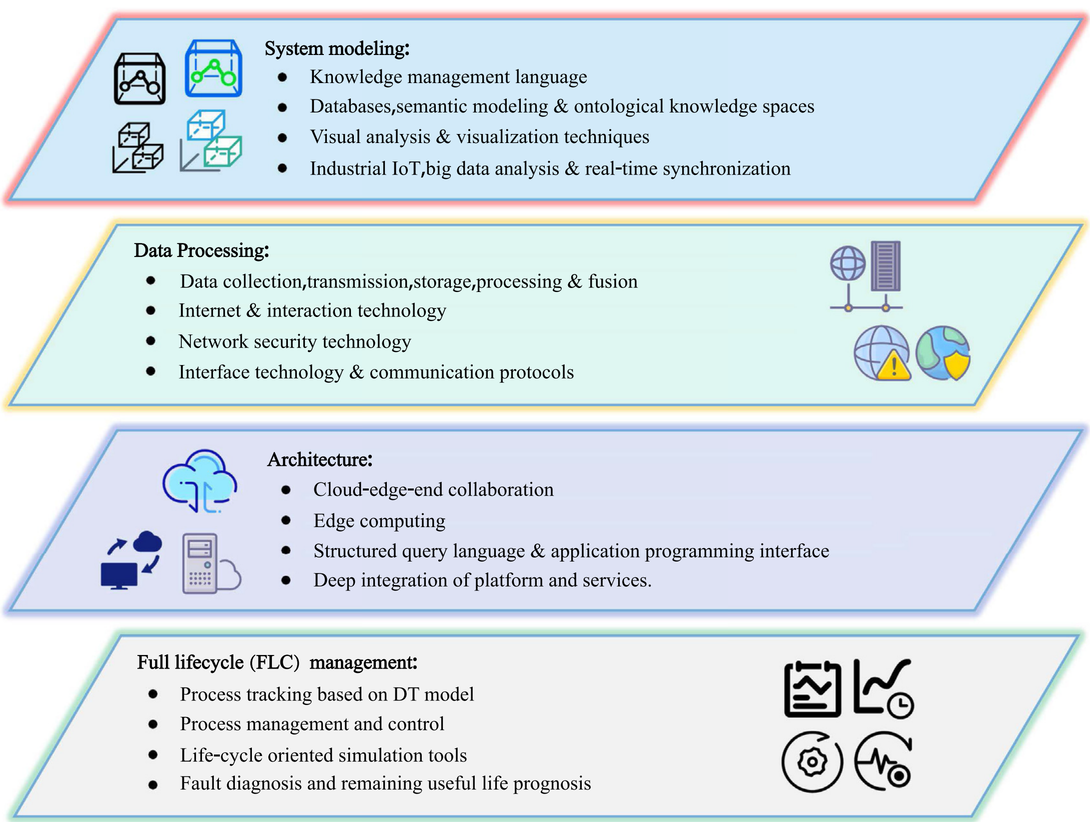

Fig. 5. Key technologies of DT.

improve the efficiency of model operation. Qi et al. [87] developed a five-dimensional DT model, which examined enabling technologies and tools for DT from different dimensions. They argued that sensor technology corresponds to physical entities, and virtual modeling and visualization technologies affect the effectiveness of DT. The collection, transmission, storage, processing and fusion of data correspond to complex DT data, while DT services need to include application services, resource services, knowledge services and platform services. The connection between the relevant layers involves internet technology, interaction technology, network security technology, interface technology, communication protocols. Xia et al. [88] proposed a method to create a virtual replica of a robotic manufacturing system using DT simulation and communication. On top of this it is also possible to safely train an intelligent scheduler. System-level DT can be extended to complex manufacturing systems with deep neural networks. The authors also believed that the implementation of DT is centered on data and interface communication, while open platform communication technologies are more widely used in industry. The authors also argue that the implementation of DT focuses on data and interface communication, while open platform communication technologies are more widely used in industry.

4.3. Architecture

Architecture is a fundamental principle for understanding how to design a Digital Twin, and these papers have made some progress in studying the overall framework of DT. Wang et al. [89] proposed a four-layer network architecture of cloud-side-end collaboration for battery management system. They also developed a Digital Twin model of the battery to achieve fine-grained and safe management of the battery throughout its life cycle. The technologies used are cloud-edge-end collaboration and edge computing. Onile et al. [90] proposed a framework for innovative energy services based on intelligent recommendation systems and DT, and used recent advances in DT to provide innovative solutions. For consumer demand-side management, data-driven, real--time monitoring and behavioral analysis techniques in DT can correct poor energy behavior and analyze consumption habits of specific users. They also provide a deep integration of platforms and services. Negri et al. [91] proposed two production-related DT frameworks and suggested that future research directions could investigate distributed DT architectures and the associated local and global decisions they support, assessing its impact on production and further decisions on operations. Another future direction could be to extend the functional base and the intelligence layer of DT through other frameworks integrated with MES. Structured query languages and application programming interface technologies are important technologies to implement the architecture.

4.4. Full life cycle (FLC) management

The FLC management can be considered as one of the future directions of DT, and there are some progresses in these following papers. Both human–computer interaction and data visualization enables optimization of FLC management. Human-computer interaction helps operators to make corrections and control decisions at each stage. Data visualization allows for intuitive monitoring of the model to reflect changes and trends in the data. Zhuang et al. [92] proposed a method for complex product assembly data management and process tracking based on DT model. Based on this, an assembly process management and control system based on DT model was constructed. In addition, a DT-based synchronous modeling technique and data hierarchical management technique are proposed and verified. Marco Garetti et al. [93] proposed an FLC reference architecture to support the industrial and scientific development of the next generation of life-cycle oriented simulation tools. This is largely consistent with the modeling and simulation techniques used in DT implementations. This indicates that DT can play a relevant role in the product design, manufacturing and updating process. Xia et al. [94] presented an intelligent fault diagnosis framework for machinery based on DT and deep transfer learning. This approach achieves accurate fault diagnosis of machine faults with insufficient measured fault data. They also verified that this intelligent fault diagnosis method outperforms other state-of-the-art data-driven methods.

5. Challenges and potential solutions

5.1. Main challenges

In recent years, DT technology has attracted much attention for its ability to combine virtual space with physical space, and has shown promise for a wide range of applications. However, for the time being, DT technology still faces some challenges. The challenges that need to be addressed are summarized as follows:

- The interoperability of different DT models is difficult, the semantic syntax of data is not uniform, resulting in redundant or missing resources of knowledge, and barriers to interoperability of basic knowledge bases between tiers. The connection between knowledge is not clear, the structure of each data source is not uniform, and the interpretability of knowledge is poor. It becomes increasingly important to select valuable knowledge to build a knowledge graph and create value. Traditional products and solutions focus on processing data from a single system, but when the scale of data to be processed is large and complex, it needs to be solved by building knowledge graphs using semantic engineering techniques. Traditional solutions are used to process structured data, but in reality, there is a large amount of unstructured data, which should be structured for specific scenarios before processing, and only knowledge graphs can do this task. When processing non-standard and unstructured data, the traditional solution adopts the way of searching to process, and the way of analyzing, calculating and querying a large amount of data cannot meet the requirements of precision and recall of results in the production process, while the knowledge graph can perfectly solve this problem;
- For different domains and application scenarios, it is necessary to repeat and build DT models several times, which is time-consuming and laborious. The migration of DT models to other platforms will face the difficulties of model and data sharing. At present, the construction of DT-related sharing mechanism and service system is not complete, and the sharing of data and models among different subjects has security risks and conflicts of interest, which makes it difficult to meet the relevant requirements of DT for data development and sharing;
- The traditional DT model has poor ability to transform external input information to conceptual logical information. Most of the collected data cannot be directly acted into the model. The data needs to be processed interpretively to form specific useable model parameters or operational data. On the basis of this operation, efficient real-time computing capability is required. In addition, the DT model is ineffective in logical judgment and self-determination during iterative optimization. This also increases the difficulty of building and completing the DT model;
- DT operation requires processing a large amount of heterogeneous data, which is a greater test of communication capability and storage capacity. Some Digital Twin application scenarios do not emphasize timely data processing, but require massive data storage and processing, such as fault diagnosis and preventive maintenance of complex products, which require massive data storage and big data analysis of different data sources, posing a greater challenge to data storage capacity and computing capability;
- There are no standards for DT design, development, operation and management, which makes DT difficult to replicate, learn and imitate. In the process of building and integrating DT models, various types of data transmission and interaction between different systems and

devices are required. Therefore, it is necessary to establish communication interface protocols and data standards as well as unify data semantics and codes, which are the basis for establishing a perfect multidimensional DT platform. The non-uniformity of existing communication interface protocols and data standards for different systems and devices is a big challenge for building DT;

- At the model level, the DT model is usually composed of a mechanism model or a decision model, which lacks feedback and update in FLC management. Existing DT models cannot adequately consider the management of dynamic operation processes after manufacturing and the prediction of product life. In addition, as the original purpose of the DT model, extending the product life and managing the product's health status should be the primary consideration. However, the existing DT models are mostly applied to the operation phase of the product, and there are still many gaps in the production and reuse phases. Updating and optimizing the model state and parameters using FLC data can obtain an adaptive DT model.

5.2. Potential solutions and techniques

5.2.1. Knowledge graph analysis

Knowledge base refers to the set of rules applied in the design of expert system, including the facts and data associated with the rules. Knowledge graph is a series of different graphs showing the relationship between the development process and structure of knowledge. It uses visualization technology to describe knowledge resources and their carriers, mine, analyze, construct, draw and display knowledge and the relationship between them. Building a Digital Twin model requires multiple levels of knowledge, and such databases are not yet perfect. The current difficulties in interoperability of multiple models and the lack of unified data semantics create redundant or missing knowledge. Establishing a proper knowledge graph and unifying data semantics may be a possible solution.

5.2.2. DT models migration

Model migration is the reuse of different models from different domains, or different scenarios in the same domain. For DT models with high accuracy, model migration in multiple scenarios is considered after the modeling work is completed. Or consider the linkage of DT models in different domains, with the help of the completed models against the new models, which is enlightening for model building. Model migration can reduce modeling complexity, speed up model building, and increase applicability under different operating conditions.

5.2.3. AI technologies

DT is a comprehensive technology that integrates with various AI technologies such as machine learning, IoT and CPS. For DT, real-time computing is a challenge that needs to be considered, and AI helps a lot in this regard. Combined with machine learning, it can effectively reduce the difficulty of model building and improve efficiency. IoT and CPS then enable real-time sensing and dynamic control of engineering systems, which is important in DT.

5.2.4. Data processing

For DT, the ability to hold and process more data is a key component. Data processing then includes data storage, data accuracy, data consistency and data transmission stability. Moreover, multiple sources of heterogeneous data need to be integrated and fused to form a unified data carrier at different stages of model usage. Cloud platform is commonly used to solve a large amount of complex data storage. Breakthroughs and enhancements in communication technologies will help improve the security, stability and reliability of data transmission. Communication protocols and data standards can cope with the integration and fusion of heterogeneous data. In addition, data in DT is the basis of manufacturing service collaboration, and the value of data and the added value of the model need to be evaluated. Improving the value chain of DT models and forming an industrial chain in DT are seen as having the potential to meet this challenge.

5.2.5. Standardization

The DT requires a standardized framework, including the interaction of platforms, software, interfaces, and the coordination of technical rules. The overall standardization work of the DT is also in the initial stage, and the standard research content needs to be enriched. The standardization content that can be considered includes standards for basic elements, concepts, technical implementation, testing, evaluation, and standards for collaboration between different systems.

5.2.6. FLC management

The FLC is the whole process of product design, manufacturing, sales, logistics, service, maintenance and repair, until recycling and disposal. The DT acts on the FLC of the product, which needs to collect the information of the FLC for data management and health prediction in order to achieve the purpose of extending the product life. To convert FLC information into digital form, DT need to consider not only current data, but also historical data, and link data structures and models at different stages, so that the FLC forms a circular and interconnected state.

5.2.7. Digital first

At this stage, we can regard DT as a digital parallel stage, in which the physical world and the virtual digital world are simultaneously perceived and mapped. Digital first, then, refers to the process of making digital virtual ahead of real production to actively think, deduce and argue. In the introduction of a large amount of historical or external data based on DT using the high processing power of computing equipment, there is an opportunity to do digital first. Then, with multiple iterations of low-cost experiments, significant time and capital costs can be saved. This has the potential to be a new approach to solving complex problems in the next generation.

6. Conclusion

This paper introduces the relevant definition of DT, its application in the energy field and key technologies. Firstly, the research background and development history of DT is explained, then the definition of DT is systematically analyzed, and the wide and important applications of DT in the energy field, especially in power-related systems, are emphasized. For the first time, DT is proposed to be classified from different integration levels, and four levels (low carbon city, smart grid, electrified transportation, and advanced energy storage system) are formed in the smart energy application field, and each level is explained with literature examples. Then, the key technologies related to DT are reviewed and discussed in an orderly manner with the new generation of information technologies that can be integrated. After the literature analysis, the key technologies and implementation methods required for DT to achieve different specific functions in the application are reviewed. Through such review and discussion, the future challenges to be addressed by DT and the direction of development of necessary technologies are given.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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