Digital twin enabled transition towards the smart electric vehicle charging infrastructure: A review

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ABSTRACT

Public charging infrastructure developments are the top agenda in both industrialised and developing countries during the global transition from fossil fuel vehicles to electric vehicles (EVs). Currently, the fast deployment of digital twins in the energy and transportation sectors is accelerating the fusion of the energy system and digital space, which advances the smartness of charging infrastructures to the next level. This study presents a smart EV charging infrastructure framework composed of a green power generation network, an energy storage network, and a charging network. The digital twin, as an enabling technology, is applied to realise essential smart features for the EV charging infrastructure, including cognisant, adaptive, taskable, and ethical. Based on the proposed smart charging station framework, we systematically review the existing digital twin implementations in the smart charging infrastructure. The review shows the smart charging infrastructure supported by digital twins enhances operational and managerial efficiency, economic, environmental, and social sustainability, and scalability of charging infrastructure. Further research on smart charging station architecture improvement, charging station digital twin standardisation, and best practices for smart charging station digital twins are encouraged.

Abbreviations

ESS Energy storage system

EV Electric vehicle

IoT Internet of Things

LSTM Long short-term memory

MCU Mobile charging unit

SoC State of charge

SoH State of health

Contents

ORCID(s):

1. Introduction

Electric vehicles (EVs) are the core accelerator for the green transition in the energy and transportation sector. In 2022, the global EV stock hit the 26 million mark with a 60% increase over 2021 (IEA, 2023). The fast adoption of EVs calls for urgent developments in charging infrastructures. Many existing charging infrastructures refer to charging sites equipped with charging poles, most of which are unsupervised, as shown in Fig. 1. The data from the International Energy Agency (IEA) (IEA, 2023) show that the number of publicly accessible chargers approaches 2.7 million units in 2022, demonstrating a 50% increase over 2020. China, the European Union, and the United States dominate the EV and charging markets, as seen from Fig. 2. The IEA comments that 14 million public slow chargers and 2.3 million public fast chargers will be installed globally by 2030 (IEA, 2023).

The fast growth of charging demand poses significant challenges in developing efficient charging infrastructure on a global scale. These challenges primarily revolve around three key issues: 1) the increased demand for additional power supply from the grid; 2) insufficient and poorly planned charging infrastructure layout; and 3) the need to provide EV drivers with satisfactory charging services. In this context, the need for innovative planning and operation solutions for charging infrastructure becomes increasingly apparent. Emerging technologies, such as digital twins, offer promising solutions to enable smart charging infrastructure development. In the following sections, we introduce the digital twin technology and detail the challenges faced in the development of charging infrastructure to accommodate the growing EV market.

Figure 1: Fixed charging poles (David Zhang, 2017)

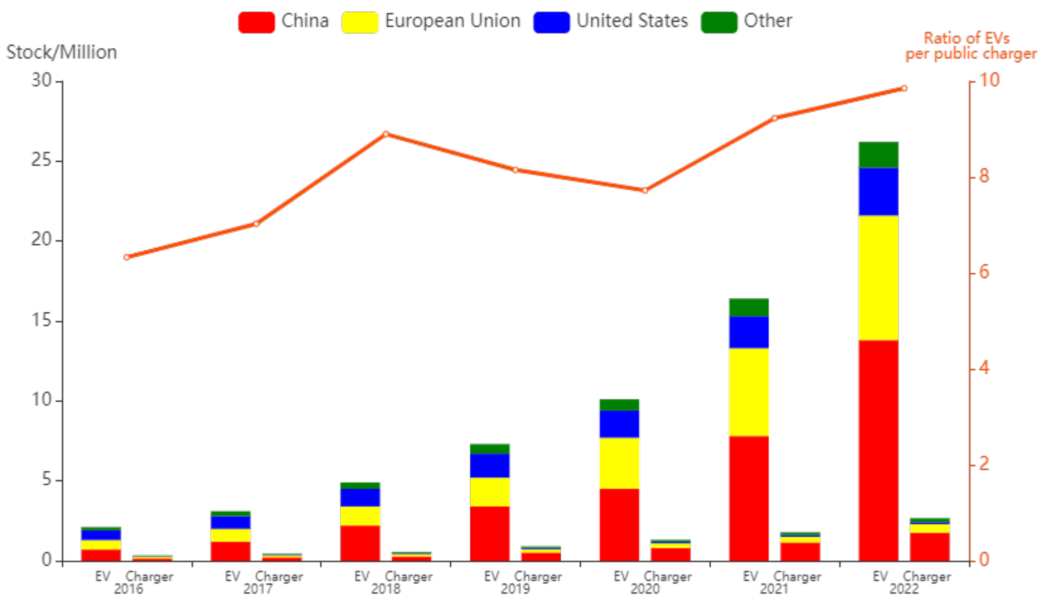

Figure 2: Global electric passenger car stock and public EV chargers stock from 2016 to 2022 (IEA, 2023).

1.1. Digital twin

The digital twin, a computer-based twin model constructed in the virtual world with the support of the Internet of Things (IoT), can fully mirror the static characteristics and dynamic evolution process of the physical entity during the lifecycle (Yu et al., 2021). The concept of digital twin was originally proposed for product life cycle management in 2003, which contains three parts: the physical entity, the virtual entity, and the information connections between them (Grieves, 2014), as illustrated in Fig. 3. The concept of digital twins is regarded as the development of digital models and digital shadows. Digital twins establish two-way automatic data communication channels between the physical and virtual entities, enabling immediate feedback to optimise and adjust physical processes while there is no and only one-way interaction between physical and virtual entities in digital models and digital shadows, respectively (Bergs et al., 2021). The virtual entities co-evolve with physical entities throughout the life cycle and exhibit excellent simulation and prediction capabilities, which enable the designers to back-track the causes of equipment failures from the design and manufacturing stage, predict and optimise the performance of products (Yang et al., 2022; Wang et al., 2020). The digital twins generated by multi-source heterogeneous information can be used to support the real-time and efficient interactions between the cyber-physical side and the operating side, and merge the physical space and the corresponding virtual model into a fully immersive human-machine collaboration space (Fan et al., 2021). Here, the virtual twin replaces the traditional manual data collection and decision-making method and achieves real-time system monitoring and automatic control, thereby solving the problems in the production process such as inconsistency between the plan and the actual production and unreasonable resource allocation (Tao and Zhang, 2017). So far, the digital twins have exhibited great application potential in the manufacturing industry, such as part manufacturing (Liu et al., 2023), anomaly detection (Huang et al., 2021), and remote commissioning (Leng et al., 2021), and gradually been extended to areas such as medical services (Xames and Topcu, 2024), smart agriculture (Kim and Heo, 2024), and smart city (Ramu et al., 2022; Xia et al., 2022) with the popularisation of 5G and IoT technologies.

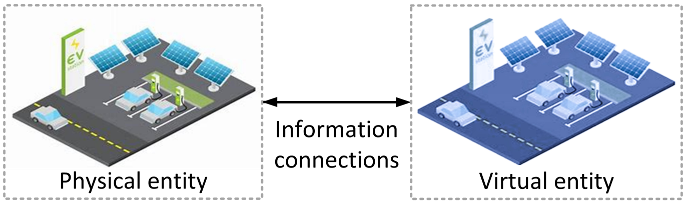

Figure 3: Digital twin schema.

1.2. Development of charging infrastructure

The rapidly increased charging power demand leads to concerns of overloading the existing grid (Hussain et al., 2021). The grid capacity to handle the charging demand can be categorised into three scenarios, as illustrated in Fig. 4. Scenario (a): the grid capacity can meet the charging load, applicable to countries with abundant power resources or lower EV penetrations, such as the USA, Germany, and China (Kintner-Meyer et al., 2007; Engel et al., 2018b; Xue et al., 2020); scenario (b): the grid capacity is capable of satisfying the most of charging demand, but the peak power exceeds the grid capacity, such as New Zealand, Poland, and Italy (Su et al., 2019; Wargers et al., 2018); scenario (c): the existing grid is incapable of satisfying the base load, let alone providing additional capacity for EV charging, such as

Sub-Saharan Africa (Tongwane and Moeletsi, 2021; Collett et al., 2021). For countries or regions that meet scenarios (b) and (c), appropriate solutions should be provided to manage charging demand and expand the grid capacities. Additionally, to achieve carbon neutrality targets, existing grids must reduce reliance on fossil fuels and incorporate

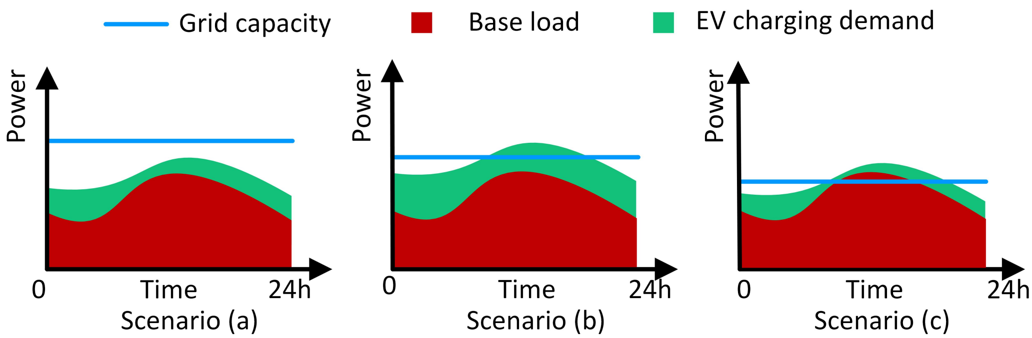

Figure 4: Grid capacity in response to the EV charging demand.

renewable energy sources like solar, wind, biomass, and biogas (Sahin et al., 2024). However, the intermittent nature of renewable sources like solar and wind can strain the grid's reliability and stability. Overcoming this challenge requires advanced energy storage solutions and effective charging load management techniques to ensure a consistent and dependable power supply and reduce excess production of renewable energy (Barman et al., 2023). Finding the right balance between EV charging and renewable energy utilisation holds significant potential for sustainable energy integration and decarbonisation.

In practice, the deployment of charging infrastructure faces challenges. The layout of the deployed charging infrastructure does not match the local charging demand (Azadfar et al., 2015). For instance, a survey conducted in China's 25 major cities revealed that the average time utilisation rate of deployed charging poles is 6.7%, falling below the expected 10% (CAUPD, 2021). Technically, this discrepancy is primarily attributed to the inaccurate estimation of the spatiotemporal distribution of charging demand. Unlike in the operational stage, where measurable historical charging demand aids in predicting future demand, the planning stage faces uncertainties influenced by factors such as the interaction between charging stations, drivers' choices, site attractiveness, etc. On a financial scale, the costs associated with charging infrastructure remain high, both in terms of upfront installation and potentially ongoing expenses (LaMonaca and Ryan, 2022). Countries like India and Brazil struggle with large-scale investment in charging infrastructure due to substantial financing gaps and fiscal debts (Barman and Dutta, 2024). On a social level, social acceptance plays a crucial role in charging infrastructure planning. Ethical considerations surrounding charging infrastructure deployment are significant factors to enable a just energy transition, such as ensuring charging stations are powered by green energy (Metais et al., 2022), promoting social equity in access to charging services (Hopkins et al., 2023), and addressing concerns about the safety of charging poles, particularly regarding fire incidents. To address these challenges effectively, charging infrastructure planning should adopt a techno-economic perspective, taking into account various factors such as urban development, advancements in charging technology, power supply capabilities, charging demands, social inclusion, and relevant policies. This comprehensive approach is essential to maximise the return on investment (Zhang et al., 2018). Despite efforts to consider some of these factors individually, existing studies still lack integrated modelling approaches and large-scale real-world case studies, which are necessary to enhance the planning and implementation of charging infrastructure (Unterluggauer et al., 2022).

Accurate real time charging demand prediction, flexible charging management strategies, and clear understanding of user satisfaction form the three pillars for delivering satisfactory EV charging services. However, implementing these pillars faces several challenges in practice. First of all, the real time charging demand is influenced by various factors such as weather, traffic flow, location, time, and charging tariff (Sadeghian et al., 2022). While data-driven approaches show promise in predicting future demand accurately. Charging demand data that contribute to the estimation of charging demand is still very scarce, particularly in countries with low EV penetrations and insufficient charging infrastructure developments. The flexible charging management strategies are capable of improving the service ability and profitability of charging infrastructure. The diversity of charging services and demand-side solutions, including battery charging/swapping (Cui et al., 2023), vehicle-to-everything (Islam et al., 2022), charging pricing (Yong et al., 2023), and demand shifting and curtailment (Liu and Zhou, 2022; Liu et al., 2019), increase complexity when applying optimal charging management strategy. Additionally, despite theoretical developments, there is a notable lack of real-world testing and comparative studies to validate the effectiveness of these strategies. EV charging, as a relatively new service from the market, is still premature to achieve a general user's satisfaction to charge a vehicle timely and cost-effectively, especially when compared to the fuel top-up services for existing vehicles with internal combustion engines. At the technical level, issues like poor identifiability and incompatibility of charging poles are painful for EV drivers who urgently need to find an available and suitable charging pole. In China, for instance, 29.2% EV drivers encounter the problem of incompatible charging interfaces (iResearch, 2020). Beyond technical factors, user satisfaction is also influenced by travel planning, driving distance anxiety, and social acceptance of charging facilities. Due to the multidimensional nature of user satisfaction in EV charging, research efforts have different engineering and sociological focuses, leading to a lack of integration in the field (Dixon et al., 2020; Delmonte et al., 2020). This lack of integration may hinder a comprehensive understanding of user needs and preferences, and consequently, it could limit the development of holistic solutions that address all aspects of user satisfaction.

Looking into the future, the smart charging infrastructure, as an energy hub in the smart city (Angelidou et al., 2022), is expected to exhibit smart functions including a stable green power supply, excellent demand-side management, comprehensive and transparent operational status monitoring, and well interaction ability with operators and EV drivers. As summarised before, there are gaps between the current charging infrastructure and expectations.

The successful applications of digital twins in several energy systems (Bhatti et al., 2021; Wu et al., 2021) inspire us to determine whether digital twins are applicable to the development of charging infrastructure, which would promote the transition to a smart charging infrastructure. Therefore, we conduct a comprehensive review to understand how digital twin applications enable smart charging infrastructure developments. Our contributions are summarised as follows:

- This review discusses the potential application of digital twins to smart charging infrastructure developments.
- We propose a unique and systematical three-network parallel architecture that consists of green power generation network, energy storage network, and charging network for the future smart charging station, which integrates scattered charging infrastructure units into a unified structure to reduce the complexity of management and operation in practice.
- A vision of the smart management functions of the future charging infrastructure based on four smart features in terms of cognisant, adaptive, taskable, and ethical is proposed. A four-layer charging station twin architecture is proposed to support the smart management functions.
- The digital twin implementations in the smart charging infrastructure are reviewed. Further research on architecture improvement, standardisation, and best practices for smart charging stations enabled by digital twins is encouraged.

The structure of this review is shown in Fig. 5. The remaining part of this study proceeds as follows: Section 2 presents a three-network parallel architecture for the charging infrastructure and defines the "smart" features. Then, a four-layer charging station digital twin architecture is established and the smart management functions are illustrated. Section 3 systematically reviews current digital twin implementations in smart charging station. Section 4 concludes this study and points out the potential research directions for the smart charging infrastructure enabled by digital twins.

2. Digital twinning the smart EV charge infrastructure

This section introduces a three-network parallel architecture for smart charging infrastructure. A broader definition of charging infrastructure is adopted, encompassing not only the physical charging poles but also the supporting independent power supply and energy storage infrastructure as they together form a complete supply-storage-load charging ecosystem. Then, the digital twinning process and the smart features of charging stations are discussed.

2.1. Three-network parallel architecture

In this study, a systematical three-network parallel architecture composed of green power generation network, energy storage network, and charging network is proposed for future smart charging stations, as shown in Fig. 6.

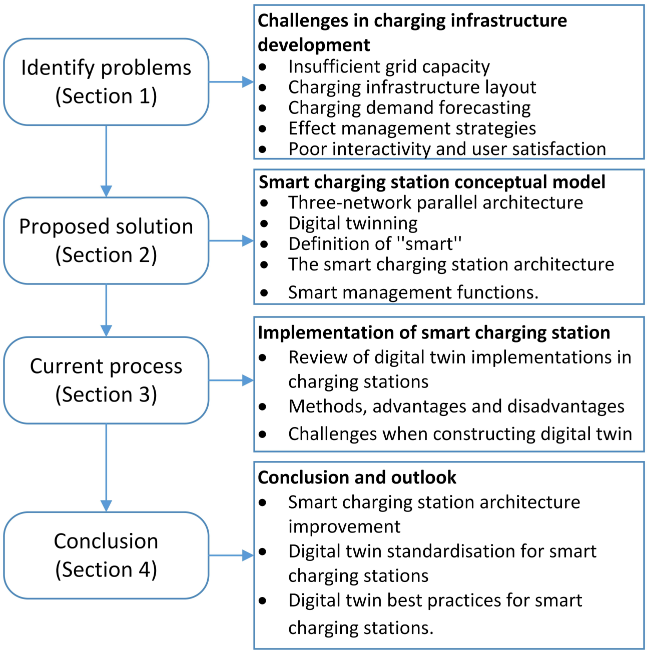

Figure 5: The structure of this review.

The architecture integrates scattered charging infrastructure units into a unified structure to reduce the complexity of management and operation in practice. The proposed architecture is grid-tied, allowing for potential vehicle-to-grid energy trading. Previous studies show that EV drivers have higher-than-average interests in renewable energy and environmental protection (Nienhueser and Qiu, 2016). Therefore, considering the global trend of carbon reduction and EV driver preference, a green power generation network supported by sustainable energy such as solar, wind, and biomass/biogas is strongly recommended. Since some green power sources are intermittent, the deployment of energy storage systems (ESSs) helps manage these uncertainties. There are numerous options for ESSs in the energy storage network, but not all of them are suitable for charging stations. As shown in Fig. 7, the total energy storage installed capacity globally reached 209.4 GW by the end of 2021, of which lithium-ion batteries account for 10.9% with an installed capacity of 22.8 GW. Lithium-ion battery tops the electrochemical storage technologies (China Energy Storage Alliance (CNESA), 2022). As a result, batteries are the most widely used ESS in charging stations, with extensive investigation into their technical, economic, and environmental performance. Other energy storage technologies, such as flow batteries and flywheels, are evaluated for techno-econo feasibility in recent studies, but they have not yet achieved widespread commercial adoption (Álvaro Cunha et al., 2016; Wang et al., 2021). The charging network consists of charging stations, independent charging poles, mobile charging units (MCUs), and EVs. Independent charging poles are distributed poles in public parking lots or other private areas. MCUs offer door-to-door charging services. It shows stronger economic competition than static charging stations in scenarios with high land costs and user time costs (Zhang et al., 2020). The proposed three-network parallel architecture sets the stage for achieving a smart charging station by effectively applying digital twins in this integrated network. With the proper implementation of digital twin techniques, the charging infrastructure can maximise its smart capabilities and offer efficient and sustainable charging services for EVs.

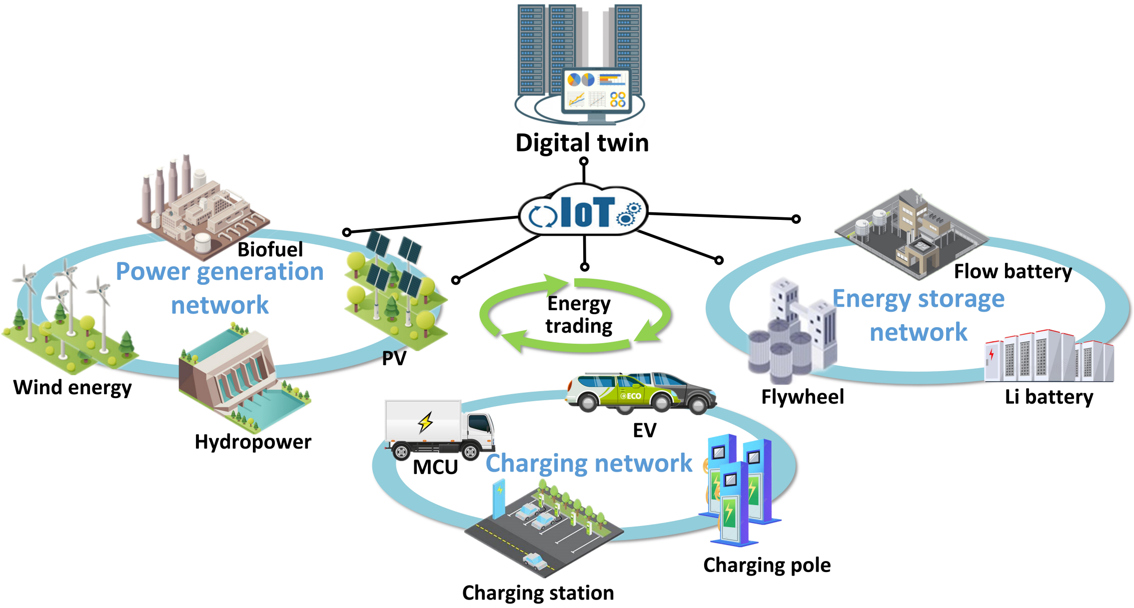

Figure 6: The smart charging station enabled by digital twin.

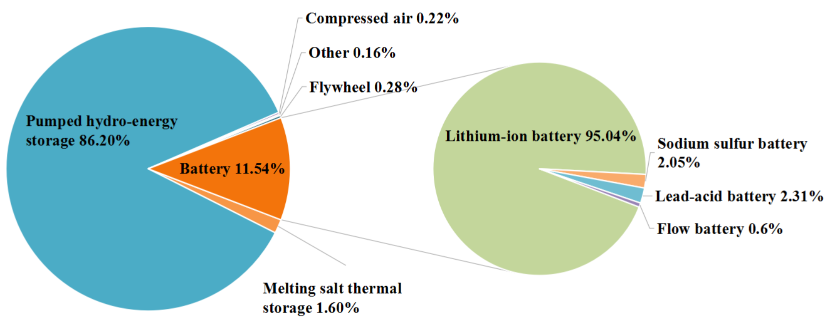

Figure 7: The global installed energy storage system capacity by 2021 (Engel et al., 2018a).

2.2. Digital twinning

The physical entity of digital twins is defined by the physical assets of digital twins from the dimensions of time and physics. Its time scale can span the entire life cycle process including design, manufacture, transportation, storage, service, reuse, and recycling, or focus on a specific stage of the life cycle. The boundary of the physical entity is determined by stakeholders' requirements. The physical boundary determination process involves integrating various opinions and concerns from experts, environmentalists, and governing bodies to form an optimal boundary for the digital twin (Solman et al., 2022). As illustrated in Fig. 8, five parts including data, models, concerns, governance, and actors are considered in this process. Taking the offshore wind turbine digital twin as an example, technology experts focus on how to twin the structure of wind turbines to monitor their operating status. Environmental experts may be concerned about its harm to birds and the marine environment. The government focuses on the transparency and regulation of digital twins. The boundary of the digital twin therefore can be formed by integrating various opinions in an optimal way. The virtual entity is the digital replica of the physical entity, characterised by looks-like attributes and behaves-like attributes. The looks-like attribute describes the appearance, structure, or architecture of the physical entity, and can be reshaped into 1-D, 2-D, or 3-D representations. The behaves-like attribute represents the ability of the virtual entity to simulate the physical entity's internal dynamics and outputs under the same input conditions. It can be roughly categorised into three levels: single-state static model, discrete-state event-triggered multiple steady-state models, and dynamic time-driven transient models (Yu et al., 2022). The similarity between virtual entities and physical entities is critical when constructing digital twins. It should be bi-directional: virtual entities should accurately mirror state changes in physical entities, while physical entities should also change according to commands from virtual entities. The similarity measures can be categorised into distance-based measures such as Euclidean distance, feature-based measures such as Fourier coefficients, and model-based measures such as auto-regressive models (Serra and Arcos, 2014). In practice, the original digital twin is often extended to multi-layer multi-dimensional frameworks to enhance its capabilities to different industries and domains. For example, the five-dimensional architecture proposed in (Tao et al., 2019) emphasises the interactions between users and digital twins by adding a service module into the original digital twin framework. Another six-layer framework proposed in (Redelinghuys et al., 2018) in the context of a cyber-physical production system focuses on secure data and information exchange between digital twins. In (Aheleroff et al., 2021), a three-dimensional architecture for the digital twin integrating the physical architecture, the evolution process of model integration level, and the iterative incremental process of product life cycle value is presented.

2.3. Concept of a smart EV charging infrastructure

Advanced sensors, communication systems, and embedded microcontrollers are the fundamental hardware infrastructure of smart charging stations. More advanced sensors are required to collect more diverse and heterogeneous data. For example, in battery systems, traditional external measurements including current, voltage, and surface (ambient) temperature are commonly used to estimate the battery's internal state. However, these measurements may not accurately represent the non-uniform electric-thermal behavior inside the battery. To address this, fiber Bragg grating sensors are developed to capture multi-point strain and temperature variation signals (Li et al., 2022). Second, the progress in communication technology leads to increased bandwidth, enabling rapid and smart control responses.

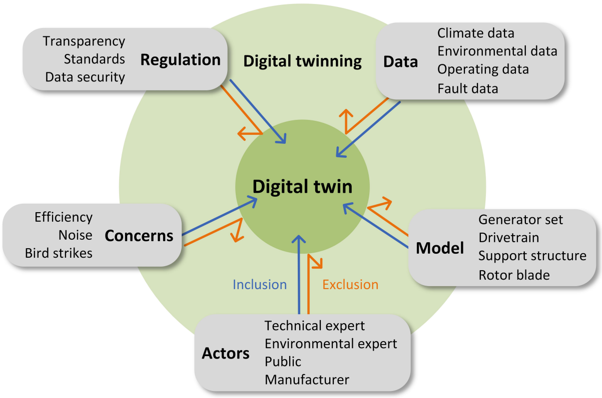

Figure 8: The digital twinning process to determine the boundary of digital twins.

The communication networks in (Lu et al., 2020) for smart charging stations are classified into three categories. The first category consists of the earliest development of industrial networks like Fieldbus, commonly used in existing industrial automation systems. The second category includes networks based on Ethernet protocols. The third category encompasses IoT communication networks, particularly those employing wireless communication technology like 5G and the upcoming 6G. With the use of ultra-reliable and low-latency 5G cellular communication technology, the communication latency can be as low as 1 ms (Park et al., 2022). Third, embedding microcontrollers into charging station components enables more control flexibility. Charging poles, for instance, can be divided into three types: simple power plugs, one-way charging poles with time and power controllers, and two-way charging poles with time and power controllers. The simple power plugs lead to uncontrolled charging while the higher-level charging poles offer greater control flexibility, allowing them to regulate the charging power and time based on price signals and driver charging requests and enabling vehicle-to-everything charging (Heilmann and Wozabal, 2021).

Smart and autonomous systems are expected to be cognisant, adaptive, taskable, and ethical (National Science Foundation, 2018). This study adopts and extends this concept to smart charging stations, and employs digital twin technology to realise these features, as shown in Fig. 9.

A charging station becomes cognisant when it demonstrates a high-level awareness of its capabilities and limitations to predict future charging demand, identify potential failures and risks, and subsequently adjust its operational actions for the management of power generation, energy storage, and charging load. Such cognisant capability can be achieved by adopting cognisant digital twins, involving the development of data perception mechanisms, data analysis, pattern recognition, prediction capabilities, and autonomous decision-making capabilities for charging stations (Intizar Ali et al., 2021). A cognisant charging station implies its strong autonomous perception capabilities to the source-storage-load network information of the charging station in real-time. This cannot rely on manual data collection and processing methods, while enabled by digital twin integrating most advanced sensors technology and energy internet. For example,

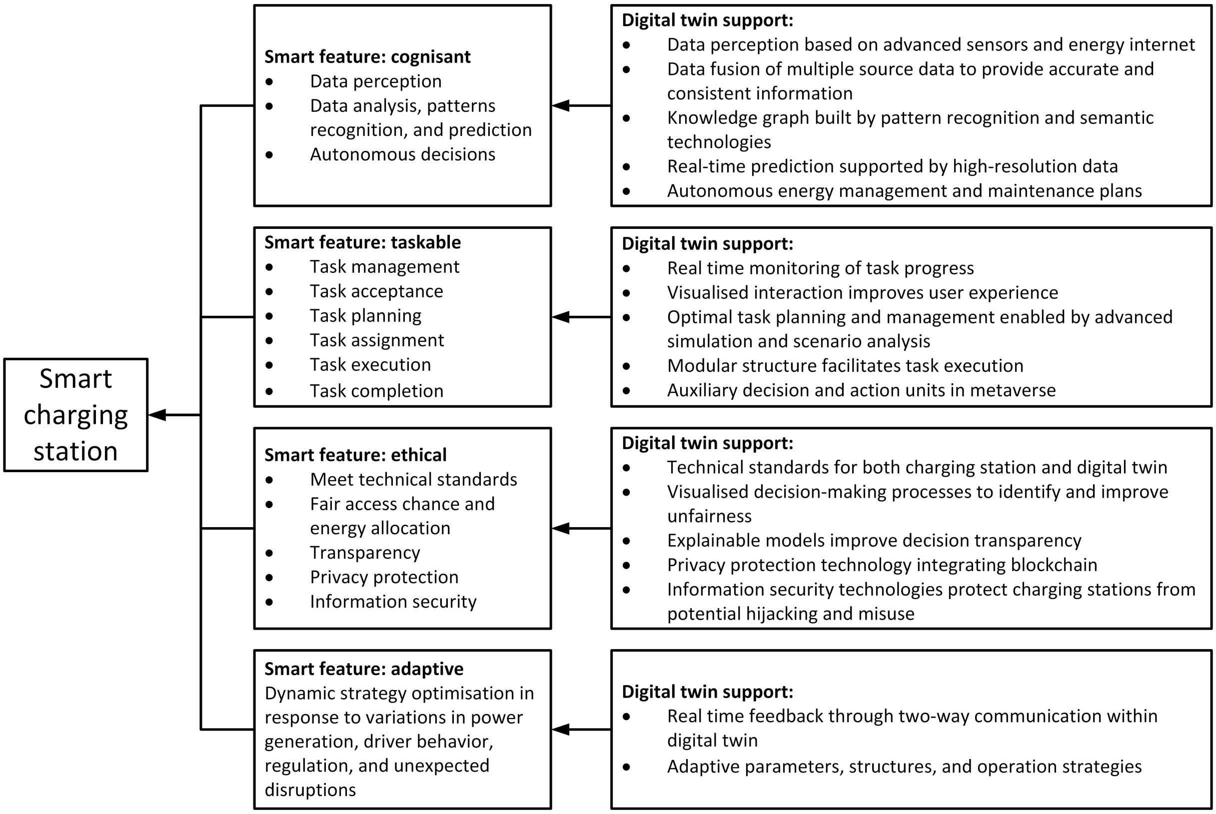

Figure 9: Smart features enabled by digital twins.

unmanned aerial vehicles equipped with sensors and a communication module are utilised in (Luong et al., 2023) to sense vehicular environments including the vehicle speed, driver's gaze, traffic light status, and event occurrences to create digital twins. The enhanced data perception capabilities increase the sampled frequency, shifting from hourly or minute levels to second and subsecond levels, and include more types and sources of data such as image data, geographical data, and user behavior data (Jorgensen et al., 2023). However, two challenges jeopardise the data quality in practice. The first challenge lies in sparse measurements, primarily attributed to the associated costs of sensors. For instance, achieving measurements for every location in offshore wind farms proves unfeasible due to physical and economic constraints. Digital twins present the capability to simulate unmeasured data by integrating measured data with prior physical modelling knowledge (Zhang and Zhao, 2023). On the other hand, 100% availability and reliability of deployed sensors and transmission networks are impossible due to unexpected weather conditions and environmental factors (Hu et al., 2021). Digital twins, with their ability to collect data from diverse sources, facilitate data verification, correction, and enhancement through data fusion, which handles data missing, noise, inconsistencies, and conflicts, ultimately leading to a more accurate and consistent description of charging station state information (Zhang et al., 2022). The integrated pattern recognition or machine learning algorithms in digital twins help convert the raw sensory input data into actionable knowledge such as the peak periods of charging demand and charging equipment aging states. Semantic technologies, such as knowledge graphs, offer a standardised approach for describing knowledge and their relationships, facilitating the creation of new knowledge through reasoning (Zheng et al., 2022). The digital twin encompasses vast amounts of real and simulated data with high time resolution, enabling real-time predictions regarding renewable power generation, charging load, energy price, equipment states, etc, especially maintaining the prediction accuracy in the face of unanticipated situations (Viola and Chen, 2023). For example, existing methods for charging load forecasting often rely on historical charging data, which, while informative, may fall short in predicting load variations induced by dynamic factors like weather changes and special events. The fusion of multi-source data enabled by digital twins, including climate data, charging records, geographical information, energy price, and special event data, not only improves forecasting accuracy during routine operational states but also enhances the model's adaptability to accurately predict charging demand even in the presence of special events (Wang and Luo, 2021). Regarding decision-making, a cognisant digital twin can decide what to know, say for learning purposes, and what to remain unknown, say for information security purposes, thereby enabling its adaptive, taskable, and ethical features with the least hardware constructions by a prioritised data management plan. Building upon this foundation, the cognisant digital twin can make optimal decisions on energy management and maintenance plans for charging stations without human assistance or a minimum level of human intervention according to the processed data and accumulated knowledge.

An adaptive charging station is capable of autonomously improving the strategies and actions as power generation, user behavior, regulation, and market policies change, which strikes a good balance between the financial return, safety, and charging satisfaction of the smart charging station. The adaptive algorithms in digital twins are able to automatically adjust the data processing method, processing sequence, and algorithm parameters for the perceived data, which makes them compatible with the statistical distribution characteristics and structural characteristics of the data and ensures the reliability of the virtual model. On this basis, the smart charging station could modify or re-plan the operational strategies. Specifically, it includes adjusting the technical specifications, updating the structure and parameters of the twin model, improving the operational strategies, or creating new business models. A feedback mechanism that enables the charging station to learn from user interactions and adjust its behavior accordingly is essential. Fig. 10 shows a control paradigm for the adaptive feature of the smart charging station enabled by the digital twin. The virtual entity of the charging station is a large-scale digital twin that collects well-developed and well-acceptable models of charging station components. $I(s)$ represents input information flows related to the charging stations, such as charging requests and preferences from EV drivers, and grid electricity prices. $O(s)$ is the output information flow of the smart charging station components. The output information can be roughly categorised as component operation data including electrical data, status data including thermal data and structural data, and power supply and load data. $O'(s)$

is the output of corresponding virtual entities. The output inconsistency between physical and virtual models drives the adaptive process. It is important to note that the inconsistency may come from an inaccurate virtual model or a failure of the physical model. Therefore, a judgment algorithm is necessary to determine the source of the inconsistency. For example, in (Tao et al., 2018), the historical state time series data of the physical equipment under the same conditions are used as a reference to determine the error source. If the inconsistency is caused by the virtual model ($E^v(s)$), then the adaptive algorithm is enabled to adjust its structure and parameters constantly in terms of historical data and real-time operational data. This process is realised by the least squares methodology. If it is caused by the failure of physical equipment ($E^f(s)$), explainable AI algorithms can be applied to analyse the cause of the failure and then provide a proper maintenance strategy (Tsoka et al., 2022).

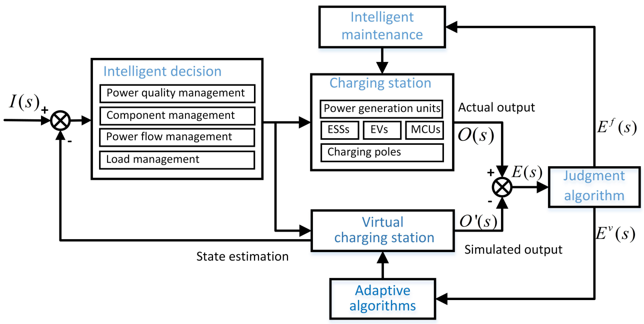

Figure 10: A control paradigm of the smart charging station enabled by digital twin.

A taskable charging station can perform specific tasks efficiently and accurately in response to drivers' requests and charging station operators' commands. It involves a well-defined process including task management, task acceptance, methodological task planning, task assignments, task execution, and task completion. For instance, the smart charging station manages existing charging requests while waiting for new charging requests. Once a new charging request is accepted, the whole charging management solution will be optimised simultaneously to maximise user experience and financial returns. The charging tasks are then assigned to the relevant components in the charging station for task execution. On receipt of feedback signals from the charging device and components, the smart charging station can further decide whether the tasks have been completed based on charging request specifications or whether the tasks must remain open for possible refinements. The taskable feature allows users to interact with and control the system effectively, thereby enhancing its utility and user-friendliness. Digital twins enhance the interactability of charging stations. Digital twins can offer users a clear and intuitive operational interface through visualisation, making it easier for them to understand and control the system and monitor task processing progress. Smart charging stations can identify and interpret specific charging requests even when the instructions provided by EV drivers are vague. This is made possible by the cognisant capabilities supported by digital twins, which enable a deeper understanding of user intentions. The digital twin allows simulations of tasks and scenarios in virtual space before they are executed in the physical world, which enables optimal task planning. Integrating the charging station digital twin into the metaverse further enhances its taskable features. Metaverse, as a cross-platform environment that hosts various digital twins, enables social, immersive, augmented, and interactive experiences for users by applying extended reality technology (Aloqaily et al., 2022). Within the metaverse, the charging station digital twins can seamlessly interact with other virtual elements such as energy prosumers and EV drivers. Drivers can visit the charging station digital twin, complete charging transactions, and monitor charging processes, more intuitively and engagingly. The metaverse, coupled with digital twins, enables advanced simulation and scenario analysis. Users can generate scenarios related to energy trading, system planning, or charging tasks and test corresponding strategies through charging station digital twins, enabling optimal task planning within the dynamic metaverse environment (Aldhanhani et al., 2024). In addition, digital twins support charging station operators in the metaverse that autonomously perform tasks, offering reliable and optimal decisions for charging station operators. For this functionality, there is an example from (Bâra and Oprea, 2024), where digital twins are created for EU Energy Communities and their members, serving as assistants to automatically engage in energy trading within the local electricity market. The proposed digital twins autonomously handle tasks such as load and generation forecasting, programmable load scheduling, bid creation, trading, settlement, and value-share. The digital twins simplify the market trading processes. On the other hand, they enable evidence-led governance for Energy Community members. Digital twins assist in system planning, tariff design, and testing of behavioral changes and provide more transparency and evidence through simulation for members to have a better understanding of potential barriers and impacts. Overall, the coupling with digital twin technology enables a taskable charging station to offer a more user-friendly and efficient experience for EV drivers and operators, optimising task management and enhancing the station's utility.

The ethical charging station system involves strict adherence to local ethics, laws, and technical regulations, ensuring that decisions and actions align with established ethical norms and values, and avoiding actions that could cause harm, discrimination, or ethical dilemmas. To meet its ethical obligations, an ethical charging station digital twin must meet technical standards and regulations that ensure the safe and efficient operation of equipment. This includes compliance with technical specifications related to the charging equipment, power supply, data collection, communication, and management, digital twin, operation strategy, intellectual property rights, and any other relevant technical aspects, as detailed in (Das et al., 2020; Shao, 2021). The ethical charging station prioritises several key aspects during its operation, including fairness, transparency, privacy, and information security. These principles should be integrated with the decision-making process in cognisant, taskable, and adaptive charging stations. The fairness issues arising from limited charging resources can be understood from two perspectives. Firstly, it should ensure equitable access chance to public charging infrastructure across various groups such as high-income and lower-income regions. For example, the authors in (Nazari-Heris et al., 2022) explore the optimal scheduling strategy for mobile charging stations while considering the imperative of ensuring social equity access across diverse regions. The equity impacts on the locations of mobile charging stations are evaluated by the quality of life indices of regions, and a higher priority is given to disadvantaged/underrepresented regions. The second consideration involves ensuring proportional fairness in charging energy allocation, taking into account variations in characteristics among EVs. This includes factors such as parking time and the amount of requested energy. The goal is to prevent the formulated charging strategy from exhibiting discrimination against either large or small-sized charging requests, especially during peak demand periods (Zeballos et al., 2019). In (Tan et al., 2023), a time-aware fairness index is introduced to assess the fairness performance of competing EVs concerning both waiting time and allocated energy. A bi-objective charging/discharging scheduling problem is solved to mitigate time-aware unfairness among EV users while minimising cost. The visualisation capability of digital twins, on the other hand, provides a clear, intuitive way to understand complex data and processes within charging stations for operators, regulators, and publics, which is essential for identifying unfairness and enhancing transparency. In addition, we suggest integrating explainable models and algorithms when constructing the charging station digital twin. They help explain the reasoning behind specific recommendations or actions, enhancing the transparency of the decision-making process and facilitating governance behavior. For instance, ref. (Ullah et al., 2023) employs the SHAP approach to reveal that factors including low start state of charge (SoC), high end SoC, peak hours, daytime charging, and specific seasons significantly influence users' preferences for fast charging, which provides valuable guidelines for deploying charging stations in metropolitan areas. To enhance privacy protection, it is recommended to collect and utilise only the essential data required to fulfill the intended purpose of the charging station digital twin. Moreover, personally identifiable information like EV driver identification should either be excluded or encrypted within the digital twin data. Techniques such as anonymization and pseudonymization can be employed for this purpose. To prevent unauthorised access and eavesdropping on sensitive information, it is crucial to ensure that data exchanged between the physical system and its digital twin is encrypted during transmission. The application of edging storage and computing can minimise the risks of data leakage during transmission. Edge servers can be strategically deployed at roadside locations. EV digital twins are implemented at the edge layer rather than the cloud layer. EVs in proximity to edge servers can wirelessly access the digital twin for real-time monitoring, route optimisation, energy trading among EVs, and other personalised services. All information about the EV is processed locally, thereby reducing communication latency and enhancing the privacy of passengers (El Azzaoui et al., 2023). An advanced ethical charging station possesses the capability to resist malicious data attacks and safeguard the charging station system from potential hijacking and misuse (Jeong and Choi, 2022). Given that communication among digital twins via Energy Internet often occurs over public networks, there exists a risk of adversaries exploiting vulnerabilities to compromise data privacy among charging stations and EVs in this interconnected environment. Cyber-physical attacks can corrupt the sensored data and disrupt the communication network, jeopardising not only the cognisant feature of charging stations but also the stability of the broader grid. This can be achieved by only using publicly available charging stations and grid data as revealed in (Acharya et al., 2020). The control paradigm illustrated in Fig. 10 presents a practical solution for implementing a security framework for vehicle-to-grid cyber-physical systems in case of cyberattacks. Twin charging stations provide an accurate approximation of the state variables of physical charging stations. When injecting fake data such as altering smart meter records, disparities emerge promptly between the actual and simulated outputs. The comparison between them facilitates the timely detection of anomalies, serving as a crucial mechanism in identifying and mitigating cyberattacks (Tariq et al., 2020). In addition, the use of blockchain technology further contributes to maintaining information security within charging station digital twins. The decentralised and tamper-resistant characteristics of blockchain, leveraging cryptographic hashing algorithms and distributed ledgers, ensure resilience against unauthorised access and alterations, enhancing the security, privacy, and integrity of data (Yaqoob et al., 2020; Suhail et al., 2022). For example, a privacy-preserving authentication protocol based on intelligent blockchain is proposed for battery-swapping (Chen et al., 2024). The incorporation of blockchain-based authentication enables connected digital twins to verify each other using their unique credentials, with key agreements facilitating the trust establishment among digital twins. Blockchain-enabled digital twins store all product-related information such as transaction records immutably, allowing buyers to trace the origin of specific products, their ownership history, and other relevant details, thereby enhancing traceability and transparency in the process (Ali et al., 2023). It should be noted that as the number of transactions increases, the process of reaching a consensus and updating the distributed ledger for each transaction can become time-consuming, leading to scalability issues. This is expected to be solved with the development of 6G with massive ultra-reliable low latency communication services (Khan et al., 2022).

2.4. The charging station digital twin development

As depicted in Fig. 11, a data layer is set for the data collection, preprocessing, and management. Real-time measured data often contains errors such as missing values, redundant data, and mixed formats, which deteriorate data quality and compromise the reliability of digital twins. To address this, data preprocessing steps, including data cleaning and normalization, become essential. An effective data preprocessing algorithm strikes a balance between time and space complexity, reducing the computational burden (Wang et al., 2022; Yang et al., 2022). The charging station digital twin is categorised into four technical functional layers in terms of time scale, including the unit layer at the sub-second level, the subsystem layer at the second-minute level, the charging station layer at the minute-hour level, and the charging station network layer at the day-year level (Xia, 2017). Each layer independently collects and processes data

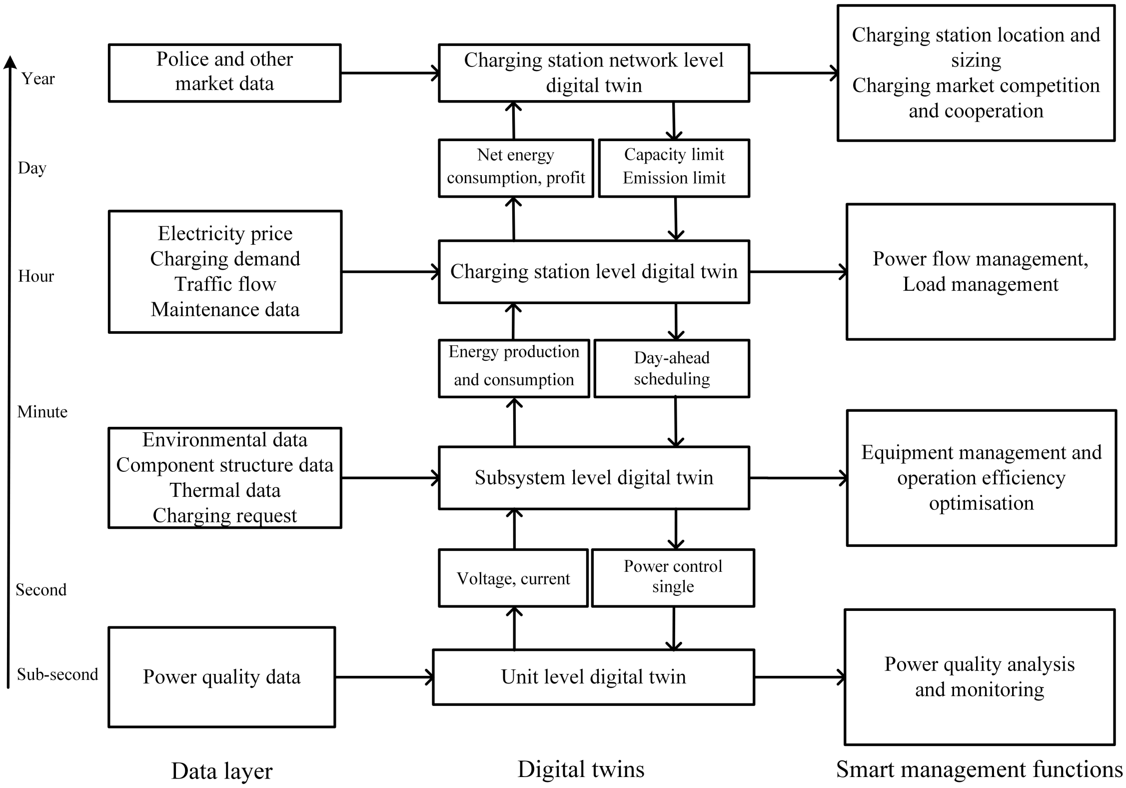

Figure 11: Smart charging station architecture and smart management functions.

while receiving inputs from lower-layer digital twins. The lower-layer digital twins carry out management functions while being regulated by upper-layer digital twins.

The unit layer digital twin integrates power quality analysis and prediction algorithms and power electronics models such as the DC/DC converters (Milton et al., 2020; Peng et al., 2021). It collects, analyses, and predicts the power quality including voltage, current, frequency, and harmonics, aiming to maintain and enhance power quality in the smart charging station.

The subsystem layer digital twin involves various independent component models within the charging station including green power generators, ESSs, charging equipment, and EVs. It aims for local management functions of charging station components, specifically, to monitor the operation state and maintain the energy efficiency of each component through the built-in control logic. A modular structure for the subsystem layer digital twin helps to reduce the complexity and improve scalability (Jones et al., 2021). In addition, the common methodology for digital twin constructions, including data modelling, prediction, and optimisation formulations and solvers, further contribute to complexity reduction. For example, the unified modelling framework and modular structure proposed in (O'Dwyer et al., 2020; You et al., 2022; Li et al., 2022) for complex energy systems provide new paradigms for reducing the complexity of digital twin charging stations. The subsystem layer digital twin collects additional data as needed for each component model such as meteorological data for PV and wind power generation, thermal data for ESSs, EVs' charging request data, as well as the power data from the unit layer digital twin. The data is utilised to build separate digital twins for those components and support real-time state monitor and short-term energy forecasts. In practice, subsystem layer digital twins may be developed by different companies, leading to two immediate problems: data handling in non-uniform formats when collecting or transmitting data between digital twins, and concerns related to privacy and intellectual property protection during integration. The last issue falls under the category of smart charging station ethics as mentioned before. Technically, these two problems can be addressed by establishing a local database for each component twin and enabling third-party communication services. The key data and model algorithms of component digital twins are stored in the local database, speeding up the responsiveness of subsystem-level digital twins and avoiding data leakage during transmission. The operation data of the component layer digital twins including energy production and consumption data is uploaded to the charging station layer digital twin through the third-party communication platform access. For example, the third-party communication platform named the Open Platform Communication Unified Architecture is introduced in (Redelinghuys et al., 2019) to unify transferred data format and avoid data/information leaks.

The charging station layer digital twin is built around the energy and information flows between the components and aims to coordinate their energy behavior on the minute-hour time scale. It formulates day-ahead scheduling plans according to the electricity price data and then assigns scheduling tasks to different components by the data feedback path (O'Dwyer et al., 2020; You et al., 2022). It also develops flexible demand-side response solutions for load management.

The charging station network layer digital twin includes other entities engaging in energy trading with the proposed smart charging station, such as the grid, other charging stations, and prosumers in the region. It includes a bidirectional interface between the smart charging station and the smart city system. Historical supply and load data will be merged with the charging station virtual ID and then uploaded to the smart city system by the interface (Deng et al., 2021). On the other hand, it also collects data from external electricity markets such as policy data and market competitor data, and enables various peer-to-peer energy trading through the virtual space. Integration of multi-objective optimisation and game theory algorithms at this layer aims to formulate competitive long-term smart charging station planning and operation strategies.

2.5. Smart charging station management functions to be enabled by digital twin

The future smart charging stations are expected to exhibit several smart functions called power quality management, equipment management, power flow management, and load management, which aim at maximising the operational efficiency of the charging station.

2.5.1. Power quality management

Power quality management is the basic function of the unit layer digital twin. On the power supply side, the output power fluctuation caused by the intermittent renewable energy resources and the operational characteristics of the generators is harmful to the charging infrastructure. On the demand side, the fast charging power demand introduced by the EVs connected to the charging station may deteriorate the node power quality. The power quality management function can guarantee the transient and steady-state performance of the smart charging station to avoid electrical equipment failures caused by declines in power quality such as frequency deviation, voltage flicker, and harmonics. By capturing the node parameters including voltage, current, frequency, and harmonics in the smart charging station, the power quality status of the charging station nodes is visualised in the virtual space via the digital twin techniques. The smart charging station performs the analysis and prediction of the bias of detection value and provides immediate power quality compensation effect to avoid severe power quality damages (Tao et al., 2018).

2.5.2. Equipment management

Equipment management maintains the maximum energy efficiency of the charging infrastructures through the built-in control logic and responds to the real-time energy scheduling plan. The equipment management includes the devices' electrical characteristic management, thermal management, and fault diagnosis (Wang et al., 2021; Panwar et al., 2021). The electrical characteristic management prioritises the power conversion process. For example, the maximum power tracking function in the renewable power generation process, charging/discharging control and cell equalization in the battery ESSs, and charging power control of the charging devices (Pozzi et al., 2020). Thermal management is responsible for controlling and regulating the temperature of diverse devices, systems, or components to ensure optimal functionality, prolonged lifespan, and prevention of thermal runaway. The digital twin is a powerful tool to improve the accuracy and reliability of fault diagnosis and prediction (Ikuzwe et al., 2020). The lack of fault data is the bottleneck for the establishment of fault models in practice. This is because the lower frequency of the fault status makes it difficult to collect sufficient fault data. Although it can be solved by experimental approaches, it is undoubtedly an expensive and slow process for charging stations. The digital twin can generate massive data through the real-time simulation of the charging station's internal dynamics. Data fusion contributes to the integrity and reliability of the fault dataset. In addition, the visualisation digital twin models are capable of revealing the internal fault evolution mechanism and clearly displaying the location and cause of abnormalities in the charging station instead of a vague fault status indicator. The smart maintenance function combining predictive models and digital twins is expected to significantly reduce the maintenance burden of maintenance personnel and the maintenance frequency while ensuring stable operation of the smart charging station (van Dinter et al., 2023).

2.5.3. *Power flow management*

Power flow management aims to optimise the operational profit of the smart charging station by employing optimal energy scheduling strategies. This involves coordinating the energy flow within power generation, energy storage, and charging networks according to the dynamic electricity price, charging demand, and prediction output of power generation units. The incorporation of smart features in digital twins helps mitigate risks arising from uncertainties in power supply and load by employing long and short-term energy simulations and forecasting. In addition, the power flow management enables flexible energy trading schemes between EVs, the smart charging station, and the electricity market such as battery swapping, mobile charging, vehicle-to-everything trading, and peer-to-peer energy trading (Rodrigues et al., 2020; Rehman et al., 2023).

2.5.4. *Load management*

Load management enables a flexible demand-side management solution to smooth the total demand curve such that charging sessions will be distributed more evenly during the scheduling duration, thereby improving the utilisation of charging facilities and reducing operational costs while meeting the same charging demand level (Woo et al., 2021). The digital twin-supported load management enables the real-time optimal dispatch to manage the charging requests in the smart charging station in terms of the EV drivers' real-time charging behavior and charging demand prediction. Due to the diversity of charging demands and charging preferences, the digital twin enables an optimal power distribution simulation to pursue the maximum profit while satisfying the charging demands. Digital twin-supported demand prediction models, which integrate historical charging load analysis, deep learning algorithms, and visualisation tools, can be expected to reduce the uncertainties on demand-side (Onile et al., 2021). Load management can adjust the balance between supply and demand through the charging price. Charging pricing is the interaction between charging stations and EV drivers. A price response model describing the customer's response to different prices is critical for the electricity pricing of charging stations. Digital twins of EV drivers could assist the smart charging station in setting a more competitive charging price for fixed charging and mobile charging.

3. Built in digital twins in the EV charging infrastructure

This section reviews the existing digital twin implementations in smart charging stations. The review focuses on peer-reviewed journal articles. The keywords "(wind turbine or photovoltaic) and digital twin", "(energy storage or battery) and digital twin", and "electric vehicle and digital twin" are applied for the literature search in the IEEE, ScienceDirect, and Google Scholar databases. Advanced filters are adopted to enhance the relevance of the literature search, and 88 journal articles are obtained as the literature search outcome. After manual screening and selection, 31

Table 1
Application of digital twin technology in green energy power generation units.

Article	Main Objective	Methodology	Application of digital twin
(Jain et al., 2020)	PV panels	First principle approach	Estimate energy outputs and perform fault diagnosis.
(Yalçin et al., 2023)	PV panels	Data-driven approach	State monitoring and malfunctioning detection.
(Delussu et al., 2021)	PV panels	Hybrid approach	Forecast of power production by PV panels
(Moghadam and Nejad, 2022)	Drivetrains of wind turbines	First principle approach	Remaining useful life estimation.
(Chetan et al., 2021)	Wind turbine blade	Finite element analysis, BeamDyn	Verify the performance of the operating two-bladed.
(Fahim et al., 2022)	Wind turbine	Microsoft Azure platform	Wind farms monitoring and power generation prediction
(Wang et al., 2023)	Wind turbine planetary gear	Unity3D	Online real-time diagnosis and quick fault location through 3D visualisation.
(Wang et al., 2021)	Wind turbine support structures	Finite element analysis	Assess the reliability probability of offshore wind turbine support structures.
(Jorgensen et al., 2023)	Wind turbine structures	First principle approach	Assess the fatigue limit state of a bolted ring-flange connection in an OWT structure under uncertainties.
(Liu et al., 2024)	Wind farm	Data driven approach	Propose multi-digital twin for wind power forecasting.
(Zhang and Zhao, 2023)	Wind farm	Hybrid approach	Use digital twin to predict spatiotemporal flow fields across the wind farm.

articles are identified as suitable for this review, including 8 articles related to wind energy digital twins, 3 articles for solar panel digital twins, 15 articles for battery digital twins, and 5 articles for EV digital twins.

3.1. Green power generation network and relevant digital twin applications

In literature, digital twins for wind turbines (farms) and solar panels (farms) are utilised to monitor damage and aging in real-time, evaluate the reliability and remaining service life of system components, and energy forecasting. The first principle approach, data-driven approach, hybrid approach, and computer-aided design approach are proposed to create digital twins, as shown in Table 1.

In (Chetan et al., 2021), virtual twins with multi-fidelity for wind turbine rotor blades are established based on finite element analysis and calibrated. The mass properties, blade frequencies, and deflection of the developed virtual twin are within 1%, 3.2%, and 6%, respectively. In (Moghadam and Nejad, 2022), the authors build the digital twin framework for the wind turbine drivetrain system to monitor the remaining useful life of the components. The framework consists of three steps: establish an online equivalent torsional model according to the system's dynamic properties, design load observers to estimate input such as load and stress, and build a degradation model based on the stress-life method to estimate the damage. Compared to the traditional approach that only relies on the finite element method, the proposed digital twin method can support real-time monitoring and handle uncertainties on load, material, and model parameters. In (Jain et al., 2020), a digital twin-supported holistic fault diagnosis approach for holistic solar panel systems including PV panels, power convertors, and sensors is developed. The digital twin improves fault detection and identification times, with 290 μs and 4 ms for both power converters and electrical sensors, and 80 ms and 1.2 s for PV panels. In (Wang et al., 2023), a digital twin for wind turbine planetary gear is developed for online real-time diagnosis. It provides 3D visualisation of the wind turbine transmission system and is able to quickly locate the fault location. The diagnostic accuracy of the digital twin model is 94%, which is 6.67% higher than that of the traditional fault diagnosis model supported by the support vector machine. In (Wang et al., 2021), a schematic diagram of the digital twin of the offshore wind turbine support structure is proposed. The framework consists of a physical model, a virtual model, a twin database, and a service system, where the virtual twin model is constructed at multiple scales including the overall, the partial, and the unit. The digital twin enables real-time collection of the support structure load and the damage parameters, integrates multi-source heterogeneous data, and uses a dynamic Bayesian approach to assess the reliability probability of offshore wind turbine support structures. In (Jorgensen et al., 2023), a digital twin is applied to the assessment of the fatigue limit state of a bolted ring-flange connection in wind turbines under uncertainties. In (Fahim et al., 2022), the authors develop a digital twin for wind turbines based on the Microsoft Azure platform and combine it with a convolutional neural network to predict electricity production. The developed method shows the lowest mean absolute error compared to decision tree, random forest, and support vector regression. In (Yalçin et al., 2023), a solar PV plant digital twin is created by machine learning techniques for state monitoring and malfunctioning detection, including PV panel, DC-DC converter, and grid. The accuracy of power generation prediction achieves 98.3%. Notably, the developed digital twin adopted a chain structure with several small models, enabling fast and convenient locating of the reason for deviations but increasing data collection and processing costs for middle nodes. In (Delussu et al., 2021), a hybrid modelling method is introduced for the virtual twin to forecast power production of PV panels, combining the electrical-thermal coupled model with long short-term memory (LSTM). The results demonstrate superior performances than using the electrical-thermal coupled model or LSTM independently in terms of hourly error and root mean square error. In (Liu et al., 2024), a multi-digital twin concept is proposed for wind power forecasting, where many virtual entities are created for one physical entity. The authors take LSTM, gate recurrent unit networks, long short-term memory convolutional neural networks, and gate recurrent unit convolutional neural networks as examples to construct four digital twins for wind power forecasting and establish synergistic operation mechanisms to fuse the forecasting outputs of these models. The results indicate that the multi-digital twin yields more accurate results compared to a single digital twin. The maximum improvements in the mean absolute error (MAE), root mean square error (RMSE), and R-squared metrics are observed to be 7.83%, 5.01%, and 1.24%, respectively. In (Zhang and Zhao, 2023), a digital twin is created to forecast both spatiotemporal wind speed and static pressure across the entire wind farm. This research addresses the challenge posed by sparse measurements in both time and space throughout the wind farm site. The digital twin is developed using a hybrid approach that combines Lidar measurement data, the Navier–Stokes equations, turbine modelling, and deep neural networks, allowing extrapolation of unmeasured wind field information. The average prediction error for the flow fields is 4.7% of the value range.

3.2. Energy storage network and relevant digital twin applications

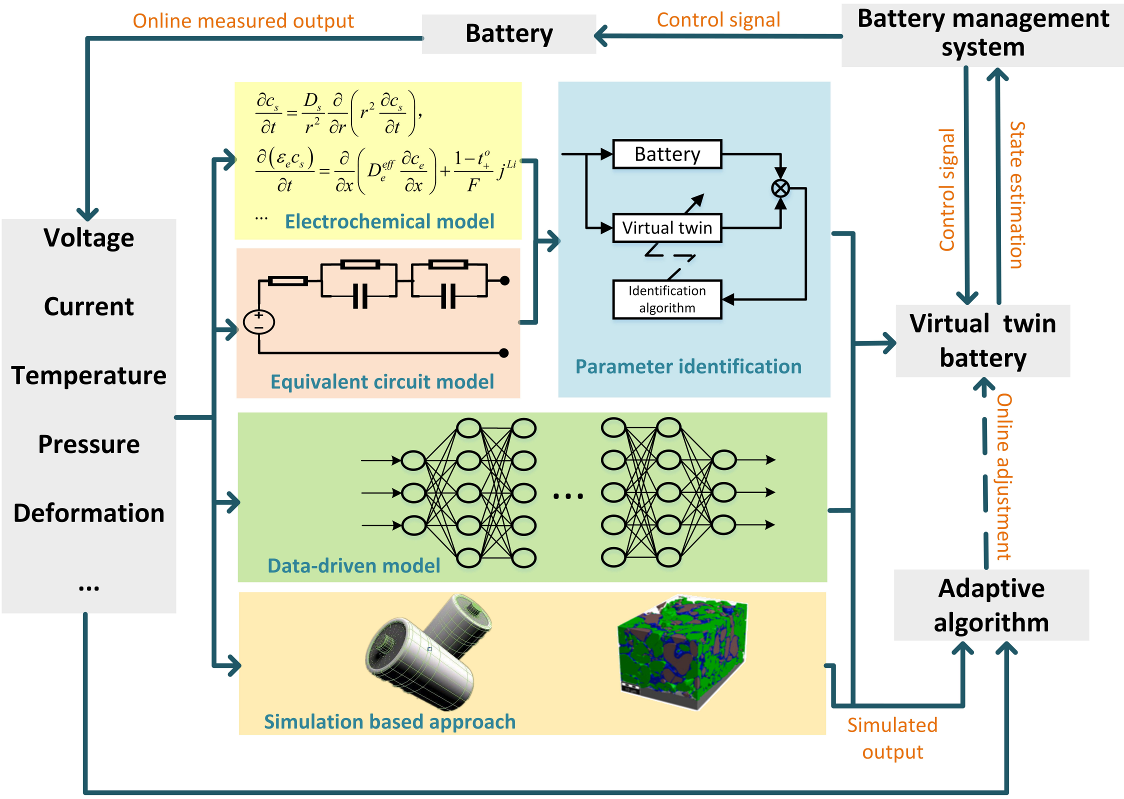

Figure 12: Technical procedure to create a battery digital twin.

Basically, the three-layer framework is applied for Li-ion battery digital twins development, including the physical, digital, and network layers. The physical layer consists of batteries and sensors. The digital layer contains twin models to simulate the geometric shape and behavior of the Li-ion battery (Semeraro et al., 2023). The network layer creates links between the physical and digital layers based on protocols like open platform communications unified architecture and MT-Connect. In the literature, various approaches are proposed for battery digital twins construction, including simulation approach, electrochemical approach, equivalent circuit approach, data-driven approach, and hybrid approach, as summarised in Table 2.

The simulation-based approach involves reconstructing the battery's internal structure using computer-aided design software such as Avizo and GeoDict (Avizo Software, 2023; GeoDict Software, 2023). In (Park et al., 2021), a 3-D

Table 2
Application of digital twin technology in batteries.

Modelling methodology	Advantage	Disadvantage	Application of digital twin
Electrochemical modelling approach	1. Clear physical meaning 2. Highest accuracy	1. Complex structure with many parameters 2. Hard to solve	(Reniers and Howey, 2023) MWh-scale battery digital twin system is built to explorethe long-term performance.
Equivalent circuit modelling approach	1. Simple structure 2. Accuracy increases with the order of the circuit	1. Low precision 2. Requires parameter identification	(Li et al., 2020) Monitoring of battery SoC and SoH through digital twins. (Merkle et al., 2021) A battery digital twin which relies on diagnostic data provided by the on-board diagnosis interface is established. (Tang et al., 2022) A 3-D visualisation battery digital twin is built for SoC estimation.
Data-driven modelling approach	1. High accuracy 2. Requires less prior knowledge of battery 3. Massive data available in digital twins	1. Poor interpretability 2. Long training time 3. Overfitting	(Qu et al., 2020; Qin et al., 2023; Li et al., 2024) Digital twin are built to assess the degradation of the battery. (Eaty and Bagade, 2023) Employ a continual learning framework to avoid over-fitting and catastrophic forgetting. (Kharlamova and Hashemi, 2023) Predict short-term SoC for battery system providing frequency regulation. (Li et al., 2023) A digital twin model is built for the fault diagnosis of battery packs.
Hybrid modelling approach	1. Adaptive to different environment 2. Less data required	1. Complicated 2. Physical meaning is unclear	(Sancarlos et al., 2020) Develop a hybrid twin for the vehicle battery with reduced calculation load while maintaining its accuracy. (Xie et al., 2024) A dual digital twin is proposed for fault diagnostic and real-time management of EV batteries to adapt the cloud-edge hierarchy.
Simulation based approach	1. Visualised 2. Capable of simulating physical and electrochemical processes 3. Software-aided design	1. High cost of tools 2. Skills on professional tools	(Park et al., 2021) A 3-D digital twin for all-solid-state electrodes is built to visualise and quantify the structural defects. (Ngandjong et al., 2021) Reveal electrode calendering and its impact on electrochemical performance by digital twin. (Park et al., 2020) The digital twin reveals the relationship between physical and electrochemical parameters and performance of the electrodes.

structure digital twin of solid oxide electrolytes is created by utilising a large number of tomographic images and the Avizo software. The 3-D digital twin visualise structural defects in all-solid-state electrodes and provides valuable insights for electrode design. Similar digital twins are developed in (Ngandjong et al., 2021; Park et al., 2020) to reveal the relationship between internal structures and electrochemical performance. The simulation-based approach provides a new vision for battery digital twin development, but it is still in the laboratory stage due to its reliance on professional software and equipment.

The electrochemical approach relies on a group of partial differential-algebraic equations that describe the spatiotemporal distribution of battery internal electrochemical variables. In (Reniers and Howey, 2023), an MWh-scale battery digital twin system is established to explore the long-term impact of cell-to-cell variations, electrical contact resistances, and thermal management methods on battery performance, where all cells are modelled with individual electrochemical models including degradation and thermal effects. Nonetheless, electrochemical modelling is limited by the model's dimension, making it less compatible with heterogeneous data. Additionally, it is challenging for electrochemical modelling to capture the high-dimensional, time-varying, strongly coupled, and nonlinear characteristics of the electrochemical processes. The equivalent circuit approach simplifies the complex electrochemical and thermodynamic processes occurring within a battery into a circuit with electrical components. High-order equivalent circuit models and fractional-order based models are able to capture the finer scale of the electrochemical and electro-thermal processes inside the battery, such as the Warburg impedance or constant phase element (Kalalaand et al., 2019; Wang et al., 2019). In (Li et al., 2020), a cloud digital twin battery management system with the extended Thévenin model as the core is developed, addressing the problem of insufficient computing power and data storage capacity of the onboard battery management system by cloud calculation. In (Tang et al., 2022), a 3-D visualisation representation is built for battery digital twin, where SoC estimation is achieved by combining with an equivalent circuit model and an $H\infty$ filter - particle filter algorithm.

The data-driven approach establishes the input-output models for the batteries by combining machine learning algorithms and extensive training data. This approach holds natural advantages in constructing digital twins due to the vast amount of real and virtual data available. However, it also presents challenges such as long training times, model overfitting, and poor model interpretability. In (Qu et al., 2020; Qin et al., 2023; Li et al., 2024), the digital twin is employed to access the degradation of batteries, capable of simulating the full discharge process using partially discharged data to an accurate estimation of the maximum available capacity of batteries. Specifically, in (Qu et al., 2020) and (Li et al., 2024), LSTM model and convolutional neural networks-long short term memory-attention model are proposed, respectively, to construct twin models. The comparison results using Oxford University dataset (Howey, 2011) indicate that both models achieve R-squared values exceeding 99%. However, the convolutional neural network-long short-term memory-attention model outperforms the LSTM model, exhibiting a higher R-squared value. In (Qin et al., 2023), the digital twin is improved from three aspects: a data synchronisation approach aligning the cycling data with variable length into the same structure, a time-attention LSTM SOH estimation model assigning more weights to data at crucial sampling times, and a future data reconstruction strategy enabling real-time estimation rather than estimation at the end of a cycle. The test results on the Massachusetts Institute of Technology dataset (Severson et al., 2019) indicate that the average R-squared for the proposed twin is 98.03 ± 1.65, higher than LSTM model's average R-squared of 87.70 ± 7.59. In (Eaty and Bagade, 2023), a digital twin model is developed for EV batteries to estimate SoC and SoH, employing a continual learning framework to avoid the problems of over-fitting and catastrophic forgetting. In (Kharlamova and Hashemi, 2023), data-driven digital twins are employed to predict the short-term SoC for battery systems providing frequency regulation. The performance of multiple data-driven digital twin models including feedforward neural network, gated recurrent unit, long short-term memory, support vector regression, random forest, and AdaBoost methods are evaluated. The authors conclude that the most accurate method for given datasets is random forest but computationally heavy, while AdaBoost combines relatively short computation time and accuracy. In (Li et al., 2023), a digital twin model based on the backpropagation neural network algorithm and the whale optimisation algorithm is proposed for the fault diagnosis of battery packs of cloud battery management systems. The proposed framework is based on battery pack states rather than cell information, reducing the afford of data transmission.

The hybrid approach combines physical-based models and data-driven methods, showing superiority in adaptability to new environments and reduced dependence on the amount of data (Chinesta et al., 2020). According to the hybrid framework, a hybrid digital twin for vehicle battery is introduced in (Sancarlos et al., 2020), which corrects the electrochemical model by combining a data-driven error model based on dynamic mode decomposition. In (Xie et al., 2024), a dual digital twin is introduced for EV batteries, consisting of two interconnected twins. The primary twin is a partial differential equations model designed for diagnostic purposes. The secondary twin is a reduced-order version derived from the primary twin and updated using incremental learning techniques, intended for real-time charging control and monitoring. The primary and secondary twins are deployed on the cloud and edge sides, respectively, with intermittent data exchange. This dual digital twin architecture aligns with the cloud-edge hierarchy, enabling the primary digital twin to harness the cloud for its higher computing power to provide more intricate results, and the secondary twin to achieve real-time state monitoring using less computing power.

The digital twin battery management system is given by Fig. 12. The battery management system based on digital twins exhibits several advantages. The digital twin dynamically reproduces the SoC inside the battery, the aging state of each component, the temperature gradient inside the battery, the physical and chemical reaction process, and micro and macro structures, and is able to show them in a visualised way. At the same time, the integration with more heterogeneous data improves the fidelity of the digital twin.

3.3. Charging network and relevant digital twin applications

In the charging network, digital twins of MCUs, EVs, and drivers are expected. The MCU, serving as a mobile ESS mounted on EVs, shares similarities with EVs' digital twin model. Ref. (Bhatti et al., 2021) comments that predictive mobility, advanced driver assistance systems, vehicle health monitoring, battery management systems, power electronic converters, and power drive systems are the core concerns when building EV digital twins. Several EV-level digital twins are proposed in the literature such as powertrain system (Zhang et al., 2021) and engine (Li et al., 2021). In (Wu et al., 2021), the combination of the five-dimensional framework and the TRIZ (Latin acronym for Theory of Inventive Problem Solving) function model leads to the development of a conceptual digital twin unmanned vehicle model. The digital twin model effectively captures the principles and functionalities of unmanned vehicle components and the interactions between the digital twin, the environment, and the drivers. The integration of digital twin technology in the EV industry brings revolutionary changes. It simplifies the development and test process of EVs in the virtual space, reducing the need for on-site testing and associated costs. During virtual tests, the EV digital twins can be reused infinitely to predict the performance of real vehicles under various extreme scenarios, leading to more comprehensive test reports (Rjabtšikov et al., 2023). During the service phase of EVs, digital twins can be applied to monitor vehicle status, assist in personalised trip planning, and improve the driver experience. In (Ebadpour et al., 2023), the author introduces a digital twin for the traction drive system of unmanned EVs. The digital twin contains the brushless direct current motors model, vehicle dynamic model, and an improved electronic differential system model. Virtual testing is conducted within a Metaverse framework to assess the stability of unmanned EVs under challenging road conditions with diverse surface profiles.

A digital twin for the charging behavior of EV drivers aids the smart charging station in load forecasting, charging pricing, and power dispatch, while also providing drivers with personalised charging services and promoting sustainable energy practices. Though the implementation of this digital twin model is yet to be found in existing literature, there are various approaches that facilitate the development of such digital twins. For the smart charging station, the digital twin can be designed to simulate the charging behavior in terms of arrival time, parking time, and drivers' charging preferences. These behaviors can be modelled by statistical methods or deep learning methods, such as the Markov chain and LSTM network (Arias et al., 2017; Xiao et al., 2020), but the applicability to specific scenarios must be carefully considered. In addition, the elusive price responses of EV drivers are also the focus of the human digital twin model. With sufficient data support, the data-driven approach can achieve a high-precision description of the nonlinear characteristics of price response. For instance, in (Kong et al., 2020), the LSTM network is employed to predict the customer's response to a given price. The network is trained by the historical price and demand data, and also considers the customer's comparison behavior of prices at different periods. It needs to be emphasised that security and social ethical issues are inevitable when building digital twins for drivers' behavior. Therefore, smart charging stations need to strictly abide by the charging station ethics to collect, store, process, and use data.

3.4. The challenges when implementing charging station digital twins

According to the review results, the challenges when implementing digital twins are summarised as follows:

- Implementing digital twins requires the deployment of advanced sensors, smart meters, and smart charging poles. While adopting these smart devices may increase the initial investment cost, they offer greater control flexibility and potential energy-saving benefits. Evaluating the technical and economic feasibility of these devices is essential to ensure their cost-effectiveness.

- Smart charging stations are complex systems consisting of various heterogeneous subsystems, including power generation units, ESSs, charging equipment, and EVs. Developing digital twins for these subsystems is still an ongoing process, and data-driven solutions are not yet fully utilised. The integration of data between different subsystems raises challenges related to data security, ownership, cleaning, and fusion. Furthermore, benchmarks and guidelines for assessing the accuracy, efficiency, and overall effectiveness of charging station digital twins are absent currently, making it difficult to compare and validate the efficacy of different digital twin implementations.

- Incorporating human behavior into charging station digital twins presents challenges. First, training workers to interact effectively with these digital twins requires new skills. Second, the uncertainty associated with human behaviors can impact the accuracy of digital twins. Lastly, charging station ethics, including data security risks and privacy concerns, must be carefully addressed to gain social acceptance and trust in the development of digital twins.

4. Conclusion and future work

This study proposes a smart three-network parallel charging infrastructure architecture. The smart charging stations are expected to exhibit smart features in terms of cognisant, taskable, adaptive, and ethical with the support of the digital twin techniques, contributing to increased efficiency, sustainability, and scalability of charging infrastructure. The cognisant feature involves the charging station's capabilities to perceive internal status within the charging station and external environment to monitor system status, predict future charging demand, identify potential failures and risks, and subsequently adjust its operational actions. Improved cognisant capabilities contribute to improving operational and managerial efficiency. The adaptive feature requires charging stations to dynamically adjust strategies based on real-time changes in power generation, user behaviors, regulations, and market policies. This adaptability ensures that the charging station remains efficient operation and business sustainability in different operating conditions. An adaptable charging station can integrate new technologies and respond to the green transition of energy systems, fostering environmental sustainability. The taskable feature focuses on refining the charging station's ability to perform specific tasks accurately and efficiently. This includes optimising charging processes, handling various charging standards, and minimising downtime. Standardised task execution and modular structure enable a taskable charging station can be easily integrated into diverse charging infrastructures, enhancing the scalability of the overall charging network. Ethical feature, the basis of the other three smart features, ensures that charging stations operate within legal and ethical frameworks, preventing potential legal challenges or disruptions and building trust among users, regulators, and stakeholders. The ethical feature enhances the social sustainability of charging stations and facilitates the scalability of the charging network across regions. Based on the review results, we categorise future research directions into three sections and present them in order of priority: smart charging station architecture improvement, digital twin standardisation for smart charging stations, and digital twin best practices for smart charging stations.

(1) Smart charging station architecture improvement. The differences in power supply, policy, and financial support among different countries and regions have caused the uneven development of the global charging market. As mentioned before, China, the European Union, and the United States have almost occupied the global charging market, while only a small amount of charging infrastructure has been deployed in regions such as Africa, the Middle East, and South America. Although a generic architecture of smart charging stations is proposed in this study, the government and investment departments in different countries shall adjust it for specific needs, including reasonable planning for the type, size, capacity, and time control of power generation, energy storage, and charging systems. In addition, it should be recognised that not all regions may require the full spectrum of proposed smart capabilities. Diverse regions may express varying demands for the extent of proposed smart features in charging infrastructure, influenced by factors such as local labor costs, economic development, the degree of EV marketization, and policy orientations. Consequently, the suggested smart charging station architecture should undergo further refinement to align with specific regional conditions, ensuring an optimal balance between social, economic, and environmental benefits. Assessments on technical feasibility, financial viability, environmental impact, and social considerations are essential before implementing smart charging stations for different regions with specific requirements for smart features.

(2) Digital twin standardisation for smart charging stations. To advance smart charging stations enabled by digital twins, collaboration among industry stakeholders, including charging equipment manufacturers, EV manufacturers, regulators, research institutions, and standards organizations, are encouraged to develop standards that encompass various crucial aspects of digital twins, data formats, communication protocols, data storage, performance assessment, and security. Standardised data models that define the structure and format of digital twin information for charging station components should be developed to ensure easy data integration while reducing data security risks. Establish interoperability standards to ensure that digital twins from different suppliers can effortlessly collaborate within the smart charging station system. Define protocols for communication between digital twins and other components within the smart charging stations to enhance the efficiency and reliability of data exchange among various subsystems. Develop standards for the testing, performance assessment, and certification programs of digital twins, covering accuracy, efficiency, and cost analysis. Develop standard test datasets and scenarios for different digital twin applications. This enables consistent validation and comparison across different digital twins created for the same equipment. Lastly, integrate stringent data security measures into the standards to protect sensitive information associated with smart charging station operations.

(3) Digital twin best practices for smart charging stations. The digital twin charging station exhibits the key characteristics of timeliness, fidelity, integration, intelligence, and complexity (Verdouw et al., 2021). These advantageous features require powerful technological support of modelling, data science, IoT, and computational capabilities. As reviewed in this study, it is evident that advanced technologies, including data perception, data fusion, machine learning, virtual reality, explainable AI, 6G, blockchain, and the metaverse, are gradually integrating into the realm of charging station digital twins. However, how to optimally integrate these most advanced technologies into one subsystem to enable the expected functions remains open for further research investigations. The digital twin based smart charging station can provide the optimal decision for power generation, power procurement, and charging/discharging scheduling in response to various charging requests. Practically, uncertainties from climate conditions, charging queues, emergency charging, and traffic jams will pose significant challenges to finding the optimal charging operation strategies in real time. Research should focus on refining algorithms and decision-making processes to enhance efficiency and accuracy. In addition, research on mechanisms that facilitate continuous learning and improvement within the digital twins at service in the charging stations is required. This ensures that the charging station remains cognisant, adaptive, and intelligent over time, evolving in tandem with advancements in technology and changing operational environments.

The research direction of smart charging station architecture improvement emphasises the need for tailored solutions for charging infrastructure to accommodate regional variations. Given the urgency of expanding charging infrastructure to support the growing EV market, this research direction is suggested to highest priority. Standardisation of charging station digital twins creates a foundation for consistent and reliable smart charging infrastructure. Once a standardised foundation is established, it is important to optimise and enhance the capabilities of digital twins. Researching best practices for integrating advanced technologies, refining algorithms for decision-making, and enabling continuous learning within digital twins will contribute to the long-term efficiency and adaptability of smart charging stations.

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