Towards Cognitive EV Charging Stations Enabled by Digital Twin and Parallel Intelligence

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2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI) | 978-1-6654-3337-2/21/$31.00 ©2021 IEEE | DOI: 10.1109/DTPI52967.2021.9540103

***Abstract*—Smart autonomous systems are expected to be cognisant, taskable, adaptive and ethical. Digital twin (DT) and parallel intelligence (PI) techniques are ideal candidates to further advance the smart autonomous systems to the next level. The DTPI techniques are under fast deployments in both the energy and transportation sectors due to the inevitable transition from fossil fuel vehicles to electric vehicles (EVs). The dramatic increase in EV charging demand yields a huge power supply gap. Currently, the low coverage and outdated management system of charging infrastructure have led to poor user experience and increased user range anxiety. To this end, we propose a cognitive charging station architecture for future charging infrastructure, which consists of power generation network, energy storage network, and charging network. DTPI techniques enable the cognitive charging stations to provide smart functions such as energy management, energy storage system health management, load management, intelligent maintenance, and smart user services.**

***Index Terms*—Cognitive charging station, digital twin, parallel system.**

I. Introduction

Digital twin (DT) is a computer based twin model in a virtual space that mirrors the static characteristics and operational dynamics of a physical entity, which truly reflects the dynamic evolution process of physical entities throughout the life cycle with the support of the Internet of Things (IoT). A methodological framework for developing DT is available in [1] and an information theory based criterion to determine the optimal DT model is given in [2]. DT has a stricter correspondence between virtual and real systems, which requires a clear understanding on the system structure. Due to the practical challenges to create high fidelity DT, the concept of parallel intelligence (PI) is derived based on artificial intelligence, computational experiments, and parallel execution (widely regarded as the ACP method), which is also used to model complex systems. Practically, the PI not only simulates the known components of complex systems, but also exhibits the function of modeling and explaining unclear mechanisms [3], [4]. According to this argument, the DT can be regarded as a special case of the PI, which both provide real-time monitoring and control services for specific complex systems.

This study is supported by the South African National Research Foundation under the Grant No.: 116309, the UK Royal Academy of Engineering under the Grant No.: TSP1020, and the Research Development Programme from University of Pretoria.

The DT can dynamically reflect the state changes of physical entities and reduce the information asymmetry, which enables an new management idea in the context of IoT to improve the status quo of various types of equipment, complex operating conditions, and poor human-computer interaction. The global electric charging stations has exceeded 1 million in May 2020 [5]. However, due to the geographical dispersion of charging infrastructure and outdated management system, they have exhibited severe defects such as low utilization rate, poor identifiability, high maintenance fees, and poor user experience. These problems have been plagued the charging market. In this study, we propose a DTPI based cognitive charge stations architecture for the future charging infrastructure, which is powered by a renewable power generation network and a energy storage network. With the help of DT, high-precision reconstruction of the charging infrastructure including power generation units, energy storage system, mobile charging units, and fixed charging poles is built in the virtual space. The cognitive charge station monitors and adjusts its own operating status. When a charge request comes, the cognitive charge station generates and simulates the energy management process in the virtual space, which guide the charging station to apply the best operational strategy for smart user services.

II. Characteristics of the cognitive EV charge stations

The EV charging station is expected to be cognisant, taskable, adaptive and ethical. Each charging station can only be cognizant when demonstrating high-level awareness of their own capabilities and limitations, anticipating potential failures, and re-planning its operational actions for energy, power, energy storage, and load managements accordingly. This expectation is achievable by the technical support of DTPI to create a DT of the charging station. The DT charging station must be a dynamic adaptive system, which will constantly learn from physical charging station operation data and their own experiences to improve the operational strategy.

In addition, it can also detect abnormal behaviors in charging stations such as power generation unit failure, energy storage system aging and node power quality degradation on different time scales and perform predictive maintenance. According to the forecast of charging demand and the charging market information, the cognitive charging station will automatically adjust operation strategies to ensure the realization of investment goals and provide strategic planning suggestions for operators. From the user side, the cognitive charging station creates a user-friendly paradigm. It can receive and interpret advanced voice and linguistic instructions, including operator's control instructions and EV drivers' charging requests, and formulate and execute combination strategies with good interpretability and transparency to manage the energy flow of the charging station.

III. DTPI APPLICATIONS IN THE EV CHARGING INFRASTRUCTURE

Our proposed charging station serves a new node in the power generation and delivery supply chain. The charging station and its associated charging poles and mobile charging units (MCUs) forms the charging station network. This network will demonstrate massive communication interactions for the exchange of energy, information, and transactions with the power generation and delivery network, energy storage network, and the EV network. A brief concept of these interactive networks is shown in Fig. 1. The charging station network can only be deemed as smart when they are cognitive, taskable, adaptive, and ethical. This target is achievable with proper applications of DTPI in renewable power generation network, energy storage system network, and the charging station network. In the following, we share our vision of potential DTPI applications in these areas based on the summary of state of the art research development in the DTPI applications.

A. DTPI applications in renewable power generation network and energy storage network

The fast growth of EV charging demand can easily pose severe impacts on the existing power grid, such as increase peak load, instability due to uncertain EV charging behaviours, and tariff increase. Smart grid equipped with green power generators and local energy storage systems can effectively alleviate the grid power supply pressure, reduce electricity cost of supply, enabling flexible electricity trading schemes, enhance power supply reliability, and contribute to renewable energy market penetration hence reducing carbon emissions. In the existing studies, DTPI has been widely used to manage power generation units such as photovoltaic panels and wind turbines in the network, and perform maximum power point tracking and fault detection to ensure that they provide energy to the energy storage network and charging network smoothly and efficiently. Ref. [6] and Ref. [7] developed DTs for photovoltaic cells and wind turbines respectively and applied them to off-board diagnostics of the cells. So far, the first principle energy modelling, data-driven energy modelling, and a hybrid of the two energy modelling approaches are widely applied to build DTs for lithium-ion batteries. The electrical and thermal dynamics of the lithium-ion batteries are properly described by partial differential equation models or equivalent circuit models. Ref. [8] established a cloud battery DT management system based on the extended Thevenin model. The data-driven approach employs machine learning algorithms and a large amount of experimental data to establish the input-output models of batteries. Ref. [9] established a DT model of the relationship between voltage and state of charge (SoC) through the long short-term memory algorithm. The hybrid approach establishes a paradigm that combines physical and data models. The hybrid DT framework proposed in [10] has better accuracy and is adaptive to the environment, it also reduces the dependence on the amount of data. Based on the existing applications to create DTs or parallels systems of the renewable power generation and battery energy storage systems, we identify tremendous research potentials developing the DTs for various renewable power generation units such as the wind turbines, solar panels, biomass/bio gas generators, mini hydro power stations, etc., and the energy storage systems, namely the air compressors, lithium-ion batteries, supercapacitors, thermal energy storage units, pumped hydro power, flywheel, redox flow batteries, hydrogen fuel cells, etc. These DTs are high fidelity energy models that illustrates the physical characteristics and operational dynamics of the renewable power generation and energy storage units. The DTs are further supported by real-time communication technologies such as IoT and edge computing.

B. DTPI applications in EV charging network

The charging network consists of charging stations, independent charging poles, mobile charging units and EVs in the network. They are connected via the energy internet, which enables flexible electricity trading opportunities. Independent charging poles refer to distributed charging poles deployed in public parking lots or private areas. The geographically dispersed independent charging poles increase the difficulty of management. To reverse these negative factors, we take the charging stations, charging poles and MCUs as one system for energy management purpose. Specifically, we will develop a DTPI system for the charging station network in the virtual space. So far, there is no solid research work done to create DTs or parallel systems for the charging stations, charging poles, and the MCUs. To fill this research gap, we believe technical challenges to setup the DTPI system for the charging station network shall be low. In the next subsection, we share our vision on the DTPI enabled smart management of the charging stations.

IV. DTPI ENABLED SMART MANAGEMENT OF THE CHARGING STATIONS

In Fig. 1, the DT is capable of reconstructing the operating dynamics of the charging station in the virtual world using real-time data and intelligent analytics supported with visualization software and respond optimally to environmental changes to improve charging station efficiency. The DTPI

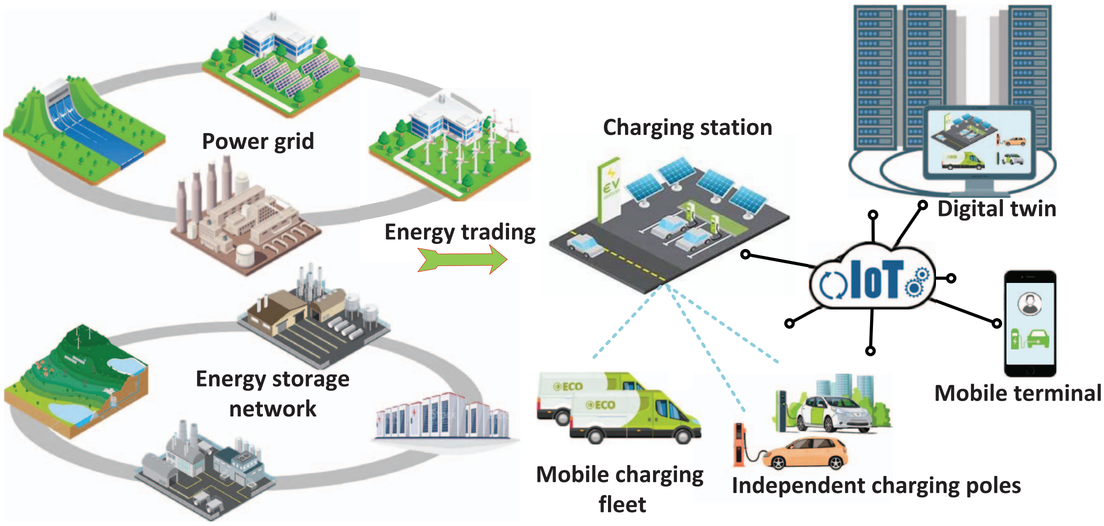

Fig. 1. The cognitive charging station enabled by DTPI.

enables five basic functions of the cognitive charging station, namely energy management, energy storage system health management, load management, intelligent maintenance, and smart user services.

A. Energy management

The power flow management and power quality management are the core functions of charging station energy management. With proper energy management strategies, the charging station can maximize its profit with optimal charging scheduling strategies while satisfies the charging requests of EV users. At the same time, the energy storage system can optimise charging and discharging behaviours based on real-time electricity prices to minimize electricity bills. The power flow management also supports multiple forms of energy trading between charging stations and EVs to enable the vehicle to everything (V2X) trading functions to the charging station network.

Power quality problems such as voltage deviation, frequency deviation, and harmonics will cause damage to the charging station equipment and charging EVs. The power quality control device with high-power power electronic devices as the core unit can be used to effectively guarantee the transient and steady-state performance of the charging station. By collecting the current, voltage and other parameters of each node in the charging station circuit, DT can visualize the power quality status model of the line in the virtual space, and generate control signals to control the power quality control device to achieve the ideal compensation effect. In addition, DT technique can evaluate the effectiveness of new power electronic equipment and monitor its real-time status. For example, Ref. [11] proposed a real-time, probabilistic DT to realize the online diagnostic analysis of power electronic converters.

B. Energy storage system health management

The energy storage system health management includes the functions of state of health (SoH) estimation, battery electrical and thermal dynamics monitoring and control, cell balancing, battery fault detection and tolerance, which guarantee the safe, reliable, and efficient operation of the ESSs. The DT system enables the collection of battery operation data such as voltage, current, temperature, and pressure to establish a high-fidelity model and realize state estimation, temperature management, and balance control. Ref. [9] utilized a deep learning-based DT to evaluate lithium-ion battery degradation. With the help of DT technique, Ref. [8] achieved continuous and accurate monitoring of SoC and SoH. The maximum temperature rise and the maximum temperature difference of the battery pack are two criteria to evaluate the performance of the temperature control unit. When the system is overheated or under zero, the cognitive charging station will take measures such as air cooling and liquid cooling to handle the temperature. The high-fidelity DT clearly reveals the inconsistency between batteries, which allows us to formulate more precise control strategies to achieve high-performance balance control. In addition, DT with powerful computing ability can generate a comprehensive and authoritative report on the status of the EV batteries and calibrate the EV battery management system.

C. Load management

Load management enables EV charging load and charging schedule to adjust the aggregate demand curve for peak shaving and valley filling. In this way, charging sessions can be distributed more evenly throughout the entire time period, thereby reducing the construction and operation cost of the cognitive charging station while still ensuring the same quality of service [12]. When EVs park in charging station, the cognitive charging station can adopt a variety of strategies to manage the charging demand. Demand forecasting based on DTs can integrate historical charging load data analysis, short-term/long-term energy forecasting, machine learning algorithms, and visualization techniques to predict user charging behavior, and adopt strategies to ensure smooth operation of the charging station [13]. For a fixed charging station, the prediction model includes the EV's arrival rate in each time period, the SoC value when the EV arrives at the charging station and the target SoC, the maximum charging time and the user's charging mode preference. These indicators can be modeled by statistical methods, such as utilizing the Poisson process to describe the arrival rate of the EV, and utilizing the normal distribution to estimate the SoC of EVs when they arrive at the charging station. It can also be modeled by data-driven models such as temporal graph convolutional networks and long and short-term memory neural networks.

D. Intelligent maintenance

Preventive maintenance aims to minimize the production life cycle cost by addressing machine failures before they occur [14], [15]. With the help of DT, comprehensive analysis methods based on high-fidelity models and comprehensive data can be used to support fault diagnosis and prediction of charging station facilities, which can improve the accuracy and reliability of the results. DT techniques are capable of revealing the internal interaction mechanism of the physical entity's fault evolution process, thereby associating the fault status with specific components, rather than just providing a vague fault status indicator. In addition, when some data types have perception difficulty problems caused by the complex environment and sensing technology limitations, data fusion of virtual data and physical data can be utilized to ensure the integrity of the data to be analyzed. Moreover, DT can also reduce the frequency of maintenance and eliminate unnecessary maintenance activities while ensuring the safe operation of charging stations [16].

E. Smart user services

A smart mobile APP based on the proposed DTPI techniques will be developed to enable smart charging services, which helps users find idle charging poles, formulate the optimal route, book charging services, and monitor the charging status of EVs. Mobile charging services are also enabled by the charging station to deliver the charging services to users with emergency demand via a fleet of MCUs. The mobile charging can significantly improve the coverage rate of charging facilities, and reduce the user's range anxiety. In addition, the cognitive charging station can automatically match standardized services according to the user's semantic information, and provide combine services according to some complex requirements to satisfy the charging requests of EV drivers.

V. Conclusions and Future Work

This study shares our initial vision of developing a cognitive charging station infrastructure that consists of power generation network, energy storage network, and charging network. The proposed smart and cognitive charging station infrastructure is achievable with the enabling DTPI techniques. Based on the DTPI techniques, the charging stations are able to provide smart functions such as energy management, energy storage system health management, load management, intelligent maintenance, and smart user services. More technical works on the DTPI of the renewable power generation units, energy storage systems, and the charging station network are expected to be constructed in the near future.

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