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RESEARCH ARTICLE

Blockchain-Based Intelligent Charging Station Management System Platform

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ABSTRACT A smart electric vehicle (EV) charging station energy management system (CSMS) based on blockchain technology, which aims to protect privacy of EV users, ensure fairness of power transactions, and meet charging demands for large numbers of EVs, is proposed in this study. EV charging pile is designed as a local blockchain distributed ledger node, which operates synchronously with blockchain system and blockchain distributed ledger in cloud server. This paper integrates CSMS through smart contracts, providing EV users that ability to conduct power transactions and perform optimal charging and discharging control in real-time. The distributed ledger is in charge of recording all the EV charging and discharging data to maintain fairness of power transactions, protects data from being maliciously tampered, and enables the EV user to monitor status of the EV participating in power transactions and dispatching. The intelligent CSMS consists of an artificial intelligence (AI) module, centralized optimal scheduling module, and decentralized optimal control module. The AI module is responsible for forecasting renewable energy generation and load consumption. There is a two-layer architecture consisting of centralized and decentralized optimal control modules; the upper layer performs optimal charging and discharging scheduling of the entire EV charging station at time 15-min time segments, the bottom layer performs distributed optimal scheduling control in each EV charging pile at 5 min time interval. Proposed system in this paper can deal with feeder congestion and real-time power supply and grid demand imbalance, which are caused by high numbers of EVs.

INDEX TERMS Artificial intelligence, blockchain, charging station management system, distributed ledger, decentralized charging algorithm, electric vehicles, the Internet of Thing, power trading.

I. INTRODUCTION

With the rising awareness of the importance of energy saving and carbon emission reduction worldwide, application of renewable energy is bound to increase rapidly for the foreseeable future. However, due to renewable energy power generation being intermittent and subject to weather conditions, as its proportion gradually increase in grid, it will seriously affect stability and power quality of power system. Photovoltaic (PV) power generation converts solar radiation

into power by the principle of the photovoltaic effect. PV is widely installed with the advantages of noiseless, pollution-free generating, ease of merging into design of buildings, and life span up to 25 years. Nevertheless, its generation efficiency is influenced by its geographical location, seasonal changes, cloud coverage, and meteorological changes. PV power generation quickly increases at sunrise and suddenly decreases at sunset. Full output of PV is reached at noon, resulting in decreasing of total load in grid, such that the load curve trend is like a duck's belly. In the evening, due to sudden drop in output of PV and household load rise, the total load curve becomes like a duck neck, so it is called a duck curve.

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The higher the proportion of PV, the bigger the duck's belly, which makes it more difficult for scheduling of traditional fossil fuel generators, which in turn affects power quality, causes regional power rationing or power outages. In the meantime, when proportion of intermittent power resources increases in power grid, in order to stabilize power supply, huge challenge in operation scheduling of traditional base load power plant is started, which causes lots of burden to traditional generator units. Therefore, in areas with high penetration of renewable energy, energy storage systems (ESSs) are usually applied to support load regulation. To enhance operation efficiency of an ESS, by combining with an energy management system (EMS) to perform charging and discharging scheduling. Moreover, if power generation of renewable energy at a certain period can be predicted in advance, power dispatching and load curve control will be more accurate and effective.

As the manufacturing technology of electronic vehicles (EVs) become mature in recent year, in response to policies of energy saving and carbon emission reduction worldwide, governments around the world takes relevant policies to advocate EVs as the main transportation in the future to replace petroleum-fueled engine vehicles [1], [2], the utilization of EV will increase greatly in the next few years.

To avoid a huge impact on the power system, appropriate scheduling strategy must be taken between EV charging demand and power grid supply. For example, a management mechanism including time of use (ToU) pricing and demand response (DR) can be adopted on the supply side, while a demand side management (DSM) [3] method can be adopted on demand side. With the emergence of bidirectional EV charging piles, the mode of discharging stored power to grid is high-profile [4].

With artificial intelligence energy management system (AI EMS), considering renewable energy power generation and load consumption, EVs can be used to maintain reliability of grid with regulating effective and reactive power, and shaving power grid load peak [5], [6], [7]. Most of the current EV charging mode only consumes power from the grid. In the future, as the ubiquity of EVs increases, EV users will transform from consumer to prosumer, with popularization of bidirectional charging piles, including vehicle-to-grid (V2G) and grid-to-vehicle (G2V) functions. The participation of EVs in power market will also require a fair and impartial trading platform.

Due to development of emerging technologies such as blockchain and Internet of Things (IoT), many innovative applications have been introduced in the power industry, and these technologies can also accelerate realization of decentralized power sharing. Blockchain technology is a decentralized and distributed system which is employed to solve security and trust problems by using cryptography to encrypt data and executing decentralized algorithms that require users to reach consensus without third-party certification.

The remarkable value of blockchain technology includes inerasability of transaction data: the data cannot be tampered

once it being chained, which ensures data on the blockchain is fair, impartial and open. Using the blockchain technology in green power sharing network can quickly and accurately record power resource footprints and transaction data. The blockchain distributed ledger is used to record user's renewable energy power generation and load consumption, then smart contract is able to perform cash flow settlement based on this information.

The framework of this paper is as follows. First, related technologies proposed in the existing literature is analyzed and discussed in Section II, and then Section III presents the system architecture and the operation processes proposed in this paper. The objective functions and constraints of centralized charging station energy management system (CSMS) and decentralized EMS is elaborated in Section IV, followed by the discussion of research results in Section V. Finally, the conclusion and future prospects are given in Section VI.

In this paper, "charging pile" is used to describe the EV charging equipment and "charging station" is used to express the place which has installed plural charging piles.

II. RELATED WORKS AND OUR CONTRIBUTIONS

The existing papers on optimal charging and discharging scheduling of EV charging station [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31] are mainly divided into centralized and decentralized architectures. The advantage of centralized architectures [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21] is minimization of operation cost through considering charging demands of EV users, PV power generation, and building load consumption for optimal EV charging and discharging scheduling. The disadvantage of centralized architecture is long computing time, such that it may not able to satisfy conditions of optimal control where frequency of scheduling control has increased or number of EV charging pile has soared.

In addition, many centralized architectures also consider power transaction, and regard EVs as a decentralized power resource. The EV charging station operator acts as an aggregator, integrates EVs to participate in DR bidding and ancillary services, and conducts bidirectional charging and discharging power transactions of EVs in charging station. However, complicated and large-scale power transactions rely on high-frequency optimal control. In a charging station with a large quantity of EV charging piles, the optimization calculation time will exceed the control time segment, which is unable to satisfy conditions of optimization.

The concept of decentralized architecture [22], [23], [24], [25], [26], [27], [28], [29], [30], [31] aims to solve the above-mentioned problems. Each EV charging pile can independently perform optimal scheduling control according to charging demands of EVs. Calculation time can be greatly reduced, which is the advantage of decentralized architecture, so the very short-term forecasting results of renewable energy power generation and load consumption can be applied to

optimal scheduling in shorter time segments, to diminish the impact of uncertainty.

However, the major problem of decentralized architecture is overall charging station power optimal dispatching, which necessitates coordination of the upper limits of available charging power of each EV charging pile at each time segment. Otherwise, the total charging power may exceed transformer capacity limit and affect microgrid safety. At present, most of the papers adopt game theory to perform optimal dispatching of available charging power, by iteration between EV charging piles and CSMS until the optimal dispatching amount is obtained. However, when bidirectional charging and discharging scheduling of EVs is introduced, the maximum charging capacity and power dispatching must be considered simultaneously, its iterative process is more complicated, resulting in significant increase in computing time, the advantage of decentralized architecture is offset.

Regardless of centralized or decentralized architecture, it is necessary to collect a large amount of user data, such as arrive and departure time of EV, arrive and departure state-of-charge (SOC) of EV, user behavior, and power transaction information. Nowadays, the user privacy and security of data are highly-valued, requiring a fully-functioning information security mechanism for defense.

In [31], [32], [33], [34], [35], and [36], blockchain technology is adopted to encrypt power transaction data, power data, and user data. However, most of these papers adopt Ethereum technology, which relies on miners to conduct chaining verification, resulting in long waiting time while chaining. Furthermore, additional commission is required. The EV charging pile is used to upload power data to a cloud database through a centralized data transmission method and then conducts a chaining process, which may risk data tampering or attack actions, entailing possibility of system crush.

In sum, as high-proportion of EVs arises in the future, substantial bidirectional charging and discharging transactions of EVs will follow by increasing installation of charging piles. The existing centralized optimal scheduling method is unable to satisfy optimal control conditions of EV charging station. A decentralized scheduling architecture with combination of an effective upper limit allocation method of charging and discharging must be adopted to achieve management of a large number of EV charging piles and the goal of maximizing power utilization efficiency. However, the minimization of operating cost cannot be achieved as centralized algorithm does.

Given the imbalance problem of power supply and demand in the grid due to rapid increase in proportion of renewable energy and EV, considering popularization of small-scale PV generation devices and manufacturing technology of ESS becoming mature, this paper attempts to develop a multifunctional CSMS. It is assumed that the renewable energy power generation equipment, ESS device, and charging station have been constructed in commercial building. With introduction of EMS, a system to effectively improve utilization of renewable energy and grid stability is proposed, thereby fulfilling

maximization of power utilization efficiency, green power transaction, and peak load shaving of DSM.

The concepts of an intelligent CSMS are proposed in this paper by combining the blockchain technology, AI internet of thing (AIoT), optimal distributed EMS, and blockchain power transaction technology. Contributions of this paper are illustrated as follows:

- An Innovative intelligent CSMS of an EV charging station: Based on AIoT, this paper proposes the architecture for the CSMS by combining blockchain technology and double-layer optimal scheduling and control technologies. The centralized optimal scheduling module for the charging station is performed by a cloud server at time segment of 15 mins for the distributed optimal charging and discharging control of EV to be performed by each charging pile at every 5 mins.
- Blockchain based power-trading platform of EVs: A power trading platform is developed in this paper based on the blockchain technology to integrate the decentralized power resource data storage, point-to-point (P2P) transaction, consensus mechanism, and encryption algorithm for power trading of EV users in charging stations.
- Local blockchain distributed ledger node: With the blockchain distributed ledger, all the power data and transaction data can be shared with each charging pile and charging station server. Safety and avoidance of information asymmetry can be achieved. Also it's a new scheme proposed to have a blockchain distributed ledger node implemented in an EV charging pile with Raspberry Pi as the computing module.

With this double-layer architecture, CSMS is capable of managing large quantities of EV charging piles, achieving maximization of power utilization efficiency, decreasing charging cost of EVs, suppressing peak load of grid, smoothing renewable energy power generation output, and maintaining power supply and demand balance, as well as power quality in grid.

III. PROPOSED SYSTEM OVERVIEW

This study presents a blockchain intelligent CSMS platform of EV charging station combined with AIoT technology, double-layered optimal energy management technology and blockchain technology, its architecture is shown in Fig. 1. It integrates renewable energy power generation equipment, ESS device, a large quantity of EV charging piles, building load, and other distributed power resources, and adopts a centralized and decentralized double-layered optimization algorithm architecture to achieve an optimal ESS and EV charging and discharging strategy. The proposed approach employs blockchain technology to develop a power trading platform, which enables charging station operator to effectively manage distributed power resources under its governance through scheduling in order to participate in DR bidding and ancillary service market of transmission and distribution system operator and conduct green power trading. The detailed

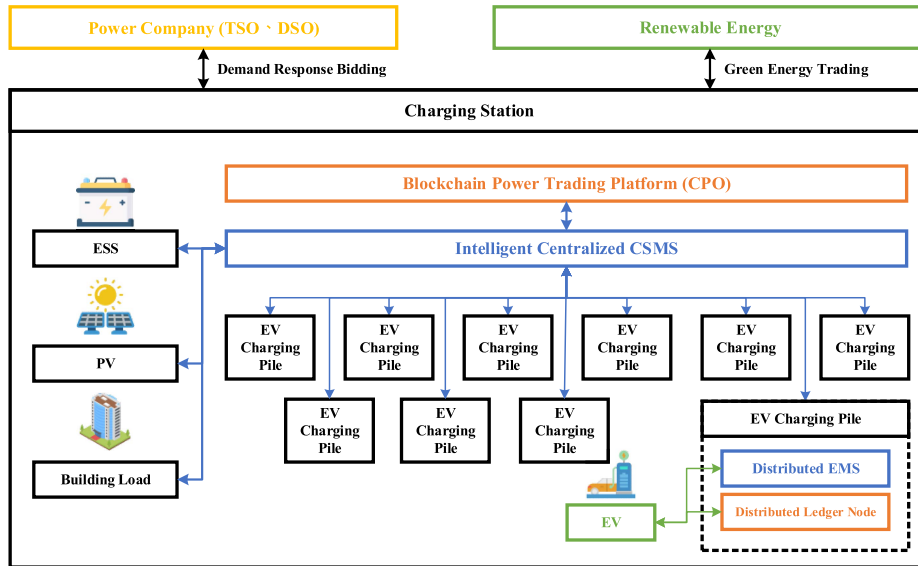


FIGURE 1. Proposed blockchain-based intelligent CSMS platform structure.

architecture of the system platform is shown in Fig. 2, including a blockchain power transaction platform, an edge AI forecasting system, and a double-layered centralized CEMS and decentralized EMS of an EV charging station, which is elaborated below.

A. BLOCKCHAIN POWER TRADING PLATFORM

Fig. 3 shows the architecture of the blockchain power transaction platform, which consists of a blockchain system, blockchain distributed ledger, and user interface. The three related designs and functions are illustrated in order as follows.

1) BLOCKCHAIN SYSTEM

The blockchain system as a power trading operating platform is a decentralized system in charge of verifying transactions, chaining, and employing smart contracts to perform bidding, matching, and settlement of power transaction, which consists of more than three blockchain nodes. The hardware required includes three servers (an orderer server and two peer servers). The orderer server is responsible for receiving transaction requests from the front-end user interface and dispatching chaining verifications of transactions and computation of smart contract tasks into the two peer servers. Each peer server can be used to execute bidding, matching, and settlement of transaction through built-in smart contract, as well as conducting chaining verification of transaction. If the orderer node malfunctions, a new orderer node is elected by the rest of peer nodes to maintain operation of trading platform, which means more power transactions can be conducted as system possess more peer nodes, while operation of system is further stable.

In this paper, the Redundant Byzantine Fault Tolerance (RBFT) mechanism [37] is adopted as a consensus method for chaining verification of blockchain. Each peer node is assigned a unique hash certificate and provided with private and public keys. The hash certificate is used to identify the node, and the private and public keys are used for data encryption. The process is responsible for transaction verification computation with a voting mechanism used to determine whether the transaction can be chained or not. If two-thirds of the peer nodes agree, the transaction can be chained. Unlike Bitcoin's proof-of-work consensus mechanism, the process adopted does not require miners to conduct verification computation to greatly reduce verification latency, speed up the transaction, and to exempt additional commission. The sequence of the complete power transaction process is as follows: the user initiates a transaction request on front-end user interface, the orderer node is called to receive the transaction event via API, one of the peer nodes which is used to execute smart contract, verification and voting for chaining is then conducted; after reaching consensus, the transaction is uploaded to chain.

A smart contract operates on all peer nodes and writes all types of power trading rules on it, and is in charge of executing bidding of transaction, matching of transaction, and settlement of transaction automatically. After the chaining process is completed, detailed power transaction information is stored in distributed ledger, then matching and settlement are finished according to detailed power transaction information and power data recorded in the ledger. The detailed information in the transaction process is written into the distributed ledger through the blockchain ledger node located in the cloud server, and is announced synchronously on the user interface, including a webpage and

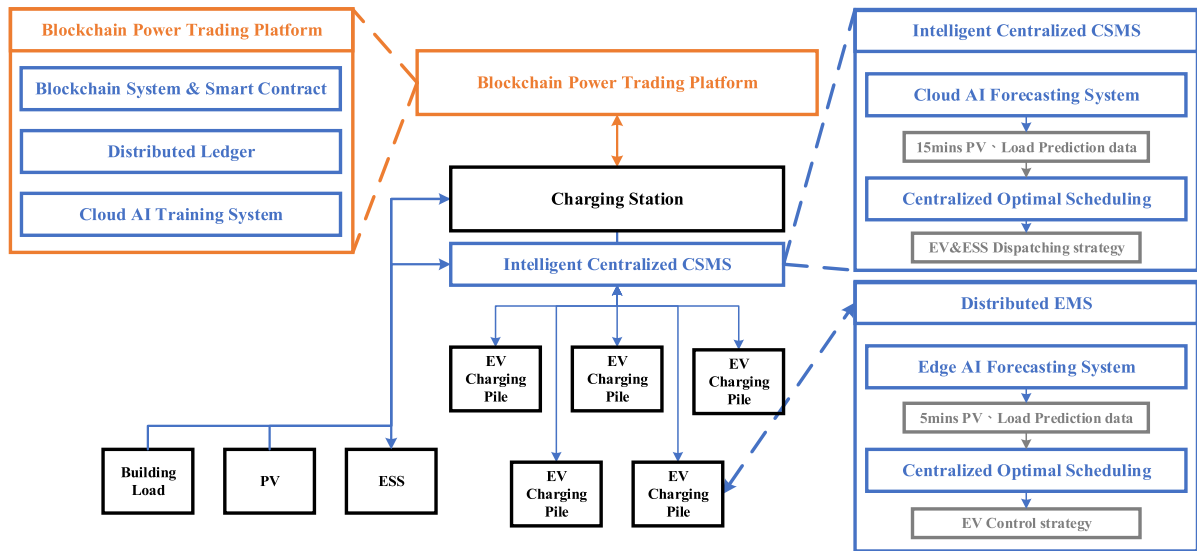


FIGURE 2. Proposed blockchain-based intelligent CSMS platform block diagram.

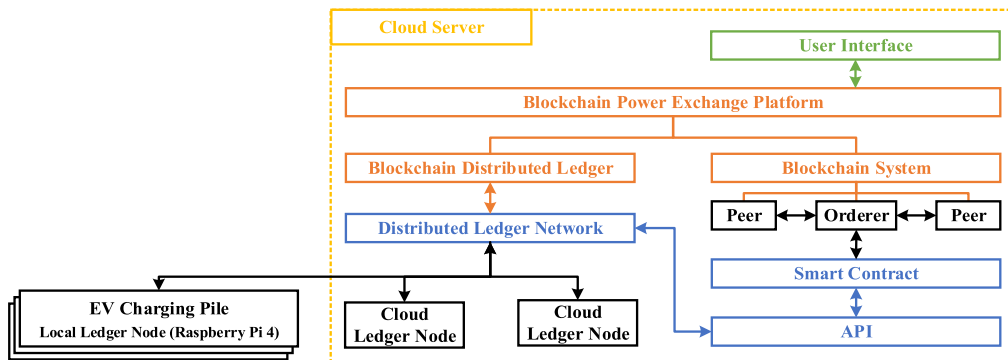


FIGURE 3. Proposed blockchain trading platform structure.

smart device application program (APP), of the power trading platform.

2) BLOCKCHAIN DISTRIBUTED LEDGER

A local blockchain distributed ledger node is responsible for operating the distributed intelligent EMS of EV charging piles and acting as a distributed ledger data node. The distributed ledger data node is used to connect the EV charging pile through the IoT technology to perform forecasting of power generation and load consumption and optimal charging and discharging scheduling control with intelligent EMS.

Compared with centralized power data uploading method, in the proposed blockchain distributed ledger system, the power data are directly measured by the charging pile and then uploaded via the process described above. The measured information is can thus be accessed and saved in the distributed ledger with the lowest possibility of errors due to human intervention or communication, and its correctness is highly enhanced. Smart contract is able to precisely settle the power trading with the power data from ledger.

Located in the cloud and local side, the distributed ledger network, consisting of blockchain distributed ledger data nodes, is employed as the database in the proposed system. It receives power data uploaded by each local blockchain ledger-node in every minute and records detailed power transaction information, which is sent from the blockchain power trading platform. The data recorded in ledger are then used for the settlement references in the designed smart contract. As it is needed, the data can be also used as the training data needed by the AI forecasting model. Once the settlement/accounting and training purpose is achieved, the power data can be deleted and updated thus without the data storage issue.

The steps of data uploading to distributed ledger are shown in Fig. 4. A light-weighted proof-of-work (LWPoW) must be performed first when writing data. In general, proof-of-work (PoW) is regarded as solving a complex mathematical problem, which requires quite a lot computing power, usually handled by a server computer or graphics card computing unit. Raspberry Pi is a cheap and functional embedded device, acts as a local side blockchain ledger node, but has computing

power far less than the above-mentioned devices, not to speak of being used to deal with PoW.

Due to high-frequency of recording the power data and power transaction data, a LWPoW is used in this study, which aims to shorten time delay of power data uploading and lighten computation load. After finishing calculation of LWPoW, the distributed ledger network finds the other two blockchain ledger nodes to check the result through directed acyclic graph (DAG) algorithm. If the result is correct, the data is allowed to be written into distributed ledger and stored on all ledger nodes of distributed ledger network synchronously. Therefore, fairness and impartiality of transactions can be guaranteed, and the situation of a single ledger node data damage resulting in all transactions being stopped or affected can be prevented.

3) USER INTERFACE

Web page and smart device APP are used as the user interface of the blockchain power trading platform in this paper. The power transaction process of EV users is shown in Fig. 5. When the user arrives at the charging station, he may either login to the platform through a webpage or smart device APP, enters expected departure time and expected EV departure SOC, selects charging service, and then submits the charging demand.

The platform will automatically execute the power transaction through a smart contract, which will not only conduct chaining and store the detailed transaction information in the distributed ledger, but also perform charging and discharging scheduling through double-layered CSMS. All EV charging and discharging actions will be recorded in the distributed ledger, and users can clearly view transaction process and result at any time on the user interface. The corresponding service is briefly described as follows.

- Only charging service: The only charging service includes the 30-kW fast charging and the 7-kW slow charging. The double-layered CSMS is used to perform optimal charging scheduling control on the premise of meeting EV charging demand.
- Green power charging service: The green power charging service includes fast charging (30kW) and slow charging (7kW). Users need to make a reservation on the platform a day ahead, and arrive at the charging station at the reservation period. The double-layered CSMS is used to performs optimal charging and discharging scheduling control on the premise of meeting charging demand of EV program control.
- Smart charging and discharging service: The smart charging and discharging service includes fast charging (30kW) and slow charging (7kW). EV smart charging service is controlled by the optimal scheduling control which is conducted double-layered CSMS under conditions of not affecting existing charging service. The EV user receives a certain percentage of reward for discharging; if participating in DR bidding, the reward will

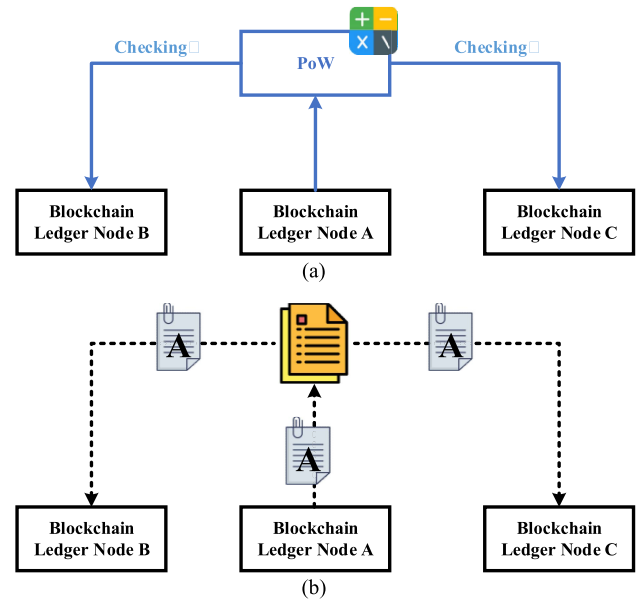


FIGURE 4. The process of data uploading to the distributed ledger.

be given depending on DR bidding price after deducting commission.

- Smart green power charging and discharging service: The smart green power charging and discharging service includes the 30-kW fast charging and the 7-kW slow charging. Users need to make a reservation on the platform one day ahead, and arrive at the charging station at the reservation period. The EV smart green charging service is controlled by the optimal scheduling control which is conducted double-layered CSMS under conditions of not affecting existing charging service. The EV user receives a certain percentage of reward for green power discharging; if participating in DR bidding, reward will be given depends on DR bidding price after deducting commission.

In sum, when the number of blockchain nodes and blockchain distributed ledger nodes increases, the power transaction processing capability of the blockchain power trading platform is increased, since more nodes join in computing. In addition, system stability and data storage are also improved with more nodes built. When a large quantity of bidirectional EV charging piles are introduced into the grid in future, the blockchain system design in this paper will be more efficient when processing high-frequency power trading and power data recorded by a large number of distributed power resources.

B. INTELLIGENT CHARGING STATION MANAGEMENT SYSTEM

Apart from the current AI model training method, a centralized architecture is usually adopted to collect and store data. To protect privacy of user behavior, although there is de-identification design of current architecture, in the centralized data collection process, user privacy would be

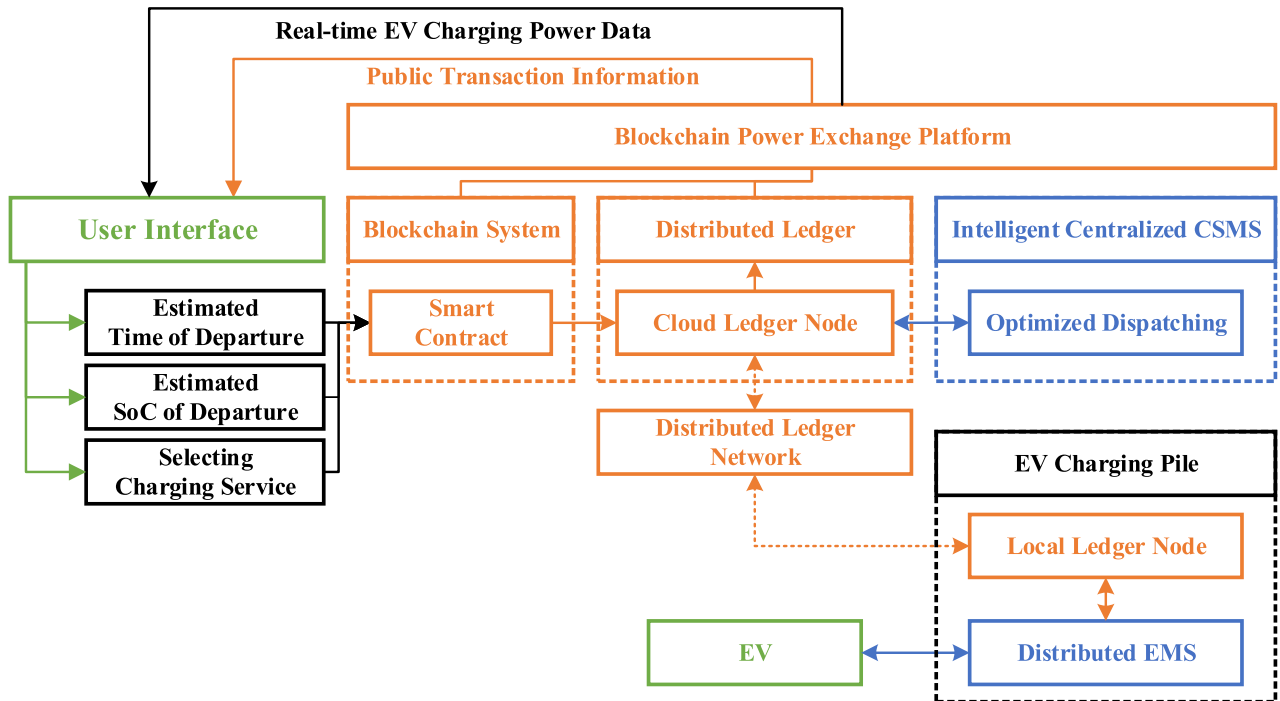


FIGURE 5. The process of power trading for EV user.

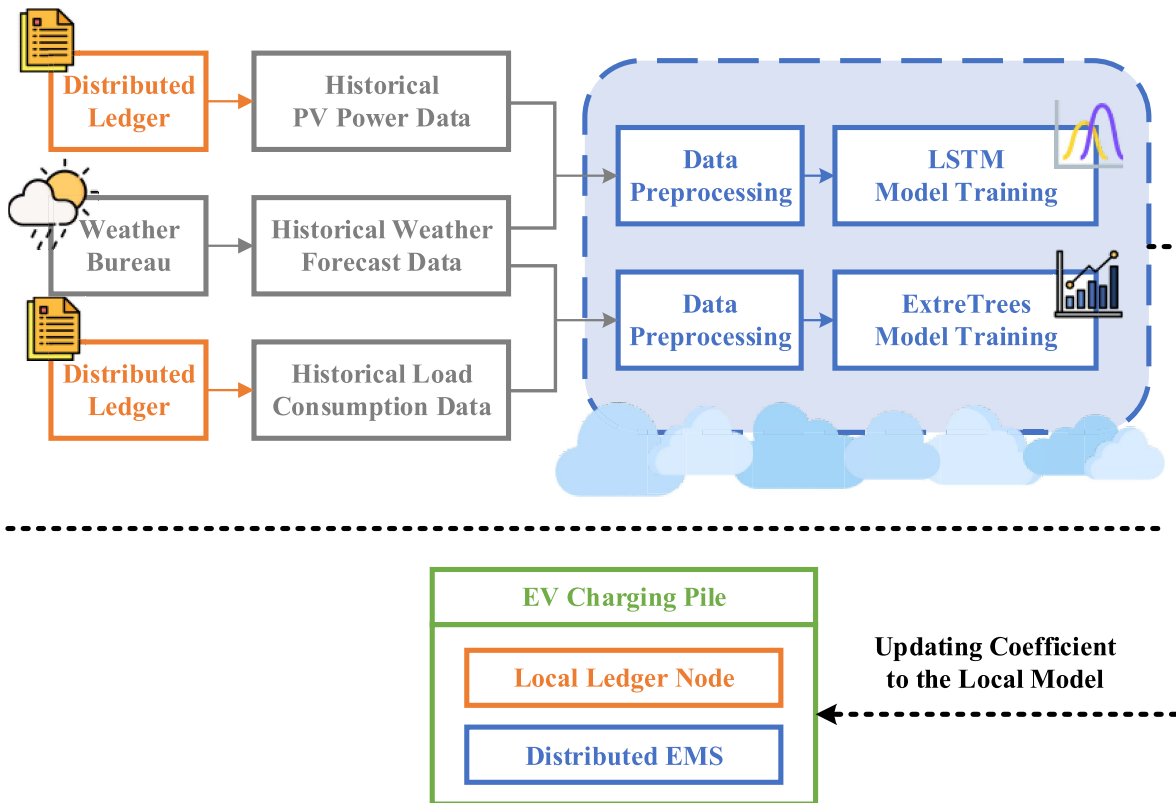


FIGURE 6. Proposed blockchain-based AI training block diagram.

harmful if data leaking or attacking actions took place. The proposed method adopts distributed ledger technology of blockchain to protect user privacy.

The consensus mechanism of blockchain, collecting power and environment data of each user in an anonymous and secure way, and the training of renewable energy generation

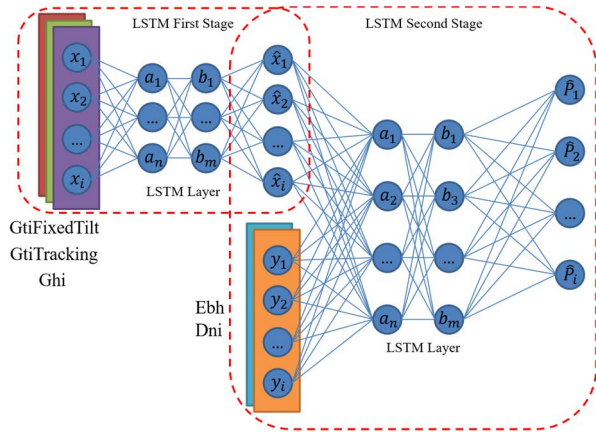


FIGURE 7. Structure of the proposed two-stage LSTM model.

and load consumption forecasting models in the proposed blockchain-based AI training approach, as shown in Fig. 6. Thus, it not only can solve concerns about user privacy, but also can ensure correctness of data resource and the security of data storage.

1) RENEWABLE ENERGY POWER GENERATION FORECAST

Regarding PV power generation forecasting, this paper designs a lightweight forecasting method adopting a two-stage long short-term memory (LSTM) model, considering computing power of edge devices. Its architecture is shown in Fig. 7.

Three types of weather data, including global tilted irradiance (GTI) Fixed Tilt, GTI Tracking and global horizontal irradiance (GHI), are used as input features of the first-stage LSTM model, the first forecasting result is yielded as output, and then become input features of the second-stage LSTM model, combined with two types of weather data, including horizontal irradiance (EBH) and direct normal irradiance (DNI), to conduct final PV power generation forecasting at intervals of 15 min and 5 min. This paper divides the historical PV power generation data and historical weather forecasting data of 2019 into training and testing data in the ratio of 1:1. The results show good performance, as discussed in Section V.

2) LOAD CONSUMPTION FORECAST

Fig. 8 shows the proposed load forecasting framework, which is based on ExtraTrees regression combining Ridge regression method. With weather data and historical load consumption as input features, including GHI, EBH, Air Temp, DNI, DHI, Zenith, Azimuth, Cloud Opacity, Dewpoint, Wind Speed, Wind Direction, Relative Humidity, Precipitable Water, Surface Pressure, GTI Tracking, GTI Fixed Tilt, Albedo, etc., multiple decision trees are generated through the ExtraTrees regression method.

The classification feature of each decision tree is randomly selected, and training load prediction data and training load target data of each decision tree are then fitting into the weight

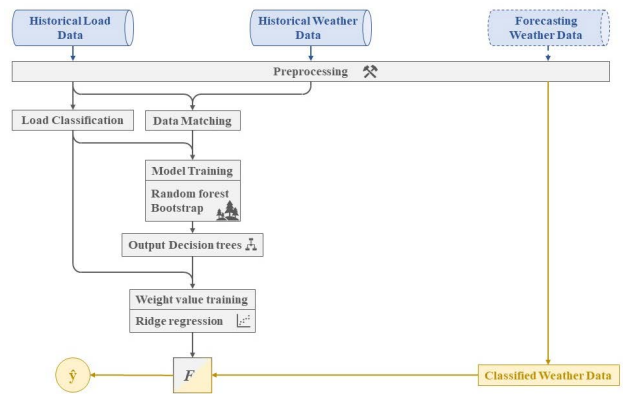


FIGURE 8. Structure of the proposed combining ExtraTrees regression and ridge regression model.

matrix of Ridge regression method. The prediction of load consumption is conducted at intervals of 15 min and 5 min, and long-term and short-term power consumption forecasts are carried out. This thesis divides the actual field historical load power consumption data and historical weather forecast data for the whole year of 2021 into training and test data at a ratio of 8:2. The test results show excellent performance, which will be discussed in Section V.

3) AI EDGE COMPUTING

At present, AI technology has been widely used in various systems. This paper considers the computing power of each EV charging pile used to conduct blockchain distributed ledger data node and distributed EMS is finite. Therefore, this paper adopts the method of model training in the cloud and updates trained model coefficients to a local forecasting model to perform real-time edge computation of predictions.

C. DOUBLE-LAYERED CENTRALIZED CSMS AND DECENTRALIZED EMS OF EV CHARGING STATION

A double-layered optimization architecture is proposed here to realize the goal of management for large numbers of EV charging piles and maximization power utilization efficiency of EV charging stations.

The upper layer performs optimal charging and discharging scheduling of entire EV charging station at time interval of 15 min, the bottom layer performs optimal charging and discharging scheduling control with a distributed architecture developed in each EV charging pile at a 5-min interval. The architecture is described below and is shown in Fig. 9.

1) UPPER-LAYERED CENTRALIZED CSMS OF EV CHARGING STATION

The upper layer considers all the distributed power resources of the entire charging station, including each EV charging pile, PV power generation equipment, ESS devices, and building load to realize the goal of maximization of power utilization efficiency. The scheduling result is written into

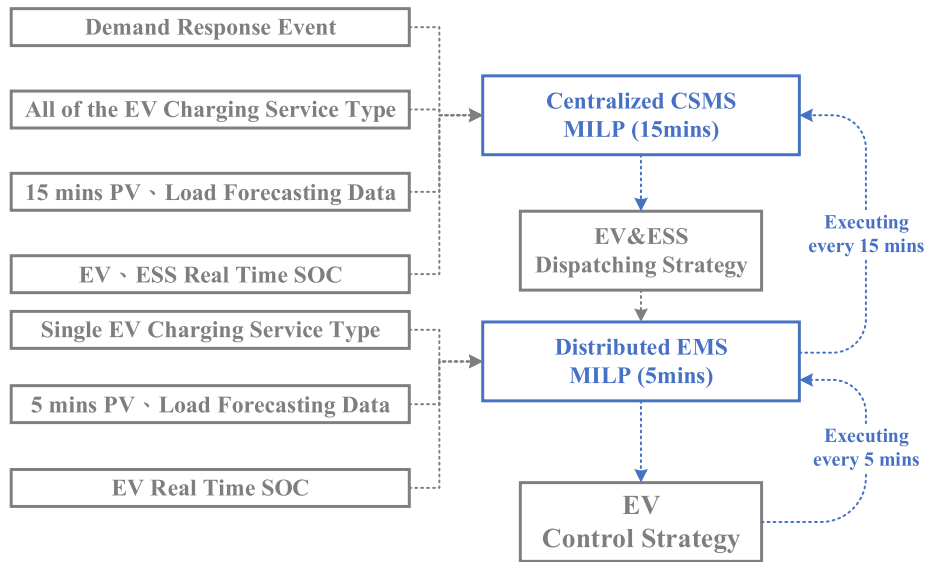


FIGURE 9. Structure of double-layered centralized CSMS and decentralized EMS.

blockchain ledger and provided to each EV charging pile as reference to perform optimal control.

The process is shown in Fig. 10 and the algorithm is shown in Fig. 11. In the first step, CSMS reads existing scheduling information of all EV charging piles and ESS devices, and calculates the current time window t . The second step is to update the time window $t = t + 1$, then read the forecasting results of 15-min power generation and 15-min load consumption predicted by AI prediction model, and detailed power transaction information in the distributed ledger.

The third step is to update the system information after altering, such as real-time price, system parameters in micro-grid, real-time SOC of each EV, and dynamic window end-time of EV and start the optimal scheduling. In a centralized architecture, under consideration of real-time state of power supply and demand, its end condition is reaching the global optimal solution. This is so to achieve balance of power of renewable energy power generation, power of EV charging and discharging, power of ESS device, overall load consumption, and to perform optimal scheduling by adopting a mixed-integer linear programming (MILP) algorithm. Finally, in the fourth step, the output of optimization amount of EV charging and discharging per 15 min is yielded.

2) BOTTOM-LAYER CENTRALIZED EMS OF EV CHARGING STATION

All EV charging piles in a charging station operate respective bottom-layer distributed EV charging pile EMSs; the process is shown as Fig. 12 and the algorithm is shown in Fig. 13. In the first step, EMS reads EV power transaction data of blockchain distributed ledger, 15 min upper-layer optimization amount of EV charging and discharging, existing EV

charging and discharging scheduling information, to calculate the current time window, t .

The second step is to update the time window $t = t + 1$, then EMS reads the forecasting results of 5-min renewable energy power generation and 5-min load consumption predicted by AI prediction model, then the EV charging power upper bound and discharging power lower bound will be calculated with the priority of EV charging and discharging.

The third step is to update the system information after altering, such as real-time price, EV charging power upper bound and discharging power lower bound and dynamic window end-time of EV, and start the optimal scheduling. In a decentralized architecture, optimal control of each EV charging pile is performed by adopting the MILP algorithm, in case of satisfying conditions of objective functions and constraints. Finally, in the fourth step, the output of EV charging pile control command is yielded.

IV. CENTRALIZED CSMS, DISTRIBUTED EMS, AND OPTIMIZATION ALGORITHM

When a battery is repeatedly charged and discharged, its life span decreases, depending on its type and chemical composition. This paper assumes that both EV and ESS use lithium-iron phosphate (LFP) batteries, and considers the effect of total number of cycles on battery capacity. Fig. 14 illustrates the relationship between the number of cycles of LFP battery and battery capacity.

The points in the figure are actual data provided by battery manufacturer, the right-side vertical axis presents the assumed battery life. As shown in Fig. 14, it assumes that when battery capacity drops below 65%, the battery is no longer used, which means its life has ended. When the battery capacity on left side y-axis drops to 65%, the battery life on

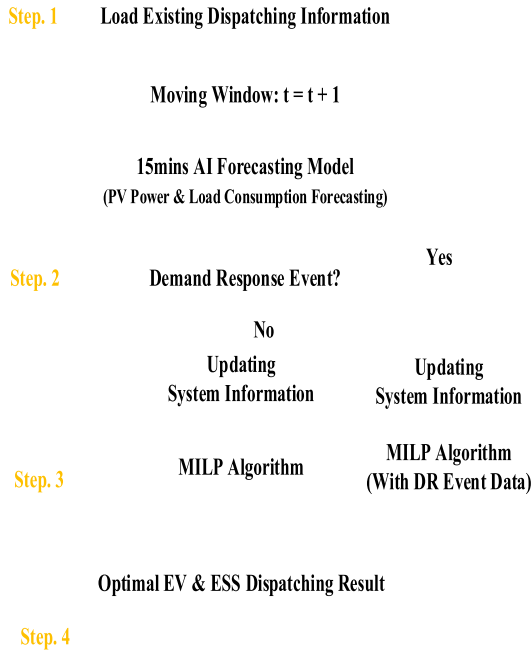


FIGURE 10. The process of upper-layered centralized CSMS.

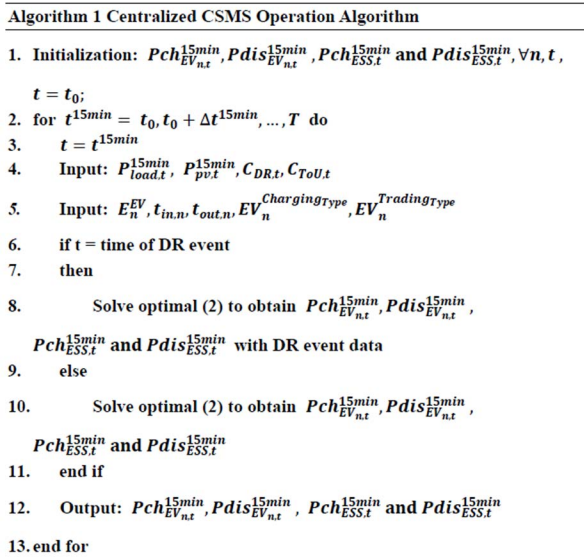


FIGURE 11. The algorithm of centralized CSMS operation.

right side y-axis down to 0%, and the battery degradation is represented in (1).

$$C^{deg} = \left| \frac{m_1}{100} \right| \frac{P \cdot \Delta t}{B^{cap}} C^{bat} \quad (1)$$

A. UPPER-LAYER CENTRALIZED EMS OF EV CHARGING STATION

All parameters and variables of the optimization problem are described and organized in Table 1. The objective function is to minimize operating cost of EV charging station, as shown in Eq. (2), which includes purchasing power cost

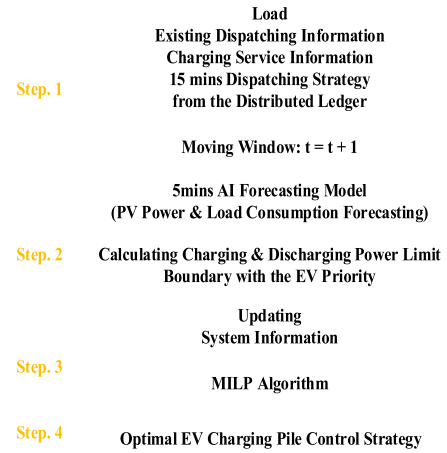


FIGURE 12. The process of bottom-layer decentralized EMS.

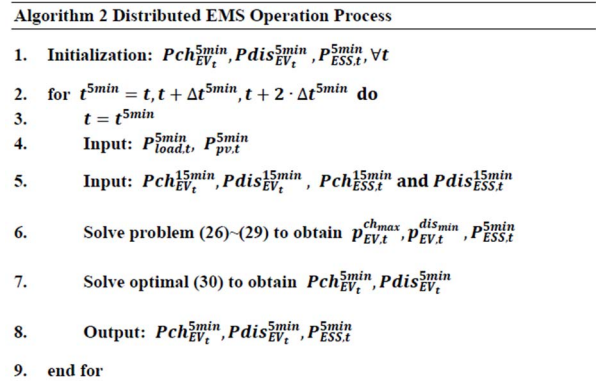


FIGURE 13. The algorithm of decentralized EMS operation.

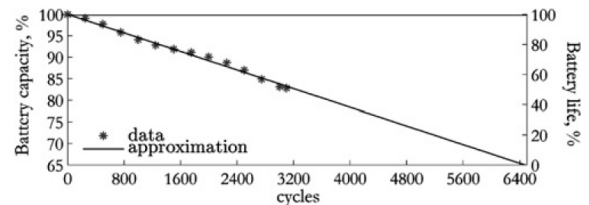


FIGURE 14. Cycle-life performance of a Nanophosphate® Li-ion battery for charging and discharging rates.

from microgrid, battery degradation cost caused by charging and discharging scheduling of ESS, reward for EV users participating in smart charging and discharging, profits from participating in DR bidding of the power company, penalty cost for not meeting charging demand of EV users, and penalty cost for exceeding contract capacity.

Eq. (3) defines power purchased from the microgrid, taking into account building load consumption, PV power generation, total power of EV, and ESS charging and discharging. Eq. (4) calculates the purchasing power cost from the microgrid of the EV charging station. Eq. (5) represents cost calculation of battery degradation that caused by charging and discharging scheduling of ESS. Eq. (6) is a battery

degradation coefficient of ESS.

$$\min \sum_{t=t'}^T \left(C_{net,t}^{15min} + C_{ESS_{deg},t}^{15min} + C_{EV_{feedback},t}^{15min} + C_{exceed_{contract},t}^{15min} + I_{DR,t}^{15min} \right) + \sum_n^N C_{EV_{deficiency},n}^{15min} \quad (2)$$

$$P_{net,t}^{15min} = P_{load,t}^{15min} + P_{PV,t}^{15min} + \sum_n^N P_{ch_{EV_n},t}^{15min} - \sum_n^N P_{dis_{EV_n},t}^{15min} + P_{ch_{ESS,t}}^{15min} - P_{dis_{ESS,t}}^{15min} \quad (3)$$

$$C_{net,t}^{15min} = P_{net,t}^{15min} \cdot C_{ToU,t} \cdot \Delta t^{15min} \quad (4)$$

$$C_{ESS_{deg},t}^{15min} = P_{ch_{ESS,t}}^{15min} \cdot \gamma_{ch}^{ch} \cdot \Delta t^{15min} + P_{dis_{ESS,t}}^{15min} \cdot \gamma_{dis}^{dis} \cdot \Delta t^{15min} \quad (5)$$

where

$$\begin{cases} \gamma_{ch} = \left| \frac{m_1}{100} \right| \frac{1}{B_{ESS}^{cap}} C_{ESS}^{bat} \eta_{ESS}^{ch} \\ \gamma_{dis} = \left| \frac{m_1}{100} \right| \frac{1}{B_{ESS}^{cap}} C_{ESS}^{bat} \frac{1}{\eta_{ESS}^{dis}} \end{cases} \quad (6)$$

The cost of reward given to EV users for participating in smart charging and discharging transactions is calculated by (7). Eq. (8) represents penalty cost for exceeding contract capacity more or less than 10%. Eq. (9) represents the penalty item for exceeding contract capacity less than 10%.

Eq. (10) indicates the penalty item for exceeding contract capacity by more than 10%. Eq. (11), as shown at the bottom of the next page, represents profits which are obtained by CPO participating in DR. Eq. (12), as shown at the bottom of the next page, represents the penalty item for not satisfying the charging demand of the EV user.

$$C_{EV_{feedback},t}^{15min} = \sum_n^N P_{dis_{EV_n},t}^{15min} \cdot C_{feedback} \cdot \Delta t^{15min} \quad (7)$$

$$C_{exceed_{contract},t}^{15min} = C_{exceed_{contract},t}^{15min,lower10\%} + C_{exceed_{contract},t}^{15min,upper10\%} \quad (8)$$

$$\begin{cases} C_{exceed_{contract},t}^{15min,lower10\%} \geq (P_{net,t}^{15min} - P_{contract}) \cdot 2 \cdot C_{contract}^{penalty} \\ C_{exceed_{contract},t}^{15min,lower10\%} \geq 0 \end{cases} \quad (9)$$

$$\begin{cases} C_{exceed_{contract},t}^{15min,upper10\%} \geq (P_{net,t}^{15min} - 1.1 \cdot P_{contract}) \cdot C_{contract}^{penalty} \\ C_{exceed_{contract},t}^{15min,upper10\%} \geq 0 \end{cases} \quad (10)$$

The overall EV charging station transformer constraint is as (13), and optimal scheduling problem of centralized EV must satisfy the constraints (14) to (20). Eqs. (14) and (15) are the charging and discharging power limitation of EVs.

TABLE 1. Nomenclature of parameters.

IDENTIFIERS AND BINARY VARIABLES	
T	Total time
t_0	Initial time
Δt^{15min}	Time interval of 15min
Δt^{5min}	Time interval of 5min
VARIABLES AND CONSTANTS	
P_{tr}^{max}	Upper limit of transformer
P_{ESS}^{max}	Upper limit charging and discharging
$P_{contract}$	Upper limit of contract capacity
$P_{ch_{EV_n},t}^{15min}$	15-min charging power of EV n at time t
$P_{dis_{EV_n},t}^{15min}$	15-min discharging power of EV n at time t
$P_{ch_{ESS,t}}^{15min}$	15-min charging power of ESS at time t
$P_{dis_{ESS,t}}^{15min}$	15-min discharging power of ESS at time t
$P_{net,t}^{5min}$	5-min power purchase from utility at time t
$P_{load,t}^{5min}$	5-min forecasting power consumption of load at time t
$P_{PV,t}^{5min}$	5-min forecasting power generation of PV at time t
$P_{ESS,t}^{5min}$	5-min charging and discharging power of ESS at time t
$C_{ToU,t}$	Time of use at time t
C_{ESS}^{bat}	Construction cost of ESS
γ_{ch}	Coefficient of ESS charging degradation
γ_{dis}	Coefficient of ESS discharging degradation
$C_{ESS_{deg},t}^{15min}$	15-min degradation cost of ESS at time t
$C_{feedback}$	Cost of feedback fund for EV users
$C_{contract}^{penalty}$	Penalty of contract capacity exceeding
$C_{DR,t}$	Tender awarding price of DR bidding at time t
$C_{EV}^{penalty}$	Penalty of EV charging deficiency
$C_{charging\ price,t}$	Charging price of EV at time t
$C_{power\ dispatching,t}$	Reward of EV participating dispatching
$B_{EV,n}^{cap}$	Battery capacity of EV n
B_{ESS}^{cap}	Battery capacity of ESS

TABLE 1. (Continued.) Nomenclature of parameters.

VARIABLES AND CONSTANTS	
E_n^{EV}	Discharging and charging demand of EV n
$EV_n^{Charging_Type}$	Charging speed of EV n
$EV_n^{Trading_Type}$	Trading type of EV n
$t_{in,n}, t_{out,n}$	Arriving time and departure time for EV
m_1	Slope of the linear approximation of the battery life

The power of EVs is limited to charging and discharging state and maximum charging and discharging power of EVs; $Pch_{EV,n,t}^{15min}$ means charging and $Pdis_{EV,n,t}^{15min}$ means discharging.

Eq. (16) is corresponding maximum discharging power limitation according to types of EV charging pile. The charging power is zero while EV is not in the charging station which is as Eq. (17). Eq. (18) indicates upper and lower limitation of SOC of EV at any time. Eq. (19) calculates volume change of EV battery SOC.

The optimal scheduling of ESS device must satisfy the constraints in Eqs. (20) to (24). Eqs. (20) and (21) represent charging and discharging power limitation of ESS, where the power of ESS is limited to charging and discharging states and maximum charging and discharging powers of ESS, $Pch_{ESS,t}^{15min}$ means charging, and $Pdis_{ESS,t}^{15min}$ means discharging.

Eq. (22) indicates that charging and discharging state of ESS would not occur simultaneously. Eq. (23) indicates upper and lower limitations of SOC of ESS at any time. Eq. (24) calculates change volume of ESS SOC. Eq. (25), as shown at the bottom of the next page, represents that there are corresponding charging and discharging state to different EV power transactions.

$$|P_{net,t}^{15min}| \leq P_{tr}^{max}, \quad \forall t \in T \quad (13)$$

$$0 \leq Pch_{EV,n,t}^{15min} \leq Uch_{EV,n,t}^{15min} \cdot P_{EV,n}^{max}, \quad \forall n \in N, t \in T \quad (14)$$

$$0 \leq Pdis_{EV,n,t}^{15min} \leq Udis_{EV,n,t}^{15min} \cdot P_{EV,n}^{max}$$

$$\forall n \in N, t \in T \quad (15)$$

$$\begin{cases} P_{EV,n}^{max} = P_{EV,fast}^{max}, \\ \text{if } EV_n^{Charging_Type} = \text{fast charging} \\ P_{EV,n}^{max} = P_{EV,slow}^{max}, \\ \text{else if } EV_n^{Charging_Type} = \text{low charging}, \end{cases} \quad (16)$$

$$\forall n \in N \\ Uch_{EV,n,t}^{15min} = 0, \quad Udis_{EV,n,t}^{15min} = 0, \quad (17)$$

$$\text{if } t < t_{in,n} \text{ or } t > t_{out,n}, \quad \forall n \in N, t \in T$$

$$SOC_{EV}^{min} \leq SOC_{n,t}^{EV} \leq SOC_{EV}^{max}, \quad \forall n \in N, t \in T \quad (18)$$

$$SOC_{n,t+1}^{EV} = SOC_{n,t}^{EV} + Pch_{EV,n,t}^{15min} \cdot \frac{\eta_{EV}^{ch} \cdot \Delta t^{15min}}{B_{EV,n}^{cap}} - Pdis_{EV,n,t}^{15min} \cdot \frac{\Delta t^{15min}}{B_{EV,n}^{cap} \cdot \eta_{EV}^{dis}} \quad (19)$$

$$0 \leq Pch_{ESS,t}^{15min} \leq Uch_{ESS,t}^{15min} \cdot P_{ESS}^{max} \quad (20)$$

$$0 \leq Pdis_{ESS,t}^{15min} \leq Udis_{ESS,t}^{15min} \cdot P_{ESS}^{max} \quad (21)$$

$$Uch_{ESS,t}^{15min} + Udis_{ESS,t}^{15min} = 1 \quad (22)$$

$$SOC_{ESS}^{min} \leq SOC_{ESS,t} \leq SOC_{ESS}^{max} \quad (23)$$

$$SOC_{ESS,t+1} = SOC_{ESS,t} + Pch_{ESS,t}^{15min} \cdot \frac{\eta_{ESS}^{ch} \cdot \Delta t^{15min}}{B_{ESS}^{cap}} - Pdis_{ESS,t}^{15min} \cdot \frac{\Delta t^{15min}}{B_{ESS}^{cap} \cdot \eta_{ESS}^{dis}} \quad (24)$$

B. BOTTOM-LAYER DECENTRALIZED EMS OF EV CHARGING PILES

Before optimizing scheduling of distributed EV charging piles, it is necessary to calculate allocation of charging and discharging. In Eq. (26), as shown at the bottom of the next page, $pr_{n,t}^{ch}$ means the charging priority of the nth EV in the time window t, based on comparison between renewable energy power generation and load consumption forecasting data per 5 min and 15 min. If there is surplus power, it will be allocated to EVs for charging. Instead, ESS would discharge to meet the charging demand of EVs. In Eqs. (27) and (28), as shown at the bottom of the next page, $P_{EV,n,t}^{ch,max}$ means maximum charging power of EVs at time window t, whereas $P_{EV,n,t}^{dis,min}$ means minimum discharging power of EVs at time

$$I_{DR,t}^{15min} = \left(\sum_n Pch_{EV,n,t}^{15min} - \sum_n Pdis_{EV,n,t}^{15min} + Pch_{ESS,t}^{15min} - Pdis_{ESS,t}^{15min} \right) \cdot C_{DR,t} \cdot \Delta t^{15min} \quad (11)$$

$$\begin{cases} C_{EV,n}^{deficiency} \geq C_{EV}^{penalty} \cdot \left(E_n^{EV} - \left(\sum_{t=t'}^T Pch_{n,t}^{EV} \cdot \eta_{EV}^{ch} \cdot \Delta t - \sum_{t=t'}^T Pdis_{n,t}^{EV} \cdot \frac{1}{\eta_{EV}^{dis}} \cdot \Delta t \right) \right), & \text{if } E_n^{EV} > 0 \\ C_{EV,n}^{deficiency} \geq C_{EV}^{penalty} \cdot \left(-E_n^{EV} - \left(\sum_{t=t'}^T Pdis_{n,t}^{EV} \cdot \frac{1}{\eta_{EV}^{dis}} \cdot \Delta t - \sum_{t=t'}^T Pch_{n,t}^{EV} \cdot \eta_{EV}^{ch} \cdot \Delta t \right) \right), & \text{otherwise} \\ C_{EV,n}^{deficiency} \geq 0 \end{cases} \quad (12)$$

window t , as well as $P_{ESS,t}^{5min}$ means charging and discharging power of ESS at time window t in Eq. (29), as shown at the bottom of the page.

Distributed optimization conducts scheduling for a single EV, using optimization scheduling data of 15-min EV charging and discharging, and conducts power limitation guiding for each EV through charging and discharging priority. Finally, optimal charging and discharging power control of EV per 5 min is generated. The objective function is to minimize the EV charging cost, as in (30), shown at the bottom of the next page, which includes charging cost of EV, reward for EV users participating in smart charging and discharging dispatching, and penalty cost for not meeting charging demand of EV users. Eq. (31), as shown at the bottom of the next page, calculates charging cost of EV, Eq. (32), as shown at the bottom of the next page, calculates reward for EV users participating in smart charging and discharging of charging station, and Eq. (33), as shown at the bottom of the next page, presents calculation of penalty cost for not meeting charging demand of EV users.

Eq. (34), as shown at the bottom of the next page, represents that there are corresponding charging and discharging state to different EV power transactions. The optimal scheduling problem of decentralized EVs must satisfy the constraints

in Eqs. (35) to (43). Eqs. (35) and (36) are the charging and discharging power limitations of EVs. The power of EVs are limited to charging and discharging state and maximum charging and discharging power of EVs, $Pch_{EV,n,t}^{5min}$ means charging and $Pdis_{EV,n,t}^{5min}$ means discharging.

Eq. (37) is corresponding maximum discharging power limitation according to types of EV charging pile. Eq. (38) and (39) indicate maximum charging and minimum discharging power limitation of EV according to allocation of priority. The charging power is zero when the EV is not in the charging station, which is as per Eq. (40). Eq. (41) indicates upper and lower limitation of SOC of EV at any time. Eq. (42) calculates change volume of battery SOC.

$$0 \leq Pch_{EV,n,t}^{5min} \leq Uch_{EV,n,t}^{5min} \cdot P_{EV,n}^{max} \quad (35)$$

$$0 \leq Pdis_{EV,n,t}^{5min} \leq Udis_{EV,n,t}^{5min} \cdot P_{EV,n}^{max} \quad (36)$$

where

$$\begin{cases} P_{EV,n}^{max} = P_{EV,fast}^{max}, & \text{if } EV_n^{ChargingType} \\ & = \text{fast charging} \\ P_{EV,n}^{max} = P_{EV,slow}^{max}, & \text{else if } EV_n^{ChargingType} \\ & = \text{low charging}, \end{cases} \quad \forall n \in N \quad (37)$$

$$\begin{cases} Uch_{EV,n,t}^{15min} + Udis_{EV,n,t}^{15min} = 1, \\ \text{if } EV_n^{TradingType} = \text{Auto Controlling Service} \\ Uch_{EV,n,t}^{15min} = 1, \quad Udis_{EV,n,t}^{15min} = 0, \\ \text{else if } EV_n^{TradingType} = \text{Only Charging Service} \\ Uch_{EV,n,t}^{15min} + Udis_{EV,n,t}^{15min} = 1, \\ \text{else if } EV_n^{TradingType} = \text{Green bidirection Chargig Service} \\ Uch_{EV,n,t}^{15min} = 1, \quad Udis_{EV,n,t}^{15min} = 0, \\ \text{else if } EV_n^{TradingType} = \text{Green Power Charging Service}, \end{cases} \quad \forall n \in N \quad (25)$$

$$pri_{n,t}^{ch} = \frac{E_n^{EV}}{(t_{out,n} - t' + 1) \times \Delta t^{5min} \times P_{EV,n}^{max}}, \quad \forall n \in N, \quad t \in T \quad (26)$$

$$\begin{cases} P_{EV,n,t}^{ch,max} = \left(\sum_n Pch_{EV,n,t}^{15min} - (P_{load,t}^{5min} + P_{PV,t}^{5min}) + (P_{load,t}^{15min} + P_{PV,t}^{15min}) \right) \cdot \frac{pri_{t,n}^{ch}}{\sum_n pri_{t,n}^{ch}}, \\ \text{if } P_{load,t}^{5min} + P_{PV,t}^{5min} < P_{load,t}^{15min} + P_{PV,t}^{15min} \\ P_{EV,n,t}^{ch,max} = \sum_n Pch_{EV,n,t}^{15min} \cdot \frac{pri_{t,n}^{ch}}{\sum_n pri_{t,n}^{ch}}, \quad \text{otherwise}, \end{cases} \quad \forall n \in N, \quad t \in T \quad (27)$$

$$P_{EV,n,t}^{dis,min} = Pdis_{EV,n,t}^{15min}, \quad \forall n \in N, \quad t \in T \quad (28)$$

$$\begin{cases} P_{ESS,t}^{5min} = Pch_{ESS,t}^{15min} - Pdis_{ESS,t}^{15min} \\ \quad + (P_{load,t}^{5min} + P_{PV,t}^{5min}) - (P_{load,t}^{15min} + P_{PV,t}^{15min}), \quad \text{if } P_{load,t}^{5min} + P_{PV,t}^{5min} > P_{load,t}^{15min} + P_{PV,t}^{15min} \\ P_{ESS,t}^{5min} = Pch_{ESS,t}^{15min} - Pdis_{ESS,t}^{15min}, \quad \text{otherwise}, \end{cases} \quad t \in T \quad (29)$$

$$Pch_{EV,n,t}^{5min} \leq P_{EV,n,t}^{chmax} \quad (38)$$

$$P_{EV,n,t}^{dismin} \leq Pdis_{EV,n,t}^{5min} \quad (39)$$

$$Uch_{EV,n,t}^{5min} = 0, \quad Udis_{EV,n,t}^{5min} = 0, \quad \text{if } t < t_{in,nort} > t_{out,n} \quad (40)$$

$$SOC_{EV}^{min} \leq SOC_{EV,n,t} \leq SOC_{EV}^{max} \quad (41)$$

$$SOC_{EV,n,t+1} = SOC_{EV,n,t} + Pch_{EV,n,t}^{5min} \cdot \frac{\eta_{EV}^{ch} \cdot \Delta t^{5min}}{B_{EV,n}^{cap}} - Pdis_{EV,n,t}^{5min} \cdot \frac{\Delta t^{5min}}{B_{EV,n}^{cap} \cdot \eta_{EV}^{dis}} \quad (42)$$

V. CASE STUDIES AND DISCUSSIONS

The case study simulates an EV charging station located in a commercial building, which consists of the commercial building load itself, EV charging station, PV power generation equipment, and ESS. The detailed specifications are shown in Table 2. The EV user model of a commercial building [38] is employed as the simulation basis. The programs are coded in Python to simulate the case study in the time frame of 5 mins. The EV user model of a commercial building is employed as a simulation. The present section details AI renewable energy power generation and load consumption forecasting results, optimal scheduling results and analysis, and test results of the blockchain system.

A. AI FORECASTING RESULTS

The accuracy of renewable energy power generation forecasting is evaluated in terms of mean relative error (MRE) as defined in Eq. (43). The historical data for PV power generation and the corresponding weather forecasting data of 2019 are utilized in a ratio of 1:1 for training and

TABLE 2. Simulation parameters of microgrid.

Item	VALUE
Transformer Limit	2500 kVA
Contract Capacity	2200 kW
EV Charging pile Amount	500
EV Charging Power	30 kW
Daily EV Arrive Number	700
EV Charging Efficiency	0.9
EV SOC Range	20% - 100%
ESS Capacity	600kWh
ESS Power	200kW
ESS SOC Range	20% - 90%
EV Charging Fee	Fast: 9 (kWh/NTD) / Slow:3 (kWh/NTD)
EV Discharging Reward	2 (kWh/NTD)

testing, respectively. The testing results show the average MRE of 0.67124% is achieved. The comparison of half-month forecasting and actual power generation data in June 2019 is shown in Fig.15. Compared with the existing literature [39], [40], [41], the results of the proposed load power consumption forecasting model are suitably accurate for use in the optimization scheduling algorithm.

$$MRE = \frac{1}{n} \sum_{i=1}^n \left| \frac{X_{predicted}[i] - X_{actual}[i]}{P_{PV}^{Capacity}} \right| \times 100\% \quad (43)$$

where $X_{predicted}[i]$ and $X_{actual}[i]$ are the forecast value and actual value of the PV power output at the i th point, respectively. n is the number of prediction points, and $P_{PV}^{Capacity}$ is the nominal power capacity of the PV site.

$$\min \sum_{t=t'}^T (C_{charging\ price,t}^{5min,n} + I_{power\ dispatching,t}^{5min,n}) + C_{EV\ deficiency,n}^{5min} \quad (30)$$

$$C_{charging\ price,t}^{5min,n} = Pch_{EV,n,t}^{5min} \cdot C_{charging\ price,t} \cdot \Delta t^{5min} + I_{power\ dispatching,t}^{5min,n} \quad (31)$$

$$= (Pch_{EV,n,t}^{5min} + Pdis_{EV,n,t}^{5min}) \cdot C_{power\ dispatching,t} \cdot \Delta t^{5min} \quad (32)$$

$$\left\{ \begin{array}{l} C_{EV\ deficiency,n}^{5min} \geq C_{EV}^{penalty} \cdot \left(E_n^{EV} - \left(\sum_{t=t'}^T Pch_{EV,n,t}^{5min} \cdot \eta_{EV}^{ch} \cdot \Delta t^{5min} - \sum_{t=t'}^T Pdis_{EV,n,t}^{5min} \cdot \frac{1}{\eta_{EV}^{dis}} \cdot \Delta t^{5min} \right) \right), \\ \quad \text{if } E_n^{EV} > 0 \\ C_{EV\ deficiency,n}^{5min} \geq C_{EV}^{penalty} \cdot \left(-E_n^{EV} - \left(\sum_{t=t'}^T Pdis_{EV,n,t}^{5min} \cdot \frac{1}{\eta_{EV}^{dis}} \cdot \Delta t^{5min} - \sum_{t=t'}^T Pch_{EV,n,t}^{5min} \cdot \eta_{EV}^{ch} \cdot \Delta t^{5min} \right) \right), \\ \quad \text{otherwise} \\ C_{EV\ deficiency,n}^{5min} \geq 0 \end{array} \right. \quad (33)$$

$$\left\{ \begin{array}{l} Uch_{EV,n,t}^{5min} + Udis_{EV,n,t}^{5min} = 1, \quad \text{if } EV_n^{Trading\ Type} = \text{Auto Controlling Service} \\ Uch_{EV,n,t}^{5min} = 1, Udis_{EV,n,t}^{5min} = 0, \quad \text{else if } EV_n^{Trading\ Type} = \text{Only Charging Service} \\ Uch_{EV,n,t}^{5min} + Udis_{EV,n,t}^{5min} = 1, \quad \text{else if } EV_n^{Trading\ Type} = \text{Green bidirection Chargig Service} \\ Uch_{EV,n,t}^{5min} = 1, Udis_{EV,n,t}^{5min} = 0, \quad \text{else if } EV_n^{Trading\ Type} = \text{Green Power Charging Service} \end{array} \right. \quad (34)$$

TABLE 3. Comparison of 15-min and 5-min centralized optimal scheduling computing time.

Charging Pile Amount	15-MIN CENTRALIZED	5-MIN CENTRALIZED	5MINS DECENTRALIZED
100	00:31.3	04:35.5	3sec
200	01:04.1	08:56.9	3sec
300	01:33.0	13:17.1	3sec
400	02:03.4	17:49.2	3sec
500	02:33.7	22:14.4	3sec
600	03:04.4	27:27.4	3sec
700	03:34.9	31:58.9	3sec
800	04:08.4	38:22.0	3sec
900	04:40.8	41:18.4	3sec
1000	05:14.8	46:05.1	3sec

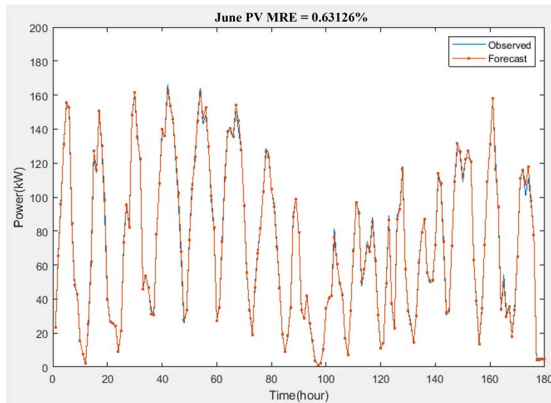


FIGURE 15. The result of PV forecasting.

The load consumption forecasting accuracy takes the mean absolute percentage error (MAPE) as the evaluation index as defined in Eq. (44). The historical load power consumption data and the corresponding weather forecast data of 2021 are utilized with the ratio of 8:2 for training and testing, respectively. The testing results shows average MAPE of 2.95 % is obtained. Compared with the existing literature [41], [42], [43], the results of the proposed load power consumption forecasting model are suitably accurate. As an example, the comparison of forecasting and actual load consumption data on July 23th, 2021 is shown in Fig. 16.

$$MAPE (\%) = \frac{1}{N} \sum_{t=1}^N \frac{|y_t^{pre} - y_t^{true}|}{y_t^{true}} \times 100 \quad (44)$$

where y_t^{true} represents the real value at the time t , y_t^{pre} is the corresponding predicted value, and N is the total cases in the test set.

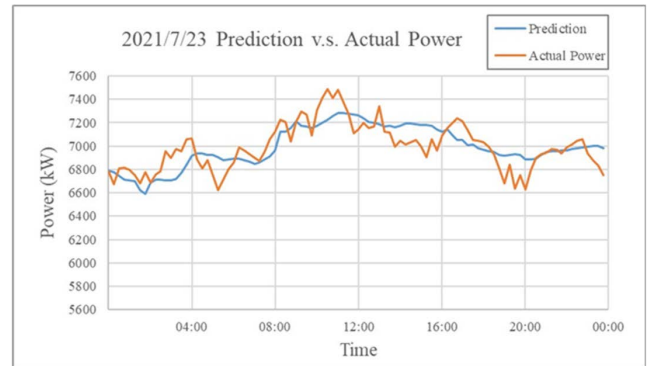


FIGURE 16. The load consumption forecasting.

B. OPTIMAL SCHEDULING RESULTS

If the microgrid is not engaged in any power transaction mode and does not perform optimal scheduling, the EV adopts the method of first come first served upon arrival at the charging station. The overall power of the microgrid is shown in Fig. 17. Because there are commercial buildings in the microgrid, lots of EVs enter buildings after 8:00. If EMS does not perform scheduling control, power congestion of load consumption happens in microgrid, causing instantaneous power to exceed contract capacity and upper limit of transformer capacity, endangering stability and safety of microgrid.

Fig. 18 shows the overall power diagram of centralized optimal EV charging pile control per 15 min of EV charging station. In contrast to Fig. 17, it can be clearly seen that the congestion caused by the arrive of large quantity EVs is solved. Moreover, EV charging station can integrate EVs in its field, participate in DR bidding of power utility, to obtain additional profits, and reward users participating in this power transaction.

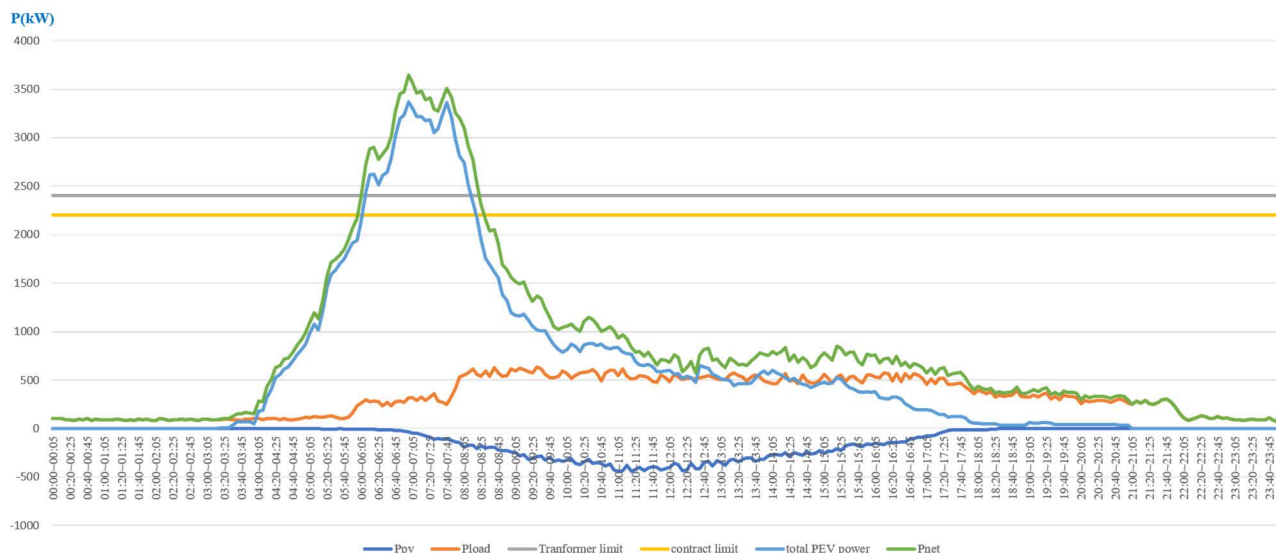


FIGURE 17. Overall power of charging station microgrid without optimal scheduling.

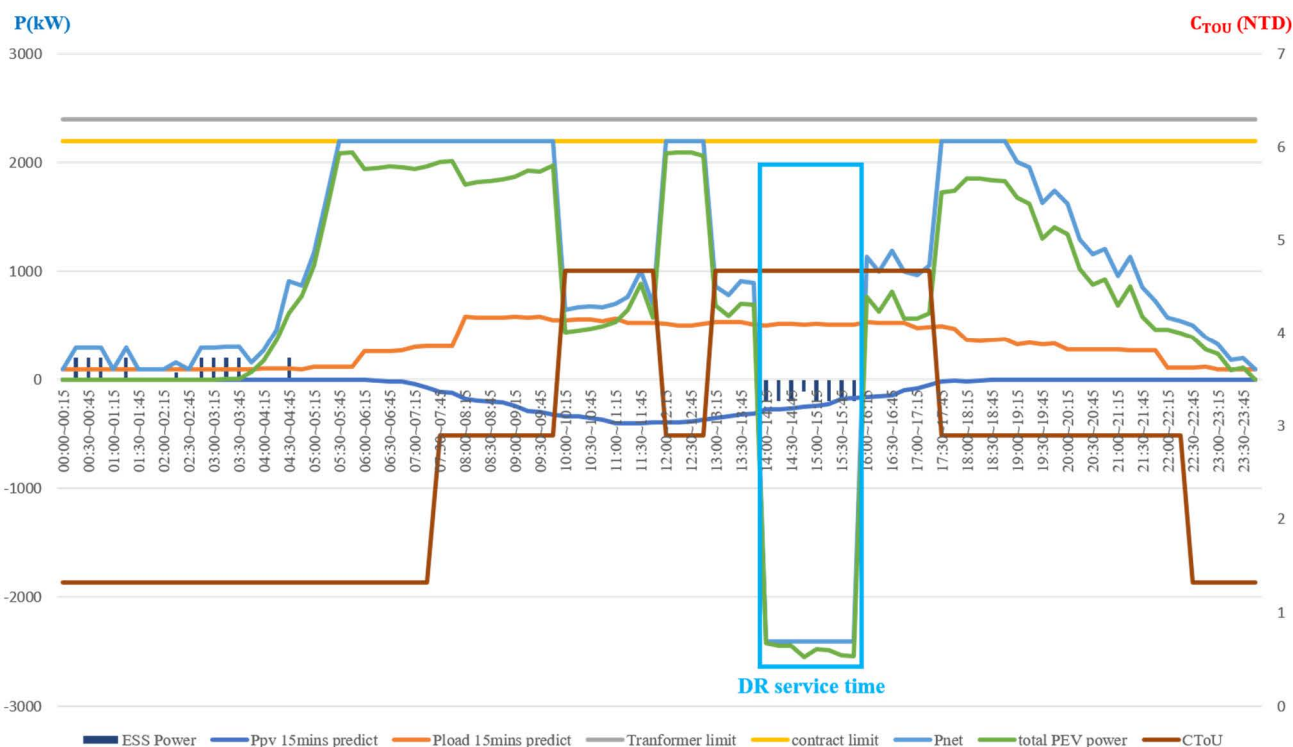


FIGURE 18. Overall power of charging station microgrid with 15-min centralized optimal scheduling.

In simulation considering uncertainty of renewable energy power generation and load consumption, Figs. 19 and 20 illustrates the results of centralized optimal scheduling for 15 min and 5 min respectively. It can be observed that centralized optimization per 5 min has better load peak suppression performance. However, as shown in Table 3, computing time

needed for centralized optimization per 5 min has significantly exceeded its scheduling requirement.

In an EV charging station with more than 100 EVs, centralized optimization architecture for 5 min cannot perform real-time EV charging pile optimal scheduling control. Although centralized optimization architecture for 15 min can meet

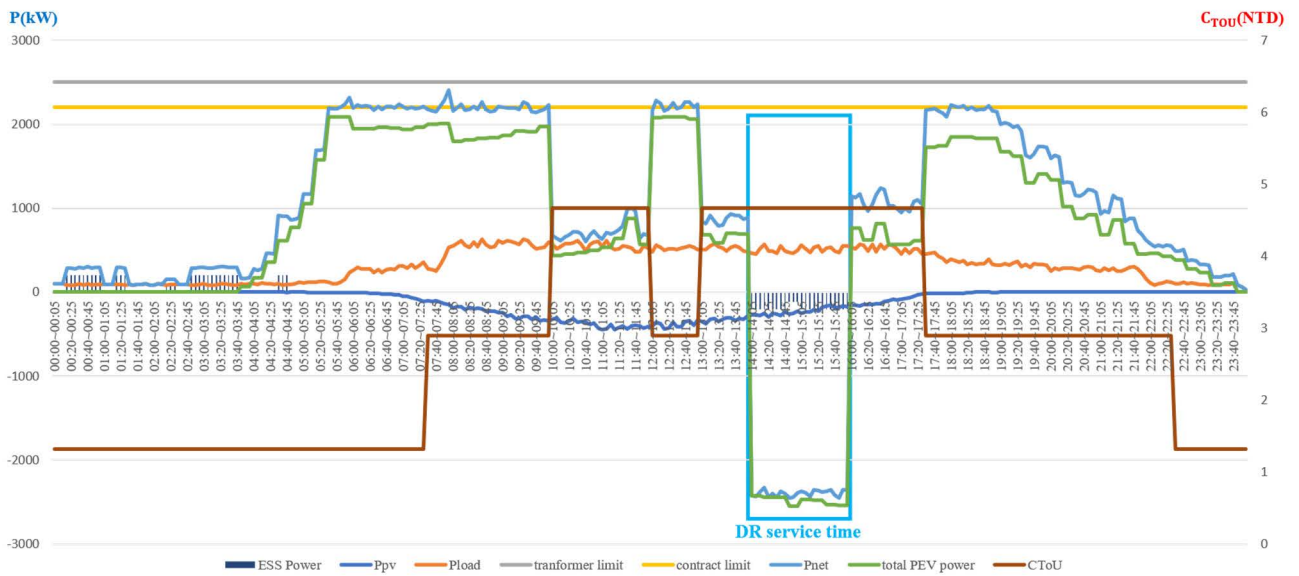


FIGURE 19. Overall power of charging station microgrid with 15-min centralized optimal scheduling considering uncertainty.

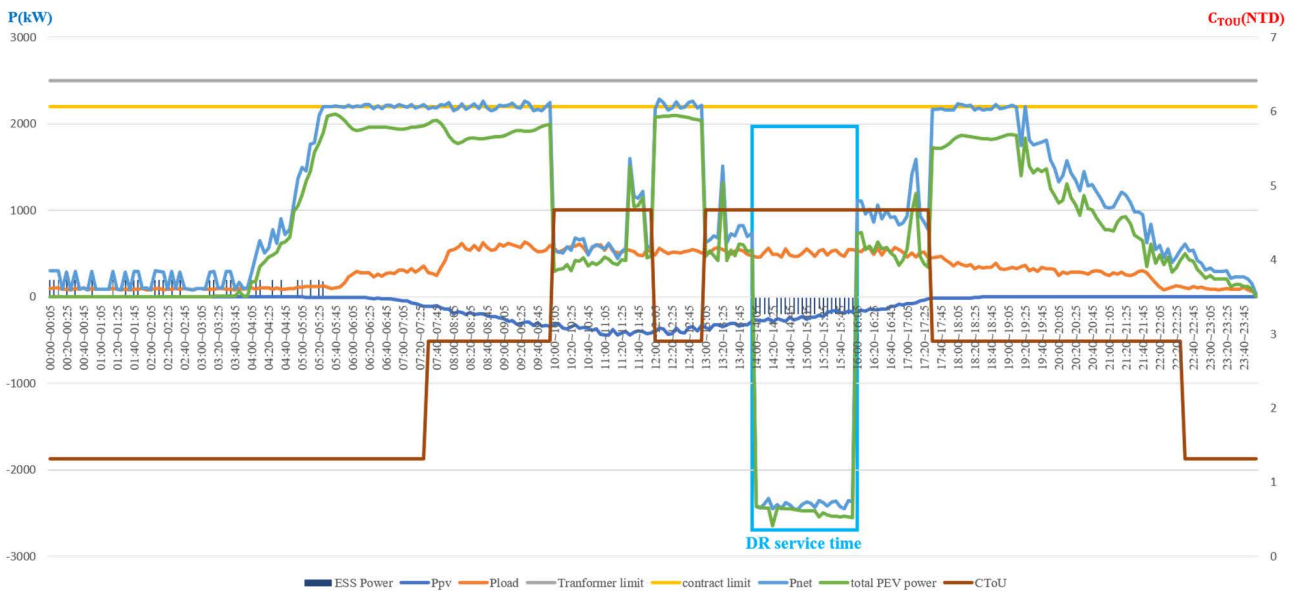


FIGURE 20. Overall power of charging station microgrid with 5-min centralized optimal scheduling considering uncertainty.

scheduling requirement, its control effect did not conform to expectation.

Fig. 21 is the operation result diagram of the double-layer centralized CSMS and decentralized EMS proposed in this paper, considering the uncertainty of power generation and load consumption. On the premise of meeting limited computing time, through taking optimal scheduling guidance of centralized EV charging station performed every 15 min and in cooperation with real-time optimal control of each charging pile executed every 5 min, the goal of peak load

suppression and shaving, and maximization of power utilization efficiency can be achieved.

Fig. 22(a) and (b) show the results of EV charging and discharging scheduling results diagram, which present service mode of only charging in low speed or smart charging and discharging in fast speed, respectively, choosing by EV user. In the only charging mode, EMS performs optimal scheduling control according to actual operation situation in the premise of satisfying the EV charging demand. On the other hand, in the smart charging and discharging mode, EMS

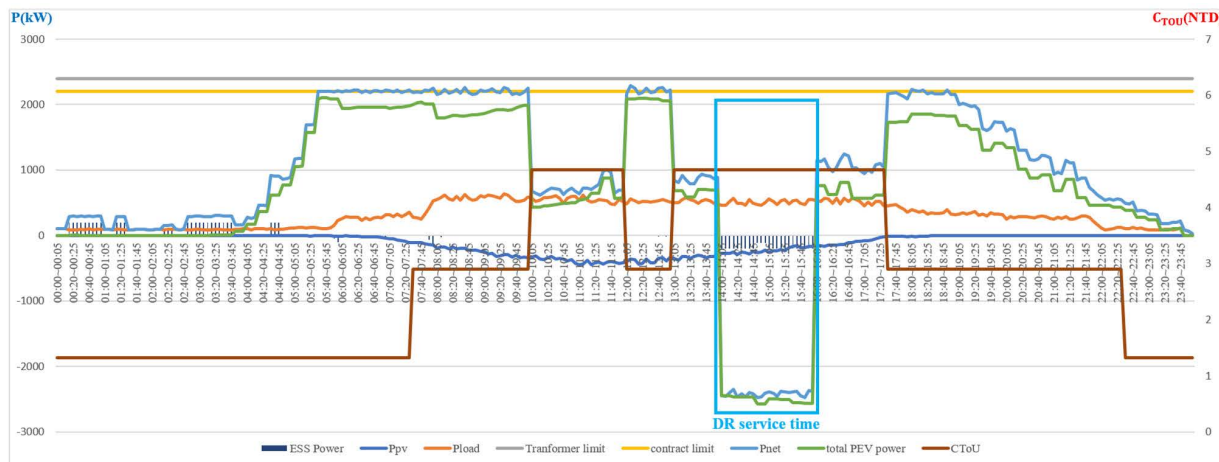


FIGURE 21. Overall power of charging station microgrid with double-layered centralized CSMS and decentralized EMS optimal scheduling considering uncertainty.

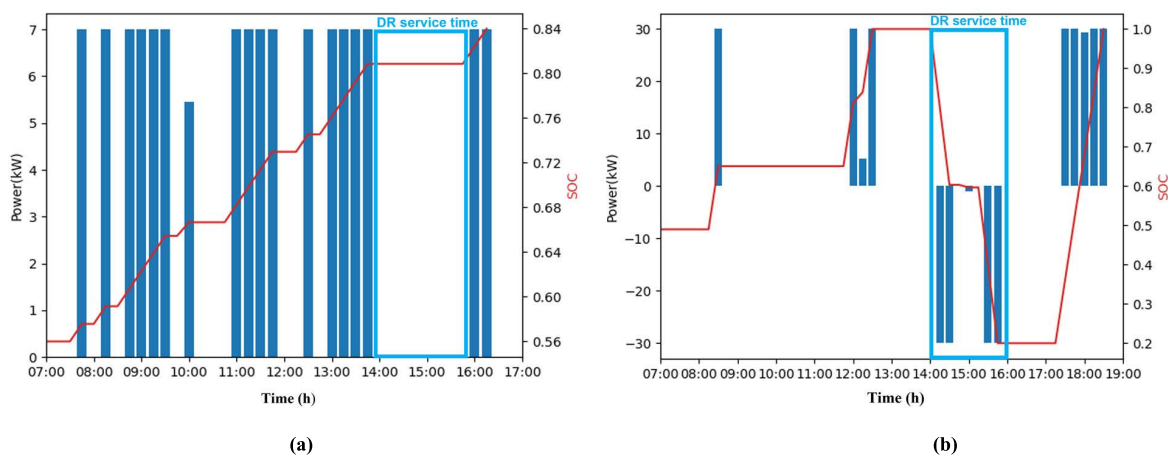


FIGURE 22. EV optimal scheduling result. (a) Only charging service—slow charging, (b) Auto controlling service—fast charging.

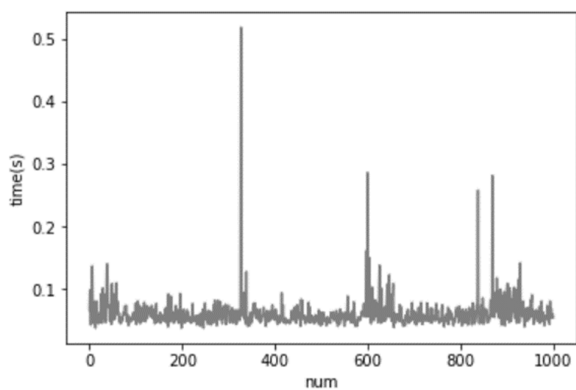


FIGURE 23. Impact of 1000 times of transactions on latency, the average latency is 0.06 sec.

performs optimal scheduling control according to operation situation in the reality of meeting the EV charging demand as a precondition, and discharges in the DR execution period to earn additional profits for EV users.

Table 4 describes comparisons of 15-min and 5-min centralized architectures, and the architecture proposed in this paper. Although the proposed method cannot realize maximization of power utilization efficiency as well as 5-min centralized architecture does, it can reduce penalty cost of contract capacity by 58%, increase operating profit by 2.3%, and decrease charging cost of EV users participating in smart bidirectional charging and discharging by about 10%. The 15-min centralized type, since its incapability of conducting optimal control in short time, is less able to resist fluctuation uncertainty caused by prediction error.

When PV power generation is insufficient, it is necessary to purchase additional high-priced power from the grid, increasing power purchase cost compared to the 5-min centralized architecture. However, the double-layer architecture proposed in this paper is an optimization architecture. By adopting 5-min optimal control, uncertainty of PV power generation is compensated by EVs and ESS devices.

Therefore, PV power generation can be deposited in EVs, and released during DR execution periods. Not only can this

TABLE 4. Comparison of 15-min and 5-min centralized architecture and the architecture proposed in this paper.

	5-MIN CENTRALIZED	15-MINCENTRALIZED	THIS PAPER PROPOSED
Cost			
Contract Capacity Fee	12,239 (NTD)	12,239 (NTD)	12,239 (NTD)
Contract Capacity Penalty	950 (NTD)	2,262 (NTD)	950 (NTD)
Utility Buying Cost	71,291 (NTD)	71,963 (NTD)	71,983 (NTD)
EV User’s Feedback Fund	9,963 (NTD)	9,939 (NTD)	10,032 (NTD)
Total Cost	94,443 (NTD)	96,402 (NTD)	95,203 (NTD)
Income			
EV User’s Charging Fee	100,195 (NTD)	100,195 (NTD)	100,195 (NTD)
DR Event Revenue	68,032 (NTD)	67,912 (NTD)	68,376 (NTD)
Total Income	168,227 (NTD)	168,107 (NTD)	168,572 (NTD)

TABLE 5. Comparison of simulation results of the proposed scheme with the existing schemes.

	Z. WU ET AL. [45]	Y. Li et al. [46]	G. Sun et al. [47]	S. Aggarwal et al. [48]	Y. Li et al. [49]	This Paper
Power Trading Platform	✗	✗	✓	✓	✓	✓
Smart Contract	✗	✗	✓	✓	✓	✓
Miner	✗	✗	✓	✓	✗	✗
Power Data Uploading Way	✗	✗	Centralized	Centralized	Centralized	Decentralized
Ledger Node	✗	✗	Computer	Computer	Computer	Raspberry Pi
Chaining Speed	✗	✗	1.5s	2.3s-3s	1s	0.06s
Optimization Method	PSO	Centralized MILP	✗	✗	Centralized MILP	Centralized + Decentralized MILP
EMS Execution Time in 10 Charging Piles	312.75s	3.02s	✗	✗	4.35s	3s
EMS Execution time in 700 Charging Piles	N.A.	N.A.	✗	✗	213s	3s
DDOS	✗	✗	✗	✓	✗	✓

earn more income for EV charging station, but also additionally reward EV users.

C. BLOCKCHAIN SYSTEM TEST RESULTS

The blockchain system proposed in this paper operates on computer with Intel 4 Core CPU. The blockchain system

built up in this paper for the experiment has 1 orderer node, two peer nodes and two cloud-ledger nodes on an Intel server, and three local ledger-nodes on Raspberry Pi. The blockchain platform is all self-designed. The 1000 times consecutive transactions are tested on chaining process, its results are shown in Fig.23. The average latency

is 0.06 secs. A few long latencies may cause by network delay.

Compared with most of the existing papers, which adopt the Ethereum blockchain technology, the latency of the proposed blockchain system is greatly reduced, making it more suitable for power transaction scenarios. Table 5 provides detail comparisons between this paper and the existing papers. Compared with the latencies of most Ethereum blockchain systems, that of the proposed blockchain system is greatly reduced, making it more suitable for power transaction scenarios.

Compared with the execution speed of optimal scheduling system for numerous EV charging piles in existing schemes, that of the proposed CSMS system is greatly accelerated, making it more suitable for future application scenarios.

VI. CONCLUSION AND FUTURE WORK

The intelligent CSMS of EV charging station based on blockchain technology proposed in this paper, is a relatively complete and forward-looking system with larger numbers of EV charging piles built in, compared to existing methods. This system platform is based on AIoT, combined with blockchain and distributed ledger technologies as a platform capable of conducting power trading, forecasting analysis, performing optimal scheduling management, and dispatching of power transaction automatically.

With the centralized CSMS and distributed EMS to optimize the scheduling of EVs, which enables EV users to participate in green power trading, DR bidding, and a bidirectional charging and discharging dispatching program in charging stations. Not only will EV users obtain extra profits to reduce charging costs, but also the microgrid avoids power congestion, maximizes utilization of renewable energy for power generation, and maintains power supply and demand balance, as well as power quality, to achieve maximization of power utilization efficiency.

In order to manage 700 EV charging piles simultaneously, a double-layer centralized and decentralized optimization algorithm is employed to maximize operating profit of EV charging stations, minimize charging cost for EV users, and avoid congestion of load consumption in charging stations, thereby realizing real-time power supply and demand balance, shaving peak load and reducing power loss.

The innovative design of the proposed system platform redresses disadvantages of the existing EV charging and discharging trading. With the distributed method of the power data collection, this system platform can greatly improve the privacy and safety concerns than other centralized models in existing literature, its data uploading and transaction chaining latency is 0.06 seconds, which can, therefore, accommodate a large number of EV charging piles.

In cooperation with the double-layer optimization architecture proposed in this paper and optimal charging and discharging control of EVs in a decentralized and distributed way, the proposed model can reduce charging station penalty cost of contract capacity by 58%, increase operating profit

by 2.3%, decrease charging cost of EV users participating in smart bidirectional charging and discharging by about 10%, and hundreds of charging piles can be managed within acceptable execution time.

Thus far, the 1,000 charging piles have been simulated for EV charging stations in commercial buildings. Next, the authors plan to implement the platform in a real virtual power plant (VPP) to verify the system platform performance and meet demands for charging and discharging transactions, when the number of EVs increases rapidly. Meanwhile, by integrating more distributed power resources in the power grid through the power trading platform, the overall power utilization efficiency can be maximized to assist the energy management of the participants in the VPP.

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