IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

SPECIAL SECTION ON GREEN INTERNET OF THINGS

Received December 5, 2019, accepted December 17, 2019, date of publication December 23, 2019, date of current version January 16, 2020.

Digital Object Identifier 10.1109/ACCESS.2019.2961394

Optimal Dispatching of Electric Vehicles Based on Smart Contract and Internet of Things

BIN DUAN[1,2], KAIHUA XIN[1,2], AND YING ZHONG[2]
[1]Key Laboratory of Intelligent Computing & Information Processing, Ministry of Education, Xiangtan University, Xiangtan 411105, China
[2]Cooperative Innovation Center for Wind Power Equipment and Energy Conversion, Xiangtan University, Xiangtan 411105, China

Corresponding author: Kaihua Xin (xinkaihua1202@163.com)

This work was supported by the National Nature Science Foundation of China under Grant 61379063.

ABSTRACT The stability and economy of the electronic vehicle distribution network system is increasingly important as the number of electric vehicles in use continues to rise. An electric vehicle (EV) and Internet of things (IoT) charge scheduling method is proposed in this paper which uses smart contract in the distribution network (DN) with uncertain renewable energy output. Based on user charging demand and power grid load level, this paper explores peak load shifting, guiding EV charging options by electricity price to change the demand response of each node, thereby regulating the DN power quality. A smart contract is created between the user and the charging station to realize the electricity price renewal in the power flow calculation cycle. This enhances the rationality of electricity price formulation and reduces deviation between the forecast load and the actual load, ensuring the validity of the method to a certain extent. According to the achievement of the smart contracts signed with the charging station, users are given rewards or fines, which reduces the default rate of the user. This decentralized transaction process improves the security and completeness of the transaction. The feasibility of utilizing this method for the distributed power grid is verified through simulation on a 34-node test system.

INDEX TERMS EV, power sensitivity, power flow calculation, price guidance, smart contract, Internet of Things.

I. INTRODUCTION

Power grid energy is gradually diversifying as the Internet and new energy technology continues to develop. Distributed energy shares the power supply of the power grid and reduces environmental pollution, but because of its dependence on the environment, it increases the instability of power system [1]. As the use of EVs increases, the large-scale charging of EVs will also have a significant impact on the stable operation and planning of the power system [2], [3]. This impact is particularly evident when a large amount of users select fast charging modes. Such modes are different from diffusive and low-power residential charging, which is more suitable for long-distance and energy-consuming residential charging. Because of the need for specific charging facilities, vehicle charging mainly occurs at fixed commercial charging stations, which results in increased centralization and scale of the charging station load.

Faced with the increasing number of charging piles, user privacy protection and transaction security of decentralized power transactions must also be urgently solved. Block-chain technology provides a new solution for distributed resource storage, data protection and historical traceability, which can ensure the storage security and traceability of all historical data. To reduce the deviation between predicted load and actual load, users sign intelligent contracts with charging stations. By using block-chain intelligent contract technology, contracts are saved on block-chain in the form of computer code and automatically triggered to execute, providing a simple and effective settlement process.

The charging choice of EVs is a stochastic and dynamic problem. There are uncertainties in time and space, and users will make different decisions according to their behavior preferences and varying environmental conditions, thus affecting the distribution network load balance [4], [5]. It is therefore necessary to guide the charging selection of electric vehicles to balance the power quality problems caused by renewable energy and reduce the impact of electric vehicle charging on the power grid. Domestic and foreign scholars

The associate editor coordinating the review of this manuscript and approving it for publication was Jun Wu.

have conducted pioneering research into the charging choice of electric vehicles. In [6], a charging dispatching method for grid-based electric vehicles was proposed, which takes into account the uncertainty of wind and photovoltaic output, to reduce the peak-valley load difference and the cost of power purchase. However, the guidance provided by this method is limited, and the results do not correspond well with the predicted values. Literature [7], [8] presented a load forecasting method for charging stations based on large data. Considering the accuracy and reliability of data sources, this method also has some limitations. For the application of block-chains in the field of EV, literature [9] adopted the EV charging strategy based on adaptive module to reduce grid fluctuation and charging cost. In [10], the lightning network and intelligent contract technology was used in block-chain to provide a decentralized security model to improve the security of electric vehicle and charging pile transactions. Literature [11] proposed a smart grid platform EV participation scheme based on adaptive block-chain, which can minimize the power fluctuation level in the grid and the total charging cost of EV users.

This paper uses power flow calculation to predict the line current of the distribution network short-term, formulates the electricity price according to the power sensitivity of the EV charging station node to the overload line, and introduces block-chain technology into the calculation cycle [12]. Within this methodology, the price of electricity is adjusted according to the number of charging vehicles at each charging station and the difference between the actual load and the predicted load is reduced. After responding to the charging decision, the user selects a suitable charging station to submit the power demand, and the charging station can obtain the charging information of the user, thereby improving accuracy of the information source. In addition, a smart contract is arranged between the user and the selected charging station. If the user completes the contract within the specified time, a certain amount of reward will be obtained, otherwise the owner's account will automatically deduct the corresponding liquidated damages. Using this method, the user default rate is reduced to some extent, and the response sensitivity of the pilot price to the line power flow adjustment is increased.

II. ELECTRIC VEHICLE CHARGING FRAMEWORK AND PROCESS

A. OVERALL FRAMEWORK

The optimization of charging options for electric vehicle users has become an important issue due to the gradual popularization of electric vehicles, charging station planning and operation, and grid operation requirements. The charging decisions of electric vehicle users are influenced by various factors which include individual charging habits and preferences, charging station electricity price, road condition information, and battery charging status.

In this paper, user charging selection is completed in the vehicle navigation system of the EV. The vehicle navigation system can carry out an information interaction with the charging station. This system is predominantly comprised of the Internet of Things (IoT) and blockchain, and its overall framework is shown in Fig 1. Its three main components are the information center, central server, and navigation terminal [13]. The information center is the IoT module, which is mainly responsible for collecting the real-time dynamic traffic information, real-time electricity price issued by the distribution network control center to the charging station, and vehicle sate of charge (SOC) information. The central server is the IoT transaction buffer module, which buffers all kinds of transaction information transmitted by the IoT module, and sends the information of alternative charging stations and electricity prices to the navigation terminal. At the same time, the information terminal of the distribution network reads the charging request sent by the EV from the blockchain as the real-time load of charging station node and the basis for the periodic adjustment of the electricity price.

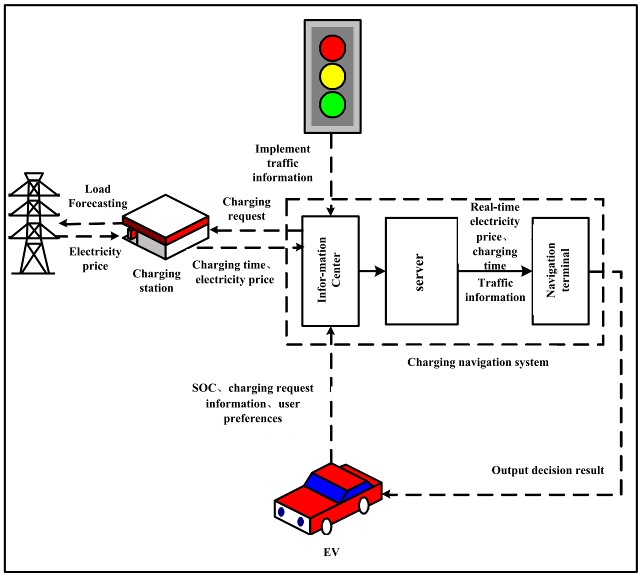

FIGURE 1. Vehicular navigation system structure diagram.

B. EV CHARGING SELECTION DECISION PROCESS

The decision-making process for a single EV user is shown in Fig. 2.

1) ACQUIRE EV CHARGING DEMAND

For a single EV charging decision, it is first necessary to judge the charging demand of the vehicle. When the SOC of the EV is lower than the remaining power threshold S of the user charging habit or the remaining power cannot reach the purpose, the charging demand is triggered and the owner will choose to charge at the surrounding charging station. The charging requirements for EVs are as follows:

$$C = \begin{cases} 1, & SOC \leq S \\ 0, & SOC > S \end{cases} \tag{1}$$

where $C = 1$ means that charging is required, and $C = 0$ means that charging is not required.

The threshold S is determined by the charging habits and preferences of each vehicle owner and can be obtained from

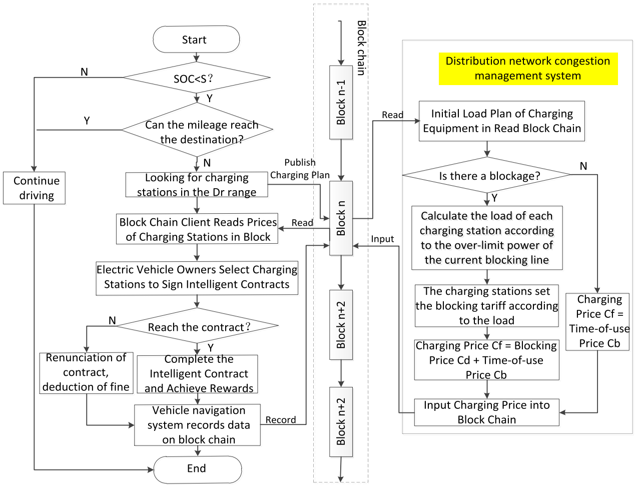

FIGURE 2. **Decision process chart.**

the historical charging data recorded by the EV terminal equipment, subject to a certain probability distribution. This is expressed as follows:

$$P\{S = s_i\} = p_i \quad i = 1, 2, \cdots, I \; 0 \le p_i \le 1 \tag{2}$$

where Si is the SOC value that the user is ready to charge under the i-th charging habit, Pi is the probability that the i-thcharging habit occurs, and the sum is equal to 1.

2) CALCULATE THE RANGE AND OPTIONAL CHARGING STATION SET

By calculating the mileage Dr of the remaining battery SOC, it is found that the current remaining capacity can support the mileage of the vehicle:

$$D_{\mathrm{r}} = \frac{SOD}{\eta} \tag{3}$$

where η is the average energy consumption per kilometer. When the remaining power is insufficient to support the vehicle to reach the destination, the charging demand is triggered, then all the charging stations in the Dr range are calculated according to the current position as an alternative charging station set. The charging station with the lowest electricity price is the optimal choice.

3) BASIC ELECTRICITY PRICE DEVELOPMENT AND UPDATE

The electricity price is set according to the charging demand and the system operating state. The charging station aims to achieve peak clipping and valley filling. To meet the constraints of customer charging demand and grid load balance, the real-time electricity price for the user is dynamically formulated, and the price includes points. The electricity price Cb and the electricity price Cd.

4) ENTER INTO THE CONTRACT TO COMPLETE A TRANSACTION

After the charging station releases the real-time electricity price, the user responds by selecting the charging station and signing the smart contract.The contract contains information including the electricity price, trading time, and default amount, and the user in the regulation. If the charging is completed within the time, a certain reward will be obtained. If the contract is abandoned, the corresponding fine will be deducted for the specific implementation scheme.

III. USER TRANSACTION METHOD BASED ON BLOCK-CHAIN TECHNOLOGY

A. BASIC ELECTRICITY PRICE DEVELOPMENT AND UPDATE

The real-time electricity price for guiding the peak-filling valley is established according to the status of the distribution network. The line current of the distribution network is first predicted. Sensitivity calculation is then performed for the overload branch with the highest severity of voltage and power limit. Finally, the corresponding safety correction strategy is given to improve the safety and stability of the distribution network operation. Considering that the static voltage instability of the system is often caused by the transmission power of a weak branch exceeding its power transmission capability, active power constraint of the weak branch is proposed as the constraint target of static voltage stability (the active power flow of the branch is mainly affected by the node). The injection has an active influence, and the reactive power is increased or decreased according to the power factor.) The optimal compensation scheme and floating electricity price is formulated according to the compensation scheme in order to guide the charging of the electric vehicle to achieve the goal of load peaking and filling the valley.

The distribution network control center obtains the node voltage of each node and the active power of each branch through power flow calculation. If there is a branch overload, the sensitivity matrix of the active point injection active to the active change of the branch and the best compensation power (active power)must be calculated. Branch overload severity [14] Sij is obtained by Eq. (4):

$$S_{ij} = \frac{P_{ij}}{P_{ij\,\max}} \tag{4}$$

where Pij is the active power of the branch, and $Pijmax$ is the maximum active power that the branch can withstand.

The active power Lij in the transmission line can be expressed by the polar coordinate AC power flow model according to Eq.(5). The power sensitivity of the highest branch power to the node injection power is as shown in Eq.(6):

$$\mathrm{L}_{ij} = G_{ij}V_i^2 - G_{ij}V_iV_j\cos\left(\delta_{ij}\right) - B_{ij}V_iV_j\sin\left(\delta_{ij}\right) \tag{5}$$

$$S_i = \frac{\partial L_j}{\partial P_i} = \frac{\partial L_{ij}}{\partial V_i}\cdot\frac{\partial V_i}{\partial P_i} + \frac{\partial L_{ij}}{\partial V_j}\cdot\frac{\partial V_j}{\partial P_i} + \frac{\partial L_{ij}}{\partial \delta_j}\cdot\frac{\partial \delta_j}{\partial P_i} + \frac{\partial L_{ij}}{\partial \delta_j}\cdot\frac{\partial \delta_j}{\partial P_i} \tag{6}$$

where $\partial Lij/\partial Vi$, $\partial Lij/\partial Vj$, $\partial Lij/\partial \delta i$, and $\partial Lij/\partial \delta j$ are obtained by formula (7):

$$\begin{cases} \frac{\partial L_{ij}}{\partial V_i} = 2V_iG_{ij} - V_jG_{ij}\cos\left(\delta_{ij}\right) - V_jB_{ij}\sin\left(\delta_{ij}\right) \\ \frac{\partial L_{ij}}{\partial V_j} = -V_jG_{ij}\cos\left(\delta_{ij}\right) - V_jB_{ij}\sin\left(\delta_{ij}\right) \\ \frac{\partial L_{ij}}{\partial \delta_i} = V_iV_jG_{ij}\sin\left(\delta_{ij}\right) - V_iV_jB_{ij}\cos\left(\delta_{ij}\right) \\ \frac{\partial L_{ij}}{\partial \delta_j} = -V_iV_jG_{ij}\sin\left(\delta_{ij}\right) + V_iV_jB_{ij}\cos\left(\delta_{ij}\right) \end{cases} \tag{7}$$

where Gij and Bij are the conductance and susceptance of line i,j, respectively, Lij is the branch active power, Pi is the n-order node injection power, Vi and Vj are the voltage amplitudes of nodes i and j, respectively, and δi and δj are the phase angle of nodes i, j. The inverse matrix of the iterative equation for the Newton-Raphson method is obtained according to:

$$\begin{bmatrix} \Delta\delta \\ \Delta V \end{bmatrix} = \begin{bmatrix} JB_1 & JB_2 \\ JB_3 & JB_4 \end{bmatrix} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \tag{8}$$

$$\frac{\Delta P_{Ri}}{\Delta P_{Rj}} = \frac{S_{Ri}}{S_{Rj}} \tag{9}$$

where ΔP is the overload of the branch, ΔP_{Ri} is the load that should be adjusted for each load point, and S_{Ri} and S_{Rj} are the sensitivity of the charging station nodes i and j to the branch respectively.

According to the current electricity pricing mechanism, the Cf expression of the charging station can be set as follows:

$$C_f = C_b + C_d \tag{10}$$

where Cb is the time-of-use electricity price of the charging station in operation. The time-sharing electricity price takes the construction cost of each charging station and the charging load margin as the influencing factors on the basis of the trough, average and peak time reference price of the grid, and surrounds the benchmark. As electricity prices fluctuate, Cd is the blocking electricity price for adjusting the grid congestion. When the system has no power limit, it means that no blockage occurs, no adjustment is made, and the electricity price is taken. The formulation of the blocking price Cd is considered from the relative level g and the absolute level h of the node load at the charging station [8]. The expressions are as follows:

$$g = \begin{cases} \sum_{j=1}^{n} E_j - \Delta P_{Ri}, & \sum_{j=1}^{n} E_j > \Delta P_{Ri} \\ k(k < 0), & \sum_{j=1}^{n} E_j < \Delta P_{Ri} \end{cases} \tag{11}$$

where Ej represents the load of the EV j that is added to the charging station node, and k is a constant. When $g > 0$, it means that the load of the charging station node exceeds the load of the charging station at this time, and g is used as a penalty factor on the blocking price. When $g < 0$, it means that the load of the charging station is lower than the load that should be adjusted, and g is deducted as the bonus factor on

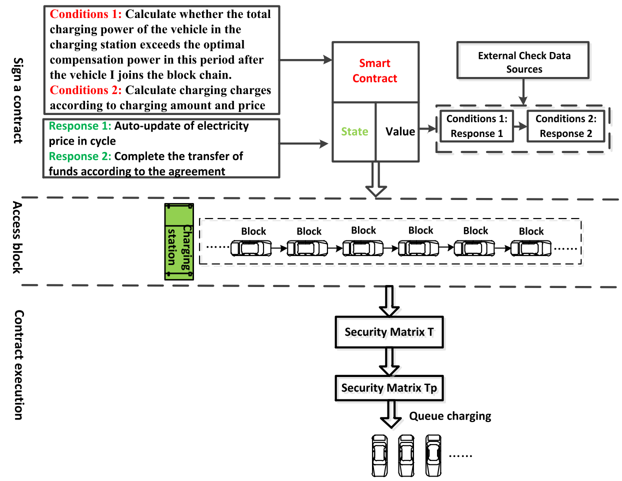

FIGURE 3. Trading framework based on blockchain.

the blocking price. The absolute level h of the charging station load is expressed as follows:

$$h = \left[\frac{\partial L_{ij}}{\partial \theta}\right]^T \cdot \frac{\partial \theta}{\partial P} \tag{12}$$

When $h < 0$, it indicates that the power sensitivity of the charging station node is negative, the load amount is relatively high, and h is used as a penalty factor to increase the blocking power price to reduce the load demand at the point. Additionally, the power negative compensation is completed to make the branch power tend to stable, and power sensitivity is negatively correlated with power negative compensation. When $h > 0$, it indicates that the power sensitivity of the charging station node is positive, the load amount is relatively low, h is deducted as the bonus factor in the floating electricity price, and the power positive compensation is completed by increasing the load demand. In this scenario, the power sensitivity and the power positive compensation are positive correlation.

The blocking electricity price Cd of the charging station is:

$$C_d = (\alpha \cdot g + \beta \cdot h) \cdot C_r \tag{13}$$

where α and β are price adjustment factors, which are used to reflect the weight of g and h, which can be revised according to the feedback effect of the user, and Cr is the compensation unit price.

B. TRADING FRAMEWORK BASED ON BLOCKCHAIN TECHNOLOGY

The EV charging transaction framework designed in this paper is shown in Fig.3. A decentralized trading mechanism is adopted to guide the EV users by establishing a real-time electricity price that is favorable for adjusting the load balance of power grid charging, thereby eliminating power quality disturbances caused by load imbalance.

Each EV user will become a unified blockchain client, and the owner will receive an e-wallet containing real-time information on all transactions. After responding to the charging decision, the user selects the appropriate charging station to submit the power demand in combination with the price of the charging station, concludes the smart contract, and obtains the public key. The optimal control amount of each charging station is used as the condition for automatically pre-writing the smart contract. When the user completes the charging, the total power of the EV in the current period is calculated. If the compensation amount of the charging station exceeds the contract condition, Condition 1 is triggered, automatically updating the electricity price during the calculation period. This price will be the electricity price of the next user arriving at the charging station.

For all EVs that join the blockchain, the safety matrix *Tp* (according to the time when the EV arrives at the selected charging station area) is queued for charging, and the user signs the transaction with the public key as the transaction voucher. When the EV charging is completed, the smart contract Condition 2 is reached. According to the actual power consumption data of the user and the pre-agreed electricity price, the blockchain system automatically executes a contract to complete the transfer of funds and provides the corresponding reward for the contract. If the contract is breached, the corresponding liquidated damages will be automatically deducted from the account. Throughout the process, the smart meter keeps track of power usage including power, price, transaction time, and the default amount [15]–[17], records it on the blockchain and broadcasts it to the entire network. The node reached a consensus.

Using blockchain technology, market participants can manage transactions spontaneously, and the information exchange between the EV and the distribution network can be completed through the smart contract. In the whole response process, real-time data sharing and automatic operation can be realized without the participation of a third party. This paper divides the automatic payment process of EVs into three steps. These include constructing the transaction security matrix *Tp*, user transaction voucher acquisition [18], and identity verification and transaction settlement. The power flow calculation and electricity price update are in a cycle of 30 minutes, so a cycle is set for the transaction and a set of transactions is reached within this time frame.

(1) According to the local charging request of each charging station, the matrix T is formed in chronological order, then the matrix *T* is modified according to the time when the EV reaches the selected charging station area and the secure transaction matrix *Tp* is obtained.

(2) Each charging station obtains the hash value of the last local transmission, signs it through its own private key R, and packages the signature and public key H (R) to each EV with the security matrix in order, as the transaction voucher [19]. After charging the electricity submitted in accordance with the contract, two intelligent contracts are triggered and settled according to the electricity price agreed in the contract, the value transfer is completed, rewards are received,and it is announced to the network, and updated in the blockchain account book. If the transaction is not completed during the clearing period, the default penalty is automatically deducted from the user's wallet [20].

TABLE 1. Optimal load work adjustment measures.

Charging station	Sensitivity to branch 6-7	Optimal compensation
1	0.68867	-0.09879
2	0.65937	-0.09491
3	0.28566	0.03965
4	-0.28566	0.03965
5	0.65947	-0.09480

TABLE 2. Price parameter.

Serial number	Compen sation price (yuan/k W•h)	Load capacity of each EV (MW)	Floating price (yuan/kW •h)	Time -of- use price (yuan /kW· h)	Trans- action reach- ed a reward amount (yuan/k W•h)	Transac tion default penalty amount (yuan/k W•h)
2	3.5	0.10	-0.10	0.95	1	-2
3	2	0.28	-0.71	1.1	2	-1
5	2	0.30	0.58	1.05	0	-1

- Charging stub master B obtains the hash hash value of the previous block, uses the private key to sign it to generate the public key H(R), sets the agreed charging amount and the updated electricity price, sends the public key H(R) to the electric car owner A, and keeps the hash key R.
- The EV owner provides the public key H(R) for charging the main verification key R, and if it matches the charging main B configuration opening key, the charging is completed.
- The EV owner A submits H(R) and triggers the smart contract, settles according to the electricity price agreed in the contract, completes the value transfer, and obtains the reward.
- The transaction will announce the transaction information in all directions, including the electricity price transaction time and reward or punishment amount, and update the blockchain ledger.

IV. METHOD VALIDATION

A. PARAMETER SETTINGS

In this paper, the 34-node distribution network system and 36 network nodes are used for verification. The photovoltaic (PV) cells are added at node 34, and the predicted PV output power and short-term load forecast of the PV power plant are read into the distribution network control center for power flow. When the distribution network is in normal operation, the node voltage amplitude is [0.950, 1.050] *pu*, and the active limit of the line is 0.70 *pu*. Based on the results of the power flow calculation, the node voltage over-limit reactive power compensation and the branch power over-limit active compensation are shown in Table 3 and Table 4 respectively (see Appendix A, B).

TABLE 3. Reactive power deviation corresponding to node voltage limit.

Node number	U_{MEAN}/PU	Overshoot or not	Voltage deviation	Node number	U_{MEAN}/PU	Overshoot or not	Voltage deviation
1	1.0300	No	0.0000	18	1.0249	No	0.0000
2	1.0267	No	0.0000	19	1.0249	No	0.0000
3	1.0256	No	0.0000	20	1.0247	No	0.0000
4	1.0239	No	0.0000	21	1.0247	No	0.0000
5	0.9979	No	0.0000	22	1.0135	No	0.0000
6	0.9970	No	0.0000	23	1.0112	No	0.0000
7	0.9929	No	0.0000	24	1.0105	No	0.0000
8	0.9910	No	0.0000	25	1.0105	No	0.0000
9	0.9274	Yes	-0.0226	26	0.9971	No	0.0000
10	0.9461	Yes	-0.0039	27	0.9979	No	0.0000
11	0.9456	Yes	-0.0044	28	0.9978	No	0.0000
12	0.9440	Yes	-0.0060	29	0.9977	No	0.0000
13	0.9395	Yes	-0.0105	30	0.9982	No	0.0000
14	0.9352	Yes	-0.0148	31	0.9982	No	0.0000
15	0.9351	Yes	-0.0149	32	0.9985	No	-0.0000
16	0.9274	Yes	-0.0226	33	1.0003	No	-0.0000
17	0.9832	No	0.0000	34	1.0006	No	-0.0000

TABLE 4. The active deviation of the branch power exceeding the limit.

LINE	P_{MEAN}/PU	OVERSHOOT OR NOT	ACTIVE POWER DEVIATION	LINE	P_{MEAN}/PU	OVERSHOOT OR NOT	ACTIVE POWER DEVIATION
1-2	1.1658	Yes	0.1658	15-16	0.1997	No	0.0000
2-3	0.8491	No	0.0000	16-17	0.0000	No	0.0000
2-18	0.0651	No	0.0000	18-19	0.0650	No	0.0000
3-4	0.4578	No	0.0000	19-20	-0.0000	No	0.0000
3-22	0.3903	No	0.0000	20-21	0.0000	No	0.0000
4-5	1.0980	Yes	0.0980	22-23	0.2377	No	0.0000
5-6	1.0711	Yes	0.0711	23-24	0.1367	No	0.0000
6-7	1.2089	Yes	0.2089	24-25	0.0000	No	0.0000
6-26	-0.1387	No	0.0000	26-27	-0.2802	No	0.0000
7-8	1.2039	Yes	0.2039	27-28	0.1962	No	0.0000
8-9	0.8296	No	0.0000	28-29	0.0726	No	0.0000
9-10	0.8232	No	0.0000	29-30	-0.0783	No	0.0000
10-11	0.6668	No	0.0000	30-31	-0.2142	No	0.0000
11-12	0.5323	No	0.0000	31-32	-0.3358	No	0.0000
12-13	0.3454	No	0.0000	32-33	-0.4829	No	0.0000
13-14	0.2007	No	0.0000	33-34	-0.4839	No	0.0000
14-15	0.1997	No	0.0000	--	--	--	--

After the power flow calculation, the current power limit of the three branches is obtained. According to the priority, the block adjustment of branch 6-7 with the most severe active power limit is targeted. After adjusting the optimal load power shown in Table 1, the node voltage and the branch power can be adjusted to the normal range, which proves the effectiveness of the method (see Appendix C, D for adjustment results).

B. CHARGING DECISION MAKING.

It is assumed that each EV is equipped with a car navigation device, which can obtain the road condition information and

TABLE 5. Node voltage adjusted at optimum load power.

Node number	U_{MEAN}/PU	Overshoot or not	Voltage deviation	Node number	U_{MEAN}/PU	Overshoot or not	Voltage deviation
1	1.0300	No	0.0000	18	1.0246	No	0.0000
2	1.0274	No	0.0000	19	1.0246	No	0.0000
3	1.0268	No	0.0000	20	1.0245	No	0.0000
4	1.0265	No	0.0000	21	1.0245	No	0.0000
5	1.0081	No	0.0000	22	1.0146	No	0.0000
6	1.0075	No	0.0000	23	1.0124	No	0.0000
7	1.0043	No	0.0000	24	1.0117	No	0.0000
8	1.0028	No	0.0000	25	1.0117	No	0.0000
9	0.9968	No	0.0000	26	1.0076	No	0.0000
10	0.9684	No	0.0000	27	1.0083	No	0.0000
11	0.9680	No	0.0000	28	1.0083	No	0.0000
12	0.9669	No	0.0000	29	1.0084	No	0.0000
13	0.9636	No	0.0000	30	1.0086	No	0.0000
14	0.9611	No	0.0000	31	1.0087	No	0.0000
15	0.9611	No	0.0000	32	1.0090	No	-0.0000
16	0.9566	No	0.0000	33	1.0108	No	-0.0000
17	0.9566	No	0.0000	34	1.0110	No	-0.0000

TABLE 6. Node voltage adjusted at optimum load power.

Node number	U_{MEAN}/PU	Overshoot or not	Voltage deviation	Node number	U_{MEAN}/PU	Overshoot or not	Voltage deviation
1	1.0300	No	0.0000	18	1.0246	No	0.0000
2	1.0274	No	0.0000	19	1.0246	No	0.0000
3	1.0268	No	0.0000	20	1.0245	No	0.0000
4	1.0265	No	0.0000	21	1.0245	No	0.0000
5	1.0081	No	0.0000	22	1.0146	No	0.0000
6	1.0075	No	0.0000	23	1.0124	No	0.0000
7	1.0043	No	0.0000	24	1.0117	No	0.0000
8	1.0028	No	0.0000	25	1.0117	No	0.0000
9	0.9968	No	0.0000	26	1.0076	No	0.0000
10	0.9684	No	0.0000	27	1.0083	No	0.0000
11	0.9680	No	0.0000	28	1.0083	No	0.0000
12	0.9669	No	0.0000	29	1.0084	No	0.0000
13	0.9636	No	0.0000	30	1.0086	No	0.0000
14	0.9611	No	0.0000	31	1.0087	No	0.0000
15	0.9611	No	0.0000	32	1.0090	No	-0.0000
16	0.9566	No	0.0000	33	1.0108	No	-0.0000
17	0.9566	No	0.0000	34	1.0110	No	-0.0000

charging station electricity price data related to the charging decision in real time [21] (the current flow calculation takes 30 min as a cycle, the electricity price is also updated in 30 min cycles). The current EV trigger charging demand is set, and the nearest three charging stations are determined as 2, 3, and 5, respectively. The charging station is then selected by the user.

C. CLUSTER EV CHARGING ADJUSTMENT RESULTS

To verify the effectiveness of the power sensitivity-based charging decision method in this paper, the average power consumption of each household in the distribution network during the peak load period to 4 kW, and 500 households were set up in the area, with 550 EVs [22] that require fast charging every day. The average daily travel distance

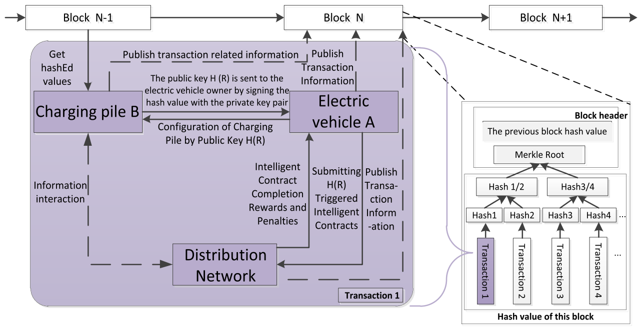

FIGURE 4. Trading example based on blockchain.

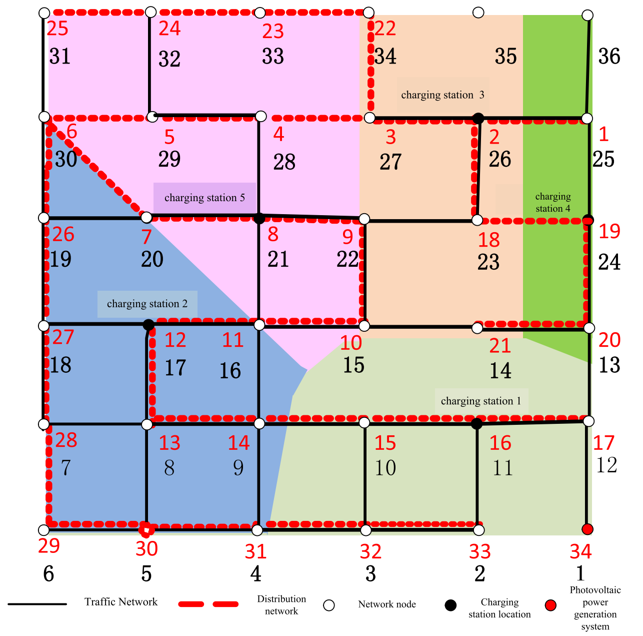

FIGURE 5. Structure diagram of 34 node circuit and traffic routes.

of the car was 54.3 km (see Appendix E for the probability distribution map). The time-of-use electricity price was the peak electricity price from 6 am to 11 pm in the daytime, and the trough price was from 11 pm in the night to 6 am the following day. In addition, the fast charging power is 50 kW.

To more accurately verify the effect of introducing blockchain technology and guiding the price of the peak to fill the valley, the reality that some owners may eventually abandon the execution of the contract for various objective reasons must be considered. According to experiments conducted in literature [23] the use of blockchain smart contracts can effectively reduce the default rate of users. This paper simulates the charging demand of EVs in one day by Monte Carlo method. After using the guiding price, the default rate was set to 0, 20%, and 40% to compare the load curve of the conventional load. As shown in Fig. 6, the load before adjustment has obvious peaks and valleys. After adjusting the demand response by the charging decisions used in this paper, the daytime load tends to decrease, and at 6 am and 11 pm (the critical point of time-sharing electricity price division),

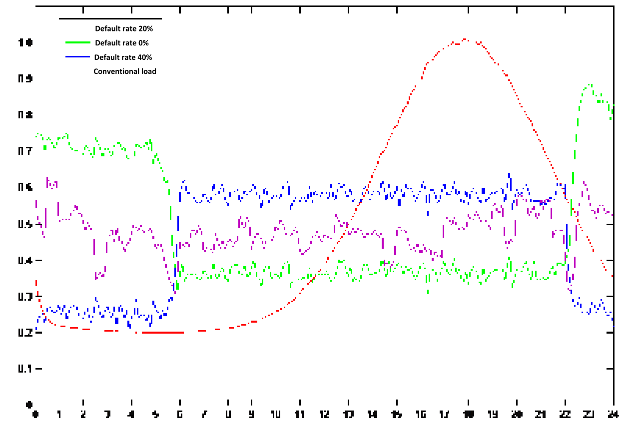

FIGURE 6. Load comparison before and after adjustment.

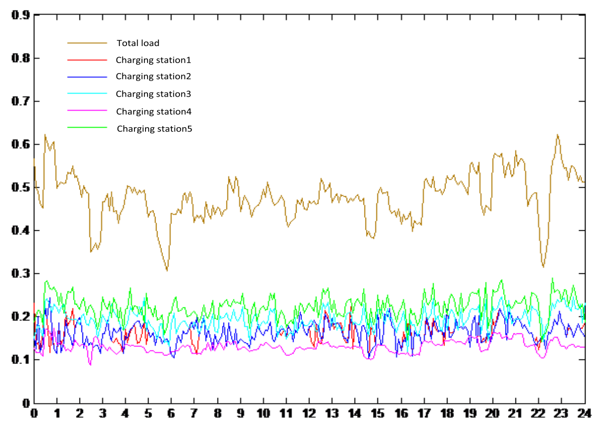

FIGURE 7. Load curve of each charging station.

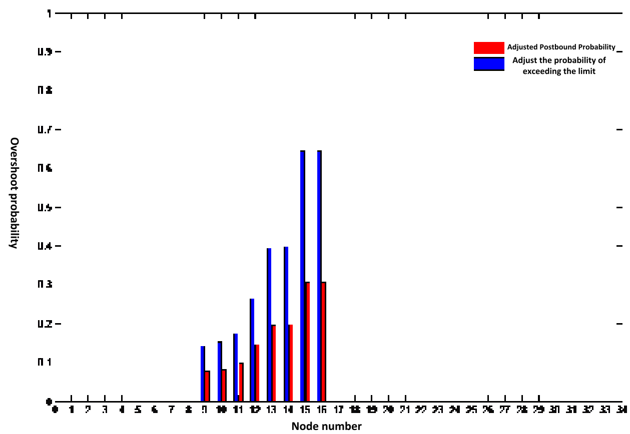

FIGURE 8. Load curve of each charging station.

a sudden drop in the vicinity occurs. However, as the default rate increased, the adjustment effect dropes significantly[24]. The result of this experiment shows that the default rate is reduced and the load adjustment effect is improved. When the default rate of 20%, the charging curve of each charging station is as shown in Fig. 7, in which charging station 5 has a relatively high total load due to the largest number of traffic branches connected to the network node.

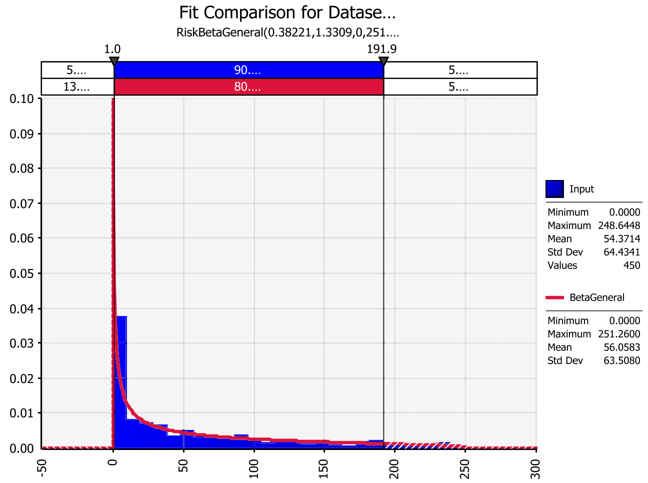

FIGURE 9. **Probability distribution of daily mileage of electric vehicle.**

Based on the semi-invariant method and the Gram-Charlier series expansion [25], random power flow calculation is performed on the system with the default rate of 20%. The voltage over-limit probability of the 33 nodes except the node 1 (balance node) in the distribution network is shown in Fig. 8. It can be observed that after adjusting the demand response, the probability of each node exceeding the limit is reduced to a certain extent, and node 14 drops by up to 65.55%, which is more conducive to the safe operation of the power grid system.

V. CONCLUSION AND DISCUSSIONS

Charging choice has a great influence on stable operation of the power system for the random load of electric vehicles. Based on comprehensive consideration of user charging demand and grid load level, this paper aimed to cut the peak, reduce the valley, and guide charging price. EVs are charged to alter the demand response of each node to ensure the stability of the grid. By creating a smart contract between the user and the charging station, adjusting the electricity price during the power flow calculation cycle, and enhancing the rationality of the electricity price setting, the default rate selected by the user is reduced, and the effectiveness of the method is guaranteed a certain extent. When the EV is charged on demand, the smart contract conditions are fulfilled, the system automatically executes the contract, and the transaction is completed. This decentralized transaction process improves the security and completeness of the transaction.

CONFLICTS OF INTEREST

The authors declare that there are no competing interests.

APPENDIXES

APPENDIX A

See Table 3.

APPENDIX B

See Table 4.

APPENDIX C

See Table 5.

APPENDIX D

See Table 6.

APPENDIX E

See Figure 8.

REFERENCES

[1] G. N. Wang, J. F. Yang, and S. Wang, "Distributed optimization of power grid considering dispatch of electric vehicle battery swapping station and blockchain storage," *Electr. Power Autom. Equip.*, vol. 34, no. 2, pp. 19–23 and 29, 2014.

[2] A. Karpenko, T. Kinnunen, and M. Madhikermi, "Data exchange interoperability in IoT ecosystem for smart parking and EV charging," *Sensors*, vol. 18, no. 12, p. 4404, 2018.

[3] Q. Guo, S. Xin, H. Sun, Z. Li, and B. Zhang, "Rapid-charging navigation of electric vehicles based on real-time power systems and traffic data," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1969–1979, Jul. 2014.

[4] Z. Zhou, J. Gong, Y. He, and Y. Zhang, "Software defined machine-to-machine communication for smart energy management," *IEEE Commun. Mag.*, vol. 55, no. 10, pp. 52–60, Oct. 2017.

[5] C. W. Gao and L. Zhang, "A survey of influence of electrics vehicle charging on power grid," *Power Syst. Technol.*, vol. 35, no. 2, pp. 127–131, 2014.

[6] Z. Zhou, C. Sun, R. Shi, Z. Chang, Y. Li, and S. Zhou, "Robust energy scheduling in vehicle-to-grid networks," *IEEE Netw.*, vol. 31, no. 2, pp. 30–37, Mar./Apr. 2017.

[7] L. Ma, N. Liu, J. Zhang, and L. Wang, "Real-time rolling horizon energy management for the energy-hub-coordinated prosumer community from a cooperative perspective," *IEEE Trans. Power Syst.*, vol. 34, no. 2, pp. 1227–1242, Mar. 2019.

[8] X. Huang, W. Chen, H. Yang, L. Jiang, Y. Cao, and Y. Chen, "Load forecasting method for electric vehicle charging station based on big data," *Autom. Electr. Power Syst.*, vol. 40, pp. 68–74, Jun. 2016.

[9] X. Huang, Y. Zhang, D. Li, and L. Han, "An optimal scheduling algorithm for hybrid EV charging scenario using consortium blockchains," *Future Gener. Comput. Syst.*, vol. 91, pp. 555–562, Feb. 2019.

[10] C. Camus, T. Farias, and J. Esteves, "Potential impacts assessment of plug-in electric vehicles on the Portuguese energy market," *Energy Policy*, vol. 39, no. 10, pp. 5883–5897, 2011.

[11] Z. Su, Y. Wang, Q. Xu, M. Fei, Y.-C. Tian, and N. Zhang, "A secure charging scheme for electric vehicles with smart communities in energy blockchain," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4601–4613, Jun. 2019.

[12] S. Su, J. W. Sun, X. N. Lin, and X. Li, "Electric vehicle smart charging navigation," *Proc. CSEE*, vol. 33, no. s1, pp. 59–67, 2013.

[13] C. Liu, K. K. Chai, and X. Zhang, "Adaptive blockchain-based electric vehicle participation scheme in smart grid platform," *IEEE Access*, vol. 6, pp. 25657–25665, Jul. 2018.

[14] X. Huang, C. Xu, P. Wang, and H. Liu, "LNSC: A security model for electric vehicle and charging pile management based on blockchain ecosystem," *IEEE Access*, vol. 6, pp. 13565–13574, Jan. 2018.

[15] D. Liu, Y. Chen, K. K. Chai, and T. Zhang, "Optimal user association for delay-power tradeoffs in HetNets with hybrid energy sources," in *Proc. IEEE PIMRC*, Sep. 2014, pp. 1857–1861.

[16] P. Huang, C. Shen, and Y. Chen, "An asynchronous iterative distributed algorithm for unified power flow calculation of vertically integrated power systems," *Power Syst. Technol.*, vol. 32, no. 7, pp. 19–24, Apr. 2008.

[17] S. W. Zhang, Y. G. Luo, and K. Q. Li, "Multi-objective optimization for traveling plan of fully electric vehicles in dynamic traffic environments," *J. Tsinghua Univ. (Sci. Technol.)*, vol. 56, no. 2, pp. 130–136, 2016.

[18] N. Liu, J. Wang, and L. Wang, "Hybrid energy sharing for multiple microgrids in an integrated heat-electricity energy system," *IEEE Trans. Sustain. Energy*, vol. 10, no. 3, pp. 1139–1151, Jul. 2019.

[19] B. Li, Q. Y. Qin, B. Qi, Y. Sun, D. Z. Li, K. Shi, B. Yang, and P. F. Xi, "Design of distributed energy trading scheme based on blockchain," *Power Syst. Technol.*, vol. 43, no. 3, pp. 961–972, 2019.

[20] G. Ramezan and C. Leung, "A blockchain-based contractual routing protocol for the Internet of Things using smart contracts," *Wireless Commun. Mobile Comput.*, pp. 1–14, 2018.

[21] J. Kang, R. Yu, X. Huang, S. Maharjan, Y. Zhang, and E. Hossain, "Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains," *IEEE Trans. Ind. Informat.*, vol. 13, no. 6, pp. 3154–3164, Dec. 2017.

[22] N. Liu, M. Cheng, X. Yu, J. Zhong, and J. Lei, "Energy-sharing provider for PV prosumer clusters: A hybrid approach using stochastic programming and stackelberg game," *IEEE Trans. Ind. Electron.*, vol. 65, no. 8, pp. 6740–6750, Aug. 2018.

[23] L. Ma and S. Zhu, "Application and risk of block chain technology in payment and settlement," *Financial Rev.*, vol. 10, no. 4, pp. 83–94 and 121, 2018.

[24] I. Alqassem and D. Svetinovic, "Towards reference architecture for cryptocurrencies: Bitcoin architectural analysis," in *Proc. IEEE Internet Things (iThings), IEEE Int. Conf. Green Comput. Commun. (GreenCom), IEEE Cyber, Phys. Social Comput. (CPSCom)*, Sep. 2014, pp. 436–443.

[25] Z. Y. Zhou, B. C. Wang, M. C. Dong, and K. Ota, "Secure and efficient vehicle-to-grid energy trading in cyber physical systems: Integration of blockchain and edge computing," *IEEE Trans. Syst., Man, Cybern. Syst.*, to be published.

BIN DUAN received the M.E. degree in industrial automation specialty from Beihang University, China, in 1992. He is currently a Professor and a Ph.D. Supervisor with Xiangtan University. He has published about 30 high quality referred articles in international conferences and journals. His current research interests include power systems and automation, power communication network and systems, and smart grid.

KAIHUA XIN is currently pursuing the M.E. degree in electrical engineering with Xiangtan University, China. She is currently working on the optimal scheduling of electric vehicles. Her current research interests include blockchain, the Internet of Things, and optimized scheduling.

YING ZHONG is currently pursuing the master's degree in electrical engineering from Xiangtan University, China. She is currently studying power system automation and electric vehicles. Her current research interests include smart micro grid, the Internet of Things, and blockchain.