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Blockchain-based Renewable Energy Trading Using Information Entropy Theory

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***Abstract*—Renewable energy sources (RES) and electric vehicles (EVs) are widely recognized as primary ways to reduce carbon emissions and essential components of low-carbon power systems. However, both of them have strong uncertainties which bring great challenges to power transactions and the operation of power grids. This paper defines the uncertainty cost of wind power producer(WPP) in day-ahead(DA) market pricing based on information entropy theory for the first time and proposes a EV charging management strategy with DA contract. The constructed low-carbon emission electricity market(LCEM) quantifies the uncertainty cost and contracts the disordered charging of EVs. It reduces the uncertainty and ensures the balance of power supply and demand. In addition, the transaction between WPP and EVs is described as the Stackelberg game, and its communication network is constructed through a blockchain network to ensure transaction efficiency and privacy security. Experiments show that LCEM can accurately measure the uncertainty of wind power generation, increase the net profit for WPP by more than 2% when the prediction error is greater than 10%, and adopt EV contract charging management in the DA market to minimize charging costs.**

***Index Terms*—Renewable energy trading, Stackelberg game, information entropy, blockchain, low-carbon emissions.**

NOMENCLATURE

Abbreviations

DA	Day-ahead
EV	Electric vehivles
IE	Information entropy
LCEM	Low-carbon emission electricity market
RES	Renewable energy sources
RT	Real-time
WPP	Wind power producer

Indexes

$\mathcal{N}$	Set of EV nodes
i	Sequence number of the EV node
X	Set of power generation forecasts

Parameters

$\eta_t^{\mathrm{cha/discha}}$	Charge and discharge efficiency of energy storage at t
λ^{av}	Average value of DA price
a	Information entropy capacity compensation coefficient
$B_{ES,ini}$	Initial energy storage capacity
H_M	Maximum entropy of the system in probabilistic scenarios
k_1	Conversion coefficient of information entropy price
k_2, k_3	Conversion coefficient of information entropy capacity
T	LCEM transaction cycle
x	Power generation forecast

Variables

λ^{IE}	Information entropy electricity price
$\lambda_t^{(\cdot)}$	Price of electricity in market $(\cdot)$ at t
B_{ES}	Energy storage capacity
B_i	Battery capacity of EV node i
b_t	Boolean variable for transaction status
H	System information entropy
$P(x)$	Probability of random forecast
P^{RES}	WPP purchases electricity from RES outside the market with contract in DA market
$P_{ES,t}^{RT,Sell/Buy}$	Electricity sold/buyed by energy storage in RT market at t
$P_{i,t}^{(\cdot)}$	Charging power of EV node i at time t in $(\cdot)$ market
$P_t^{discha/cha}$	Energy storage discharge/charge power at period t
S^{IE}	Information entropy electricity capacity
t	Charging period of EVs

This work was supported in part by the National Key Research and Development Program of China under Grant 2018YFA0702200, the National Natural Science Foundation of China under Grants U20A20190 and 62073065 and the Liaoning Revitalization Talents Program under Grant XLYC2007181.
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Manuscript received xxx xx, xxxx; revised xxxx xx, xxxx.

I. INTRODUCTION

THE electricity market serves as a concrete expression of energy policy. It is an essential measure to deal with the energy crisis caused by the expansion of population and industries, and the climate deterioration caused by excessive

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carbon dioxide(CO2) emissions [1]. In addition, the development of renewable energy sources(RES) and low-carbon loads in new power systems also aim to solve the above problems [2]–[4]. However, the increase in the proportion of low-carbon loads such as electric vehicles(EVs) and RES such as wind power generation has brought new challenges to the low-carbon emission electricity market(LCEM) [5]–[7].

The uncertainty of RES in LCEM poses security challenges and economic losses. For example, wind power generation under the control of mechanical devices aims to maximize generation capacity but does not consider the power balance of the grid [8]. If there are critical deviations in wind power, conventional generators will be used to provide deficit energy, or the grid will abandon excess wind power. Thus, there is an urgent need for an economical and efficient solution to smooth out wind power fluctuations for efficient use of renewable energy [9]. At the same time, EVs as the alternative to traditional fossil fuel vehicles, can effectively reduce CO2 emissions, but their centralized charging will pose an impact on the stability of the grid [10]–[12]. Therefore, countries are establishing new spot electricity markets in response to the above problems, including a balancing market to deal with the uncertainty of renewable energy generation. For example, the European balancing market determines the balancing clearing price based on the invoked energy offer [13]. They use methods such as zonal marginal pricing and weighted average pricing to settle unbalanced energy. Researchers are also paying more attentions to the problem. Huang *et al.* [14] proposed a Cournot equilibrium model for energy storage providers in a market where wind power producer(WPP) is the main energy supplier, which boosted social welfare. However, the model did not consider the influence of accurate measurement of WPP generation uncertainty on the equilibrium solution. Shen *et al.* [15] proposed a real-time (RT) energy management algorithm based on Lyapunov stochastic optimization considering the charging characteristics of EVs and the demand uncertainty without knowing the RT price. Moreover, market mechanisms for EV charging were also established [16].

The above-mentioned does not account for the uncertain cost of renewable energy generation in the day-ahead(DA) market. What's worse, the adjustment method by the balancing market will cause too much damage to the interests of RES. Given the increasing penetration of RES, it is urgent to establish a mechanism to more accurately quantify the uncertainty of generation to ensure its reasonable participation in market to promote renewable energy development [17].

Information entropy(IE) was proposed by Shanon to measure the uncertainty of information sources in the 1940s [18]. Since the IE theory was proposed, it has played a great role in measuring uncertainty. Recently, researchers interest in using it to describe the uncertainty of renewable energy generation power [19], [20]. This measure of uncertainty can be seen as one of the costs of RES market pricing. Meanwhile, to charge EVs orderly, they need to be reasonably guided by price signals in the DA market [21]. Transaction between EVs and RES could facilitate the construction of a regional LCEM.

All along, the cost of RES is regarded as zero when market pricing except for construction and maintenance. However, this is contrary to the incentive compatibility principle in the electricity market. Moreover, existing studies often use value-at-risk to measure the uncertainty of RES [22], which overemphasizes economic attributes and ignores power information, resulting in insufficient knowledge and guidance for RES. Also, the orderly charging of EVs needs to be reasonably guided by the price signals of the electricity market. Therefore, the pricing of RES plays a crucial role in balancing the supply and demand of energy in the process of trading with EVs. The novelties compared to the existing work mentioned above are as follows. An LCEM between WPP and EVs is constructed. Using IE in the DA market quantifies the uncertainty cost of WPP and leverages the flexibility of EV charging. A decentralized transaction is designed using blockchain technology to ensure the power balance while protecting privacy.

This paper aims to quantify the uncertainty of renewable energy by introducing IE and incorporating it into the pricing of the DA market to more accurately measure the generation cost. In the constructed LCEM, the EVs are charged orderly through price signals in DA market contract. In this market, RES producers such as WPP act as market price makers. Controllable loads such as EVs are price takers. However, as a flexible load, EVs can choose the best charging method according to their interests, which affects the pricing of WPP. Therefore, we describe the relationship between WPP and EVs as the Stackelberg game. WPP is the leader in the game, and EVs are the followers in the game. When the game reaches equilibrium, the optimal pricing strategy and charging method for both parties are obtained. As we all know, the Stackelberg game is a dynamic game with complete information. Therefore, to protect the privacy and security of market participants, corresponding systems need to be established. Blockchain is one of the core infrastructures of the future value Internet. Its core application value lies in establishing trust and solving the trust problem in the information world. Moreover, it has the advantages of traceability, openness, transparency, and the prevention of a single point of failure. Therefore, we use the blockchain network to build the communication network of the market. To sum up, we construct a blockchain-based electricity trading market between WPP and EVs. The market considers the uncertainty of WPP and the flexibility of EV charging and reduces carbon emissions on the premise of ensuring the multi-party interests of the market and the balance of supply and demand.

The main contributions and organization are given as follows:

- An LCEM considering renewable energy uncertainty is constructed, which promotes the reduction of carbon emissions through market transactions.The market ensures a balance between supply and demand in the region through electricity trading between WPP and EVs.
- An uncertainty cost based on IE for the WPP power generation forecast is defined. It is introduced into DA pricing as a factor affecting WPP pricing strategy to reduce the impact of power generation uncertainty on the market economy.
- An information system based on blockchain technology

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is constructed to support the complete information feature of the Stackelberg game. The blockchain guarantees the transparency of transactions for all entities in the system.

- The Stackelberg game pricing is transformed into a mixed linear integer programming(MILP) problem through karush-kuhn-tucker(KKT) optimality conditions and strong duality theory, and the feasibility and effectiveness are verified by the Ethereum platform.

The rest of our article is organized as follows. Section II describes the mathematical model of the main entites. In section III, a blockchain-based Stackelberg game electricity trading market for WPP and EVs is proposed. Section IV presents the results of the digital simulation. Finally, the section V summarizes the main work of this paper.

II. RELATED WORK

With the increasing penetration of renewable energy, multiparty collaboration and data sharing have become the development trend of electricity market. In order to establish the trust relationship between trading parties and maintain the trustworthiness of the collaboration and sharing process, the blockchain technology, which is de-trusted, open and transparent, is one of the important infrastructures for the development and construction of LCEM.

Researchers have made many contributions to work related to blockchain-based renewable energy trading schemes. Mengelkamp *et al.* [23] proposed a blockchain-based P2P local energy market for microgrids with a framework consisting of seven components. Small-scale energy trading was realized in the community of Brooklyn. Although it promotes local renewable energy consumption, it does not consider the uncertainty of renewable energy and specific pricing mechanisms. Hua *et al.* [24] designed a marketplace for energy and carbon allowances in the framework of blockchain trading. The framework provides overall planning of carbon emission shares on the user side. However, the reduction of carbon emissions on the user side contributes less to the low-carbon network of the environment than on the generation side. Doan *et al.* [25] proposed a blockchain energy trading market based on bilateral auction theory. The interests of buyers and sellers are maximized through the game theory approach. However, this is a small-scale P2P transaction, and its users are only household users relatively single, which has limited contribution to reducing carbon emissions. Similarly, petri *et al.* [26] proposed an energy community for energy transactions between prosumers, in which the behavior and benefits of transactions are recorded in a blockchain system. Smart contracts constrain the trading scenarios and user behavior of this energy community. However, the community-level energy contribution is less in terms of carbon emission reduction compared to renewable energy participation in the electricity market. Similar work was done by Zhang *et al.* [27] based on demand response. The authors [28] proposed an RT market that uses prosumers and EVs to smooth out renewable energy fluctuations. The market uses smart contracts to compute and publish power balancing trading plans. The blockchain is responsible for recording transactions and regulating the users. However, this work imposes a tremendous cost on renewable energy generators to smooth out power fluctuations in the RT market, reducing their incentive to develop it. Similarly, Bischi *et al.* [29] proposed a blockchain-based multi-temporal energy trading market. Pre-trading based on renewable energy forecasts is performed in the DA market. Then, power imbalances due to generation deviations are traded in the RT market. Baza *et al.* [30] proposed a privacy-preserving Vehicle-to-Vehicle(V2V) energy trading scheme, and not only that, the blockchain architecture is also well robust to cyber attacks. In contrast, the authors have also proposed a V2V trading scheme, and the work focuses on the pricing of energy transactions and the design of user reputation. In addition, the authors [31] have analyzed V2V transaction models for different scenarios. As a flexible load, the inclusion of EVs in the overall energy trading market would enhance the reduction of carbon emissions and help to smooth out the volatility caused by RES. Christidis *et al.* [32] designed three configurations of local energy blockchain to analyze energy transactions. It gives the analysis of market efficiency under different secret key scenarios. However, it did not consider the problems caused by the specificity of the market transaction subjects. For example, the participation of renewable energy generators in the market will bring changes to the transactions.

The blockchain-based energy trading schemes mentioned above have contributed to the construction of low-carbon networks. However, these works have the following shortcomings: First, the implementation scale is small, and they do not consider the participation of RES. Although they can reduce the peak load to a certain extent, they have limited contribution to reducing the overall carbon emissions. Second, research on renewable energy participation in market trading often uses only RT regulation to cope with power fluctuations. The method seriously undermines the profitability of RES and limits its development. Third, the situation of the subject considered in the design of the blockchain framework is too homogeneous. The performance of the blockchain is not sufficiently adaptable when the users lead to a huge change in demand and decision-making. The research proposed in this paper quantifies the uncertainty cost of RES using IE theory and incorporates it into the DA market clearing. The scheme maximizes the benefits of RES while considering the uncertainty of RES. Meanwhile, the scheme constructs an LCEM considering EVs and RES. Smart contracts deployed on Ethernet, the largest platform for blockchain, are responsible for regulating and recording transactions, and their measurement metrics are more relevant and acceptable.

III. DEFINITION AND MODELS OF LCEM

In this section, the mathematical model of the related entities in LCEM is established. As the primary energy supplier in the proposed market, WPP sets the charging price for EVs in the market by calculating the electricity prices of other RES and the charging time of EVs. We assume that EVs participate in the blockchain-based electricity market by connecting to the distribution network through the charging pile. Moreover, according to the information on the chain, the pile can trigger

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TABLE I
RELATED WORKS ON BLOCKCHAIN-BASED RENEWABLE ENERGY TRADING SCHEMES

Reference	[23] [26]	[30] [31]	[29] [32]	[24] [25] [27]	[28]	Our scheme
Objective	Prosumers	EV	MG	MG+Prosumers	MG+EVs	MG+EVs
RES uncertainty	N	N	N	Y	Y	Y
Measure	Optimal scheduling	Optimal scheduling	Game theory	Game theory	Optimal scheduling	Game theory
Experimental environment	Hyperledger	Ethereum	Hyperledger	Ethereum	Ethereum	Ethereum

the smart contract to calculate the optimal charging strategy and execute it automatically.

Let $i \in \mathcal{N} = \{1, 2, ..., N\}$ denote the index the nodes of EVs in market. Participants in LCEM interact through decision periods consisting of $t \in T$.

A. Problem Description

In LCEM, the decision that WPP needs to make is to set the electricity price for each period. Unlike the convention optimization problem, WPP's profit depends on the charging strategy of EVs, which is not directly controlled by WPP but depends on the price set by WPP. We assume that the average electricity price for one day is fixed. If WPP raises the price in a certain period, there will be other periods when the price is lower than the average. The smart piles will automatically choose the time when the charging cost is low. Since EVs can choose their charging time, they are no longer the "takers" of the price.

More importantly, the competitive relationship between WPP and EVs is described by the Stackelberg game shown in Fig. 1. The interests of each party are maximized and the market is cleared at the equilibrium of the game. In addition, the market sets up an uncertainty cost for the uncertainty of WPP generation. The charging demand of EVs is transformed into deterministic load demand through the power purchase contract with WPP, which reduces the disturbance of the supply-demand balance in the LCEM caused by random charging and discharging behavior.

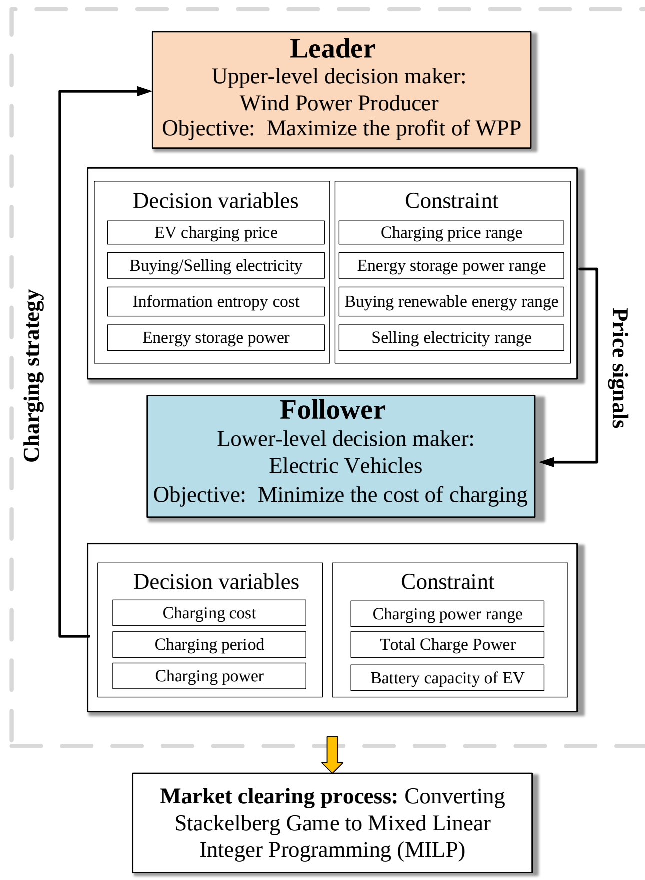

Fig. 1. Low-carbon emissions electricity market Stackelberg game framework.

B. Wind Power Producer Model

In DA market, WPP enters into contracts with other energy-supplying RES outside the market and power-purchasing EVs, and publishes electricity price information for each period of the next day. Since WPP's generation characteristics do not necessarily meet the supply-demand balance, it needs to determine the amount of electricity to be purchased from other RES for each period.

The power shortage by wind power generated is purchased from other RES in DA and RT markets. The electricity price in the RT market is usually higher than that in the DA market, which will cause the loss of WPP's interests. Therefore, this paper introduces the uncertainty cost to quantify the uncertainty of WPP in the DA market. It is reflected in the corresponding energy storage device for WPP. The model describing the supply-demand balance of the market that WPP needs to satisfy is given next

$$\sum_{i \in \mathcal{N}} P_{i,t}^{\mathrm{DA}} + P_t^{cha} - P_t^{discha} = P_t^{RES} + P_{ES,t}^{RT,Sell} - P_{ES,t}^{RT,Buy} \tag{1}$$

where $P_{i,t}^{\mathrm{DA}}$ is the charging power contract of EV node i in DA market, P_t^{RES} is the contracted electricity purchased by WPP in the DA market with other RES at time t, and $P_{ES,t}^{RT,Sell}$ and $P_{ES,t}^{RT,Buy}$ are the power sold and bought by WPP in the RT market with RES, respectively. P_t^{cha} and P_t^{discha} are the charging and discharging powers of the energy storage devices at time t and their constraints are as follows

$$0 \leq P_t^{cha} \leq b_t P_{t,max}^{cha} \tag{2}$$

$$0 \leq P_t^{discha} \leq (1 - b_t) P_{t,max}^{discha} \tag{3}$$

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where $P_{t,max}^{cha}$ and $P_{t,max}^{discha}$ are the charging and discharging limits of the energy storage device at time t. b_t is a Boolean variable of energy storages status that ensures the energy storage device cannot be charged or discharged at the same time.

$$b_t = \begin{cases} 1 & \text{transaction status} \\ 0 & \text{non-transactional status} \end{cases} \tag{4}$$

Similarly, the transaction constraint in the RT market is as follows

$$0 \le P_t^{RT,Buy} \le b_t^{RT} P_{t,max}^{RT,Buy} \tag{5}$$

$$0 \le P_t^{RT,Sell} \le (1 - b_t^{RT}) P_{t,max}^{RT,Sell} \tag{6}$$

where $P_{t,max}^{RT,Buy}$ and $P_{t,max}^{RT,Sell}$ are trading amount constraints, which are determined by the surplus power of other RES and WPP in the system.

The reserve of energy storage device changes as follows [33],

$$\begin{cases} 0 < B_{ES,t} = B_{ES,t-1} + P_t^{cha}\eta_t^{cha} \\ -P_t^{discha}/\eta_t^{discha} \le B_{ES,t}^{max} \\ B_{ES,1} = B_{ES,ini} \end{cases} \tag{7}$$

where B_{ini} is the initial reserve of the energy storage device, B_t is the power of the energy storage device at period t, and η_t^{cha} and η_t^{discha} are the charging and discharging efficiency.

The uncertainty cost of wind power generation is quantified by the IE. This method was proposed by Shannon C. E. to determine the amount of information [18]. Therefore, the value of the amount of information can be used to indicate uncertainty. The IE H of a random variable vector X = [x1, x2,..., xn] can be expressed as:

$$H = -\sum_{x \in X} P(x) ln P(x) \tag{8}$$

where x is the forecasted result in a probabilistic scenario, and $P(x)$ is the probability of occurrence of x. In detail, x is the WPP power generation forecast result, and $P(x)$ is the probability of the result appearing.

The introduction of IE can measure the uncertainty of RES generation forecast. Furthermore, to measure the cost of the uncertainty, we define IE price λ^{IE} and IE capacity S^{IE}, and their product is the cost. The cost is paid to the energy storage company in advance in the DA market. When the actual deviation is less than the WPP's IE representation, the energy storage company can resell this part of the capacity in the RT market without refunding the uncertainty cost.

Since the uncertainty cost of WPP is the cost paid to the energy storage entropy in the day-ahead market, its price cannot be higher than the RT market price. At the same time, to encourage energy storage companies to trade with WPP at the IE price in the DA market, the IE price should be greater than the DA price. It is defined as follows:

$$\lambda_t^{IE} = \lambda_t^{\mathrm{DA}} + (\frac{\lambda_t^{\mathrm{RT}} - \lambda_t^{\mathrm{DA}}}{\lambda_t^{\mathrm{DA}}})(1 + e^{-\frac{k_1(H_M - H)}{H_M}})^{-1} \tag{9}$$

where λ^{DA} and λ^{RT} are the average value of the DA and RT price respectively, H and H_M are the IE and maximum entropy of WPP in the scenario, and k_1 is the conversion coefficient.

$$S^{IE} = k_2 S^{RES} (1 - \frac{k_3}{(H_M/H) - a})^{-1} \tag{10}$$

where S^{RES} is the RES generator capacity, k_2 and k_3 are the conversion coefficient, and a is the correction coefficient, which is related to the forecast scenario.

The WPP's objective function is to maximize its profitability. The profit consists of four items, where the first item represents the cost of purchasing electricity from other RES; the second item is the revenue from selling electricity to the day-ahead market; the third item is the revenue from the sale of electricity in the RT market; the fourth item is the uncertainty cost determined by the power generation department.

$$\text{Max} \sum_{t \in T} \begin{bmatrix} -P_t^{RES}\lambda_t^{DA,Buy} \\ +\sum_{i \in \mathcal{N}} P_{i,t}^{\mathrm{DA}}\lambda_t^{\mathrm{DA,Sell}} \\ (P_{ES,t}^{RT,Sell}\lambda_t^{RT,Sell} - P_{ES,t}^{RT,Buy}\lambda_t^{RT,Buy}) \\ -\lambda_t^{IE}S^{IE} \end{bmatrix} \tag{11}$$

$$\text{s.t. (1)-(10), (12)-(13)}$$

Notes that the electricity price of WPP must not be higher than the RT price. At the same time, the upper bound of the average price should be limited to ensure the interest of EVs. The above constraint is expressed as follows

$$\lambda_{t,min}^{\mathrm{DA,Sell}} \le \lambda_t^{\mathrm{DA,Sell}} \le \lambda_{t,max}^{\mathrm{DA,Sell}} \tag{12}$$

$$\lambda^{av} = \sum_{t=1}^{T} \lambda_t^{\mathrm{DA,Sell}}/T \tag{13}$$

where $\lambda_{t,min}^{\mathrm{DA,Sell}}$ and $\lambda_{t,max}^{\mathrm{DA,Sell}}$ are the lower and upper bounds of electricity price during the period t, λ^{av} is the average price for a day.

C. Electric Vehicle Model

EVs are gradually replacing fossil-fueled vehicles because of their low carbon emission attributes. However, their uncertain behavior of uncontrolled charging can impact the RT supply and demand balance of LCEM. In the model, the decision factors of EVs are the charging period and price. For each EV node i, its battery charging constraint is as follows

$$0 < P_{i,t}^{\mathrm{DA}} \le P_{i,max}^{\mathrm{DA}} \tag{14}$$

where $P_{i,max}^{\mathrm{DA}}$ is the maximum charging power of EV node i. In addition, in order to ensure that the amount of each charge meets the driving demand, its charging behavior should satisfy the following constraints.

$$\sum_{t \in T} P_{i,t}^{\mathrm{DA}} = 0.8 B_{i,max} - B_{i,ini} \tag{15}$$

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where B_i is the capacity of the EV node i power battery, $B_{i,ini}$ and $B_{i,max}$ are the initial and maximum value of the capacity of the power battery.

The objective function of EV node i is to minimize its charging cost.

$$\mathrm{Min} \sum_{t \in T} P_{i,t}^{\mathrm{DA}} \lambda_t^{\mathrm{DA,Sell}} \tag{16}$$
$$\text{s.t. (14) (15)}$$

Notes that in the LCEM transaction, the EV uploads its transaction information through the charging pile. Therefore, the EV node i is in the parked charging state during the planned charging period t. This paper does not consider the sudden charging demand and the driving cost of EVs.

D. Solution of the LCEM clearing model

The transaction between WPP and EVs in LCEM constitutes a Stackelberg game [34] that is a two-stage complete information dynamic game as shown in Fig.1. The participants choose their strategies according to the other party to maximize their own benefits under the other party's strategy. In the game model, WPP makes a decision called the leader. Then, the remaining EVs make decisions based on the leader's decisions, called followers. The leader adjusts their decision according to the followers' decisions, and so on until a Nash equilibrium is reached. In addition, since the charging price $\lambda_t^{\mathrm{DA,Sell}}$ and charging power $P_{i,t}^{\mathrm{DA}}$ of EVs are both variables, the game problem posed by WPP and EVs is neither a linear nor a convex problem. Therefore, the game between WPP and EVs should be transformed into MILP based on the KKT condition and the strong duality theorem [35].

Transformation of the lower level problem into a KKT optimality condition using Lagrange multiplier method. Equations (14)-(16) of the lower model are transformed into equations (17)-(20). Let the dual variable be γ_i^1, $\mu_{i,t}^1$, $\mu_{i,t}^2$.

$$\sum_{t \in T} P_{i,t}^{D} A - 0.8 B_{i,max} + B_{i,ini} = 0 \quad \Rightarrow \quad E \tag{17}$$

$$\begin{cases} 0 \le P_{i,t}^{DA} \perp \mu_{i,t}^1 \ge 0 \\ 0 \ge P_{i,t}^{DA} - P_{i,max}^{DA} \perp \mu_{i,t}^2 \le 0 \end{cases} \Rightarrow \quad G_\alpha$$

Among them, λ_i^1 the dual variable of (17), $\mu_{i,t}^1$, $\mu_{i,t}^2$ are dual variables of (18). E denotes the set of equation constraints and G_α denotes the set of inequality constraints.

Lagrange function of lower level is obtained as below:

$$L = \sum_{t \in T} P_{i,t}^{DA} \lambda_t^{DA,Sell} - \gamma_i^1 E - \sum_{\alpha} \mu_\alpha G_\alpha \tag{18}$$

The derivatives of the Lagrangian function with respect to the variables in the lower level problem satisfy the following constraint.

$$\frac{\partial L}{\partial P_{i,t}^{DA}} = \lambda_t^{DA,Sell} - \gamma_i^1 - \mu_{i,t}^1 - \mu_{i,t}^2 \tag{19}$$

Equation (17)-(20) convert the lower level optimization into a constraints. However, equation (18) is nonlinear.

The constraint equation (18) is transformed into the following linear inequality by introducing the binary variable b_α.

$$G_\alpha \mu_\alpha = 0, \forall \alpha \tag{20}$$

$$\begin{cases} 0 \le G_\alpha \le b_\alpha K \\ 0 \le \mu_\alpha \le K(1 - b_\alpha) \end{cases}$$

For equations (14)-(16), the following equation is obtained.

$$\sum_{t \in T} P_{i,t}^{DA} \lambda_t^{DA,Sell} = \gamma_i^1 (0.8 B_{i,max} - B_{i,ini}) + \sum \mu_{i,t}^2 P_{i,max}^{DA} \tag{21}$$

Under the KKT condition constraint, the objective function (11) is equivalent to:

$$\sum_{t \in T} \begin{bmatrix} -P_t^{RES} \lambda_t^{DA,Buy} \\ +\gamma_i^1 (0.8 B_{i,max} - B_{i,ini}) + \sum \mu_{i,t}^2 P_{i,max}^{DA} \\ (P_{ES,t}^{RT,Sell} \lambda_t^{RT,Sell} - P_{ES,t}^{RT,Buy} \lambda_t^{RT,Buy}) \\ -\lambda_t^{IE} S^{IE} \end{bmatrix} \tag{22}$$

In summary, the pricing game can be transformed into the following mixed integer linear programming:

$$\mathrm{Max} \sum_{t \in T} \begin{bmatrix} -P_t^{RES} \lambda_t^{DA,Buy} \\ +\gamma_i^1 (0.8 B_{i,max} - B_{i,ini}) + \sum \mu_{i,t}^2 P_{i,max}^{DA} \\ (P_{ES,t}^{RT,Sell} \lambda_t^{RT,Sell} - P_{ES,t}^{RT,Buy} \lambda_t^{RT,Buy}) \\ -\lambda_t^{IE} S^{IE} \end{bmatrix} \tag{23}$$

s.t. (1)-(10), (12)-(13), (17), (20), (22).

Thus, it can thus be possible to find the global optimal solution using commercial software such as YALMIP and GRUOBI.

IV. Design of Blockchain System for LCEM

A. Overview

As shown in Fig. 2, the proposed LCEM information system is deployed on the blockchain. RES with a good reputation is used as the authoritative node to maintain the blockchain. Market participants such as EVs and WPP also join the blockchain network maintenance work as light nodes. For WPP, the market transaction form can sell as much renewable energy as possible, and for EVs, participating in LCEM can obtain lower charging prices. Therefore, EVs and WPP have enough motivation to participate in and maintain the blockchain-based LCEM.

B. Phases

The proposed LCEM mainly includes four phases: initialization system phases, upload information phases, power transaction phases, and distribution feedback phases. During the initialization and upload phase, the manager deploys the blockchain-based system, and participants who meet the low-carbon requirements such as WPP and EVs join the blockchain and upload data such as electricity demand, generation forecast, and price information.

- **Phase 1**: Initialization system

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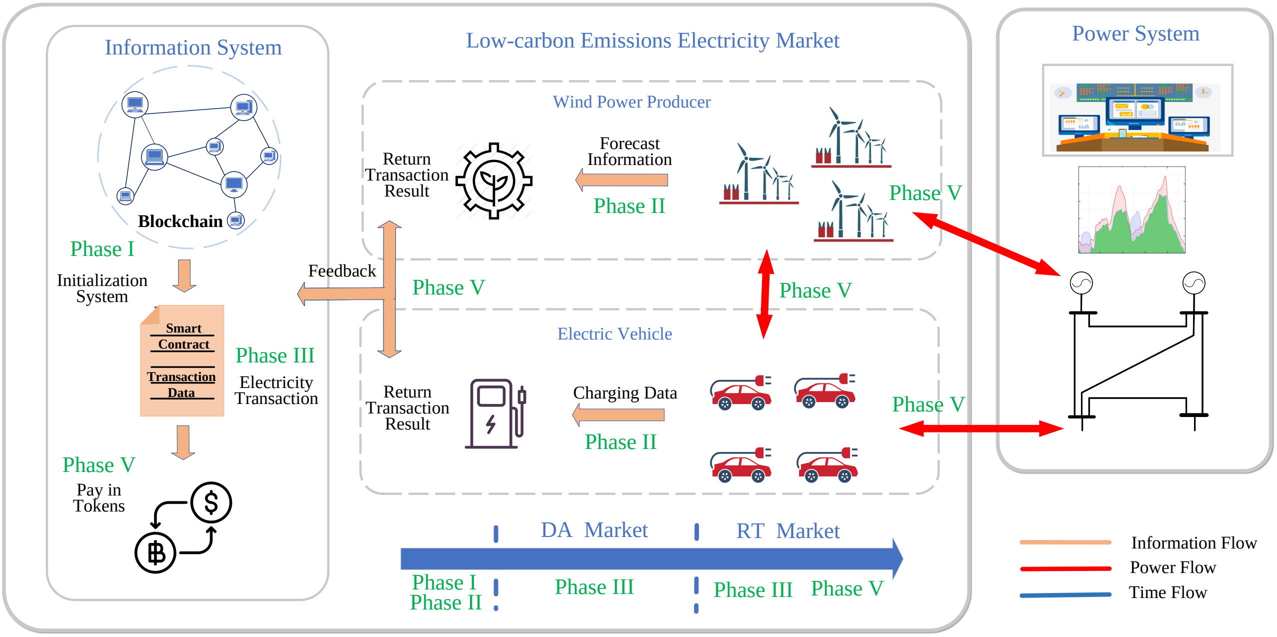

Fig. 2. The LCEM framework based on blockchain and smart contract.

During the DA transaction initialization phase of LCEM, the authoritative node of the system deploys the blockchain and registers WPP nodes and EV nodes participating in the transaction in the network. Smart contracts that solve game pricing are deployed on the consortium blockchain. The administrator determines the cost-saving parameters of LCEM such as T and electricity price λ^{av} according to the actual market situation, and uploads them to the chain. The charging station, as a light node in the blockchain network, periodically publishes the status information of LCEM to all roadside units (RSUs) with cycle T. After completing the above operations, the system administrator will be offline and not participate in LCEM transaction management until the system parameters need to be updated.

• **Phase 2**: Upload information

Before the DA market opens, WPP nodes first upload their price $\lambda_t^{\mathrm{DA,Sell}}$, electricity demand P_t^{RES}, and uncertainty cost $\lambda_t^{IE} S^{IE}$. Subsequently, the EV node i upload their charging period t and power requirements $P_{i,t}^{\mathrm{DA}}$. As the leader of the Stackelberg game, WPP will publish its information on the chain, affecting the decision-making of EV nodes i. The EVs receive the updated service information published by the RSUs. EVs adjust decisions according to their interests after learning the price information published by WPP. This information is also published on the chain, which affects the price setting of WPP in turn.

In the RT market, WPP's IE deviation and temporary changes in EV's charging strategy are updated every 15min in a rolling optimization, with market participants' information updated and uploaded to the blockchain each period.

• **Phase 3**: Electricity transaction

At the beginning of the trading period, the authority nodes trigger the smart contract, and WPP and EVs trade in the DA market, and their trading prices are published on the chain according to the results of the Stackelberg game in the smart contract. The DA market publishes price signals according to WPP's generation forecasts to guide EVs to charge at reasonable times and promote renewable energy consumption. Based on the information obtained from RSUs, EVs that need to be charged make autonomous decisions to receive and participate in the LCEM with a period t for each scheduled update. In addition, when WPP's forecasted generation causes a supply shortage, contracts are made and traded with other RES in the DA market.

In the RT transaction of LCEM, the difference between WPP IE and the actual deviation will cause a supply and demand imbalance in the RT market. For this reason, as the principal power producer in LCEM, WPP has to cover the cost of deviation other than the uncertainty cost. WPP should reduce the price of surplus power to incentivize consumption or raise the case of energy purchase to get enough power from other RES to ensure the balance of supply and demand.

• **Phase 4**: Result and feedback

Ultimately, WPP and EVs trade according to the price published on the blockchain and pay in tokens to complete the transaction plan TP and upload the execution results for feedback. The final trading price of EV and WPP will be transmitted to the chain via RSUs. After the transaction is completed, WPP can improve its device to enhance forecast accuracy and reduce the uncertainty cost.

Note that if participants in the market, such as EVs or WPP, have questions about the transaction process, they can access all the data used to generate this transaction from the blockchain.

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V. Case Studies

A. Experiment Environment

The effectiveness and performance of LCEM is validated on a laptop with an Intel Core CPU i7-9750H @ 2.6 GHz, 16 GB RAM. The DA price λ_t^{DA} of the LCEM for an operating period $T = 24h$ is modified from [36], and the RT market price λ_t^{RT} is assumed to be $1.5\lambda_t^{DA}$. The generation data of the WPP participating in the LCEM obeys a Gaussian distribution [37]. We modify IEEE 33-bus test feeder and place wind generation and EV nodes in the network. WPP generation capacity were obtained from China east coast producers [38], and the time-of-use price of grid used to calculate λ^{av} is sourced from [28]. The number of EVs is 80 whose driving behavior is divided into three types, typical day, night work, and random travel. We solve the pricing problem of the Stackelberg game in LCEM based on YALMIP and GUROBI under the MATLAB platform. The algorithmic procedure of the Starkberg game for LCEM is shown in **Algorithm** 1. The transaction information transmission experiment of LCEM is to build a consortium blockchain with PoA consensus mechanism based on Ethereum to realize on-chain functions, and test the performance with Truffle.

Algorithm 1: LCEM Trading Mechanism

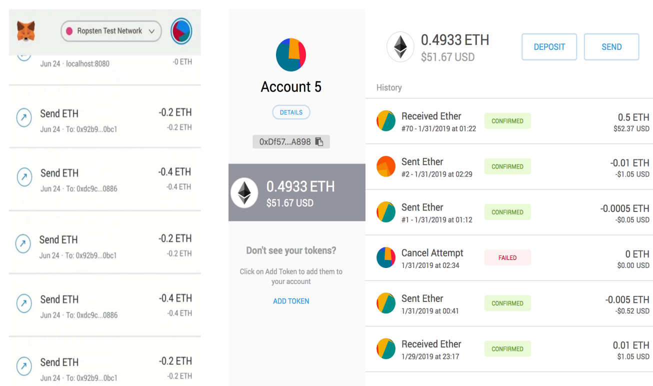
Input: RT price $\lambda^{RT,Sell}$, electricity demand P_t^{RES}, uncertainty cost $\lambda_t^{IE}S^{IE}$; Energy storage charging and discharging in RT market $P_{ES,t}^{RT,Buy/Sell}$; charging power $P_{i,t}^{DA}$ of EV node i, charging period t ($i \in \mathcal{N}$, $t \in T$)
Output: DA price λ_t^{DA}, LCEM trading plan TP

At period t, find the reserve of energy storage $B_{ES,t}$ and the number of charging EV i ($i \in \mathcal{N}$)
forall $t = 1;\ t \le T;\ t{+}{+}$ **do**
  if *Nash equilibrium not achieved* **then**
    if *WPP's revenues have the potential to increase* **then**
      Update $\lambda_t^{DA,Sell}$ based on Equation (11);
    else
      Update $\lambda_t^{DA,Sell}$ and $P_{i,t}^{DA}$ based on Equation (16);
  else
    Nash equilibrium achieved and trading cleared;
return λ_t^{DA}; PT

B. Results and Discussions

1) Performance analysis of blockchain information systems: The LCEM consortium blockchain information system is designed on the Ethereum platform. The realization of its prototype is shown in Fig. 3. It also shows the transaction accounts of WPP and EVs, that is, the Ethereum address. The address is represented by a hash value and has privacy protection. The gas consumption of the operation is also included. As mentioned in Section III, the transaction account addresses of WPP and EVs are replaced by hash values, which protect the user's privacy information and give the gas consumption of the transaction process. And we demonstrate the transaction between WPP and EV based on the METAMASK platform as shown in Fig. 4.

Fig. 3. Blockchain test.



(a) EV charging (b) WPP profit

Fig. 4. Metamask case

The blockchain framework LCEM has excellent scalability. Since EVs act as light nodes in the blockchain system, the increase in their number can not be a significant burden on the system. As shown in Fig. 5, the time delay of the blockchain system increases slightly when the number of EVs is expanded from the initial set of 80 to 700. However, the changes in time delays are all at the millisecond level, and the delays are negligible relative to the minimum scheduling time of the power system, which is 5-15 min.

In Ethereum's smart contracts, each data transfer requires a certain amount of gas, so gas consumption can reflect the overhead of performing operations on the blockchain. Usually, this is an important criterion for measuring whether a blockchain network design is reasonable. Fig. 6 shows the gas consumption of the main operations that need to be performed on the blockchain in our scheme. In the process of energy trading based on blockchain, WPP and EVs need to upload information and operate on the chain.

As shown in Fig. 6, due to the large amount of information that WPP needs to upload, the reputation ranking of EVs by smart and contract processing information is relatively large, consuming about 600, 000 units of gas. The actual generated data that needs to be stored is relatively less amount

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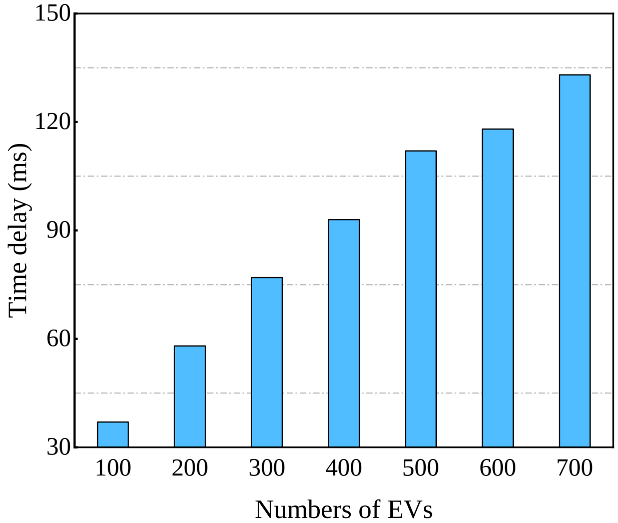

Fig. 5. LCEM Blockchain Information System Scalability for EV.

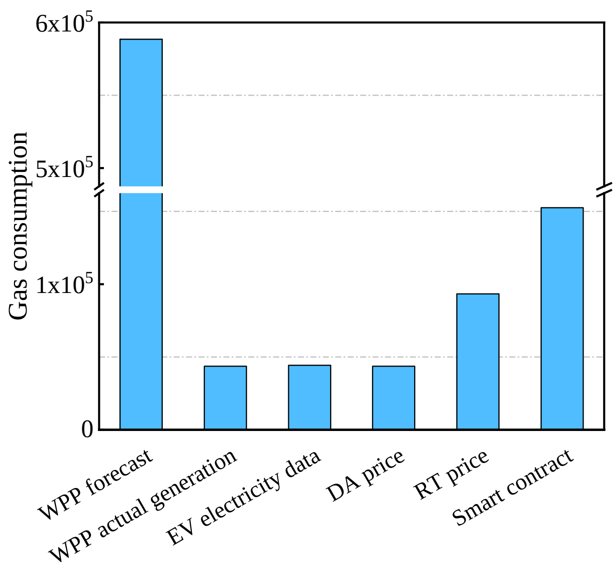

Fig. 6. LCEM blockchain information system node gas consumption.

of operation. The number of EVs in one RSU area is small, so the data it uploads and stores consume less gas than 100, 000. The smart contract needs to store the transaction completion of LCEM, so it consumes 150,000. The rest of the operations are mainly to store data on the blockchain. Their gas consumption is less than 150,000, which is acceptable to all nodes in the system.

2) LCEM Transaction effectiveness: To deal with the uncertainty of LCEM Stackelberg pricing game caused by renewable energy power generation and EV charging in the market, we introduced WPP's IE pricing mechanism and EV's DA contract charging method.

The optimal solution of MILP is the market clearing price of LCEM which is the equilibrium of the Stackelberg game. Since the MILP model is an NP-hard problem, its solution performance is mainly influenced by variables and constraints. The scale of LCEM is the dominant representation of the model variables and constraints. As shown in Fig. 7, 1X represents the original system and 2X is the scale expanded two times. It can be seen that the computation time is still less than the power system scheduling time(15 min) when the system scale is expanded to 32X. When the scale is 16x or less than the original system, the solution time of the model is at the second level. The model shows good performance for system scaling.

LCEM deals with the uncertainty of renewable generation in a different way than conventional electricity markets that rely only on RT market transactions. WPP measures it through IE and expresses this cost in the DA market through the product of the IE price and the IE capacity, which is paid to the energy storage. As can be seen in Fig. 8, our mechanism has an

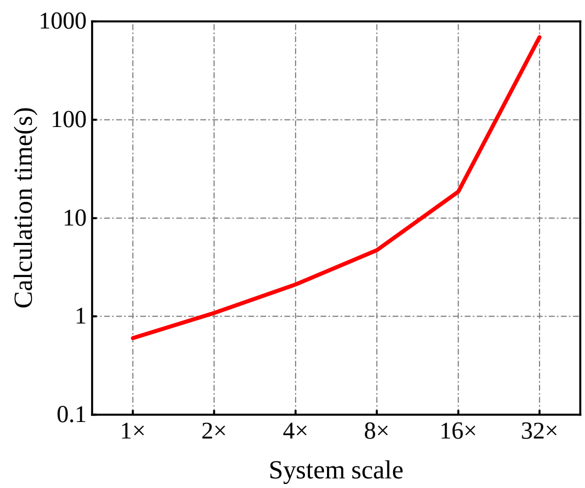

Fig. 7. Performance analysis of LCEM trading model.

advantage when the prediction accuracy is 90% and below. Because the more uncertainty costs quantified by information entropy in the DA market, the less high adjustment costs paid in the RT market, and the fewer total costs incurred by WPP due to generation errors. The net profit for WPP by more than 2% when the prediction error is greater than 10%. This is because the IE price is lower than the RT price. When the RT deviation of power generation is too large due to the uncertainty of the forecast, the high RT price will make WPP pay too much. In contrast, our mechanism measures the uncertainty of WPP power generation in the DA market and converts it to cost in the DA market to the transaction with energy storage with IE prices.

Fig. 9 shows the price changes of LCEM, RT market electricity price, and DA price as constraints considering WPP cost electricity price and EV charging contract in DA market. From 3 A.M. to 8 A.M. when there is less electricity purchased in the DA market, the WPP electricity price considering IE cost is higher due to the high uncertainty cost. On the contrary, when the transaction volume from 8 P.M. to 12 P.M. is large, the cost is lower, so there is not much difference between the price considering and not considering the IE cost.

As an important part of uncertainty cost, IE capacity is affected by WPP generation forecast IE and WPP capacity as shown in Fig. 10 and Fig. 11. The former shows that the IE

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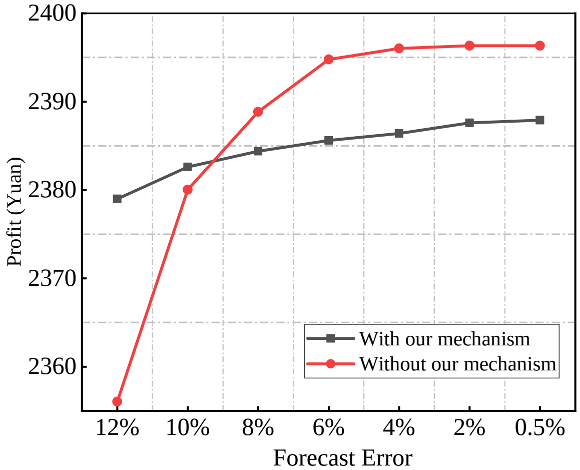

Fig. 8. WPP total net profit.

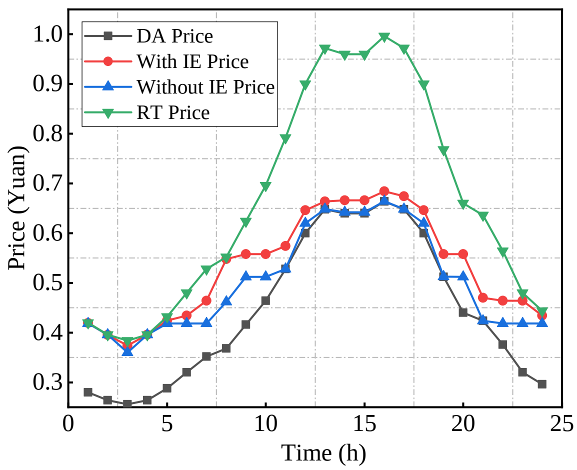

Fig. 9. LCEM trading price changes.

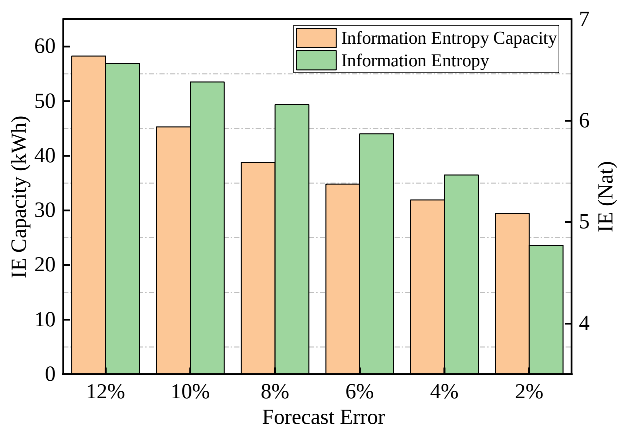

Fig. 10. Information entropy and information entropy capacity.

capacity increases as the IE increases when the WPP capacity remains unchanged and the generation uncertainty increases. Fig. 10 illustrates that, in the case of IE determination, the increase of WPP capacity will lead to the increase of IE capacity, which increases the uncertainty of WPP and reduces its profit.

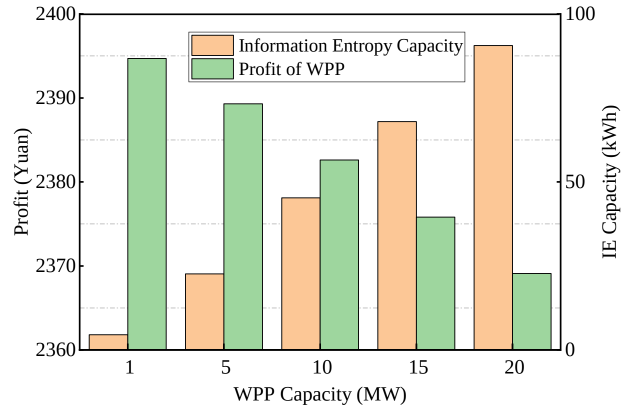

Fig. 11. Profit and information entropy capacity of different capacity WPP.

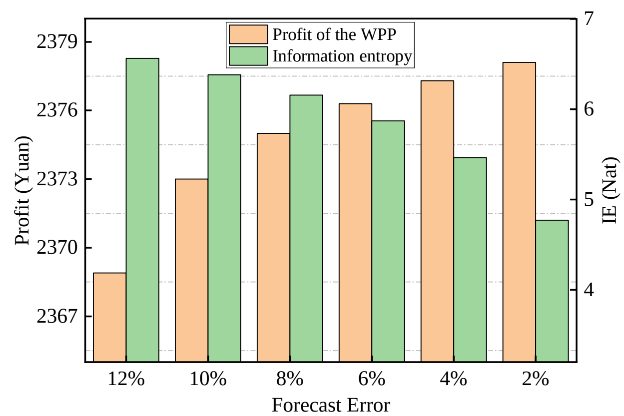

Fig. 12. Information entropy and profit of WPP.

As shown in Fig. 12, the IE of WPP corresponds to its power generation forecast accuracy, which affects the profit of WPP. It can be seen that as uncertainty costs are taken into account in the pricing mechanism of IE, when the IE of WPP increases that is, the accuracy of power generation forecast decreases), the net profit of WPP decreases because of the elevated uncertainty costs. The net profit with a forecast error of 12% and IE of 6.56 Nat is reduced by about 10 yuan compared to the forecast error of 2% and of 4.77 Nat.

The EV charging method in LCEM is the DA market contract charging. Since the DA price proposed by WPP in LCEM is a time-of-use price, the driving behavior of EVs has a significant impact on the net profit of WPP and its own charging cost.

We set five groups of EV charging behavior as shown in Fig. 13, and adjusting the ratio of three behavior typies as shown in **TABLE II** can get different WPP profit and EV charging costs. The 80 EVs in group A are all typical day driving behaviors and have the highest WPP profit, but the charging cost of EVs is too high due to the high electricity cost of charging time of EVs in typical day behaviors. The majority of EVs in group E work at night and travel randomly, resulting in the need for WPP to purchase additional low-carbon energy to meet the charging power of EVs that travel randomly outside the contract resulting in lower benefits. Taking into account the charging cost of EVs and the net benefit of WPP,

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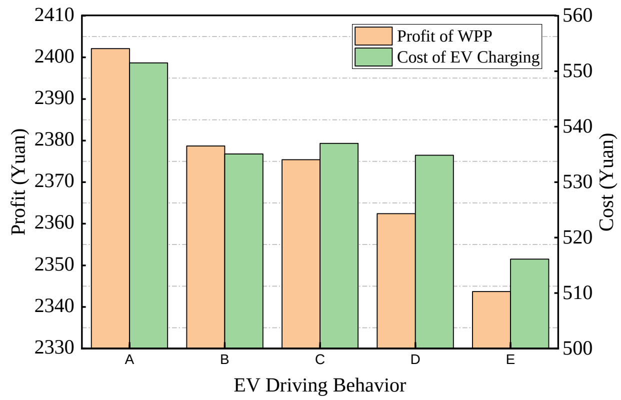

Fig. 13. WPP profit and EV charging costs.

TABLE II
EV DRIVING BEHAVIOR GROUP

Group	Typical day	Night work	Random travel
A	80	0	0
B	65	10	5
C	50	20	10
D	35	30	15
E	20	40	20

the ratio of EV behavior in group B is optimal and is also the ratio of EV charging behavior set in other experiments in this paper.

VI. CONCLUSION AND FUTURE WORK

This paper proposes a blockchain-based LCEM considering renewable energy uncertainty. In the process of Stackelberg game pricing, the definition of WPP power generation uncertainty through IE theory and the DA contract charging management of EVs have a profit advantage of greater than 2% when the power generation error is 10% or more. The market facilitates WPP to set reasonable prices and capacity to improve the accuracy of generation forecasts while measuring the uncertainty. The experiment shows LCEM can accurately measure the uncertainty of wind power generation and manage EV charging in the DA market to maximize the benefits for both parties. In addition, an information system based on the blockchain have been established to complete the transmission of electricity data to ensure the trustless and privacy of the transaction.

For future work, we will deal with the uncertainty cost of the supply side and demand side based on IE theory in concert, not only limited to supply-side renewable energy in this paper. Further, a system cost function will be defined by combining the energy efficiency cost quantified by exergy with the uncertainty cost of RES quantified by IE. In addition, the construction of an integrated energy low-carbon network market that considers hot and cold loads and heat and gas transmission is also part of the subsequent work. At the level of blockchain design, we will improve the efficiency of transactions to expand the scope of blockchain deployment. We will further improve the stability and efficiency of electricity market and support the construction of a net-zero emission power system.

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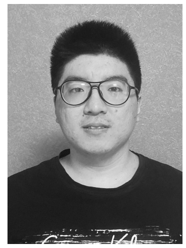

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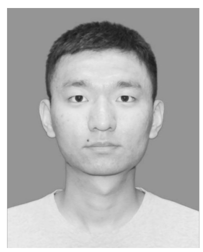

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