Blockchain-Enabled Two-Way Auction Mechanism for Electricity Trading in Internet of Electric Vehicles

Long Luo, *Member, IEEE*, Jingcui Feng, Hongfang Yu, *Member, IEEE*, and Gang Sun, *Member, IEEE*

***Abstract*—As people pay more attention to environment protection, the number of electric vehicles (EVs) is gradually increasing. Energy trading management for EVs is becoming a challenge. However, existing research has not considered the problem of information sharing between energy traders and issues surrounding the protection of user privacy. Therefore, in this article, we propose a vehicle-to-vehicle (V2V) and vehicle-to-grid (V2G) electricity trading architecture based on blockchain. All energy transactions of EVs can be recorded on the blockchain ledger to ensure privacy and smart contracts work as agents for pricing and optimal energy allocation. Furthermore, we introduce a two-way auction mechanism based on the Bayesian game and design a new price adjustment strategy. Finally, we propose a bidirectional auction mechanism based on the Bayesian game approach. We use extensive simulations to evaluate the performance of our proposed algorithm. Simulation results show that the social welfare and cost performance of our algorithm can be improved by up to 102.8% and 319%, respectively.**

***Index Terms*—Bidirectional auction mechanism, blockchain, electric vehicles (EVs), energy trading, Internet of EVs.**

I. Introduction

SMART grids are integrated, high-speed, two-way communication networks designed to improve efficiency, reliability, and safety through the use of advanced technological equipment, automated control, and modern communications technologies [1]. Environmental pollution and fossil fuel shortages have become two serious issues across the globe [2]. New electric vehicles (EVs) are environmentally friendly and energy efficient. EVs are by nature pollution-free and utilize renewable energy sources; therefore, they have great potential to alleviate environmental pollution and fossil fuel shortages. Thus, many countries are vigorously promoting the popularization of EVs.

The vehicle-to-grid (V2G) architecture is a revolutionary technology that allows for a two-way energy exchange between EVs and the grid, with advantages such as the use of auxiliary services, active power support for the grid, and reactive power compensation, in such a way that is beneficial for EVs [3]. EVs can either purchase energy from the grid or sell their excess energy to the grid. As the data and energy flow between EVs and the grid in both ways, EVs can be charged when the grid load is low, and power can be fed back to the grid during peak load periods, thus effectively allowing the grid to engage in peak load transfer, improving energy efficiency, and reducing transmission loss [4]. The vehicle-to-vehicle (V2V) architecture allows an EV to transmit energy through a two-way charger in the local grid and then distribute it among EVs through a controller, such as a local energy aggregator (LEAG). The LEAG is responsible for organizing the EVs and ensuring they can interact with each other [5]. In fact, through the use of the V2G and V2V architecture, an EV is not only a means of transportation but also a controllable load and distributed power source. However, as the number of EVs increases, it becomes increasingly difficult to manage their daily charging and discharging behavior. Therefore, the universal popularization of EVs is faced with many challenges.

First, to meet the daily charging needs of EVs, a comprehensive and powerful charging infrastructure has been built in various parts of the city. As the number of EVs rapidly increases, their charging behavior can lead to congestion, fluctuations, and extreme overload peaks in the distribution network. There are two main ways to solve this problem. First, a large number of centralized generators and amount of energy storage equipment can be deployed in the power grid to meet the energy demand during peak periods [6]. However, this arrangement greatly increases the operating costs and risk of an attack on the grid. An alternative approach is to take advantage of the two-way energy trading characteristic of EVs, which can be effectively utilized for a peak load transfer of the grid, improve energy efficiency, and reduce transmission loss by absorbing excess energy during off-peak hours and delivering energy back to the grid during peak hours [7]. This solution provides an entirely new and low-cost approach that solves the problem of grid load without additional operating costs.

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Second, the existing research lacks a distributed convenient, efficient, and secure mechanism that can be used for V2G or V2V energy trading. The traditional energy trading platform used by EVs relies on a centralized and trusted third party, where all EVs are identified, authenticated, authorized, and connected through a central cloud server. This centralized system has many shortcomings [8]: 1) the cloud server is a bottleneck and single point such that its failure could disrupt the entire network; 2) energy trading platforms provide a complex set of services that could expose EVs to a range of security and privacy threats, such as location tracking; and 3) failures due to security vulnerabilities (such as the installation of malware) can lead to serious accidents that compromise the safety of passengers and other road users that are nearby. Therefore, there is a need for a distributed convenient, efficient and secure mechanism that can be used for V2G or V2V energy trading.

Characterized by decentralization, transparency, immutability, and global inclusiveness, blockchain has fostered a wide range of novel applications and fields and transformed the information Internet into the value Internet [9]. A blockchain is essentially a distributed database, or public ledger, that records all transactions or digital events; an energy trading system can rely on such a distributed ledger rather than a centralized and trusted third party to record transaction data. Moreover, an efficient and secure distributed energy trading system can rely on distributed redundancy and encryption technology to ensure transaction data security and user privacy protection. Blockchain has exactly these characteristics. It has provided a unique technology in a distributed network for secure energy transaction without trusted third parties through the use of an immutable ledger and encryption technology, and the execution of smart contracts. Therefore, the decentralization, transparency, and immutability of blockchain make it appropriate for secure energy trading among EVs.

To address the above-mentioned challenges and considering the characteristics of blockchain, we propose a V2V and V2G electricity trading architecture based on blockchain. First, at each charging field, we deploy an LEAG that can provide a series of energy trading services. Each LEAG acts as a blockchain node that backups all blockchain data, and jointly, the LEAGs maintain the blockchain and collect and validate energy transaction records. Due to incomplete information sharing among the charging and discharging EVs and to ensure transactions are successful, we introduce a two-way auction mechanism based on the Bayesian game that models the optimal pricing problem for maximizing the utilities of both sides of each electricity transaction. In addition, we design a new price adjustment strategy based on the continuous two-way auction mechanism. Next, we identify the optimal energy allocation by solving a convex problem that maximizes social welfare. Finally, to guarantee the fairness of transactions, this energy trading scheme is written into a smart contract that is deployed at each blockchain node.

The main contributions of this article are as follows.

1) We propose a V2V and V2G electricity trading architecture based on blockchain, where all EV transactions can be recorded on the blockchain ledger to ensure all information remains secure. Smart contracts simultaneously act as agents for pricing and the optimal energy allocation. When a transaction occurs, the trading algorithm designed in the smart contract is automatically executed.
2) The Bayesian game is adopted to determine the pricing in the distributed V2V electricity trading network with incomplete information sharing. We introduce a two-way auction mechanism based on the Bayesian game and propose a new price adjustment strategy that can improve the transaction success rate, thus improving social welfare. We model the optimal pricing problem based on maximizing the utilities of both sides of the electricity transaction and model the optimal energy allocation as a convex problem that maximizes social welfare. Finally, we propose a bidirectional auction based on the Bayesian game algorithm.
3) We use extensive numerical examples to evaluate the performance of the proposed algorithms. The social welfare and cost performance (CP) of our algorithm are better than those of existing algorithms.

The remainder of this article is arranged as follows. Related researches are reviewed in Section II. The system architecture is presented in Section III, which includes the descriptions of the system entities and the energy trading process. The problem modeling of energy trading and the details of the bidirectional auction based on the Bayesian game (BABG) algorithm are described in Sections IV and V. We provide the simulation results of the compared algorithms and analyze their performance in Section VI. Finally, the conclusion of this article is presented in Section VII.

II. Related Work

A. V2G and V2V Energy Trading Scheme

Due to the popularization and promotion of EVs, the daily energy trading behavior of EVs has attracted extensive attention from both industry and academia. There are two main types of charging and discharging scenarios: 1) V2G and 2) V2V.

For the V2G scenario, much research has focused on EV energy management in terms of charging stations [10]–[17]. Zou *et al.* [10] considered the coordination problem arising from the need to charge a certain number of EVs within a limited range and proposed a novel class of auction-based games, proving that the effective bid set of EVs during charging is a Nash equilibrium (NE) of the underlying auction game. Mohammadi *et al.* [11] modeled the plug-in EV (PEV) cooperative charging (PEV-CC) problem as a convex multitimestep problem and introduced a receding horizon to integrate feedback into the decision-making process, minimizing the charging costs. Xu *et al.* [12] prioritized the scheduling of plug-in (hybrid) EVs (PHEVs) based on the less laxity and longer remaining processing time (LLLP) principle to minimize the overall cost. Ghosh *et al.* [13] proposed an online menu-based pricing system for EV charging, where the charging station determines the price for every arriving EV based on its energy state and the time it will take for the EV to charge. In [14], considering that the charging demand of EVs cannot be matched with uncertain wind power generation, the authors studied the coordination between the charging of EVs and local wind power generation by considering a building microgrid and proposing a distributed simulation-based policy improvement (DSBPI) approach. In [15], a stochastic forecast energy management strategy was proposed based on fast rolling optimization and modeled stochastic driving behavior as a probabilistic conversion matrix of PHEV demand torque based on Markov chains to reduce energy consumption and running time. To achieve specific economic objectives related to the distribution network operators (DNOs) while ensuring that EVs benefit from the system, Su *et al.* [16] proposed a rolling horizontal scheduling method based on a genetic algorithm (GA) to maximize the DNOs' profit margin while ensuring the interests of EVs are considered. In [17], the author proposed a topology-aware V2G energy trading mechanism that aims to use the charging/discharging power of the EVs to adjust the voltage deviation of the active distribution system.

A few studies focused on distributed V2V energy trading management [18]–[20]. Alvaro-Hermana *et al.* [18] presented a novel peer-to-peer (P2P) energy trading mechanism for two groups of EVs that greatly reduces the impact of the charging process on the power system during working hours and individually optimizes the energy cost of EVs in the time-space dimension. To balance local electricity demand, Kang *et al.* [19] proposed a local P2P energy transaction model where the local purchasing and selling of energy between PHEVs were conducted using a smart grid and providing incentives for discharging PHEVs. Xia *et al.* [20] proposed a V2V energy trading scheme based on Bayesian game pricing in blockchain-enabled Internet of vehicles (BIoVs) and obtained the optimal price under the linear strategic equilibrium.

B. Blockchain-Based Applications

Blockchain is characterized by decentralization, transparency, immutability, anonymity, and auditability, and has fostered a wide range of novel applications and fields [21]. The key advantage is the peer-to-peer (P2P) distributed trust provided by blockchain [21]: 1) eliminating the use of third parties for transactions; 2) reducing transaction costs; and 3) shortening transaction time. Therefore, this new technology has received much attention in the fintech world, where it was first introduced. In [22], a portfolio management framework was proposed based on blockchain and a deep reinforcement learning framework that continues to reallocate capital into financial assets to improve expected returns and reduce risk. However, due to the development of technology, the application of blockchain is not limited to the financial field. Blockchain is closely related to the new generation of information technology, such as data sharing (DS) [23], encryption techniques [24], artificial intelligence (AI) [25], and the Internet of Things [26], [27].

Some studies have applied blockchain to energy management [28]–[33]. Liang *et al.* [28] proposed a new distributed protection framework based on blockchain to improve the self-defense capability of modern power systems by using electricity meters as nodes in the distributed network and using electricity meter measurements as blocks. Keshk *et al.* [29] proposed a privacy protection framework for the privacy and security of smart grids; the framework consisted of two main modules: 1) a two-level privacy module and 2) an exception detection module. To balance the flexible energy demand and uncertainty regarding local photovoltaic (PV) output, Zhang *et al.* [30] proposed a P2P local energy market model that includes both energy trading and uncertain trading; the predicted power was matched with demand that was flexible in terms of the timing, and the uncertain power was matched with the demand that was flexible in terms of the amount of power. Wang *et al.* [31] developed an optimization model and architecture based on blockchain to manage the operation of a crowdsourced energy system (CES) with P2P energy transactions and were able to produce the seamless exchange of energy. Li *et al.* [32] proposed a new blockchain-based energy trading scheme (BC-ETS), FeneChain, which uses anonymous authentication to protect user privacy and employs a time-commitment-based mechanism to verify the fairness of energy transactions. To address challenges, such as insufficient scalability, vulnerability to network attacks, and low processing efficiency, Guan *et al.* [33] proposed a secure and efficient BC-ETS, which can both protect privacy and balance power supply and demand.

A few studies applied blockchain to distributed V2V or V2G energy trading management [20], [34], [35]. Li and Hu [34] utilized consortium blockchain to design a scheme for bidirectional power trading between EVs and the power grid and proposed an improved krill herd (KH) algorithm to solve disordered charging of massive EVs. Sadiq *et al.* [35] developed a blockchain-based trading model for V2V or vehicle to infrastructure (V2I) in which blockchain is implemented on RSUs and introduced an account generation method based on the time-series single-exponential technique.

In conclusion, blockchain works very well in the above applications, so it has significant potential for vehicle energy trading management. However, few studies have focused on the energy scheduling management problem for V2V energy trading.

III. System Architecture

A. Architecture and Entities

As shown in Fig. 1, the proposed electricity trading architecture based on blockchain mainly consists of the following four entities.

1) *EVs:* The EVs are a new type of EV with a pollution-free, low-noise driving mode equipped with a two-way charge and discharge system. These EVs are environmentally friendly and energy efficient, so they are regarded as a promising transportation tool for green cities. In our energy trading system, EVs have three different roles (electricity buyer, electricity seller, and idle user). An EV can choose to become a charging

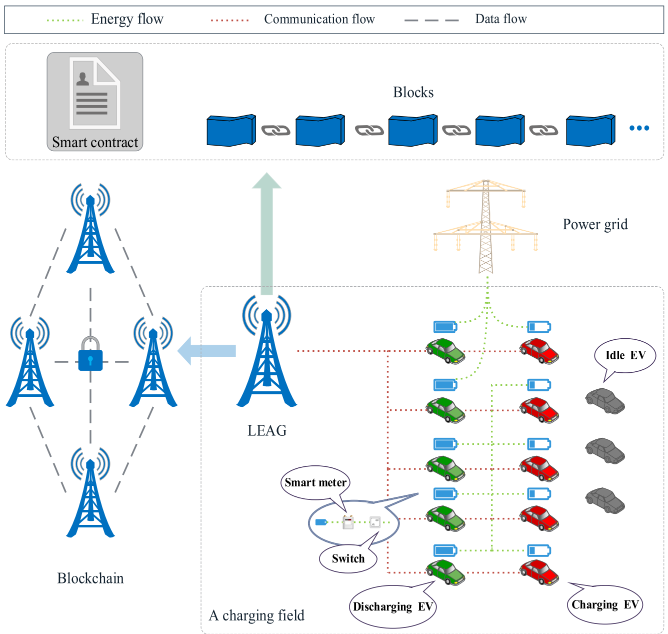

Fig. 1. Energy trading architecture based on blockchain.

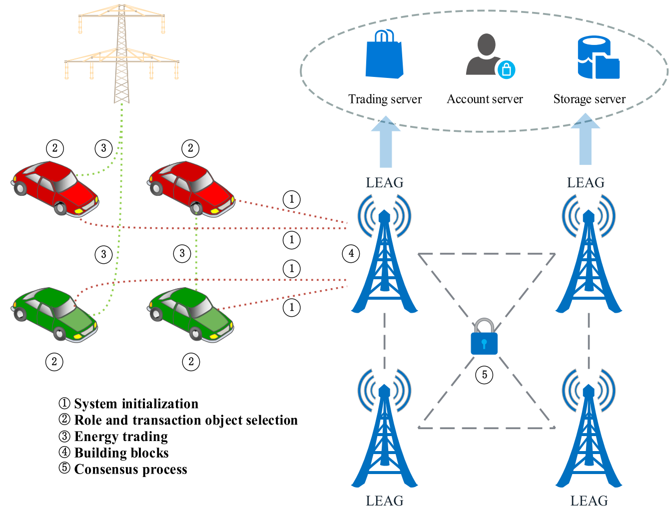

Fig. 2. Energy trading process.

EV (electricity buyer) or a discharging EV (electricity seller). Then, the EV decides to trade with either the grid or other EVs according its own requirements. The idle EVs do not participate in this energy trading. However, they can also participate in the next energy trading according to their wishes. An EV chooses its role in our system according to its energy status, its energy requirement, and the time it can spend for waiting. It takes less time to trade with the grid than other EVs; however, EVs gain more utility by trading with other EVs than the grid. The details are given in Section IV.

2) *LEAGs:* There is a LEAG deployed in each charging field, and the LEAG provides a series of energy trading services, including communication support, information collection, and charging/discharging pricing. Each LEAG is an energy consensus node, and the LEAGs jointly maintain the blockchain, act according to consensus, audit transactions, and share data. The prewritten smart contract, which is our pricing mechanism and ensures optimal energy allocation, is deployed in each energy node. When a transaction occurs, the smart contract acts as an energy trading auctioneer, and the trading mechanism designed in the smart contract is automatically executed, which coordinates charging EVs and discharging EVs. There are three major components in each LEAG: 1) a trading server; 2) an account server; and 3) a storage server. The trading server is responsible for coordinating the EVs' charging and discharging activities, collecting information on the energy demand of charging EVs and the energy supply of discharging EVs, and executing the pricing and energy allocation algorithm to match the charging and discharge EVs. The trading server also monitors feedback from smart meters in real time and intelligently controls its two-way charging switch according to the energy allocation algorithm. Each EV has a trading account that stores all its trading records. Each EV also owns a digital wallet that stores its digital assets. To protect the users' privacy and ensure anonymity, the real address of the wallet is replaced by a set of random characters. The map between a random wallet address and the corresponding trading account is stored in the account server. The storage server stores all the transaction records in the blockchain.

3) *Power Grid:* The power grid is a transmission network connecting either power plants and substations or substations and mainly undertakes the task of transmitting electric energy. In our system, the price of electricity obtained from the power grid is stable over time, so it is constant. To employ the market price, there is a need to limit the price of charging EVs and discharging EVs. Therefore, the LEAG sets the price of obtaining electricity from the grid as the upper bound of the electricity price for sellers and the price of energy sold to the grid as the lower bound of the electricity price for buyers.

4) *Smart Meters:* Traditional electricity meters manage electricity consumption; smart meters also have bidirectional metering functions and thus, can adapt to smart power grids and new energy sources. Each EV is equipped with a built-in smart meter that records the volume of energy transactions and provides strong data support that allows it to pay for both charging and discharging.

B. Energy Trading Process

This section provides a detailed description of energy trading in our system. As shown in Fig. 2, during energy trading, the EV connected to the LEAG first chooses its role according to its energy state and energy demand/surplus. Based on its own requirements, each EV can decide to trade with either the grid or other EVs. If the EV decides to trade with the grid, it can do so immediately, without waiting. Conversely, if the EV decides to trade with other EVs, it must wait for a matching period, but the price of energy is more beneficial for both the buyer and seller. The following mainly describes the transactions that take place between EVs. Charging EVs submit their energy demand to the LEAG, and discharging EVs submit their energy supply requests to the LEAG. After the LEAG collects and verifies the transaction requests for a certain amount of time, it acts as the energy auctioneer and coordinates the charging EVs and discharging EVs by triggering the pricing and energy allocation mechanism designed in the smart contract. EVs trade with other EVs according to the optimal trading scheme. The LEAG collects all the trading records over time and uses a consensus algorithm to audit and verify the authenticity and accuracy of the transactions. Then, the LEAG writes valid transaction records into the block and builds the block. This trading process mainly includes the following five steps.

1) System Initialization: Each LEAG is registered with the authority as a legitimate energy node. Each EV becomes a legitimate entity after registering with a government authority to confirm its true identity in the real world—for example, by using the resident identification card of the EV user. Then, each EV is granted a legal identification I_i and obtains a pair of public/private keys (PK_i, SK_i) after participating in the blockchain system through access to the LEAG. Here, to ensure that data transmission and access in the blockchain remain secure, we use an asymmetric encryption algorithm, such as an elliptic curve encryption algorithm, to encrypt the data. The public key is used to encrypt data, and the corresponding private key is used only to decrypt the encrypted data. The public and private keys are different, and the calculation used for one cannot be obtained from the other. The EVs also need to apply to the LEAG for a set of random wallet addresses $\{\mathrm{RWA}_{i,n}\}_{n=1}^{N}$, where N is the number of wallet addresses that can be obtained from the LEAG. Each EV owns a trading account A_i, where $A_i = \{I_i, \mathrm{PK}_i, \mathrm{SK}_i, \mathrm{RWA}_{i,n}\}$; the account is stored in the account server and is actually a map between a random wallet address and the corresponding EV's identification. While the EVs engage in the initialization process after accessing the LEAG, they upload their wallet addresses to the LEAG and verify the integrity of the wallet information. Then, the EVs download their own wallet data from the storage server of the LEAG.

2) Role and Transaction Object Selection: During the energy trading process, each EV must first choose the appropriate role according to its own energy state and energy demand/surplus. If an EV has little energy left and cannot complete its travel plan, it prefers to be a charging EV. An EV that has enough energy and is willing to take part in the V2V energy trading is referred to as a discharging EV. Next, the EV should select the transaction object. Each EV can decide to trade with either the grid or other EVs based on its own requirements. If a charging EV chooses to trade with the grid, it can execute the trade immediately without waiting. However, if the EV decides to trade with other EVs, it must wait for a matching period. In the real world, the electric price of the power grid is stable over time, so the price of electricity sold by the grid usually is a constant and always is higher than the price of electricity sold by discharging EVs. Similarly, the price of electricity sold by the grid usually is a constant and always is lower than the price of electricity sold by other charging EVs. The prices of electricity purchased from and sold to the grid limit the energy price in the V2V market.

3) Energy Trading: For EVs that choose to trade with the grid, they trade with the grid directly at the price offered by the grid. For EVs that choose to participate in V2V energy trading, the charging PHEV, as the energy consumer, sends the purchase request, which includes its energy demand, the initial expected purchase price, and the maximum acceptable purchase price, to the trading server of the LEAG. The discharging PHEV, as the energy seller, sends the sales request, which includes its energy supply, the initial expected selling price, and the minimum acceptable selling price, to the trading server of the LEAG. After the trading server has collected all trade requests for a period of time, the smart contract that has been predeployed on the trading server is automatically triggered. The contract acts as an energy auctioneer to execute the Bayesian game-based bidirectional auction algorithm for optimal energy pricing and allocation. Then, the LEAG provides the algorithm result to the EVs, and the EVs trade with other EVs according to the optimal trading scheme, which is controlled by the EVs' built-in smart meter.

4) Building Blocks: The LEAG collects all local transaction records at regular intervals, and to ensure the authenticity and accuracy of these records, it encrypts and digitally signs them. Afterward, these transaction records are structured into a block. Each block is linked to the previous block in the order of a linear timestamp created by using the encrypted hash value of the previous block. These blocks connect to form a chain. The blockchain contains all verified transaction information generated when a block is created. The storage structure of transaction data is as follows: 1) version, indicating the validation rules that this transaction must follow; 2) NumInputs, the number of inputs included in this transaction; 3) inputs, the input data contained in this transaction, including the hash value of previous transactions, the index of the associated output, and the unlocking script; 4) NumOutputs, the number of outputs included in this transaction; 5) outputs, the output data contained in the transaction, including the output value (payment amount and trading volume) and locking script; and 6) LockTime, the locking time of this transaction, setting it as 0 in our system to indicate immediate propagation and execution. The block header contains references to the previous block and the following information related to the current block: 1) the hash value of the parent block, which is the hash address pointing to the previous block, a 256-bit hash value; 2) version, which is the version number of the block header, indicating the validation rules that the block must follow; 3) Merkle root, which is the hash value of all transactions in the block; and 4) timestamp, which is the exact time that the block was generated.

5) Consensus Process: The Proof of Work (PoW) in the Bitcoin system relies on a machine that can carry out mathematical computations to obtain the right to keep accounts and consumes a large amount of computational resources. Every consensus requires the joint participation of the whole

TABLE I
DEFINITIONS OF KEY SYMBOLS

Symbol	Definition
d_i	Energy demand of charging EV CE_i.
s_j	Energy supply of discharging EV DE_j.
$U_i(d_i)$	Utility function of charging EV CE_i.
$C_j(s_j)$	Energy loss function of discharging EV DE_j.
ρ	Energy transmission efficiency.
p_{ij}	Initial expected purchase price of charging EV CE_i for discharging EV DE_j, where $p_{ij} \in [p_{ij}^{min}, p_{ij}^{max}]$.
r_{ji}	Initial expected selling price of discharging EV DE_j for charging EV CE_i, where $r_{ji} \in [r_{ji}^{min}, r_{ji}^{max}]$.
p^G	Purchase price of grid, where $p^G = p_{ij}^{min}$.
r^G	Selling price of grid, where $r^G = r_{ji}^{max}$.

network, so it takes a long time to reach a consensus. This process is not suitable for our system. In our system, we employ a Byzantine-based consensus mechanism (BCM) proposed by [36] as our consensus algorithm. The BCM is a new byzantine-based consensus algorithm based on the credit of each node. Each node's credit mechanism is introduced through a practical Byzantine fault tolerance (PBFT) algorithm. In the blockchain system, each consensus node initializes the credit as a constant; and as the consensus process progresses, the credit of good nodes gradually increases, while that of malicious nodes gradually decreases. As a result, the number of prepared and committed messages required for a good node to reach a consensus decrease, which is beneficial for reducing latency and improving throughput. This consensus algorithm, which has low latency and high throughput, is suitable for our system.

IV. Problem Modeling of Energy Trading

Based on the game theory, the Bayesian game is one in which players do not have complete information about the type of opponent. Therefore, Bayesian games are also known as incomplete information games. In practical energy trading processes, neither the energy buyers nor the energy sellers have complete information about each other. Therefore, the Bayesian game has great potential to solve the V2V energy pricing problem with incomplete information.

A. Modeling the Energy Trading Volume Problem

In the energy trading market, both sides of the transaction are made up of selfish and rational individuals, and they hope that their expected energy utility can be maximized [37]. In this section, we first model the optimal transaction volume determination as a formulated convex problem that maximizes social welfare. Then, we model the optimal pricing problem to maximize the utilities of both sides of the energy transaction. There is a LEAG deployed in each charging field, and the LEAG provides a series of energy trading services for charging EVs and discharging EVs. Each charging EV is denoted as CE_i, where $i = \{1, 2, \ldots, N\}$, and its energy demand is d_i, such that $d_i \in [d_i^{\min}, d_i^{\max}]$. $d_i^{\min}$ is the minimum energy demand of the charging EV required for its travel plan, and $d_i^{\max}$ is the maximum acceptable energy demand of the charging EV. Each discharging EV is denoted as DE_j, for which $j = \{1, 2, \ldots, M\}$, and its energy supply is s_j. Discharging EVs can provide energy up to a maximum amount $s_j^{\max}$ for energy trading. The definitions of key symbols are shown in Table I.

During the V2V energy trading process, the LEAG broadcasts the energy demand to the discharging EVs to match the charging and discharging EVs. We denote the energy that a charging EV CE_i purchases from a discharging EV DE_j as d_{ij}. Furthermore, in our system, a charging EV can choose to trade either with the grid or discharging EVs. Therefore, its energy demand is calculated as

$$d_i = d_i^G + \sum_{j=1}^{M} d_{ij} \tag{1}$$

where d_i^G is the energy purchased from the grid. If a charging EV chooses to trade with the grid, then $d_{ij} = 0$. However, if a charging EV chooses to trade with other EVs, then $d_i^G = 0$.

In the V2V energy trading process, the LEAG allocates the energy supply of a discharging EV to charging EVs. We denote the energy that discharging EV DE_j sells to charging EV CE_i as s_{ji}. Similarly, a discharging EV can choose to trade with either the grid or charging EVs. Therefore, its energy supply is calculated as

$$s_j = s_j^G + \sum_{i=1}^{N} s_{ji} \tag{2}$$

where s_j^G is the energy sold to the grid. If a discharging EV chooses to trade with the grid, then $s_{ji} = 0$. Otherwise, if $s_j^G = 0$, the discharging EV chooses to trade with other EVs.

From the perspective of charging EVs, social welfare maximization leads to the utility maximization of each participant, which, in this article, is manifested as the utility maximization of charging EVs because of individual rational constraints. Each EV is a risk-averse individual that pursues its own interests, so the utility function should be a nondecreasing and concave function of energy demand. According to [38], in the utility modeling of energy customers, the natural logarithmic function has been widely accepted. In this article, we calculate the charging EVs' utility function using the natural logarithmic function as

$$U_i(d_i) = \omega_i \ln\left(d_i - d_i^{\min} + 1\right) \tag{3}$$

where ω_i is the willingness of charging EVs to participate in energy trading, which is usually a constant within the range of [0, 1].

From the perspective of discharging EVs, social welfare maximization refers to minimizing the costs of each participant. In our system, the main cost of discharging EVs is energy transmission loss. According to [39], the loss of energy transmission in the local energy network is mainly caused by the resistance of the transmission lines. Therefore, following [39], the loss of energy transmission is modeled as a quadratic function of the amount of energy that is transferred. Thus, in this article, we can quantify the energy loss of the discharging EVs as

$$C_j(s_j) = l_1(s_j)^2 + l_2 s_j \tag{4}$$

where l_1 and l_2 are the energy cost factors. In addition, $l_1 > 0$ and $l_2 > 0$.

In conclusion, in the energy trading process, charging EVs want to maximize their utility function, while discharging EVs want to minimize their cost function. Our energy trading system should effectively maximize social welfare and realize market equilibrium. Therefore, in this article, we must calculate the optimal energy distribution by maximizing social welfare. Here, the function of the social welfare maximization problem (SWM) is formulated as follows:

$$\text{SWM} : \max_{d_i, s_j} \left\{ \sum_{i=1}^{N} U_i(d_i) - \sum_{j=1}^{M} C_j(s_j) \right\} \tag{5}$$

$$\text{s.t. } d_i^{\min} \le d_i \le d_i^{\max} \tag{6}$$

$$s_j \le s_j^{\max} \tag{7}$$

$$d_i = \rho s_j \ge 0 \tag{8}$$

where ρ is the energy transmission efficiency, which is usually a constant within the range of [0, 1].

During the energy trading process, an EV can select the transaction object (the grid or other EVs), so there are two trading scenarios, V2G and V2V.

1) *V2G:* In this scenario, the EVs trade with the grid. Here, $d_{ij} = 0$ and $s_{ji} = 0$ hold for all EVs that trade with the grid. Therefore, the SWM problem becomes

$$\text{SWM1} : \max_{d_i^G, s_j^G} \left\{ \sum_{i=1}^{N} U_i\left(d_i^G\right) - \sum_{j=1}^{M} C_j\left(s_j^G\right) \right\} \tag{9}$$

$$\text{s.t. } d_i^{\min} \le d_i^G \le d_i^{\max} \tag{10}$$

$$s_j^G \le s_j^{\max} \tag{11}$$

where N and M are the number of charging EVs and discharging EVs, respectively, which trade with the grid.

2) *V2V:* In this scenario, the EVs trade with other EVs. Here, $d_i^G = 0$ and $s_j^G = 0$ hold for all EVs that participate in the V2V energy trading. Now, the SWM problem becomes

$$\text{SWM2} : \max_{d_i, s_j} \left\{ \sum_{i=1}^{N} U_i(d_i) - \sum_{j=1}^{M} C_j(s_j) \right\} \tag{12}$$

$$\text{s.t. } d_i^{\min} \le \sum_{j=1}^{M} d_{ij} \le d_i^{\max} \tag{13}$$

$$\sum_{i=1}^{N} s_{ji} \le s_j^{\max} \tag{14}$$

$$d_{ij} = \rho s_{ji} \ge 0 \tag{15}$$

where ρ is the energy delivery efficiency, and N and M are the numbers of charging EVs and discharging EVs, respectively, which participate in the V2V energy trading.

B. Energy Pricing Problem Modeling

In our proposed energy trading system, when the EVs decide to participate in the V2V energy transaction, the charging EVs are supposed to submit their initial expected purchase price p_{ij} and maximum acceptable purchase price $p_{ij}^{\max}$, while the discharging EVs should submit their initial expected selling price r_{ji} and minimum acceptable selling price $r_{ji}^{\min}$. To adapt to the market price and encourage EVs to participate in V2V energy trading and to balance overload peaks in the grid, the LEAG sets the price for selling from grid r^G as the upper bound of electricity price for sellers $r_{ji}^{\max}$ and the price for selling energy to grid p^G as the lower bound of electricity price for buyers $p_{ij}^{\min}$. Therefore, $p_{ij} \in [p_{ij}^{\min}, p_{ij}^{\max}]$ and $r_{ji} \in [r_{ji}^{\min}, r_{ji}^{\max}]$.

In our V2V energy trading system, the LEAG acts as the auctioneer to obtain the initial expected purchase price p_{ij} of the charging EVs and the initial expected selling price r_{ji} of the discharging EVs, where $p_{ij} \in [p_{ij}^{\min}, p_{ij}^{\max}]$ and $r_{ji} \in [r_{ji}^{\min}, r_{ji}^{\max}]$. In addition, p_{ij} and r_{ji} obey a uniform distribution in the intervals $[p_{ij}^{\min}, p_{ij}^{\max}]$ and $[r_{ji}^{\min}, r_{ji}^{\max}]$, respectively. Then, the smart contract is triggered to perform the bidirectional auction mechanism.

We might also assume that the bidding of both parties leads to a linear equilibrium. The bidding strategy functions of the buyers and sellers are $W_{ij}(p_{ij})$ and $Q_{ji}(r_{ji})$, respectively. The bidding strategy function used for the bid of charging EV i for discharging EV j is expressed as

$$W_{ij}(p_{ij}) = a_b + e_b p_{ij} \tag{16}$$

where $a_b > 0$ and $e_b > 0$. The bidding strategy function of the discharging EV j bid for charging EV i is expressed as

$$Q_{ji}(r_{ji}) = a_s + e_s r_{ji} \tag{17}$$

where $a_s > 0$ and $e_s > 0$.

Because p_{ij} and r_{ji} lead to a uniform distribution in the intervals $[p_{ij}^{\min}, p_{ij}^{\max}]$ and $[r_{ji}^{\min}, r_{ji}^{\max}]$, $W_{ij}(p_{ij})$ and $Q_{ji}(r_{ji})$ are evenly distributed over interval $[a_b + e_b p_{ij}^{\min}, a_b + e_b p_{ij}^{\max}]$ and $[a_s + e_s r_{ji}^{\min}, a_s + e_s r_{ji}^{\max}]$, respectively. Therefore, the probability distribution of the bidding strategy of charging EVs can be expressed as $S_{ij}(W_{ij}) = \text{Prob}\{W_{ij} \ge Q_{ji}(r_{ji})\}$, while the probability distribution of the bidding strategy of discharging EVs can be expressed as $F_{ji}(Q_{ji}) = \text{Prob}\{Q_{ji} \le W_{ij}(p_{ij})\}$.

Specifically, $F_{ij}(Q_{ji})$ can be obtained as

$$\begin{aligned} F_{ji}(Q_{ji}) &= \text{Prob}\{Q_{ji} \le W_{ij}(p_{ij})\} \\ &= \text{Prob}\left\{Q_{ji} \le a_b + e_b p_{ij}^{\max}\right\} \\ &= \int_{Q_{ji}}^{a_b + e_b p_{ij}^{\max}} \frac{1}{e_b\left(p_{ij}^{\max} - p_{ij}^{\min}\right)} dQ_{ji} \\ &= \frac{a_b + e_b p_{ij}^{\max} - Q_{ji}}{e_b\left(p_{ij}^{\max} - p_{ij}^{\min}\right)}. \end{aligned} \tag{18}$$

Similarly, $S_{ij}(W_{ij})$ can be obtained as

$$\begin{aligned} S_{ij}\left(W_{ij}\right) &= \text{Prob}\left\{W_{ij} \geq Q_{ji}\left(r_{ji}\right)\right\} \\ &= \text{Prob}\left\{W_{ij} \geq a_s + e_s r_{ji}^{\min}\right\} \\ &= \int_{a_s+e_s r_{ji}^{\min}}^{W_{ij}} \frac{1}{e_s\left(r_{ji}^{\max} - r_{ji}^{\min}\right)} \mathrm{dW}_{ij} \\ &= \frac{W_{ij} - a_s - e_s r_{ji}^{\min}}{e_s\left(r_{ji}^{\max} - r_{ji}^{\min}\right)}. \end{aligned} \tag{19}$$

In our V2V energy trading system, both the charging EVs and discharging EVs do not have complete information about each other. The charging EVs know only their own initial expected purchase price p_{ij}; thus, the utility of the charging EV maximization problem under incomplete information is formulated as

$$\begin{aligned} P1\text{: } \max_{W_{ij}} \; & \left[p_{ij} - \frac{1}{2}\left(W_{ij} + E\left[Q_{ji}\left(r_{ji}\right) \mid W_{ij} \geq Q_{ji}\left(r_{ji}\right)\right]\right)\right] \\ & *S_{ij}\left(W_{ij}\right) \end{aligned} \tag{20}$$

where $E[Q_{ji}(r_{ji}) \mid W_{ij} \geq Q_{ji}(r_{ji})]$ indicates the expected bid of the discharging EV when the bid of the charging EV is not lower than the bid of the discharging EV.

Similarly, discharging EVs know only their own initial expected selling price r_{ji}; thus, the maximized utility of the discharging EV under incomplete information is formulated as

$$\begin{aligned} P2\text{: } \max_{Q_{ji}} \; & \left[\frac{1}{2}\left(W_{ij} + E\left[W_{ij}\left(p_{ij}\right) \mid W_{ij}\left(p_{ij}\right) \geq Q_{ji}\right]\right) - r_{ji}\right] \\ & *F_{ji}\left(Q_{ji}\right) \end{aligned} \tag{21}$$

where $E[W_{ij}(p_{ij}) \mid W_{ij}(p_{ij}) \geq Q_{ji}]$ indicates the expected bid of the charging EV when the bid of the charging EV is not lower than the bid of the discharging EV.

V. Algorithm Design

In this section, we propose a Bayesian game based bidirectional auction algorithm to solve the problems modeled in Section IV. This algorithm is written in the smart contract. When the energy trading process occurs, the smart contract is executed automatically.

A. Optimal Volume of Transactions

This section mainly describes how the optimal energy transaction volume can be obtained by solving the SWM problem. There are two trading scenarios, V2G and V2V.

1) *V2G:* In this scenario, $d_{ij} = 0$, and $s_{ji} = 0$. In the energy market, the electricity price of the power grid is stable over time, so it is set to be a constant. In addition, in our system, once the EVs trade with the grid, they cannot participate in V2V energy trading. Therefore, charging EVs trade with the grid to purchase energy d_i^G from the grid at the price of the grid selling r_i^G, where $r_i^G = r_{ji}^{\max}$. Similarly, discharging EVs trade with the grid to sell energy s_j^G to the grid at price p_j^G, where $p_j^G = p_{ij}^{\min}$. Thus, these EVs do not participate in the subsequent V2V energy pricing mechanism. In functions $U_i(d_i^G)$ and $C_j(s_j^G)$, both d_i^G and s_j^G are constant. Consequently, the functions $U_i(d_i^G)$ and $C_j(s_j^G)$ are constant. Therefore, the optimal solutions to problem SWM1 are d_i^G and s_j^G.
2) *V2V:* In the V2V energy trading market, we obtain the optimal energy transaction volume by solving the SWM2 problem. The second-order partial derivatives of objective function (12) satisfy $[\partial^2(d_i)/\partial d_i^2] < 0$ and $[\partial^2(s_j)/\partial s_j^2] > 0$, so objective function (12) is strictly concave, and the constraints are convex. Thus, this function has a unique optimal solution.

According to [40], the unique optimal solution can be obtained by using the Karush–Kuhn–Tucker (KKT) condition. We introduce Lagrangian multipliers in objective function (12) to obtain the augmented Lagrangian function ϕ. Specifically, the introduced Lagrangian multipliers are $\gamma = \{\gamma_i | i = 1, 2, \ldots, N\}$, $\delta = \{\delta_i | i = 1, 2, \ldots, N\}$, $\mu = \{\mu_j | j = 1, 2, \ldots, M\}$, $\eta = \{\eta_{ij} | i = 1, 2, \ldots, N; j = 1, 2, \ldots, M\}$, and $\xi = \{\xi_{ji} | i = 1, 2, \ldots, N; j = 1, 2, \ldots, M\}$. Thus, the Lagrange function ϕ is expressed as

$$\begin{aligned} \phi\left(d_i, s_j, \delta, \gamma, \mu, \eta, \xi\right) = & \sum_{i=1}^{N} U_i(d_i) - \sum_{j=1}^{M} C_j\left(s_j\right) \\ & + \sum_{i=1}^{N} \delta_i \left(\sum_{j=1}^{M} d_{ij} - d_i^{\max}\right) \\ & + \sum_{i=1}^{N} \gamma_i \left(d_i^{\min} - \sum_{j=1}^{M} d_{ij}\right) \\ & + \sum_{j=1}^{M} \mu_j \left(\sum_{i=1}^{N} s_{ji} - s_j^{\max}\right) \\ & + \sum_{i=1}^{N}\sum_{j=1}^{M} \eta_{ij}\left(d_{ij} - \rho s_{ji}\right) \\ & - \sum_{i=1}^{N}\sum_{j=1}^{M} \xi_{ji}\rho s_{ji}. \end{aligned} \tag{22}$$

According to the KKT condition, the optimal solutions of the SWM2 problem are supposed to satisfy the following solution conditions:

$$\begin{aligned} \nabla_{d_{ij}}\phi\left(d_i, s_j, \delta, \gamma, \mu, \eta, \xi\right) = & \frac{\omega_i}{\sum_{j=1}^{M} d_{ij} - d_i^{\min} + 1} \\ & + \delta_i - \gamma_i + \eta_{ij} = 0 \end{aligned} \tag{23}$$

$$\begin{aligned} \nabla_{s_{ji}}\phi\left(d_i, s_j, \delta, \gamma, \mu, \eta, \xi\right) = & -2l_1 s_{ji} - l_2 + \mu_j \\ & - \eta_{ij}\rho - \xi_{ji}\rho. \end{aligned} \tag{24}$$

In the real energy trading market, the volume of total energy transactions for the same batch of EVs should be stable, without large fluctuations. To ensure the stability of our V2V energy trading market, the total amount of energy traded through the optimal energy allocation scheme obtained by solving problem SWM2 should be stable. However, the total energy volume in the optimal solutions obtained by solving problem SWM2 is slightly volatile. To conform to market rules, we introduce a convergence factor (CF)

$$\mathrm{CF} = \frac{SS^{(t_1)} - SS^{(t_1-1)}}{SS^{(t_1)}} \tag{25}$$

where SS is the total volume of energy trading, $SS = \sum_{i=1}^{N}\sum_{j=1}^{M} s_{ji}$, and t_1 is the current iteration number of the energy allocation. In the first iteration, the charging EVs submit their energy demand, and the discharging EVs submit their energy supply to the LEAG according to their own circumstances. Based on this information, the LEAG solves the SWM2 problem to obtain an optimal energy distribution scheme. Then, the total volume of energy trading in this iteration is obtained, as is the energy demand/supply of the next iteration. The algorithm then goes into the next iteration. The algorithm terminates when the result satisfies the following condition:

$$\mathrm{CF} < \varepsilon_1 \tag{26}$$

where ε_1 is a constant that determines the accuracy of the final result. The final optimal energy distribution is in line with market rules.

B. Bayesian Game-Based Bidirectional Auction Mechanism

This section presents the details of the bidirectional auction mechanism based on the Bayesian game used for V2V energy trading.

Because p_{ij} and r_{ji} obey a uniform distribution over their respective intervals, according to (16) and (17), we can calculate $E[Q_{ji}(r_{ji}) \mid W_{ij} \geq Q_{ji}(r_{ji})]$ as

$$\begin{aligned} E\big[Q_{ji}(r_{ji}) \mid W_{ij} \geq Q_{ji}(r_{ji})\big] &= \int_{a_s+e_s r_{ji}^{\min}}^{W_{ij}} \frac{x}{W_{ij} - a_s - e_s r_{ji}^{\min}} \mathrm{dx} \\ &= \frac{1}{2}\Big(a_s + e_s r_{ji}^{\min} + W_{ij}\Big). \end{aligned} \tag{27}$$

Similarly, according to (16) and (17), we can calculate $E[W_{ij}(p_{ij}) \mid W_{ij}(p_{ij}) \geq Q_{ji}]$ as

$$\begin{aligned} E\big[W_{ij}(p_{ij}) \mid W_{ij}(p_{ij}) \geq Q_{ji}\big] &= \int_{Q_{ji}}^{a_b+e_b p_{ij}^{\max}} \frac{x}{a_b + e_b p_{ij}^{\max} - Q_{ji}} \mathrm{dx} \\ &= \frac{1}{2}\Big(a_b + e_b p_{ij}^{\max} + Q_{ji}\Big). \end{aligned} \tag{28}$$

According to (20) and (21), when both participants adopt a linear bidding strategy, their optimal reaction functions are correspondingly linear. Here, we substitute (19) and (27) into P1 and substitute (18) and (28) into P2. Then, we can obtain the linear Bayesian equilibrium solution under the optimal reaction conditions as

$$W'_{ij} = \frac{2}{3}p_{ij} + \frac{1}{4}r_{ji}^{\min} + \frac{1}{12}p_{ij}^{\max} \tag{29}$$

$$Q'_{ji} = \frac{2}{3}r_{ji} + \frac{1}{4}p_{ij}^{\max} + \frac{1}{12}r_{ji}^{\min}. \tag{30}$$

As we know, in real V2V energy trading, when the price W'_{ij} that charging EV i will pay is lower than the price Q'_{ji} set by discharging EV j, the transaction will not be successful. This decreases the transaction success rate, which, in turn, decreases the social welfare. In addition, the Bayesian equilibrium solution sometimes does not satisfy the above transaction conditions. Therefore, to ensure that each EV participating in the V2V energy trading scheme can successfully deal with other EVs, we introduce a two-way auction mechanism, which can be used to improve the transaction success rate.

In a two-way auction, after the current round, as long as the closing conditions have not been met, the seller and the buyer adjust their bids according to market rules and conduct a new round of trading. First, we propose a new price adjustment strategy. We assume that the bid of charging EV i in round t_2 of the auction is $W_{ij}^{t_2}$, where $W_{ij}^{0} = p_{ij}$, and the bid of the discharging EV j in round t_2 of the auction is $Q_{ji}^{t_2}$, where $Q_{ji}^{0} = r_{ji}$. Then, the bids of both charging EV i and discharging EV j in round $t_2 + 1$ of the auction are

$$W_{ij}^{(t_2+1)} = W_{ij}^{(t_2)} - \alpha \min\left\{W_{ij}^{(t_2)} - p_{ij}^{\max}, 0\right\} \tag{31}$$

$$Q_{ji}^{(t_2+1)} = Q_{ji}^{(t_2)} - \beta \max\left\{Q_{ji}^{(t_2)} - r_{ji}^{\min}, 0\right\} \tag{32}$$

where α is the price adjustment coefficient of the charging EVs, where $0 \leq \alpha \leq 1$, and β is the price adjustment coefficient of the discharging EVs, where $0 \leq \beta \leq 1$.

According to formula (31), the bid of the charging EVs in each round is not higher than the maximum acceptable purchase price $p_{ij}^{\max}$. When $\alpha = 0$, the bid of the charging EVs in each round is the same as their bids in the first round. When $0 \leq \alpha \leq 1$, and another auction round proceeds, the bids of the charging EVs increase continuously and approach the maximum acceptable purchase price $p_{ij}^{\max}$. The larger α is, the faster the bids converge.

Similarly, the bids of the discharging EVs in each round are not lower than the minimum acceptable selling price $r_{ji}^{\min}$. When $\beta = 0$, the bids of the discharging EVs in each round are the same as their bids in the first round. When $0 \leq \beta \leq 1$, and another auction round proceeds, the bids of the discharging EVs decrease continuously and approach the minimum acceptable selling price $r_{ji}^{\min}$. The larger β is, the faster the bids converge.

C. Algorithm Description

This section gives the details of the BABG algorithm that we proposed.

The BABG algorithm obtains the optimal energy allocation of the first iteration by solving the SWM2 problem and then determines whether the total volume of energy trading meets the solution for (26). If not, the process continues to the next iteration. Algorithm 1 shows the details of BABG.

After the LEAG obtains the optimal energy allocation, the BABG algorithm enters the bidirectional auction pricing module. In the first auction, the LEAG calculates the first bids of the charging and discharging EVs according to their initial expected prices. Then, the algorithm determines whether the bids of the buyers and the sellers meet the terms of the transaction. If the terms of the transaction are not met, then both participants adjust their bids and enter the next auction. If the

Algorithm 1 BABG Algorithm

Input: $\varepsilon_1, \varepsilon_2, \left\{d_i^{min}, d_i^{max}, p_{ij}, p_{ij}^{max}\right\}_{i=1}^{N}, \left\{s_j^{max}, r_{ji}, r_{ji}^{min}\right\}_{j=1}^{M}$

Output: $d_{ij}^{(t_1)}, s_{ji}^{(t_1)}, W_{ij}^{(t_2)}, Q_{ji}^{(t_2)}$

1: **Initialization:** $\left\{p_{ij}^{min}\right\}_{i=1}^{N}, \left\{r_{ji}^{max}\right\}_{j=1}^{M}$. Let the iteration time $t_1 = 0$, auction time $t_2 = 0$, and $flag1 = flag2 = 1$;
2: **while** $flag1$ **do**
3: The LEAG solves the SWM2 problem to obtain $d_{ij}^{(t_1)}$ and $s_{ji}^{(t_1)}$;
4: Let $t_1 = t_1 + 1$;
5: **if** $CF < \varepsilon_1$, **then**
6: $flag1 = 0$ and then broadcasts the optimal energy distribution to the charging EVs and discharging EVs;
7: **end if**
8: **end while**
9: **while** $flag2$ **do**
10: Let $t_2 = t_2 + 1$;
11: The LEAG solves the P1 and P2 problems to obtain $W_{ij}^{(t_2)}$ and $Q_{ji}^{(t_2)}$ through Equations (29) and (30);
12: **if** $W_{ij}^{(t_2)} < Q_{ji}^{(t_2)}$, **then**
13: $W_{ij}^{(t_2)} = W_{ij}^{(t_2)} - \alpha \min\{W_{ij}^{(t_2)} - p_{ij}^{max}, 0\}$ and $Q_{ji}^{(t_2)} = Q_{ji}^{(t_2)} - \beta \max\{Q_{ji}^{(t_2)} - r_{ji}^{min}, 0\}$;
14: let $p_{ij} = W_{ij}^{(t_2)}$ and $r_{ji} = Q_{ji}^{(t_2)}$, then return to Step 10;
15: **else**
16: **if** $CW < \varepsilon_2$ and $CQ < \varepsilon_2$, **then**
17: $flag2 = 0$ and then broadcasts the optimal energy price to charging EVs and discharging EVs;
18: **end if**
19: **end if**
20: **end while**
21: **return** $d_{ij}^{(t_1)}, s_{ji}^{(t_1)}, W_{ij}^{(t_2)}, Q_{ji}^{(t_2)}$

condition is satisfied, then the LEAG checks the termination condition of the pricing mechanism to determine whether the current bids meet the following condition of convergence:

$$\mathrm{CW} = \frac{W_{ij}^{(t_2)} - W_{ij}^{(t_2-1)}}{W_{ij}^{(t_2)}} < \varepsilon_2 \tag{33}$$

$$\mathrm{CQ} = \frac{Q_{ji}^{(t_2)} - Q_{ji}^{(t_2-1)}}{Q_{ji}^{(t_2)}} < \varepsilon_2 \tag{34}$$

where ε_2 is the convergence coefficient, which is a constant. If the current bids do not satisfy (33) and (34), then both participants adjust their bids and enter the next auction. When ε_2 is small enough, the final price obtained is stable.

A smart contract can be regarded as a program deployed in the blockchain that can run automatically. Because the scheme involves trusted and tamper-resistant data, the predefined rules and terms can be automatically executed, and certain predefined operations can be automatically performed when certain conditions are met. We prewrite the BABG algorithm into a smart contract. When a transaction occurs, the BABG algorithm employed in the smart contract is automatically executed.

Algorithm 2 Smart Contract Implementation

1: **Initialization** ();
2: Input: i, I_i;
3: $\{PK_i, SK_i, RWA_{i,n}\} \leftarrow register(I_i)$;
4: BuyerInput: $\left\{d_i^{min}, d_i^{max}, p_{ij}, p_{ij}^{max}\right\}_{i=1}^{N}$;
5: SellerInput: $\left\{s_j^{max}, r_{ji}, r_{ji}^{min}\right\}_{j=1}^{M}$;
6: **TradingScheme** ();
7: **Call** BABG algorithm;
8: send (d_{ij}, W_{ij});
9: send (s_{ji}, Q_{ji});

Detailed smart contract is shown in Algorithm 2. After the system initialization, each EV registers with the blockchain network and obtains a public/private key pair (PK_i, SK_i) and a random wallet address $\mathrm{RWA}_{i,n}$. In the smart contract, we use an asymmetric encryption algorithm to encrypt the data. The public key PK_i is used to encrypt data, and the corresponding private key SK_i is used only to decrypt the encrypted data. When a transaction takes place, i.e., all EVs have submitted their energy requirements and their initial bids, the LEAG automatically executes the algorithm BABG. Finally, the optimal energy distribution $\boldsymbol{d_{ij}^{(t_1)}}, \boldsymbol{s_{ji}^{(t_1)}}$ and optimal price $\boldsymbol{W_{ij}^{(t_2)}}, \boldsymbol{Q_{ji}^{(t_2)}}$ are obtained, and then,the result is broadcast to each EV.

VI. Simulation and Analysis

This section provides extensive numerical examples that are used to evaluate the performance of the proposed algorithms.

A. Simulation Setting

In our simulation, we set the purchase price p^G and the selling price r^G of the grid as 0.6 and 1 yuan/kWh according to [41]. Therefore, the grid's selling and buying prices limit the energy price in the V2V market, where $r_{ji}^{\max} = r^G = 1$ yuan/kWh and $p_{ij}^{\min} = p^G = 0.6$ yuan/kWh. According to [18], the maximum effective state of a charge is 20 kWh. The other simulation parameters are shown in Table II.

We compare our BABG algorithm with two existing V2V energy trading algorithms, i.e., the iterative double auction (IDA) algorithm proposed in [19] and the V2V electricity trading algorithm (ETA) proposed in [20]. The IDA algorithm models the energy transaction problem as a mathematical optimization problem, introduces a corresponding incentive mechanism, and uses a Lagrange algorithm to determine the optimal energy allocation and pricing strategy. In the ETA, the optimal pricing under the linear strategic equilibrium has been obtained, which maximizes the utilities of both parties. For fairness, our data represent the averages of data obtained from multiple experiments.

B. Simulation Results and Analysis

To verify the performance of our algorithm under different user scales, we test the maximum social welfare achieved under different user scales.

TABLE II
PARAMETERS USED IN OUR SIMULATIONS

Parameter	Definition	Value
d_i^{min}	Minimum energy demand of each charging EV.	[5, 10] kWh
d_i^{max}	Maximum energy demand of each charging EV.	[12, 18] kWh
s_j^{max}	Maximum energy supply of each discharging EV.	[10, 20] kWh
ε_1	Convergence factor in Formula (26).	0.001
ε_2	Convergence factors in Formulas (33) and (34).	0.001
ρ	Energy delivery efficiency.	0.9
l_1	Quadratic factor of energy loss.	0.0025
l_2	First-order factor of energy loss.	0.005

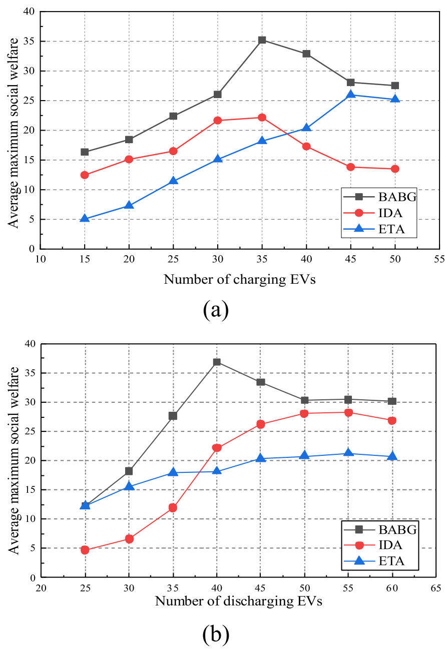

Fig. 3. Simulation results of social welfare. (a) Number of discharging EVs is 40. (b) Number of charging EVs is 35.

Fig. 3(a) shows the relationship between the maximum social welfare and the number of charging EVs when the number of discharging EVs is fixed at 40. The maximum social welfare first increases with the increase in the number of charging EVs, reaches the maximum at 35 charging EVs, and then decreases. The IDA increases with the increase in the number of charging EVs first, then decreases, and finally, flattens out. With the same input, the value of maximum social welfare of IDA is lower than that of our BABG algorithm. The maximum social welfare of the ETA increases as the number of charging EVs increase, but the overall value is still lower than that of the algorithm proposed in this article. This result shows that the BABG algorithm proposed in this article is better than the two existing algorithms.

Fig. 3(b) shows the relationship between the maximum social welfare and the number of discharging EVs when the number of charging EVs is fixed at 35. The results show that the maximum social welfare of our BABG algorithm first

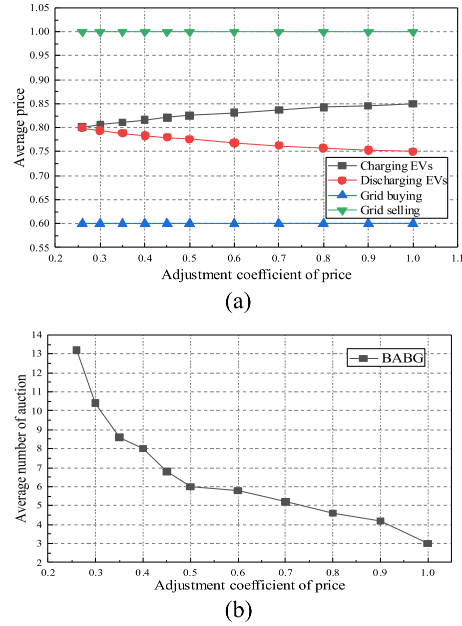

Fig. 4. Effects of the price adjustment coefficient based on the BABG algorithm. (a) Average price versus price adjustment coefficient. (b) Number of auctions versus price adjustment coefficient.

increases with the increase in the number of discharging EVs, reaches the maximum when the number of discharging EVs is 40, and then decreases. The IDA increases with the increase in the number of discharging EVs first and then decreases slightly. With the same input, the value of maximum social welfare of IDA is lower than that of our BABG algorithm. The maximum social welfare of the ETA changes gently with the number of discharging EVs, but the overall value is much lower than that of the algorithm proposed in this article. This result shows that the BABG algorithm proposed in this article is effective.

These results indicate that there is performance degradation when one side of the user scale is too large. This degradation occurs when there are a large number of discharging EVs in the energy trading scheme, and the energy supply far exceeds the energy demand, leading to the idle waste of energy and an increase in energy loss, thus reducing social welfare. However, when the number of charging EVs far exceeds the number of discharging EVs, the energy demand far exceeds the energy supply, so the energy demand cannot be met, leading to a decline in social welfare. This result is consistent with what occurs in the real energy trading market.

Our algorithm includes a price adjustment function, and the price adjustment coefficients determine α and β and the convergence rate of the pricing mechanism. Fig. 4(a) shows the relationship between the average price and the price adjustment coefficient when the number of charging EVs is 35 and the number of discharging EVs is 40. Fig. 4(b) shows the relationship between the average number of auctions and the price adjustment coefficient at the same user scale. As we can see, the difference between the purchase price of the charging EVs and the selling price of the discharging EVs increases as the price adjustment coefficient increases, while the average number of auctions decreases. This occurs because the larger

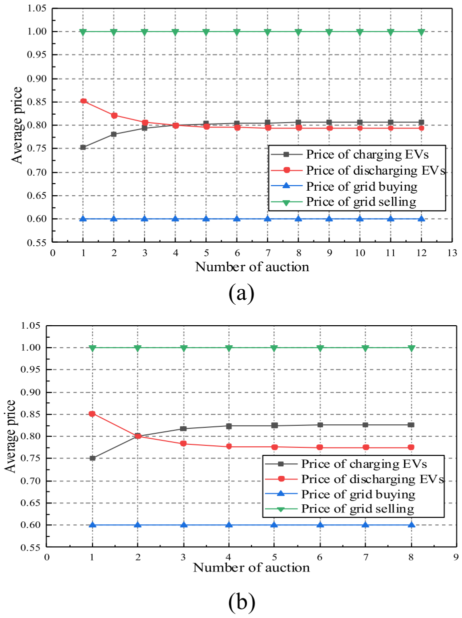

Fig. 5. Average price versus the number of auctions. (a) $\alpha = \beta = 0.3$. (b) $\alpha = \beta = 0.5$.

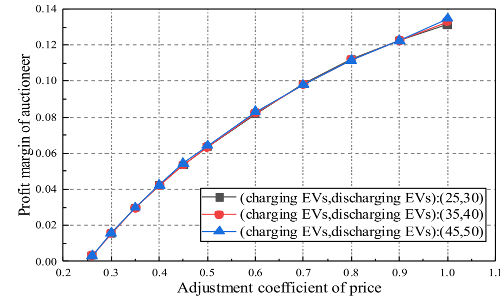

Fig. 6. PMA at various user scales.

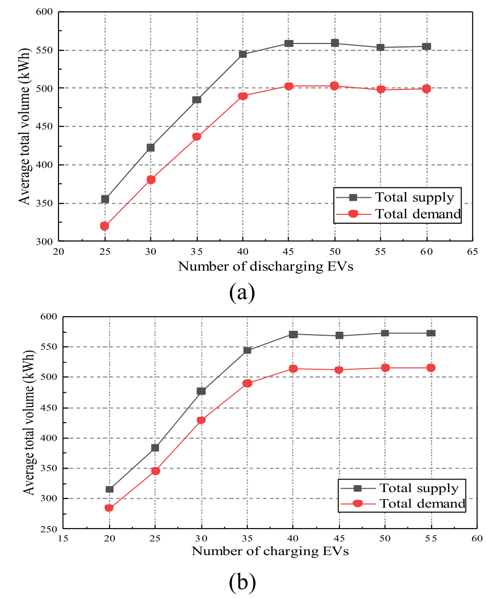

Fig. 7. Total trading volume versus the EV scale. (a) Number of charging EVs is 35. (b) Number of discharging EVs is 40.

the price adjustment coefficient is, the larger the range of each price adjustment is and subsequently, the larger the difference is. The smaller the price adjustment coefficient is, the greater the corresponding increasing in the number of auctions. A better pricing strategy is obtained, but it requires more time and computing power.

To understand the process of the Bayesian game-based bidirectional auction, we show the process where the average price varies with the number of auctions in Fig. 5. Fig. 5(a) depicts the relationship between the average price and number of auctions, where the price adjustment coefficient $\alpha = \beta = 0.3$. Fig. 5(b) depicts the relationship between the average price and number of auctions, where the price adjustment coefficient $\alpha = \beta = 0.5$. As shown in the figure, in the first auction, the selling price of the discharging EVs is much higher than the buying price of the charging EVs. As the auction continues, the difference between the selling price and the buying price decreases, and then, the buying price exceeds the selling price to reach the terms of the transaction, which tends to stabilize gradually. Therefore, in each new auction, a more stable pricing strategy is used. When $\alpha = \beta = 0.5$, the convergence speed is faster than that when $\alpha = \beta = 0.3$, which is consistent with the details mentioned above.

In our system, the difference between the purchase price of charging EVs and the selling price of discharging EVs is the profit of the auctioneer. We define the profit margin of an auctioneer (PMA) as

$$\mathrm{PMA} = \frac{\overline{p} - \overline{r}}{\overline{r}} \tag{35}$$

where $\overline{p}$ is the average value of all $W_{ij}^{(t_2)}$, and $\overline{r}$ is the average value of all $Q_{ji}^{(t_2)}$.

As shown in Fig. 6, from the perspective of the auctioneer, as mentioned above, the greater the price adjustment coefficient is, the greater the difference between the purchase price and the selling price is, and the greater the PMA is. From the perspective of users, the greater the price adjustment coefficient is, the lower the time cost is but the larger the price difference charged by the auctioneer is. In addition, under different user sizes, the change in the auctioneer's profit margin is basically the same as the change in the price adjustment coefficient, so it is little affected by the user scale. Therefore, our algorithm is applicable to different kinds of real energy transactions.

Fig. 7(a) depicts the relationship between the total volume of energy trading and the number of discharging EVs when the number of charging EVs is 35. As shown in the figure, with the increase in discharge EVs, the total trading volume tends to be stable. This is because when the number of charging EVs is fixed, the total energy demand is also fixed. Even if the number of discharging EVs continues to increase, the total trading volume remains stable, at most equal to the total demand. Fig. 7(b) depicts the relationship between the total volume of energy trading and the number of charging EVs when the number of discharging EVs is 40. As shown in the figure, with the increase in charging EVs, the total trading volume tends to be stable. This is because when the number of discharging EVs is fixed, the total energy supply is also fixed.

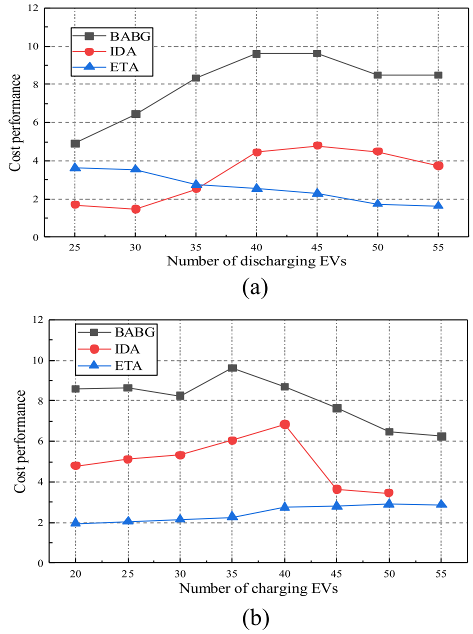

Fig. 8. CP of BABG, IDA, and ETA. (a) Number of charging EVs is 35. (b) Number of discharging EVs is 40.

Even though the number of charging EVs keeps increasing, it can provide a certain amount of energy, so the total trading volume is also a certain amount, at most equal to the total supply. Therefore, our algorithm is applicable to the real energy trading market.

To quantify the cost of the algorithm to obtain the maximum social welfare, we define the CP as

$$\mathrm{CP} = \frac{\max_{d_i, s_j}\left\{\sum_{i=1}^{N} U_i(d_i) - \sum_{j=1}^{M} C_j(s_j)\right\}}{\sum_{j=1}^{M} C_j(s_j)}. \tag{36}$$

Fig. 8(a) shows the relationship between the CP and number of discharging EVs when the number of charging EVs is 35. Fig. 8(b) shows the relationship between the CP and number of charging EVs when the number of discharging EVs is 40. Similarly, we compare the proposed BABG algorithm with IDA and ETA. The results show that the CP of the BABG algorithm proposed in this article is significantly higher than that of the existing algorithms. This result shows that our algorithm can obtain higher returns at a lower cost and thus, our algorithm is effective and excellent.

VII. Conclusion and Discussion

We developed a V2V and V2G energy trading system based on blockchain. For the energy trading, we developed LEAGs in our system. To guarantee the reliability and security of the transaction data, a prewritten smart contract that employs a Bayesian game based bidirectional auction algorithm is deployed in each LEAG. The LEAGs jointly maintain the blockchain, participate in reaching a consensus, audit transactions, and share data. Because the charging EVs and discharging EVs do not have complete information about each other, we proposed a bidirectional auction mechanism based on the Bayesian game. We modeled the optimal pricing problem to maximize the utilities of both sides of the electricity transaction and modeled the optimal energy allocation as a convex problem that maximizes social welfare. Then, we performed simulation analysis and compared the results of our algorithm with those of two existing algorithms. Under the same input, the social welfare of our algorithm is up to 66.4% higher than that of the IDA algorithm and up to 102.8% higher than that of the ETA algorithm. Furthermore, the CP of our algorithm is up to 100.7% higher than that of the IDA algorithm and 319% higher than that of the ETA algorithm. The results indicate that the algorithm we proposed provides results that align with what occurs in the real energy trading market, and its performance is significantly better than that of the existing algorithms.

In the future work, we will consider cross-LEAG energy trading between EVs. In addition, we plan to design a corresponding energy trading scheme for the charging and discharging requirements of EVs on the road.

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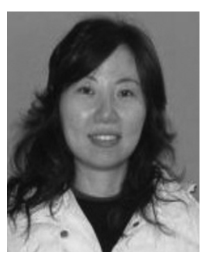

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