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A Trading Mode Based on the Management of Residual Electric Energy in Electric Vehicles

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Abstract: Aiming at the distributed resources of electric vehicles with photovoltaics (PVs) on the user side, a trading mode of surplus energy sharing for electric vehicles based on the user-side PVs is proposed by utilizing the bidirectional mobility of information and energy. Power transfer can be implemented between different electric vehicle users through vehicle-to-grid (V2G) technology with a reasonable distribution of benefits taken into account. First, the operational framework of electric energy trading is presented, and the transmission architecture of each body of interest in the system is analyzed. Second, the portraits of EV users' charging behaviors are established considering their different charging habits, and electric vehicle users are divided into electricity buyers and sellers in each trading time period. An electricity transaction model based on "multi-seller–multi-buyer" is established, and all electricity transactions are realized through blockchain-based decentralized technology. Finally, the benefit to each interest group is maximized using the improved Northern Goshawk Optimization (NGO) algorithm. Simulation results of a sample system indicate that the new power trading mode proposed in this study could lead to reasonable reuse of the electric energy of private electric vehicles and can achieve a win–win situation for all stakeholders.

Keywords: user-side photovoltaic; electric energy sharing; vehicle-to-grid (V2G); electric vehicle user portrait; blockchain

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1. Introduction

At present, electric vehicles (EVs) are a popular means of transportation. Production and sales of renewable energy vehicles ranked first in the world for eight consecutive years, and the passenger car market exceeded 20 million units for eight consecutive years. China's automobile production and sales volume reached 27.021 million and 26.864 million units, respectively, in 2022, up by 3.4% and 2.1% year on year, according to data released by the China Association of Automobile Manufacturers on 12 January 2023 [1]. The country maintained a trend of recovery growth and showed strong developmental resilience, which played an important role in stabilizing the growth of the industrial economy.

Inspired by the concept of power sharing, many researchers at home and abroad have studied power trading on the user side. Yue et al. [2], analyzed the randomness of the current EV users' participation in V2G scheduling, established an evaluation model of EV indicators and proposed an optimal scheduling strategy to achieve optimal EV cluster scheduling. However, the interaction between electric vehicle users was not considered. Jonas et al. [3] utilized the potential of EV flexibility and evaluated the behavior of real users to compare the benefits of using variable and fixed charging prices. The results indicated that variable electricity prices were more beneficial to users. In [4], a refined EV charging load simulation method that considers the demographic and social characteristics of EV users is proposed. The proposed probability model can improve the accuracy of data fitting and charging load simulation. Zhang et al. [5] proposed a robust model for the location and scale of battery exchange stations in the design of electric vehicle battery exchange service networks considering user choice behavior, achieving the advantages of reducing waiting time and early purchase costs and alleviating user range anxiety. In [6], the EV charging scheduling problem was considered with dynamic user behavior and electricity prices, the concept of aggregate anxiety is introduced, and a model-based, model-free deep reinforcement learning (DRL) method is proposed.

As a power source for electric vehicles, the lifespan of batteries is an important issue. In [7], the causes of lithium-ion battery degradation were analyzed in detail, and the main factors affecting battery life were discussed by simulating the real movement process: charging and discharging current, self-discharging current, temperature, cycle times, discharging depth, charging level working range, etc. Finally, the influence factors can be compensated and practical solutions can be provided for battery engineers and designers by the battery management system (BMS). In [8], an effective principle for starting the main internal combustion locomotive was put forward; the supercapacitor was applied to the starting system of a certain internal combustion locomotive. A new charging method for dynamic wireless power transmission has been proposed by [9], which can solve issues such as tripping hazards, damage, and the need to remain fixed for several hours before fully charging the battery by inserting cables into AC power sources. The efficiency of the dynamic wireless power transmission system was improved by maximizing the magnetic coupling coefficient between the main pad integrated into the road and the auxiliary pad installed in the electric vehicle. In a recent work [10], an effective calculation method was proposed for estimating the state of health (SOH) of lithium-ion batteries. The proposed Light GBM-WQR model achieves high accuracy in SOH estimation and provided a preliminary solution for online practical applications such as energy storage systems and electric vehicles.

However, the aforementioned studies on EVs ignore the participation of photovoltaics (PVs) and regional energy storage. PVs play an increasingly important role on the user side, and the application of user-side PV in EV scenarios allows energy utilization to be improved. Martin et al. [11] combined battery electric vehicles with rooftop photovoltaic power generation and tested four intelligent charging strategies with different levels of complexity, indicating that using rooftop photovoltaic power generation for charging pure electric vehicles has great potential to further reduce the climate impact of pure electric vehicles. Influencing due to the principle of the sharing economy, Ref. [12] proposed an equilibrium model of the P2P energy trading market, which considered the deployment of shared energy storage in residential consumers to reduce expensive initial investments and improve the utilization rate of storage devices. The results indicate that P2P energy trading is beneficial for all participants, and introducing shared energy storage can further reduce energy costs. Wang et al. [13] proposed a sharing mode for a user-side distributed optical storage system considering income fairness, which promoted the nearby absorption of PV power generation and reduced the interactive power fluctuation between the electric energy sharing park and grid. In [14], EVs and PVs were integrated into railways to minimize line losses in the objective function. Efficiency can be improved by managing EVs, powered by railway system transformers. Additionally, Khan et al. [15] studied the feasibility of a building-integrated photovoltaic (BIPV)-powered EV charging system using solar energy in a typical house to satisfy residential and EV charging requirements.

Owing to the dispersed resources of EVs, selling and using electricity are not convenient enough, and finding some useful transaction settlement methods is necessary. As a shared database and decentralized peer-to-peer network technology, blockchain technology has the characteristics of intelligent execution, collaborative division of labor, joint decision making, high security, tamper-proofing, and high transparency. It plays a significant role in EV transaction settlements [16]. Wang et al. [17] presented consensus mechanisms and smart contracts based on a consortium blockchain, completed services such as frequency modulation resource aggregation and frequency modulation instruction decomposition required by power grid dispatch centers and EVs, realized decentralized distributed frequency modulation optimization, and promoted flexible resource utilization of EVs. Additionally, a study [18] proposed an EV charging transaction model based on a consortium blockchain, established a transaction network and a channel of mutual trust between multiple charging operators and public power supply companies, realized the interconnection of charging services and autonomous management of charging transactions, and improved the convenience and flexibility of charging services. In [19], the application of blockchain technology was not reflected in EV research. From the sharing economy perspective, the work in [20] deployed a smart contract and run on the local Ethereum blockchain based on Raspberry Pie. The automatic agent simulated the energy consumption and production behavior of four families as well as their buying and selling behavior, proved the advantages of V2G vehicles in terms of economic benefits, overall power balance, and renewable energy consumption rate. A low-carbon transaction energy solution was discussed for EV-density net-zero energy buildings based on blockchain [21].

Although the aforementioned studies consider the advantages of blockchain, they lack a flexible consideration of user-side resources. For example, low-carbon travel can be realized by applying user-side PV to EV charging. For user-side PV scenarios, most studies fail to consider the participation of energy storage in regional power dispatch. Most of them considered the internal configuration of each user and distributed energy storage [22], and the role of shared energy storage in the regional scope was not been deeply considered. On this basis, the transaction scheduling of the residual electric energy for EVs was presented in this paper by combining user-side PV, regional shared energy storage and blockchain technology. The specific contents are as follows:

(1) In the user-side PV scenario, the blockchain is adopted as the underlying transaction settlement method, and different user portraits of EVs are comprehensively considered to participate in the electric energy sharing mode of EVs; (2) a "multi-seller–multi-buyer" electric energy trading mechanism for EVs is established; (3) the improved NGO algorithm is solved to address the problem, and the effectiveness of the proposed trading model is verified by an example analysis.

2. Electric Vehicle Electric Energy Trading Architecture

To meet the changing needs of different EVs users, household PV power generation devices act as power sources for EVs. The entire electric energy trading architecture is primarily composed of EV users, including household PVs, power grids, electricity sales companies, shared energy storage agents, and blockchain trading platforms. A specific scenario is shown in Figure 1.

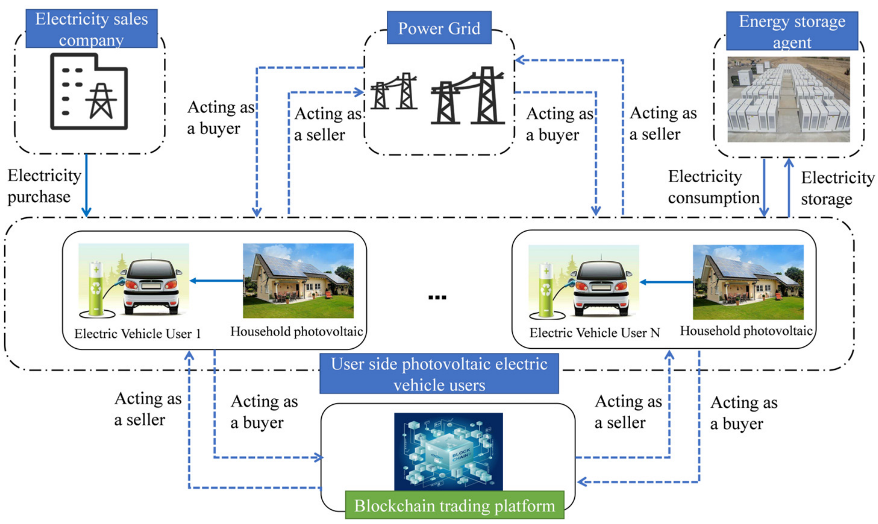


Figure 1. Schematic diagram of electric vehicle energy trading architecture.

Based on the time-of-use electricity price, the user's EV is regarded as a small energy storage unit, and the "multi-seller–grid–multi-buyer" power transaction is performed at different times of electricity consumption. Each user is equipped with PV power generation, which only charges for EVs. Both buyers and sellers can exchange their identities with each other to ensure that the electricity is only circulated among EVs users. The power grid plays a role in energy transmission, while also earning profits for buyers to purchase electricity from the power grid. The time-of-use (TOU) electricity price in the period sold by the seller should be lower than the TOU electricity price in the period sold by the state grid and the electricity-selling company. When the electricity price of the power grid is higher than that of the electricity-selling company during a certain period of time, the buyer can purchase electricity from the electricity-selling company. The flow of electrical energy is based on V2G technology to realize power transmission between users. Simultaneously, the transaction information flow is based on blockchain technology, and "multi-seller–multi-buyer" is adopted as the capital transfer path to realize the capital transaction among users and between users and platforms. Energy storage agents play the role of electric energy storing and leasing among EV users. Specifically, the seller of EV residual electricity stores excess electrical energy through the agents of shared energy storage, and takes it out when needed. The shared energy storage agents earn service fees during this process.

The implementation process of V2G technology involves the remaining electric energy of an electric vehicle being charged into an energy storage device, and the stored electricity is supplied back to the electric vehicle. The detailed process is as follows:

1. Obtaining surplus electric energy from electric vehicles: battery status and remaining energy of electric vehicles are monitored through seamless communication between the vehicles and charging facilities;
2. Receiving electric energy in energy storage devices: energy storage devices serve as important energy storage units linked to electric vehicle charging facilities in the V2G system. When electric vehicles possess surplus energy, this energy can be transmitted to the energy storage devices through the charging facilities;
3. Conversion and storage of electric energy: the remaining electrical energy can be transferred from the electric vehicle to the energy storage device, or from the energy storage device to the electric vehicle.

The V2G technology enables electric vehicles not only to serve as energy consumers but also act as energy storage and supply providers, and plays an important role in the energy systems.

2.1. Materials and Methods

Battery technology of EVs determines the EVs' performance and safety. Lithium iron phosphate batteries, as a novel lithium-ion battery technology, have several advantages. These batteries have lithium iron phosphate ($LiFePO_4$) as the cathode material; electrical energy is stored and released by the migration of lithium ions between the positive and negative electrode materials during the charging and discharging process. The cycling life is higher and the capacity degradation is minor for $LiFePO_4$ batteries, which can ensure remarkable cycling stability. Compared to other lithium-ion batteries, $LiFePO_4$ batteries maintain robust performance under high-rate charging and discharging conditions, and the battery's service life is effectively extended [23].

$LiFePO_4$ batteries act as power sources for EVs, and self-consumption and reverse power transmission are realized through V2G technology in this article. The proposed method ensures that EVs first fulfill their own energy demands. During the period with surplus energy that can be shared with other EV users in need of charging by V2G, a "seller-grid-buyer" energy transmission network is created. Additionally, the model integrates energy storage and sales companies, allowing EV users to store and utilize electrical energy from storage facilities or purchase energy from sales companies, presenting a multi-channel energy utilization method.

2.2. Advantages of User-Side PV

Through the installation of a PV power generation system on the user side, electricity needs are effectively met. Electricity can be generated independently by users, so their reliance on traditional power grids is reduced and the costs of electricity are reduced.

PV power generation holds many advantages over other new energy systems [24]. First, the applicability range of regions is wide. In contrast, wind power generation, for example, requires relatively stable wind speeds and has limited applicability. Second, PV power generation systems are adaptable to areas with limited space, such as rooftops and walls, so the flexibility is enhanced. Conversely, wind power needs substantial space for the installation of wind power systems, so the installation is unsuitable for densely populated urban areas.

Moreover, environmental pollution is low, and there are no radiation risks from PV power generation. In contrast, nuclear power generation, for example, has the risk of radiation and nuclear accidents, while wind power generation may pose threats to wildlife, such as birds and bats.

PV power generation and EVs have excellent compatibility with renewable energy matching. EVs are used during the day, when solar energy generation is at its peak, so solar power can directly charge EVs, and charging costs are effectively reduced.

In conclusion, PV power generation has the advantages of wider adaptability, greater environmental benefits, and lower investment costs for users. It can promote the coordinated development of EVs and intelligent charging technology.

3. Multiple Sellers and Buyers Electricity Trading Model

3.1. Charging Behavior of Electric Vehicle Users

With the popularity of EVs, user profiling of charging behavior has gradually become a research hotspot. By analyzing users' charging behavior, the needs and usage habits of users can be understood and more accurate services can be provided for the supply and demand sides of EV charging services. In this study, user portraits were constructed based on geographical distribution, charging frequency, charging cost, and charging mode, which can provide a reference for the planning and layout of charging facilities and market transaction flexibility.

Based on the above characteristics, three representative user portraits were established: night shift (Class A), early in the morning and late in the evening (Class B), and normal work and rest (Class C) [25]. The classification of user profiles is achieved by EVs' charging and discharging behaviors at different time periods. Different EV users have different charging needs at different times, resulting in different purchasing and selling behaviors. Different EV users have different charging demands at different times, and correspondingly, different electricity buying and selling behaviors occur.

3.2. "Multi-Seller–Multi-Buyer" User Division

Owing to the differences in the power output of the users' PV in each period and the transportation use characteristics of different users' EVs, different buyer and seller division schemes are formulated. If the PV generation of a single user can meet the requirements of EVs and still have excess power, it is regarded as a seller. Single sellers are aggregated to become multi-sellers and the excess power is sold to the buyers or stored in the shared regional energy storage system. Similarly, if the PV power of a single user is insufficient to meet the load requirements of EVs, the user is regarded as a buyer and purchases the required power from a seller, and single buyers are aggregated to become multi-buyers. If the seller cannot provide a certain amount of electricity to meet the demand of the buyer during certain periods, it must purchase electricity from the grid or an electricity-selling company.

3.3. "Multi-Seller–Multi-Buyer" Electricity Trading Income Model

The temperature at time P is set to T_P, and the PV conversion efficiency is

$$\delta = \delta_0[1 - r(T_P - T_r)] \tag{1}$$

In the formula, δ_0 is the conversion efficiency of the PV system at the reference temperature, T_r is the reference temperature of 298 K, r is the temperature coefficient of the PV system, and the power at time t is

$$P = I * A * \delta \tag{2}$$

where A is the area of PV panels, δ is the conversion efficiency, and I is the solar radiation intensity received by the inclined PV panel.

Each day can be divided into T time periods, and the electricity prices of the power grid and electricity-selling companies are used as strategies with the corresponding constraints as follows:

$$Q_{s,t} < Q_{b,t} < Q_{G,t} \tag{3}$$

$$Q_{s,t} < Q_{b,t} < Q_{C,t} \tag{4}$$

$$\Phi_t^{min} < Q_{s,t} < \Phi_t^{max} \tag{5}$$

In the formula, $Q_{s,t}$, $Q_{b,t}$, $Q_{G,t}$, and $Q_{C,t}$ refer to the selling price of the sellers, purchasing price of the buyers, charging price of the state grid, and charging price of the selling company during the tth time period of the day, respectively; Φ_t^{max} and Φ_t^{min} are the upper and lower limits of the electricity price for the tth time period in a day, respectively. Among them,

$$Q_{b,t} - Q_{s,t} = \lambda_t^G + \lambda_t^C \tag{6}$$

where λ_t^G and λ_t^C are the intermediate service fees charged by the power grid and the blockchain trading platform, respectively. The intermediate fees of the state grid include security verification fees, measurement fees, and network fees. The intermediate fee of the blockchain trading platform includes the operating and maintenance fees of the platform. Considering that the sum of the charging and discharging powers of the buyers and sellers in a cycle is zero, subsequently,

$$E_{s,t}^b = E_{b,t}^s \tag{7}$$

where $E_{s,t}^b$ represents the amount of energy sold by the sellers to the buyers in the first t time period and $E_{b,t}^s$ represents the amount of energy purchased by the buyers from the sellers in the first t time period.

The electricity selling price of the sellers includes the electricity selling cost and expected profit, and the electricity selling price $Q_{s,t}$ is

$$Q_{s,t} = C_s^t + P_s^t \tag{8}$$

$$C_s^t = C_g^t + C_e^t \tag{9}$$

where C_s^t is the cost function of the seller, C_g^t is the loss cost of PV charging and discharging, C_e^t is the loss cost of EV charging and discharging, and P_s^t is the expected profit of EV sellers from electricity sales.

The sellers' revenue is

$$R_s = \sum_{t=1}^{T} P_{s,t}^b Q_{s,t} \tag{10}$$

where R_s is the sellers' revenue and $P_{s,t}^{b}$ represents the amount of energy sold by the sellers to the buyers in the tth time period.

Because

$$E_{s,t}^{b} = \sum_{i=1}^{N} E_{s,t}^{b,i} \tag{11}$$

where $E_{s,t}^{b,i}$ represents the amount of energy sold by the ith seller to the buyer in the tth time period.

There are

$$R_s = \sum_{t=1}^{T}\sum_{i=1}^{N} E_{s,t}^{b,i} Q_{s,t} \tag{12}$$

where N represents the number of all sellers.

The buyers' cost is

$$C_b = \sum_{t=1}^{T} E_{b,t}^{s} Q_{b,t} + \sum_{t=1}^{T} E_{G,t}^{b} Q_{G,t} + \sum_{t=1}^{T} E_{C,t}^{b} Q_{C,t} \tag{13}$$

where $E_{G,t}^{b}$ is the energy purchased from the grid by the buyer, and $E_{C,t}^{b}$ is the amount of energy purchased by the buyer from the electricity-selling company.

Thus,

$$E_{b,t}^{G} = \sum_{j=1}^{M} E_{b,t}^{G,j} \tag{14}$$

$$E_{b,t}^{C} = \sum_{j=1}^{M} E_{b,t}^{C,j} \tag{15}$$

Therefore,

$$C_b = \sum_{t=1}^{T}\sum_{i=1}^{N} E_{b,t}^{s,i} Q_{b,t} + \gamma_0 \sum_{t=1}^{T}\sum_{j=1}^{M} E_{b,t}^{G,j} Q_{G,t} + \gamma_1 \sum_{t=1}^{T}\sum_{j=1}^{M} E_{b,t}^{C,j} Q_{C,t} \tag{16}$$

$$\gamma_0 + \gamma_1 = 1 \tag{17}$$

where γ_0 and γ_1 are Boolean logic variables; $E_{b,t}^{G,j}$ represents the amount of energy purchased from the grid by the buyer in the time period t; $E_{C,t}^{b}$ is the amount of energy purchased by the buyer from the electricity-selling company; $E_{b,t}^{C,j}$ represents the amount of energy purchased by the j buyer from the electricity-selling company in the time period t.

Because the cost of purchasing electricity from the seller is lower than the cost of purchasing electricity from the state grid or the electricity-selling company, the buyer will obtain part of the income indirectly. The buyers' indirect income is calculated as follows:

$$R_b = \sum_{t=1}^{T} E_{G,t}^{b} Q_{G,t} - C_b \tag{18}$$

4. Blockchain Model of V2G Transactions for EVs

4.1. Blockchain Ledger

The decentralized trading mode with blockchain technology is the key to distributed-scenario trading. Blockchain technology was first proposed by Nakamoto in 2008 to realize multi-region anonymous processing and distributed interaction of information [26]. In recent years, this technology has been widely used in power trading research. Through the application of blockchain technology, real-time information sharing of electricity prices, electricity consumption periods, and other information can be realized between the buyers and sellers of an EV's surplus energy. The real-time transaction data of both parties are written into the blockchain, and the sellers' power supply and the buyers' electricity consumption strategies can be changed based on the information provided by the blockchain. Simultaneously, the public ledger of blockchain can ensure the reliability of the electricity consumption data owing to the blockchain's non-tamability.

As shown in Figure 2, a decentralized architecture is presented for the V2G trading system in this paper, which is organized into five essential layers: data layer, network layer, consensus layer, smart contract layer, and application layer. Transaction data are efficiently stored by using Level DB or CouchDB database, and Merkle Bucke tree and blockchain table data structures are built into the data layer. An HTTP/2-based P2P protocol is adopted to communicate among nodes, and newly broadcasted blocks and transactions need to be validated in the network layer. Byzantine fault-tolerant algorithms are used to guarantee that agreement is secure and reliable among nodes in the consensus layer. V2G transaction smart contracts are encapsulated, and the Go language is programmed for enhancing efficiency and adaptability in the smart contract layer. Lastly, charging and discharging are supported for EVs, transferring and transaction functions are provided for V2G operations in the application layer.

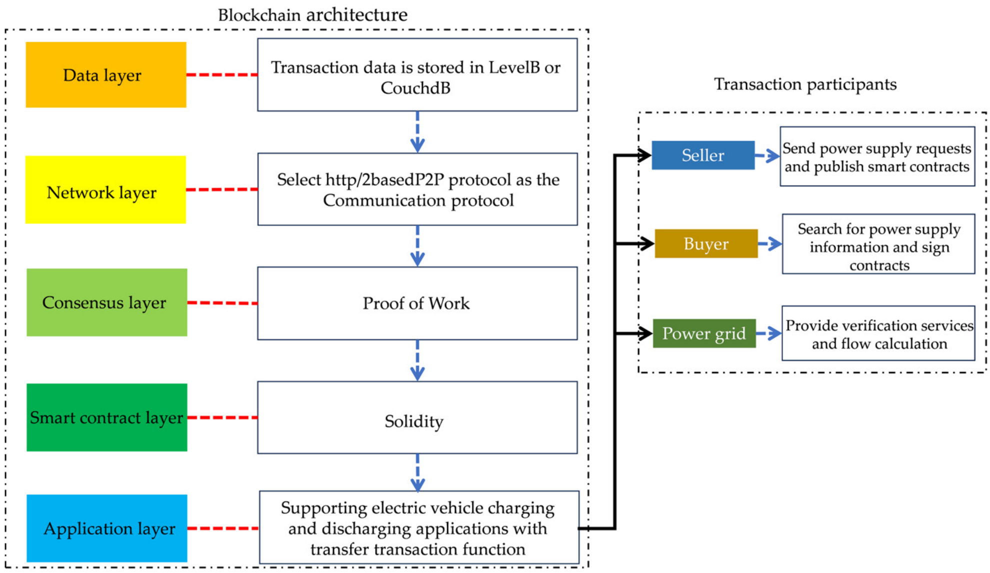


Figure 2. Blockchain-based platform architecture.

The specific transaction process is shown in Figure 2. The seller proposes a power supply request through the blockchain platform and publishes the corresponding smart contract. Subsequently, the buyer actively seeks out a suitable power supplier and signs a contract based on their specific energy requirements. Under the context of the decentralized power trading model, the power grid evaluates factors such as line flow to determine whether the transaction meets the regulatory requirements. Furthermore, a penalty mechanism is deployed to deter any malevolent user nodes. Those users with inadequate credit scores who are subject to restricted credit authority or purchase costs will be added. This stringent approach ensures the utmost stability and integrity of the power trading ecosystem while promoting trust among all participants.

In this study, the proposed decentralized architecture aims to promote efficient and secure energy exchange; building a sustainable and robust energy ecosystem is very important in the context of electric vehicle integration into the power grid.

4.2. Customer Satisfaction

In this study, a piecewise function was used to describe the degree of the buyer's satisfaction with the blockchain trading platform under the guidance of the seller's time-of-use electricity price. The buyer's preference satisfaction function is as follows:

$$Gra = \begin{cases} \cos\left(\frac{\Delta C}{C_{\max}} \cdot \frac{\pi}{2}\right), \Delta C < C_{\max} \\ 0, \Delta C > C_{\max} \end{cases} \tag{19}$$

where ΔC is the difference between the expected value of the buyer and the recommended value by the platform, and $C_{\max}$ is the maximum intolerable degree of the buyer. When $\Delta C = 0$, buyer's satisfaction is the highest at 1, and when $\Delta C > C_{\max}$, user satisfaction is the lowest at 0.

When $\Delta C < C_{\max}$, based on the properties of the cosine function, the following are true:

- $c = (\Delta C / C_{\max}) \in [0,1]$, the value of Gra is between $[0,1]$ and monotonically decreasing;
- $Gra' = \frac{dGra}{dc} = -\frac{\pi}{2} \cdot \sin\left(\frac{\pi}{2} \cdot c\right)$, $c \in [0,1] Gra' \leq 0$; therefore, when the difference ΔC increases between the buyer's expected value and the recommended value, the buyer's satisfaction decreases;
- $Gra'' = \frac{d^2 Gra}{dc^2} = -\frac{\pi}{2} \cdot \frac{\pi}{2} \cdot \cos\left(\frac{\pi}{2} \cdot c\right)$, where, $c \in [0,1]$, $\frac{\pi}{2} \cdot c \in \left[0, \frac{\pi}{2}\right]$, $Gra'' \leq 0$; therefore, when ΔC increases, the rate of decline in user satisfaction becomes increasingly faster, that is, the marginal effect decreases.

The charging price satisfaction function is given as follows:
When $\Delta\rho \geq 0$,

$$\mathrm{Gra}_{i,t}(\Delta\rho) = \alpha_1 \cos\left(\frac{\Delta\rho_1^{\max} - \Delta\rho_1}{\Delta\rho_1^{\max} - \Delta\rho_1^{\min}} \cdot \frac{\pi}{2}\right) + \alpha_2 \cos\left(\frac{\Delta\rho_2^{\max} - \Delta\rho_2}{\Delta\rho_2^{\max} - \Delta\rho_2^{\min}} \cdot \frac{\pi}{2}\right) \tag{20}$$

When $\Delta\rho < 0$,

$$Gra_{i,t}(\Delta\rho) = 0 \tag{21}$$

$$\Delta\rho = \frac{\Delta\rho_1 - \Delta\rho_2}{2} \tag{22}$$

$$\alpha_1 + \alpha_2 = 1 \tag{23}$$

Taking the current period t as an example, $\Delta\rho_1$ represents the difference between the state grid electricity price and the seller's time-of-use electricity price. $\Delta\rho_2$ represents the difference between the electricity prices of the electricity-selling company and the seller's time-of-use electricity price. When $\Delta\rho_1 \geq 0$ or $\Delta\rho_2 \geq 0$, the user's charging time is transferred. When $\Delta\rho < 0$, the buyer will not change the original charging time because no profit will occur. Therefore, the buyer will have the lowest satisfaction with the charging price at this time. $\Delta\rho_1^{\min}$ and $\Delta\rho_1^{\max}$ are the minimum and maximum values of the price difference between the state grid and the seller after charge transfer in the current period, respectively, and $\Delta\rho_2^{\min}$ and $\Delta\rho_2^{\max}$ are the minimum and maximum values of the price difference between the electricity-selling company and the seller after charge transfer in the current period, respectively. α_1, α_2 are Boolean logic variables.

4.3. Revenue of the Blockchain Platform Operator

The electricity trading platform based on blockchain technology provides transaction protection for both buyers and sellers. Its benefits are as follows:

$$R_{block} = \sum_{t=1}^{T} \mu_t E_{s,t}^b \tag{24}$$

where μ_t is the platform service fee charged by the trading platform in the t time period.

5. Revenue of Multiple Operating Entities

5.1. Revenue of State Grid

The income of the power grid primarily includes two parts: the service cost generated by the power transmission of the buyers and the sellers, and the cost incurred by the buyers when the sellers have no electricity to sell. The income of the power grid is

$$R_G = \sum_{t=1}^{T} \lambda_t E_{s,t}^{b} + \sum_{t=1}^{T} E_{G,t}^{b} Q_{G,t} \tag{25}$$

where λ_t is the grid service cost during the tth time period of a day.

5.2. Revenue from Electricity Sales Companies

The revenue source of the electricity-selling company is that buyers directly choose this channel to purchase electricity, and its revenue is

$$R_C = \sum_{t=1}^{T} E_{C,t}^{b} Q_{C,t} \tag{26}$$

5.3. Share Energy Storage Operator Revenue

The charge paid by users for storing energy is

$$F_{ES}^{+} = \sum_{t=1}^{T} \lambda_t^{ES} \left(P_t^{c} + P_t^{d} \right) \tag{27}$$

where λ_t^{ES} is the rental fee in the tth time period, and P_t^c and P_t^d are the charging and discharging power of the user in the energy storage in the tth time period, respectively.

The cost of energy storage is

$$F_{ES}^{-} = \sum_{t=1}^{T} \left(\lambda_c P_t^{c} \Delta t + \lambda_d P_t^{d} \Delta t \right) \tag{28}$$

where λ_c and λ_d is the charging and discharging cost coefficients per unit of time, respectively.

The total revenue from energy storage is

$$R_{ES} = F_{ES}^{+} - F_{ES}^{-} \tag{29}$$

Considering that in a period T, the total power charged or discharged by all users at any time cannot exceed the capacity limit of the shared energy storage system, the system capacity at any time t should satisfy:

$$E_{\min}^{ES} \le E_t^{ES} \le E_{\max}^{ES} \tag{30}$$

where $E_{\min}^{\mathrm{ES}}$ and $E_{\max}^{\mathrm{ES}}$ represent the minimum and maximum allowable capacities of a shared energy storage system, respectively. Moreover, the charging and discharging power of all users in any time period is limited by the allowable power of the shared energy storage system. For any time period t, the following constraints are applied:

$$\begin{cases} \left| \frac{E_{t+1}^{ES} - E_t^{ES}}{\Delta t} \right| \le P_{\max}^{ES,c} \left(P_t^{l,c} \le P_t^{l,d} \right) \\ \left| \frac{E_{t+1}^{ES} - E_t^{ES}}{\Delta t} \right| \le P_{\max}^{ES,d} \left(P_h^{l,c} \ge P_h^{l,d} \right) \end{cases} \tag{31}$$

where $P_{\max}^{ES,c}$ and $P_{\max}^{ES,d}$ are the maximum charging and discharging power allowed by the shared energy storage system, respectively.

6. Solution Method for the Model

The way of meta-heuristics is widely used to solve nonlinear and multi-objective problems. The "multi-seller–multi-buyer" model of EV residual electricity trading established in this article is a multi-objective function model with nonlinear constraints. The maximum profit of the sellers and the minimum cost of the buyers are the objective functions, which are to solve the electricity consumption and corresponding revenue and expenditure situation of users in each time period. The improved NGO algorithm adopted in this article has strong global search ability and avoids falling into the local optimum.

In this study, an improved NGO algorithm is adopted to solve the "multi-seller–multi-buyer" power trading model. The NGO algorithm is characterized by its global search ability, simplicity, efficiency, parallelization, and robustness [27]. The adoption of random and diverse search strategies can prevent falling into locally optimal solutions. Simultaneously, parallel computing can accelerate the solution. This makes it suitable for large-scale optimization problems. It is robust against changes in the constraints and objective functions of the problem. It can be adapted to different problems and can play a role in different application domains.

The NGO optimization algorithm has a strong global search ability to avoid falling into a locally optimal solution. Using this algorithm can better simulate the interaction process between buyers and sellers user groups as well as other multi-agent operators. Simultaneously, the objectives and strategies of the two stages are different, aiming to achieve a balance between global and local optimization.

In this study, an improved NGO algorithm was used to solve a buying and selling behavior model. The steps for solving the model are shown in Figure 3, and the process is described below.

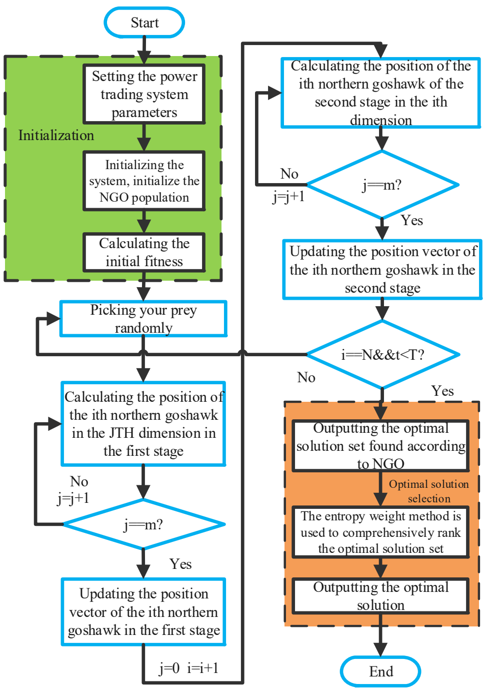


Figure 3. Improved NGO algorithm flowchart.

First, the multi-agent revenue model data are initialized, and the decision-making model of each agent is established. The maximum number of iterations, the maximum convergence error, and the initial parameters of the NGO optimization algorithm are set, and multivariate energy purchase and sale parameters are randomly initialized.

Second, the NGO optimization subroutine is employed. The electricity consumption, revenue, and expenditure are resolved for each user in each period. Maximizing the profits of the seller user groups and minimizing the costs of the buyer user groups are the objective functions. The hunting strategy of NGOs is divided into two stages.

The first stage is prey identification (exploration stage), which randomly generates a power purchase and sale scheme as the initial value, and the buyer and seller select the optimal power purchase and sale scheme at each period.

The second stage is the pursuit and escape stage (development stage). The scope of the search space and the fitness function value are updated, and the multivariate electricity of the purchase and sale scheme is updated to achieve the global optimum.

Finally, when the number of iterations is greater than the maximum number of iterations, the optimal solution is saved and fitness function value of each iteration scheme is determined, each scheme is comprehensively sorted by using the entropy weight method, then the optimal solution is selected.

7. Example Analysis

7.1. Analysis of "Multi-Seller–Multi-Buyer" Energy Purchase Strategy

The practical example described in this study is a regional EV user group with three different charging habits. The daily trading situation is also discussed. Each EV user is equipped with a corresponding PV device and a bi-directional charging pile, which is used to realize the power supply and transmission of electric energy for EVs. Typical winter data were selected for the user-side PV system, and the daily PV output curve is shown in Figure 4. Simultaneously, there is shared energy storage with a certain capacity in the area, which is used to provide rental services to sellers, realize temporary storage of electric energy, and alleviate the utilization of electric energy.

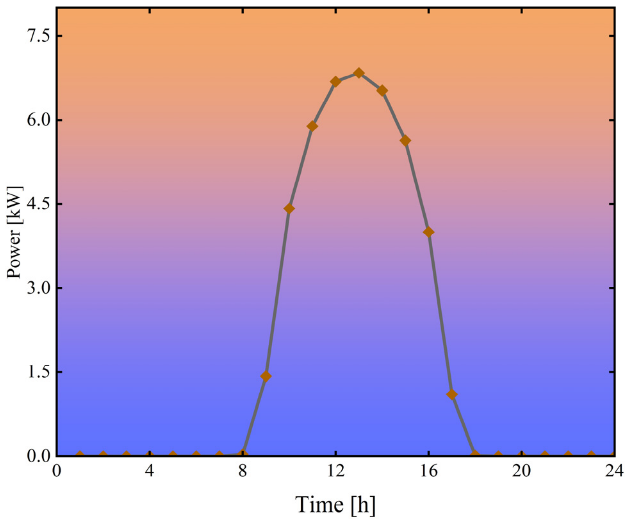


Figure 4. Typical daily PV output curve at the user side.

We assume that the three types of EV users after equivalence aggregation are night shift (Class A), early in the morning and late in the evening (Class B), and normal work and rest (Class C). To further verify the model's effectiveness, three scenarios represent three different types of EV users. Scenario I is dominated by Class A EV users. Scenario II is dominated by Class C EV users. Scenario III is dominated by Class B EV users. The parameters N = [80, 50, 40] EVs are set for Scenario I, N = [30, 50, 80] EVs for Scenario II, and N = [40, 40, 80] EVs for Scenario III. Table 1 lists the EV parameters after equivalence aggregation, where 0 indicates no charging and 1 indicates charging.

Table 1. EV charging state.

Time	A	B	C	Time	A	B	C
1	0	1	0	13	0	1	1
2	0	1	0	14	1	0	0
3	0	1	0	15	0	1	0
4	0	1	0	16	0	0	1
5	1	1	0	17	1	0	1
6	1	0	0	18	1	1	0
7	1	0	1	19	1	0	1
8	1	0	1	20	1	0	1
9	0	0	1	21	1	1	1
10	0	0	1	22	1	1	1
11	0	0	1	23	1	1	1
12	0	1	1	24	1	1	0

According to Table 1, the charging periods for Class A users are 5:00–8:00, 14:00, and 17:00–24:00. The charging periods for Class B users are 1:00–5:00, 12:00–13:00, 15:00, 18:00, and 21:00–24:00. The charging periods for Class C users are 7:00–13:00,16:00–17:00, and 19:00–23:00. The optimal power purchase strategy for Class A users is illustrated in Figure 5.

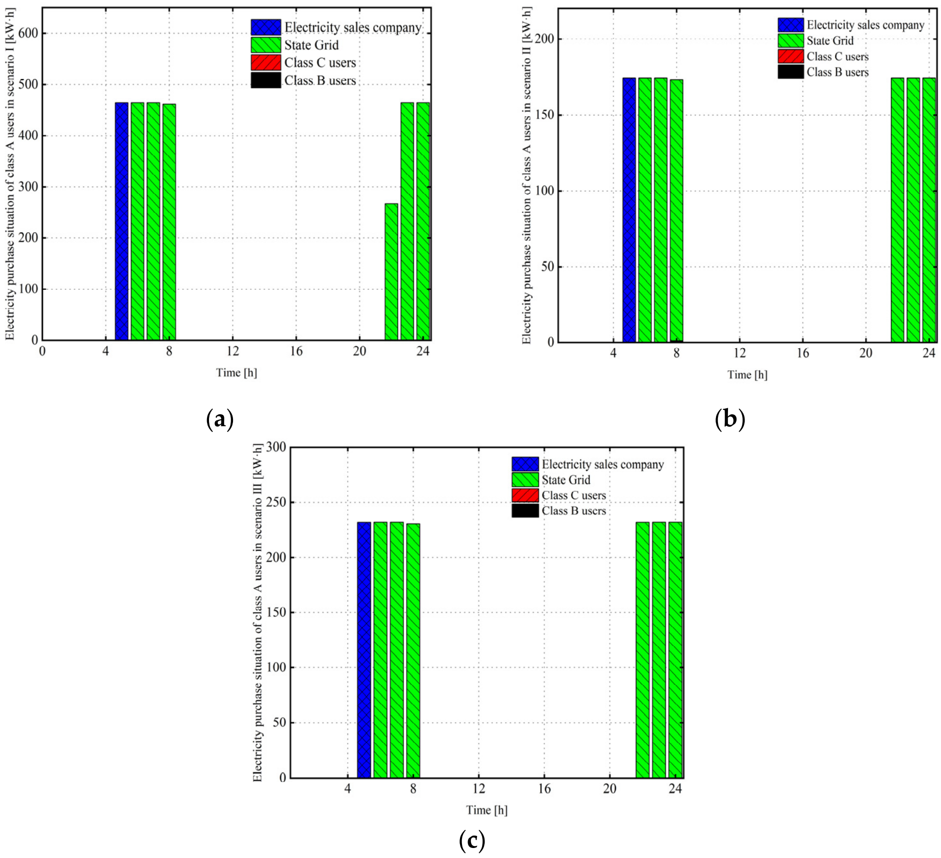


Figure 5. (**a**) energy purchase strategy of Class A users under Scenario I; (**b**) energy purchase strategy of Class A users under Scenario II; (**c**) energy purchase strategy of Class A users under Scenario III.

In Scenario I, Class A users are dominant, as shown in Figure 5a, and the energy purchase period is divided into two phases: 5:00–8:00 and 22:00–24:00. This is contrary to the charging period, and the reason is that the PV power generation of Class A users is rising at 14:00, so energy is accumulated at a certain degree. Therefore, there is no need to purchase electricity. From 17:00 to 21:00, the PV output gradually decreases. However, it can still meet the electricity demand of users. In the first stage, owing to the charging demand, Class A users are subjected to the time characteristics of PV output. Therefore, they choose to purchase electricity from the state grid or the electricity sales company. From 1:00 to 5:00, the price of the electricity sales company is lower. Therefore, Class A users choose the electricity sales company to purchase electricity at 5:00, and at 6:00–8:00, they choose the state grid with the lower price to purchase electricity. According to Table 1, during the charging periods of 14:00 and 17:00–22:00, power purchasing is not finished, the reason is that PV power generation can meet their needs. As time goes on, the PV output decreases and surplus power reduces. Therefore, a state grid with a low price is selected to purchase electricity from 22:00 to 24:00. In Scenarios II and III, as shown in Figure 5b,c, Class C and B users dominate, respectively. The number of Class A users is reduced compared to Scenario I, which results in a lower power purchase than that in Scenario I. The energy purchase period is consistent with Scenario I, and the low-price operation subject is selected for purchase. The electricity prices for each operating subject are shown in Figure 6.

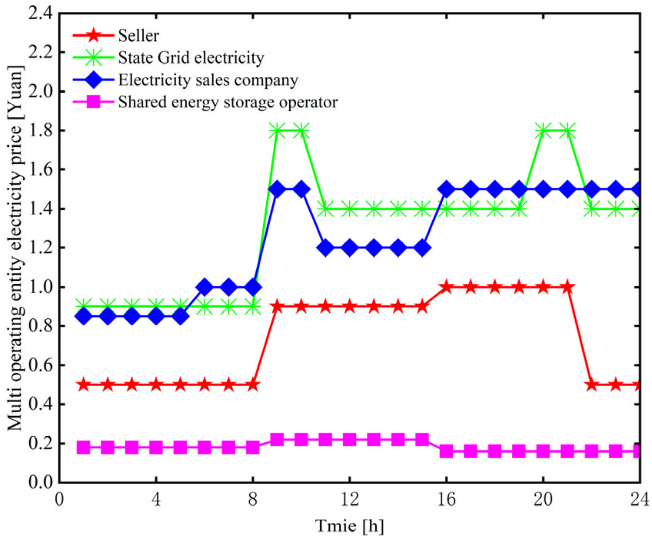


Figure 6. Multi-operating entity electricity price.

According to Table 1, from 1:00 to 5:00, Class B users must be charged, Class C users do not need to be charged, and Class A users only need electricity at 5:00. Both A and C users can provide some of their own resting power supply from 1:00 to 5:00. However, plenty of electricity is purchased by the electricity-selling company at a low price. PVs are in the period of power generation at 12:00–13:00, 15:00, and 18:00, which meets charging needs for Class B users. Therefore, no power purchase occurs.

The optimal power purchase strategy for Class B users is illustrated in Figure 7. In Scenario I, as presented in Figure 7a, Class B users purchase power from Class A users at 21:00, which is consistent with the power purchase strategy diagram of Class A users shown in Figure 5, where Class B users have no power purchase demand at this time. From 22:00 to 24:00, Class A and C users have no remaining electricity. Therefore, they purchase state grid electricity at a low price. In Scenario II, Class B users purchase electricity from Class A users and electricity from an electricity-selling company at 21:00. Compared to Scenario I, the number of Class A users has decreased, and insufficient electricity can be purchased from the electricity-selling company at a lower price. In Scenario III, compared to Scenario II, the number of Class A users has slightly increased, but compared to Scenario I, the electricity level is still insufficient at this time. The remaining electricity is also purchased from the electricity-selling company.

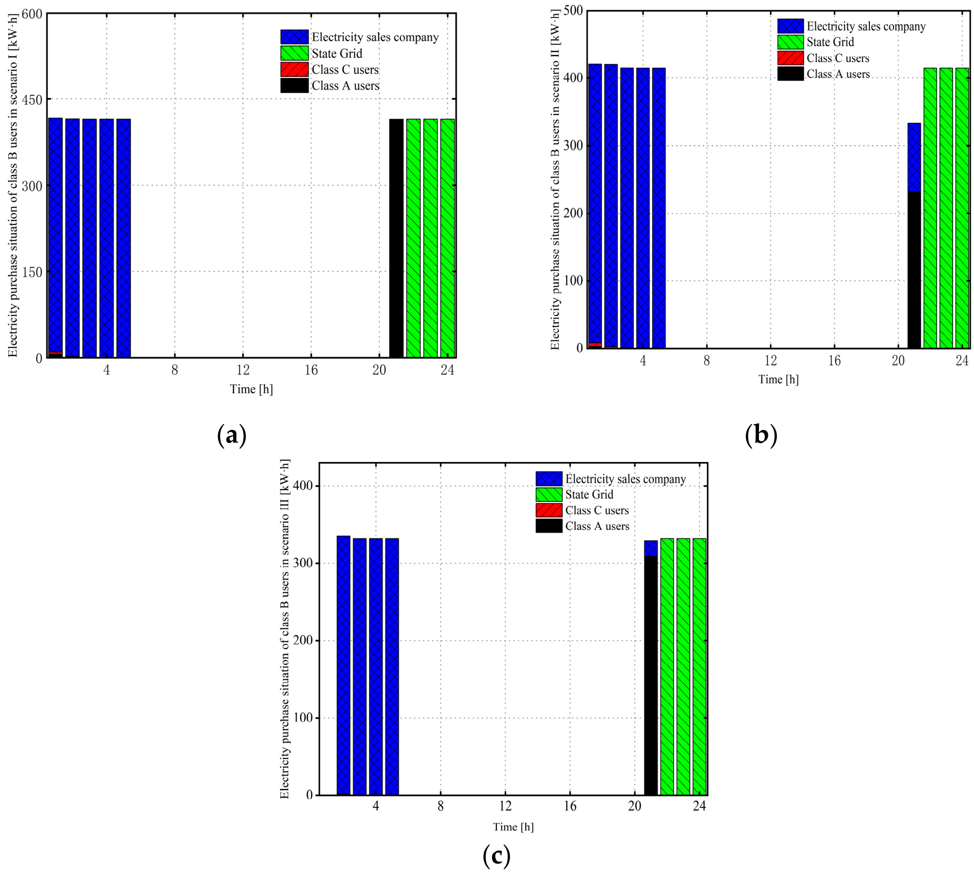
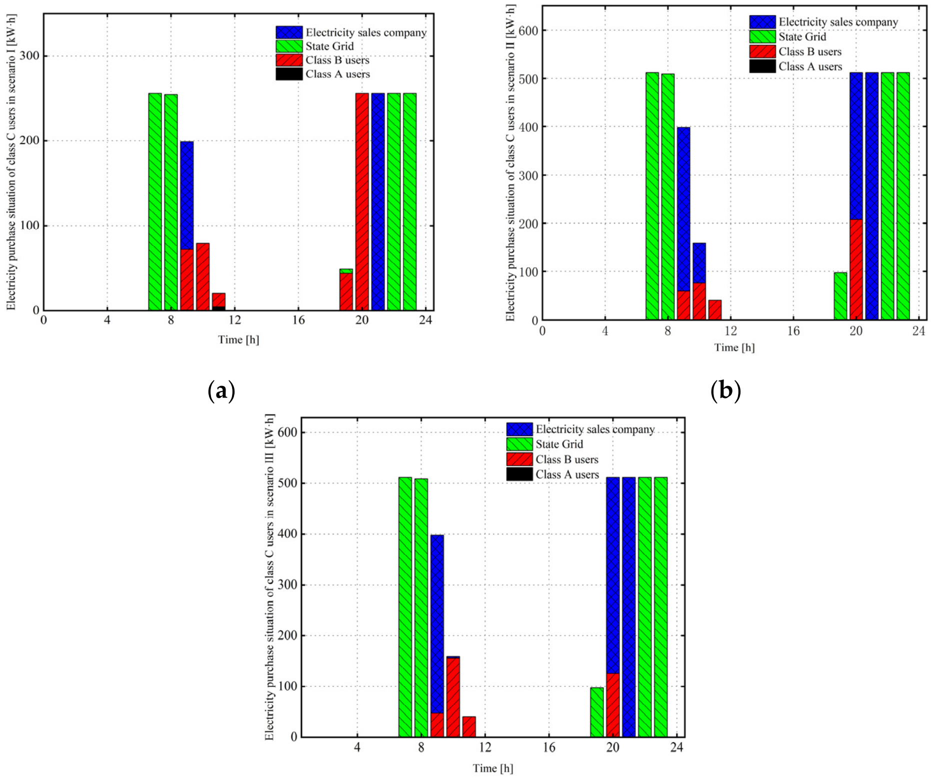


Figure 7. (**a**) energy purchase strategy of Class B users under Scenario I; (**b**) energy purchase strategy of Class B users under Scenario II; (**c**) energy purchase strategy of Class B users under Scenario III.

The energy purchase strategy for Class C users is illustrated in Figure 8. Table 1 indicates that during the period from 1:00 to 6:00, Class C users have no charging demand. Therefore, they do not purchase electricity. From 7:00 to 13:00, Class C users have a certain charging demand. As time goes by, power generation increase gradually, resulting in the power purchased by Class C users gradually declining, which is embodied in the period from 12:00 to 18:00 in Figure 8a, and Class C users no longer purchase from other channels during this period. During the period from 19:00 to 23:00, with the gradual reduction in PV output and the Class C users having a certain demand for energy purchase, the purchased electricity gradually increases. In Scenario I presented in Figure 8a, electricity is purchased from the state grid at a low price from 7:00 to 8:00. At 9:00, parts of electricity demands are provided by Class B users, and the remaining electricity demands are provided by the electricity-selling company at a low price. At 10:00, with the accumulation of PV output, only the power of Class B users can meet the electricity demands of Class C users. At 11:00, Class A users also have a certain amount of residual power, and together with Class B users, they provide power for Class C users. At 9:00–11:00, the electricity demands tend to decrease. At 19:00, the electricity demands for Class C users are provided by B users and the state grid. At 20:00, the electricity demands for Class C users are provided only by B users. From 21:00 to 23:00, no users could provide electricity, so Class C users choose to purchase from the state grid and the electricity-selling company at a low price. In Scenarios II and III, presented Figure 8b,c, the change trend of the energy purchase strategy of Class C users is consistent with that of Scenario I, but owing to the change in the number of users, the power purchased from other users, the grid, and the electricity sales company at 9:00–11:00 and 19:00–20:00 changed to a certain extent. At 11:00, Class C users in Scenarios II and III do not purchase electricity from Class A users. At 19:00, Class C users in Scenarios II and III only purchased electricity from the state grid and not from Class B users, which is different from what is presented in Figure 8a. This indicates that Class B users have no electricity to sell in these two scenarios at this time.



(**a**) (**b**) (**c**)

Figure 8. (**a**) energy purchase strategy of Class C users under Scenario I; (**b**) energy purchase strategy of Class C users under Scenario II; (**c**) energy purchase strategy of Class C users under Scenario III.

The user and seller revenues for the three scenarios are presented in Tables 2–4. In Scenario I, the revenue of Class A users is primarily at 21:00. Class B user revenue is primarily at 9:00–11:00 and 19:00–20:00. Class C user benefits are primarily at 1:00, 9:00–11:00, and 19:00–21:00. In Scenario II, the revenues of Class A users are primarily at 21:00. The revenues of Class B users are primarily at 9:00–11:00 and 20:00, and the revenues of Class C users are primarily between 1:00 and 2:00. In Scenario III, the benefits of Class A users are primarily at 1:00 and 21:00. Class B users' income is primarily at 9:00–11:00 and 20:00. Class C users' benefits are primarily from 1:00 to 2:00.

Table 2. Scenario I users' revenue situation.

Time	Class A (Yuan)	Class B (Yuan)	Class C (Yuan)	Seller's Profit (Yuan)
1	2.99	0	1.839	4.829
2	0.99	0	0.15	1.14
3–7	0	0	0	0
8	0	0.715	0	0.715
9	0.49	64.384	0	64.874
10	0	71.267	0	71.267
11	4.05	14.243	0	18.293
12–18	0	0	0	0
19	0	43.634	0	43.634
20	0	255.975	0	255.975
21	415.038	0	0	415.038
22–24	0	0	0	0

Table 3. Scenario II users' revenue situation.

Time	Class A (Yuan)	Class B (Yuan)	Class C (Yuan)	Seller's Profit (Yuan)
1	1.472	0	2.676	4.148
2	0	0	1.296	1.296
3–7	0	0	0	0
8	0	0.853	0	0.853
9	0	53.383	0	53.383
10	0	68.745	0	68.745
11	0	36.657	0	36.657
12–19	0	0	0	0
20	0	207.644	0	207.644
21	231.498	0	0	231.498
22–24	0	0	0	0

Table 4. Scenario III users' revenue situation.

Time	Class A (Yuan)	Class B (Yuan)	Class C (Yuan)	Seller's Profit (Yuan)
1	1.993	0	3.231	5.224
2	0	0	0.767	0.767
3–7	0	0	0	0
8	0	0.677	0	0.677
9	0	42.82	0	42.82
10	0	140.505	0	140.505
11	0	36.655	0	36.655
12–19	0	0	0	0
20	0	125.583	0	125.583
21	308.668	0	0	308.668
22–24	0	0	0	0

As depicted in Figure 9, the diagrams illustrate the cost state of the three scenarios. Overall, the cost of procuring energy from an electricity sales company and the power grid surpasses that of acquiring from the "multi-seller–multi-buyer" in all three scenarios, proving that the method can attract EV users to purchase energy.

When the use of electricity is at its peak, two situations will emerge: the seller possesses surplus energy or the seller lacks surplus energy. From 4:00 to 6:00, all three sellers in the three scenarios will adapt based on the buyer's demand. When the "multi-seller–multi-buyer" system lacks surplus energy, the buyer can purchase from the power grid and the electricity sales company. From 6:00 to 10:00, the costs of the power grid and power-selling company magnify, while the costs of the "multi-seller–multi-buyer" model gradually decline. This is attributed to the seller's surplus energy being diminished, and the electricity prices are lower in the "multi-seller–multi-buyer" model than the power grid and power-selling companies. From 10:00 to 18:00, the output of the PV system is at its peak and the number of buyers decreases, resulting in energy procurement requirements being diminished. From 18:00 to 24:00, the PV system gradually ceases electricity generation, and parts of sellers continue supplying energy, but primarily relying on the power grid and the power-selling company.

7.2. Trading Model Analysis of Multi-Operation Agents Considering "Multi-Seller–Multi-Buyer"

Figure 10 displays the revenue of the multi-operation agents. In Scenario I, as shown in Figure 10a, because the electricity-selling company has the lowest price on the market from 1:00 to 5:00, the buyer prioritized purchasing electricity during this period. From 1:00 to 4:00, Class B users buy it, and the revenue increases owing to the addition of Class A users at 5:00. From 6:00 to 8:00, the electricity price of the state grid is lower than that of the electricity-selling company, and the revenues of the state grid increase. The PV output is higher from 8:00 to 18:00, as shown in Figure 4. However, owing to early energy accumulation, the sharing energy storage provider still has profits from 19:00 to 21:00. From

11:00 to 12:00, the energy storage revenue decreases to zero, and the dominant Class C users must purchase electricity during this period. In contrast, Class A and B users do not purchase electricity or purchase less electricity to provide electricity for Class C users, which leads to the electricity flown to the energy storage being reduced and revenues being decreased. Energy storage has benefits from 13:00 to 21:00. However, the overall benefits are reduced compared to Scenario I, which is related to the reduction in power in energy storage.

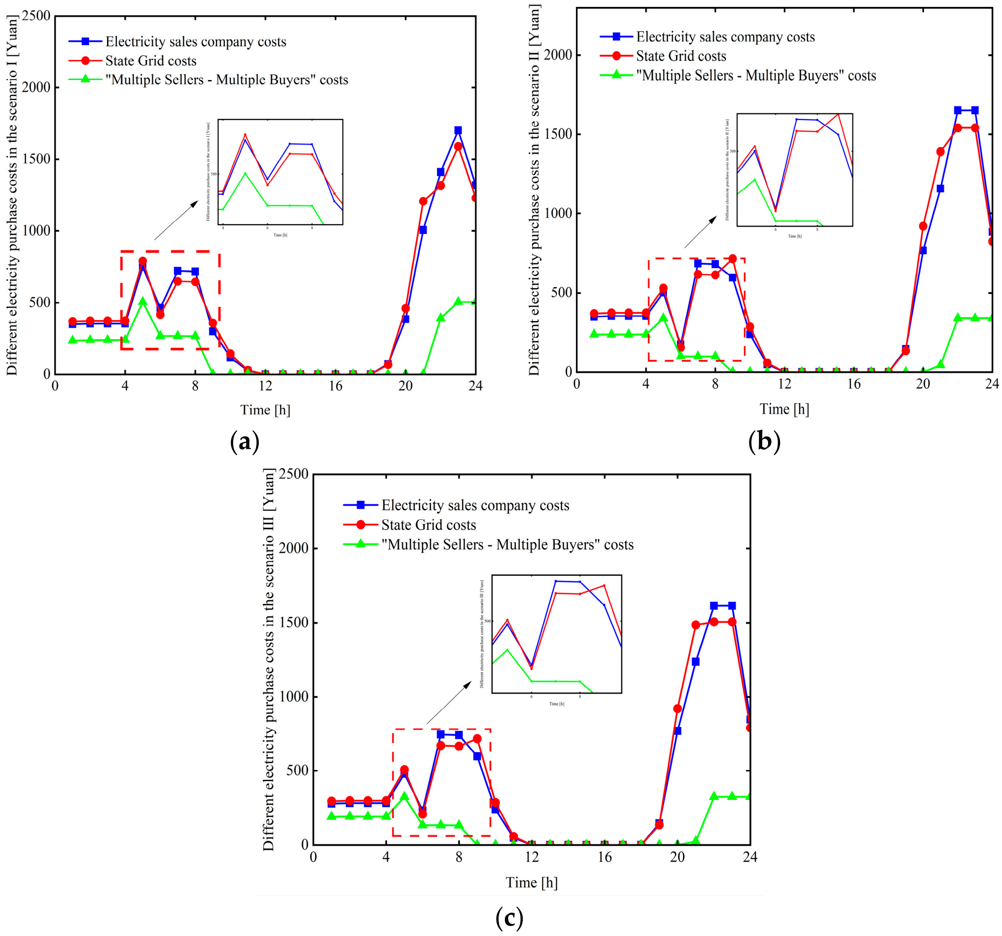


Figure 9. (**a**) comparison of costs of different power purchase channels under Scenario I; (**b**) comparison of costs of different power purchase channels under Scenario II; (**c**) comparison of costs of different power purchase channels under Scenario III.

In Scenario II presented in Figure 10b, the period from 1:00 to 8:00 is roughly consistent with the change trend in Scenario I, as electricity demand is mainly provided by electricity-selling companies from 9:00 to 10:00. However, the benefits of shared energy storage slightly increase. As the PV output increases, the benefits of multiple operators gradually decrease.

In Scenario III, presented in Figure 10c, the revenue trend of each operating entity is similar to Scenario II. In addition to the providers of energy storage, the revenue peak of each operating entity occurs in the morning and evening. Because the providers of energy storage earn the charging and discharging rental fees of the users' surplus power, their revenue peak occurs in the noon–afternoon period. The energy storage can realize peak filling of the power operation.

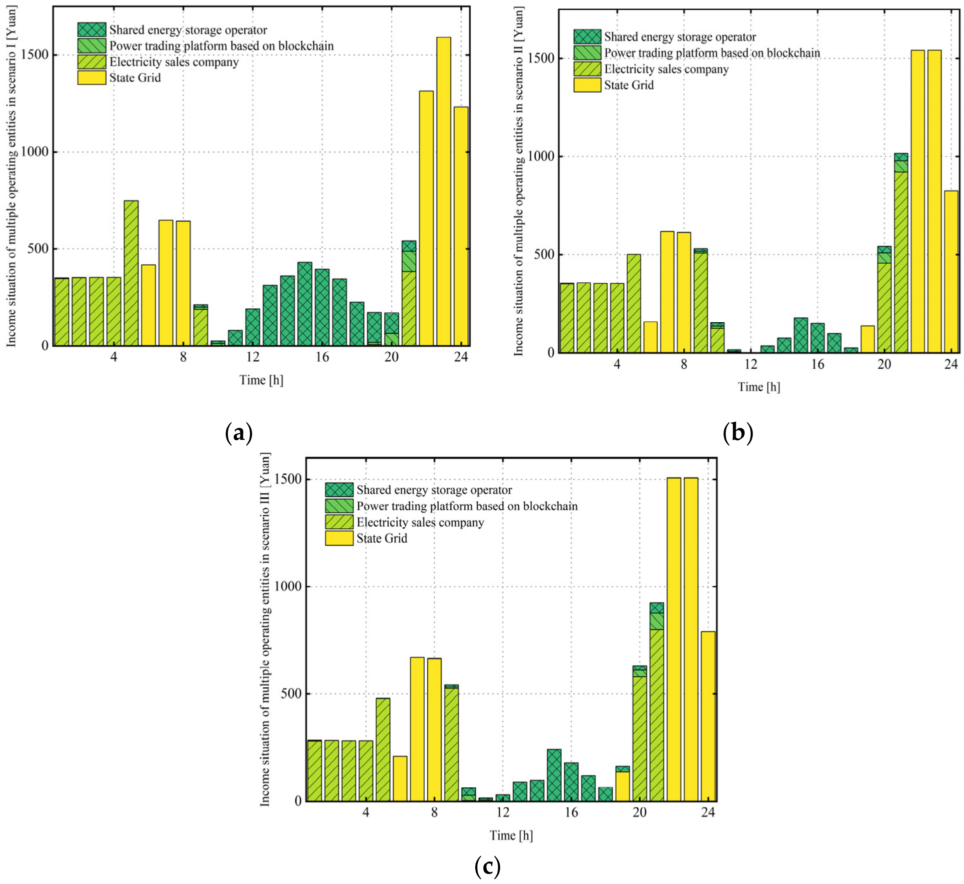


Figure 10. (**a**) revenue of multiple operators in Scenario I; (**b**) revenue of multiple operators in Scenario II; (**c**) revenue of multiple operators in Scenario III.

The "multi-seller–multi-buyer" model of EV energy purchases and sales is compared with the conventional energy purchase channels of ordinary EV users who do not join blockchain technology, and the results are presented in Table 5.

Table 5. Comparison of the "multi-seller–multi-buyer" model with and without blockchain.

User Transactions	No Blockchain Is Used	Using Blockchain
Credibility	Third-party credit guarantee	Open, transparent, and trusted
Means of information interaction	Traditional centralized transaction model	Blockchain ledger
Average cost of electricity	1.3 (Yuan/kW·h)	0.74 (Yuan/kW·h)
Utilization of new energy	Low	High

The model data without blockchain technology come from the sales platform of the state grid, and third-party charging stations. The average electricity cost of the new mode is calculated by a comprehensive calculation of the energy purchase and sales data after the user adopts the new trading mode. After joining the blockchain ledger, the cost of purchasing and selling electricity for users is significantly reduced, and the utilization time of energy storage devices is significantly improved, so the electricity cost is reduced for users. Simultaneously, the model in this study focuses on the utilization rate of distributed renewable energy and forms an effective interaction with the distributed electricity consumption scenario. The revenue of the trading platform and shared energy storage operators depends on the transaction frequency of the buyers and sellers. The trading platform and shared energy storage operators can deduct a fee from a single order, and they can maintain the stability and normal operation of the entire system. Power grid and electricity sales companies earn certain profits by supplementing the users' insufficient power.

Particle Swarm Optimization (PSO) is an intelligent optimization algorithm that simulates groups such as birds searching for food. It is derived from the research on the foraging behavior of birds, as birds can find the optimal target through collective information sharing. In this paper, an improved PSO algorithm is proposed, and the details are as follows: first, we build an inertia weight model to enhance the global search optimal capability; second, a simulated annealing strategy is integrated into the iterative process of the algorithm to periodically enhance its local search optimal ability. Through the above improvements, the improved PSO algorithm has faster convergence compared to the traditional algorithm.

For the EV power trading model proposed in this study, an improved NGO algorithm is employed for resolution. Additionally, a comparative analysis is conducted among traditional PSO algorithms, commonly improved PSO algorithms, and the improved NGO algorithm, as illustrated in Figure 11. The results indicate that the improved NGO algorithm has several advantages, including reduced iterations and higher fitness function values compared to the other optimization methods.

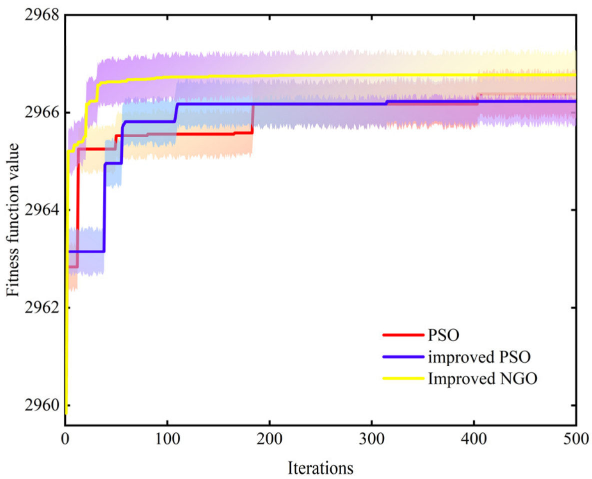


Figure 11. Comparison of the improved NGO algorithm with other algorithms.

As shown in Table 6, with under 500 iterations, the result of adopting the improved NGO algorithm has a shorter iteration time, and the user's revenue is the highest, while the result of adopting the PSO algorithm has the longest running time and lower revenue. Although the improved PSO algorithm is not as efficient and profitable as the improved NGO, it performs better than PSO [28].

Table 6. Comparison of algorithm parameter comparison.

Parameter	Improved NGO	Improved PSO	PSO
Iterations (times)	500	500	500
Run time (seconds)	1.764	1.868	3.583
Revenue situation (Yuan)	2922.221	2883.968	2621.941

Figure 12 shows the capacity curve of the shared energy storage operator. The revenue of a shared energy storage operator depends on the redundant power of the user. Energy storage began to increase at 10:00 and peaked at 16:00. At this stage, the PV power generation of the users increased, and electricity gradually accumulated. Subsequently, the PV power generation weakened, and electricity gradually slowed down accordingly. The trend of energy storage capacity changes in the three scenarios is roughly the same.

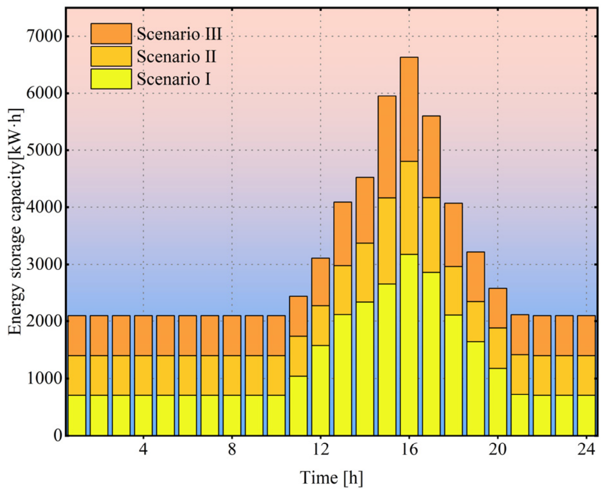


Figure 12. Shared energy storage operator's energy storage capacity curve in one day.

8. Conclusions

Based on the regional EV electricity transaction and the transaction mode of blockchain technology in this study, a new power trading mode integrating PV power generation, buyers and sellers with convertible identities, regional shared energy storage, and a power trading platform based on blockchain is proposed. The main conclusions are as follows:

1. The proposed transaction model incorporates EV buyers and sellers into a transaction system. Simultaneously, blockchain technology is considered a transaction solution for the distributed scenario of EVs, which is more suitable for the development of future scenarios;
2. The "multi-seller–multi-buyer" EV surplus electricity trading model presented in this study incorporates regional EVs into the electricity trading framework, efficiently utilizing the surplus electricity of EVs. By allowing EV users to act as sellers, they can achieve corresponding profits. Similarly, buyers can benefit from obtaining electricity at a lower price. The power grid plays an indispensable role in energy transfer. Multiple operating entities, such as electricity sales companies and energy storage operators, also make a profit from this trading process;
3. In this model, the user side achieves self-production and self-sales of energy by installing PV systems, significantly reducing reliance on primary energy sources. This approach not only meets the user's power demand but also delivers the excess energy to users in need and generates profits.
4. The model obtains the optimal solution through the improved NGO. Compared to the PSO algorithm and the improved PSO algorithm, the iteration speed of improved NGO is faster and fitness function values are optimal under the same number of iterations.

In this study, three classes of EV users' charging demand problems are considered, and further research on the realistic charging problems of EVs and their participation in power system scheduling should be researched. The next step focuses on the following:

1. A richer EV user model is established, and factors such as EV categories, battery charge and discharge attenuation, and kinetic energy recovery are considered;
2. Numerous EVs are aggregated as small energy storage stations and participate in the dispatch and regulation of the power system by the charging and discharging characteristics of the EVs.

The prospects for advancement in diverse regions worldwide are as follows:

1. Residual energy trading of EVs is presented in this article. Interchanging surplus energy among EVs to optimize energy utilization can be promoted globally. This makes the consumption of energy can be reduced, and clean energy can be efficiently utilized;

2. The security of energy trading is ensured by the application of advanced blockchain technology in EV systems. The decentralized nature of blockchain technology makes the technology easy to roll out in diverse regions worldwide;
3. V2G technology has heightened flexibility in the energy market, which enables EV owners to sell their electricity based on energy market prices, secure economic gains, and alleviate price fluctuations in the electricity market;
4. A more optimal algorithm can be adopted in utilizing the residual energy of EVs, which gives the technology proposed in this study wider applicability.

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