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ORIGINAL RESEARCH

A novel deep learning based peer-to-peer transaction method for prosumers under two-stage market environment

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Abstract

With the development of the electricity market, peer-to-peer (P2P) transaction plays an important role in promoting local consumption of renewable energy and arousing the enthusiasm of prosumers. However, due to the diversification of prosumers, the confidentiality of the information and the interaction between prosumers, there are increasing challenges for the traditional model-based optimisation methods in both P2P modelling and model solution accuracy. Therefore, this paper proposes a novel P2P transaction method based on deep learning under a two-stage market environment, which uses a data-driven approach to build a transaction behaviour model based on public information. The neural network model based on Long Short-Term Memory (LSTM) is utilised to characterise the behaviour of prosumers in P2P transactions effectively. Based on this model, the energy consumption plans and P2P bids of prosumers are optimised accordingly. Through the simulation test of an example system with six prosumers, the results show that the model established can well represent the P2P transaction behaviour of prosumers, and the proposed method can effectively improve the efficiency of P2P transactions and the economic benefits of prosumers, providing a reference for the decision-making of P2P transactions.

KEYWORDS

deep learning, peer-to-peer, prosumer, two-stage market

1 | INTRODUCTION

With the rapid development of information technology and the Internet of Energy, the amount of distributed renewable energy continues to grow. The uncertainty of renewable energy brings great pressure to the operation and management of the power grid [1, 2]. The traditional centralised energy management method needs to pay huge computing costs to deal with large-scale distributed power optimisation [3], so it is difficult to support the interaction between large-scale distributed energy prosumers. In this context, distributed interactive operation management methods, such as peer-to-peer and community-based transaction methods, are gradually emerging [4].

Under the P2P transaction market, the power and price of bidding are independently determined by market participants, and the P2P transaction process will not be interfered with by the supervising party [5]. Compared with the time-of-use electricity price [6], the profits that prosumers can obtain in the P2P market will increase, which endows the market with more vitality. Studies have shown that P2P energy trading can improve energy efficiency [7], promote the consumption of local renewable energy [8] and reduce the power loss of the network [9].

At present, P2P transactions can be classified into two types according to whether there is an agent or not. One is for agent operators to integrate prosumers, and the other is to provide an interactive platform for prosumers to interact with each other. In the first approach, agents or retailers integrate community resources, including energy storage equipment, distributed renewable energy, flexible controllable loads, etc. As the agent of prosumers, agents or retailers optimise the management of prosumers' behaviour and participate in the demand response of the power grid. Agents or retailers manage the resources among prosumers using retail electricity price, incentive price or direct control, to realise the optimisation of overall benefits and redistribution of income. The other is that prosumers trade with each other through interactive platforms. In this way, prosumers optimise and manage energy consumption plans by themselves, formulate energy trading strategies, and coordinate resources through auctions or bargaining.

In the research of the first P2P method with a central agent, the research mainly focuses on the profit distribution and pricing mechanism under various P2P transaction models. Calculation of the energy sharing index is a way to clear transaction prices, such as supply and demand ratio (SDR) [10], middle-market rate (MMR) [11], and bill sharing (BS) [12]. Reference [13] designs a P2P power transaction mechanism with the SDR price mechanism based on the blockchain. Reference [12] evaluated the normalisation of six indicators of economic indicators and energy indicators of P2P market pricing based on the MMR method, and the results showed that the MMR method has good performance when the photovoltaic penetration rate is moderate. Reference [14] used the Shapley value to redistribute the benefits of P2P, and the results showed that compared with BS, SDR and MMR, the optimality and fairness of P2P energy were improved. These mechanisms treat prosumers as price takers and determine a uniform market clearing price for prosumers which means participants do not bid. Different index clearing pricing method has their advantages and disadvantages, but the pricing method is relatively fixed. In the process of benefit distribution, prosumers have no right to directly participate in the pricing, so it is difficult to mobilise the enthusiasm of prosumers.

Subsequently, the idea of decentralised P2P is to treat multilateral P2P transactions as a matter of multilateral game or coordination. Market participants coordinate and make decisions bilaterally through the exchange of information and certain consensus. The formed market has good privacy protection and scalability. For example, Reference [15] coordinated the P2P transaction market through bilateral contracts. Reference [16] explored the influencing factors of P2P transactions in the community under continuous double auction (CDA). The P2P market established in the above ways has a good performance in privacy protection and market expansion. But the results are not necessarily optimal compared to centralised control [6]. The convergence time may not meet the requirements [16]. Further, some researchers solve P2P multilateral transactions as distributed optimisation problems. Reference [17] proposed a P2P energy transaction optimization based on the parallel ADMM algorithm and verified it on the P2P transaction of six residences. There are also studies on p2p transaction optimisation through the establishment of detailed physical models [18, 19], but detailed model parameters are required, the performance of privacy protection is poor, and the calculation intensity increases with the increase of interactive objects. Reference [20] proposed a multi-cluster deep reinforcement learning approach to provide cluster coordination and management for P2P energy management and achieved good results in aspects of system operation cost and demand peak. However, since reinforcement learning requires more computing resources than deep learning training, it requires the platform to train the agent for users.

The methods mentioned above make great contributions to the optimisation of decentralised P2P transactions, but they also have some disadvantages, such as more iterative interaction of ADMM, insufficient privacy protection of physical model, and high training cost of reinforcement learning. Considering the performance of deep learning in packaging the model, it can be used to maintain the accuracy of the calculation speed, while avoiding excessive training costs.

This paper focuses on the design of a time-series neural network-based P2P transaction method to assist prosumers to improve economic benefits under a two-stage market environment [21]. The key information of users is protected by model encapsulation, and P2P transactions can be accelerated and stability improved based on the model. Meanwhile, prosumers can optimise their energy consumption plans by using the model. P2P platform can analyse the influence of the supply demand ratio and the number of users on transaction price fluctuation.

The main contributions of this paper are as follows:

(1) A P2P transaction method based on a deep LSTM neural network is proposed. The encapsulation model method of the deep neural network is used to protect user privacy and improve the efficiency of P2P transactions of prosumers.
(2) Based on the deep learning model of P2P transaction prediction, we propose an optimisation method of electricity consumption plan for prosumers to maximum their economic benefit.
(3) This transaction mechanism, based on the deep LSTM model and P2P double auction, reduces the peak electricity sold by the power grid. The utilisation rate and safety of power system equipment have been improved.
(4) The relationship between the supply demand ratio and transaction price under this trading method is analysed, as well as the influence of user numbers on the fluctuation.

The remainder of this paper is organised as follows. The second part introduces the framework of P2P transactions under a two-stage market environment. The third part puts forward the encapsulation method of the P2P behaviour model based on deep learning. The fourth part expounds on the transaction strategy optimisation based on the deep learning P2P behaviour model. The fifth part introduces the

P2P transaction process based on deep learning behaviour model of prosumers. The sixth part introduces the network example simulation analysis with the result. The seventh part summarises this paper.

2 | DEEP LEARNING BASED P2P TRANSACTION FRAMEWORK

The main structure of the two-stage P2P transaction market [22, 23] mentioned in the paper is as follows: as shown in Figure 1, the grid provides a two-stage price and corresponding available supply. In the first state, the grid provides each consumer with a basic supply of electricity at a lower price as part of social welfare. The second stage has a higher supply price because of its cost of production. When the first-stage electricity cannot meet the demand, prosumers can meet the demand through the P2P market or choose the second-stage power supply of the grid. As shown in Figure 2a below, the maximum supply of the two stages of the grid is limited to P1 and P2, respectively, and the price is shown in Figure 2b. The price curve of the supply power in the second stage is higher than the welfare electricity in the first stage.

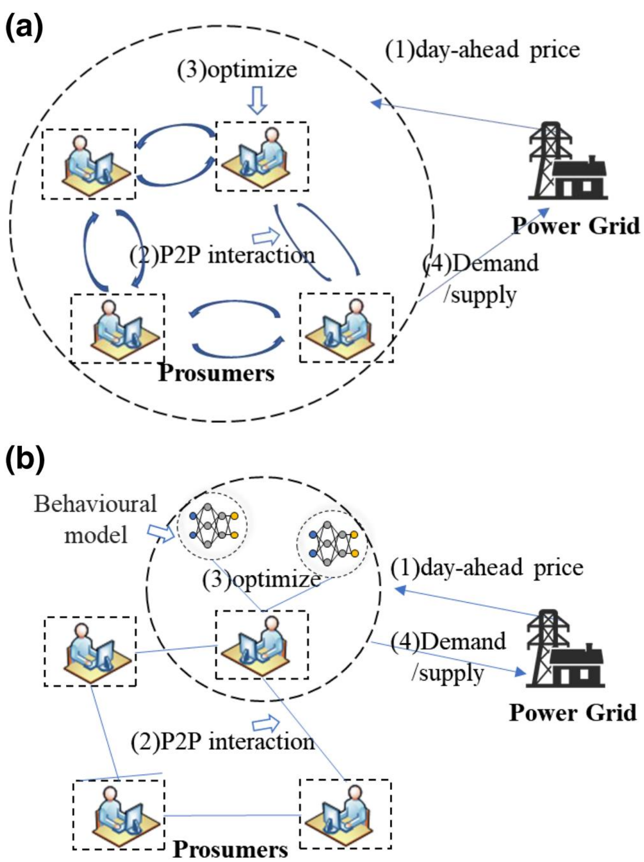

FIGURE 1 P2P transaction market structure. (a) Traditional two-stage P2P transaction market, (b) Deep-learning-based two-stage P2P transaction market

In the trading market, the connected prosumers carry out bilateral power and price, and the prosumers divide their demand into several parts and offer power bidding to the prosumers that can be traded. In the day-ahead transaction, prosumers will predict the transactions available in the P2P market based on the day-ahead price of the power grid, their prediction of new energy generation, and the P2P trading expectation model. Then, the day-ahead power consumption plan will be optimised according to the predicted P2P transaction power. Then day-ahead power purchase plan in the first and second stages of the power grid will be reported to the power grid.

In the traditional interactive iterative P2P method, such as ADMM, after the prosumers optimise their own energy consumption and quotation, the bidding and quotation information is transmitted to other prosumers, and other prosumers make new updates on the updated bidding information until no one updates it in the P2P market. The method proposed in this paper is that the prosumers establish the interaction model of prosumers he trades with. In the optimisation process, these models are used to consider the interaction behaviour of other prosumers. The solution that is close to equilibrium can be obtained after optimisation once.

In the existing methods, the normal distribution model [24] is used to estimate the upper and lower limits of power prices, in this way, the uncertainty of prices is considered. Furthermore, we use the deep neural network to model the electricity price expectation, adding the influence of time correlation, scenery output and other factors on the behaviour of prosumers.

The model based on deep learning proposed in this paper improves the prediction accuracy of P2P transactions and takes into account the influence of environmental factors on P2P transactions of prosumers, which can reduce the error of subsequent optimisation of electricity consumption plan of prosumers, thus improving economic benefits.

3 | DEEP LEARNING BASED P2P TRANSACTION BEHAVIOUR MODEL

For prosumers, complete information includes the types of equipment owned by others, the capacity parameters of storage and equipment, the electricity price, the parameters in revenue functions of others, the history transactions of everyone in the P2P market, and the public environmental information includes light intensity, wind speed and temperature. To protect privacy,

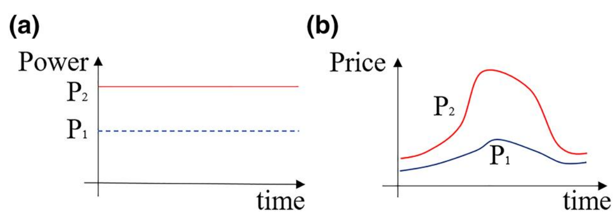

FIGURE 2 The power and price supplied by the two-stage market. (a) The available supply of the two-stage market (b) The price curve of the two-stage market

P2P interaction is carried out under the condition of incomplete information. In this case, prosumers do not have the types of equipment, device parameters and economic parameters owned by others. In the process of repeated bidding of the prosumers until the transaction, the incompleteness of information will bring difficulties to the multi-to-multi-P2P transaction. The process from bidding quotation to the transaction is prolonged. At the same time, the actual income of prosumers will be lost because of the deviation from the optimal production plan. Therefore, this study proposes to use a deep neural network to learn the interactive characteristics of the transaction of prosumers, accelerate the P2P market transactions, and improve the efficiency and economic benefits of P2P transactions under the protection of user privacy information.

The public environment data affecting distributed output and consumer demand are used as the input data of deep learning model training, and consumer history transaction data are used as the input and output data of model training. Input public environmental data include irradiance, wind speed and grid electricity price, and historical transaction data includes historical transaction object, transaction time point, transaction volume and transaction price. The P2P transaction mapping between prosumer i and j is shown as follows:

$$\begin{bmatrix} s_1 \\ s_2 \\ \cdots \\ s_{24} \end{bmatrix}, \begin{bmatrix} v_1 \\ v_2 \\ \cdots \\ v_{24} \end{bmatrix}, \begin{bmatrix} b_1 \\ b_2 \\ \cdots \\ b_{24} \end{bmatrix} \underset{f_{ij}}{\xrightarrow{\text{reflect}}} \begin{bmatrix} b_1^{ij} \\ b_2^{ij} \\ \cdots \\ b_{24}^{ij} \end{bmatrix}, \begin{bmatrix} E_1^{ij} \\ E_2^{ij} \\ \cdots \\ E_{24}^{ij} \end{bmatrix} \tag{1}$$

Long Short-Term Memory (LSTM) neural network method was used to train the model considering the high coupling between the power consumption and time. LSTM neural network method is improved from the recurrent neural network (RNN) method. It selectively remembers and forgets the historical information of the data, has good characterisation performance for the timing characteristics of the data, and avoids the problem of gradient explosion or disappearance which is easy to occur in RNN training. The network structure and expression relationship of LSTM is shown in Figure 3.

Input data of the LSTM model include time series of irradiance, wind speed, power grid electricity price and so on. $f_1(t)$ is the output of the forget gate at time t; w and b are weight matrices and bias vector; $f_c(t)$ is the current state at time t; $f_o(t)$ is the output of output gate; $F(t)$ is the output at time t including P2P transaction power and P2P transaction electricity price data. The LSTM method selectively forgot, remembered and transmitted the historical information, so that the model has a better ability to fit the temporal features.

The LSTM neural network shown in Equation (2) is trained to obtain the deep learning model of P2P transaction behaviour characteristics between prosumer i and j. Offline training uses open environmental information and public historical transaction data. The training process does not require the prosumers to disclose their internal physical model parameters, which protects the privacy of the other party. Since the training uses public environmental data and historical

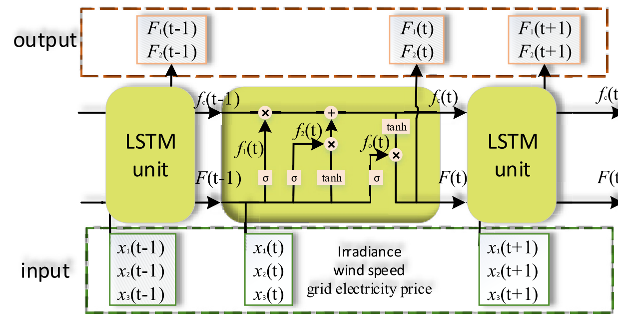

FIGURE 3 Long short-term memory neural network structure

transaction data, no private information is required, so prosumers can train the model to learn others' P2P transaction behaviour, and use it to optimise their electricity behaviour and decide their bid in the P2P market.

$$\begin{aligned} F(t) &= \left[b_{ij}(t), E_{ij}(t)\right] \\ &= \sigma\left(w_{f_o} \cdot [F(t-1), x(t)] + b_{f_o}\right) \\ &\quad \cdot \tanh\left(\begin{aligned} &f_1(t) \cdot f_c(t-1) \\ &+ f_2(t) \cdot \tanh\left(w_{f_{c0}} \cdot [F(t-1), x(t)] + b_{f_{c0}}\right) \end{aligned}\right) \end{aligned} \tag{2}$$

where, Equation (2) is the deep learning model of P2P behaviour characteristics of prosumers obtained by training; where the output b_t^{ij} and E_t^{ij} are the transaction price and transaction power of P2P transaction reached by prosumer i and j at time t; in the input $x(t) = [s_t, v_1, b_t]$, s_t is the environmental irradiance at time t, v_1 is the environmental wind speed at time t, and b_t is the electricity price provided by the power grid at time t, including basic electricity price $b_l(t)$ and stepped electricity price $b_b(t)$.

4 | P2P TRANSACTION STRATEGY OPTIMISATION OF PROSUMER BASED ON DEEP LEARNING BEHAVIOUR MODELS

An LSTM based approach is proposed to solve the P2P energy trading and energy conversion problem formulated in this section. Based on the LSTM model proposed in Equation (2), the prosumer predicts the power and price he can obtain in the P2P market. The prosumer will choose to maximise revenue by scheduling its adjustable capacitive load and energy storage equipment.

4.1 | Prosumer P2P optimisation model

The optimisation objective of the prosumer is to maximise his income, which takes into account the energy storage cost of the prosumer, the income of load output and their expenditure on power purchase from the grid and P2P. The objective is shown in Equation (3):

$$\max\sum_{\pi} p(\pi)\sum_{t} C_i(t) = \sum_{\pi} p(\pi)\sum_{t} \mathrm{g}_i(t) - \mathrm{c}_i(t) - \mathrm{v}_i(t) \quad (3)$$

$$\begin{cases} \mathrm{g}_i(t) = a \times (P_i(t) \times \Delta \mathrm{t})^2 + b \times P_i(t) \times \Delta \mathrm{t} + c \\ \mathrm{c}_i(t) = 0.5k_b|B_i(t)| + b_l(t)P_{i,G1}(t) + b_b(t)P_{i,G2}(t) \\ \mathrm{v}_i(t) = \sum_{j=1,j\neq i}^{m} b_{ij}(t)E_{ij}(t) \end{cases} \quad (4)$$

Equation (3) shows the optimisation goal of prosumer i, π represents the renewable energy output scenario and $p(\pi)$ represents the probability of occurrence of the scenario. The method of the probability scenario used to model the uncertainties of the distributed renewable energy and loads is described in our previous work [25]. $C_i(t)$ represents revenue in the scenario. $\mathrm{g}_i(t)$ and $\mathrm{c}_i(t)$, $\mathrm{v}_i(t)$ are, respectively, productivity benefit, energy storage cost and power grid electricity fee, and P2P transaction amount, respectively, of user i at time t. In Equation (4), the P2P transaction price $b_{ij}(t)$ and power $E_{ij}(t)$ can be derived by input $[s_t, v_1, b_t]$ in Equation (1). The ith prosumer power $P_i(t) = L_i(t) - B_i(t)$ consists of load $L_i(t)$ and energy storage power $B_i(t)$ which are optimisation variables. When it indicates that the storage device discharges. The parameter k_b is the unit cost of discharge.

4.2 | Constraints of prosumer optimisation model

(1) Energy storage module constraints.

The storage capacity and power of the energy storage device in time t meet the following requirements:

$$B_{i,\min} < |B_i(t)| < B_{i,\max} \quad (5)$$

$$E_{\mathrm{soc}}(t) = E_{\mathrm{soc}}(t-1) - \eta_C \times \min(0, B_i(t)) + \frac{\max(B_i(t), 0)}{\eta_D} \quad (6)$$

$$E_{\mathrm{soc},\min} < E_{\mathrm{soc}}(t) < E_{\mathrm{soc},\max} \quad (7)$$

$$E_{\mathrm{soc}}(24) - E_{\mathrm{soc}}(0) = 0 \quad (8)$$

In Equation (5) the charging and discharging power of the device meets the maximum $B_{i,\max}$ and minimum $B_{i,\min}$ constraints. The device capacity in Equation (6) meets the timing power constraint. The parameters η_C and η_D are the efficiency coefficients of charge and discharge, respectively. For the storage device, the state of capacity meets the maximum $E_{\mathrm{soc},\max}$ and minimum $E_{\mathrm{soc},\min}$ capacity requirements in Equation (7). Besides, the state of capacity after a day $E_{\mathrm{soc}}(24)$ is required to be the same as the initial state $E_{\mathrm{soc}}(0)$ in Equation (8).

(2) Prosumer load constraints.

The load power of the prosumer meets the following constraints:

$$L_{i,\min} < L_i(t) < L_{i,\max} \quad (9)$$

$$\Delta L_{i,\min} < |L_i(t) - L_i(t-1)| < \Delta L_{i,\max} \quad (10)$$

The Equation (9) represents that prosumer load satisfies the minimum basic power constraint and the maximum power constraint of equipment. The power variation constraint is limited in Equation (10).

(3) Security constraints of connection line between prosumer and grid.

The prosumers in the community only use the power grid within a very short distance. Under this premise, we ignore the changes of the node voltage and phase of the grid, and only consider the constraints of the exchanged power between the prosumers and the power grid. The power exchange between prosumer and grid satisfies the connection line security constraint:

$$P_{i\text{-net},\min} < P_i(t) - P_{PV,i}(t) < P_{i\text{-net},\max} \quad (11)$$

where $P_{i\text{-net},\max}$ means the maximum power that the grid can sell to the ith prosumer. $P_{i\text{-net},\min} < 0$ and $|P_{i\text{-net},\min}|$ represents the maximum renewable energy power repurchased by the grid.

(4) Constraints of P2P transaction.

P2P transactions between ith prosumer and other users meet the following constraints:

$$0 \leq \left|\frac{E_{ij}(t)}{\Delta t}\right| < P_{i\text{-}j,\max} \quad (12)$$

$$b_l(t) < b_{ij}(t) < b_b(t) \quad (13)$$

In Equation (12), the transaction power between prosumer i and j is less than the upper limit of line power between them. In Equation (13) the transaction price is limited between the highest and lowest price of electricity on the grid.

The main advantages of the proposed method for micro-network P2P strategy decision-making are as follows: (1) considering other users' behaviour to optimise its behaviour; (2) Deep Learning modelling method is used to deal with incomplete information and improve modelling accuracy; (3) increased energy revenue of the prosumer; (4) It is helpful to smooth the peak and valley of the total load of the grid. In the next section, simulation examples are established to verify the superiority of the proposed method.

5 | DEEP LEARNING MODEL BASED P2P TRANSACTION PROCESS

This section proposes the P2P transaction process based on the time series deep network model. Prosumers use the model to optimise the energy consumption and give the expected bid to participate in the P2P market. However, due to the error of the neural network model, there is some deviation between the optimisation result and the actual situation. The main function of this trading process is to eliminate the deviation and complete the clearing. In P2P trading market, prosumers participate in P2P bidding based on the optimisation results using deep learning model. P2P transactions take place through successive bilateral auctions, with participants bidding in both directions until trades are satisfied. This section proposes the P2P transaction process of prosumers based on a time-series deep network model. In the intra-day P2P trading market, prosumers participate in P2P bidding and reach P2P transactions based on day-ahead power consumption plan and transaction expectations based on the deep learning model above. P2P transactions are carried out by consecutive double auctions, and P2P prosumers make bi-directional bidding until the transaction is satisfied. The final P2P matching result is multiple pairs of electricity and electricity prices. If prosumers fail to meet the demand or sell excess new energy generation in the P2P market, prosumers can buy a second-stage power at a high price from the grid or sell the new energy generation at a low price. The grid will refuse to meet demand or accept new energy sources if it is outside the grid's security limits.

There are nonlinear constraints and nonlinear functions in the process of optimisation solution of prosumers. Therefore, the sequential quadratic programing (SQP) method is used in this paper to solve nonlinear optimisation problems. SQP method mainly obtains the approximate problem of the original problem by approximating the objective function to the quadratic function near the iterative point, and obtains the optimal solution of the original nonlinear problem by solving a series of simplified approximate linear problems. SQP method has proved to be a very useful tool for solving nonlinear programs, and it performs well in terms of efficiency, accuracy, and percentage of successful solutions when dealing with a large number of test problems [26].

The design details of P2P transactions based on a deep learning network are given below, consist of four phases: grouping, connecting, biding, and clearing and the pseudocodes are shown in Algorithm 1:

(1) Participating in P2P: Identify the prosumers $\{\mathbf{G}{:}1,2,...,i,...\}$ that participate in P2P market and share the neural network model of each prosumer i.

(2) Grouping: For each transaction period, prosumers are divided into purchasing group and selling group according to the expected transaction quantity E_{ij}^{pr} predicted by the LSTM model.

(3) Establishing P2P links: Establish P2P links between adjacent sellers and buyers according to geographical restrictions. Delete the links that cannot be traded based on prediction of neural network model, and prosumers without links will exit the P2P market of this round. Initialise the number of bidding rounds $k = 0$.

(4) Biding: Prosumers i submit bidding quantity $b_{ij}(k)$ and price $E_{ij}(k)$ to linked prosumers j using deep neural network model.

(5) Clearing: The transaction that meets the transaction conditions is cleared, the price and capacity of the transaction are calculated, and the P2P transaction link between the two parties is deleted. If there is no P2P transaction chain or the quantity is cleared, the prosumer shall exit the P2P market.

(6) End: The P2P market ends when the maximum number of P2P auctions $k_{\max}$ is reached or there is no prosumer to be traded in the P2P market. Otherwise, $k = k + 1$ repeat steps four to five until the end.

Algorithm 1 P2P transaction based on deep neural network

Input: Neural network model, P2P biding times $k = 0$
For each prosumer $i \in \mathbf{G}$ **do**
  predict the capacity b_{ij}^{pr}, E_{ij}^{pr} that can get in P2P using the deep neural network model.
  divide i into sellers if $\sum b_{ij}^{pr} > 0$, divide i into buyers if $\sum b_{ij}^{pr} < 0$
end for
update connectivity matrix $M^{n\times n}$: establish connection between adjacent buyers and sellers $M_{i,j} = 1$; delete connection if predicted turnover is zero $|\sum b_{ij}^{pr}|<\varepsilon$, make $M_{i,j} = 0$
while $k < k_{\max}$ and $sum(M^{n\times n}) > 0$
  For each $i \in$ G **do**
  Submit quantity $E_{ij}(k)$, and price $b_{ij}(k)$ to linked prosumers using deep neural network model.
  endfor
  For each $i \in$ G, $j \in$ G ($M_{i,j} = 1$) **do**
  Judge whether a deal can be struck:
  if buyer's bid $b_{ij}(k)$ > sell's bid $b_{ji}(k)$ **then** Clear quantity $b_{ij} = b_{ji}(k)$, clear price $E_{ij} = (E_{ij}(k) + E_{ji}(k))/2$. delete connection between ij: $M_{i,j} = 0$
  endif
  endfor
  $k = k + 1$
endwhile
return (b_{ij}, E_{ij}, k)

6 | SIMULATION RESULTS AND DISCUSSION

In this section, the proposed LSTM-based method is demonstrated through the simulation case, using price data of Micro-grids and meteorological data [27, 28]. There are six micro grids with new energy power generation equipment in the calculation example, and the structure is shown in Figure 4. These prosumers within the community only use the grid within a very short distance. Under this premise, we ignore the energy transmission loss and the variation of the node voltage and phase of the grid. The new energy equipment of Micro-grid is wind turbine or photovoltaic, which has different capacity and output characteristics. Micro grid load parameters and cost function parameters are also different. Micro grids use the deep LSTM P2P model proposed in this paper to optimising power consumption strategy, and uses the deep LSTM P2P model to make P2P bidding.

6.1 | Parameter specifications of MGs and system

The parameter settings of the six micro grids are shown in Table 1, including the income function parameters of micro grids, new energy equipment types of micro grids and upper and lower limits of output. Grid parameter settings are shown in Table 2, including upper and lower limits of grid power, upper and lower limits of P2P transaction electricity, upper and lower limits of P2P transaction electricity price, etc.

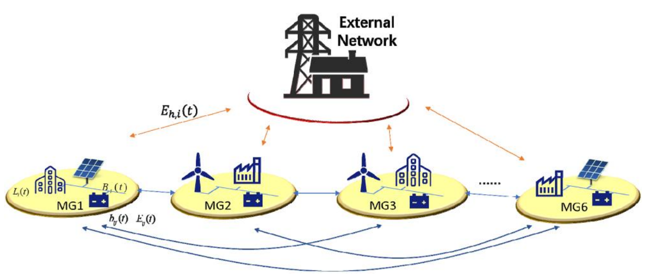

FIGURE 4 P2P transaction simulation structure of 6 prosumers

TABLE 1 Parameters of micro grid

Micro-grid	Income parameter [a, b, c]	Type	Range [min max]
1	[−1.78,3400.3,12,039.1]	pv	[0,204]
2	[−1.88,4349.4,9668.9]	pv	[0,167.8]
3	[−1.79,3769.1,9751.4]	pv	[0,223]
4	[−1.61,2658.6,12,153.8]	Wind	[0,220]
5	[−1.67,2157.8,13,254.0]	Wind	[0,220]
6	[−1.98,2074.2,6537.9]	Wind	[0,230]

6.2 | Deep LSTM model and precision analysis

LSTM deep neural network model is used to train the historical data of P2P transaction of micro grid 1. The model training convergence process is shown in the Figure 5. Root Mean Square Error (RMSE) of the LSTM model in convergence is 0.0486, which is less than 5% and meets the accuracy requirement. It takes 2min26s to train with a single GPU. The parameters of the improved deep LSTM neural network are shown in Table 3.

The number of P2P interactions is compared as shown in Figure 6. After the deep learning model is used, the interaction times of P2P interactions is reduced from 3–17 to 2–3, and the average number of interactions is reduced from 7.9 to 2.6. The cost of P2P interaction is reduced and the operating efficiency of regional energy interaction system is improved.

The relationship between the logarithm based 10 of supply and demand ratio (SDR) of P2P transactions and the transaction price of P2P is shown in Figure 7a. Then we use the P2P price constraint during the transaction, that is, the two-stage electricity price of the power grid, to regularise the P2P price, and show the relationship is shown in Figure 7b. Then we can see the following characteristics: (1) the P2P trading

TABLE 2 Grid security constraint parameters

Parameters	Value
$P_{i\text{-net,max}}$	500
$P_{i\text{-net,min}}$	200
$P_{i\text{-}j\text{,max}}$	150

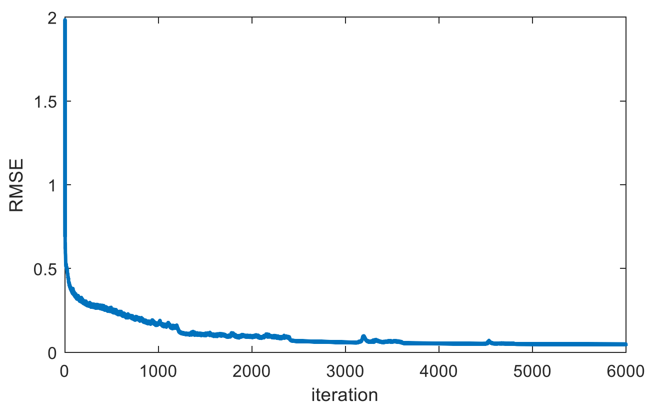

FIGURE 5 The convergence process of Root Mean Square Error (RMSE)

TABLE 3 The training parameters of the improved deep LSTM neural network

MaxEpochs	1000
MiniBatchSize	144
InitialLearnRate	0.01
LearnRateDropFactor	0.35
LearnRateDropPeriod	200

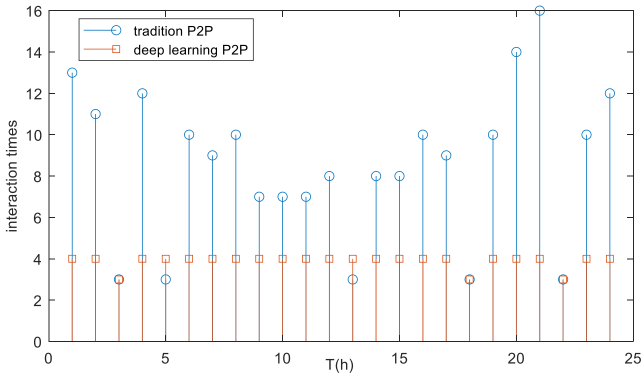

FIGURE 6 Comparison of P2P transaction iterations

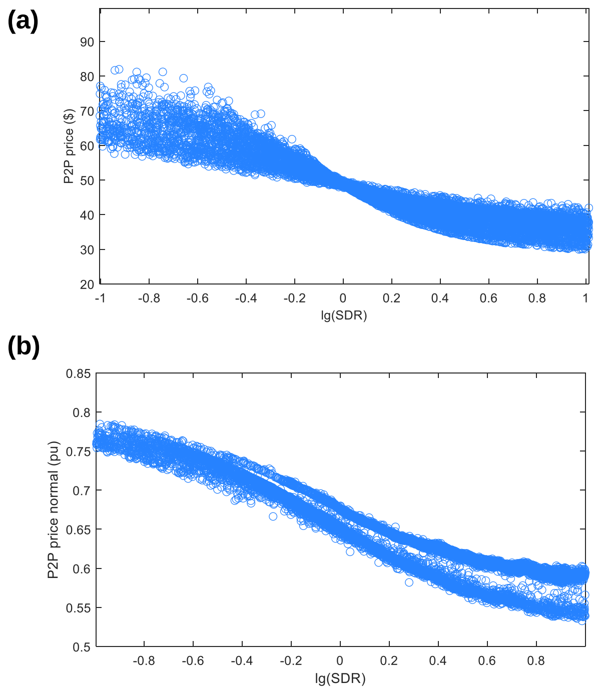

FIGURE 7 Transaction prices of P2P under different supply and demand ratio (SDR). (a) The relationship between the actual transaction price of P2P and SDR, (b)The relationship between the normalised transaction price of P2P and SDR

price regularised expectation and the logarithm based 10 of SDR shows an approximately decreasing s-curve. The price of P2P transaction decreases with the increase of supply and demand ratio. When the supply and demand ratio is very small, there is a price upper limit, and when the supply and demand ratio is very large, there is a price lower limit. (2) In terms of distribution, when the supply and demand ratio is extremely small, transaction prices are relatively dispersed. Then, with the increase of supply and demand ratio, transaction prices are distributed near two curves, and the distance between curves increases with the increase of supply and demand ratio. (3) Under different supply and demand ratios, the distribution volatility of P2P transaction prices is different.

In view of the above, combined with the P2P power that prosumer supply or demand under the different supply and

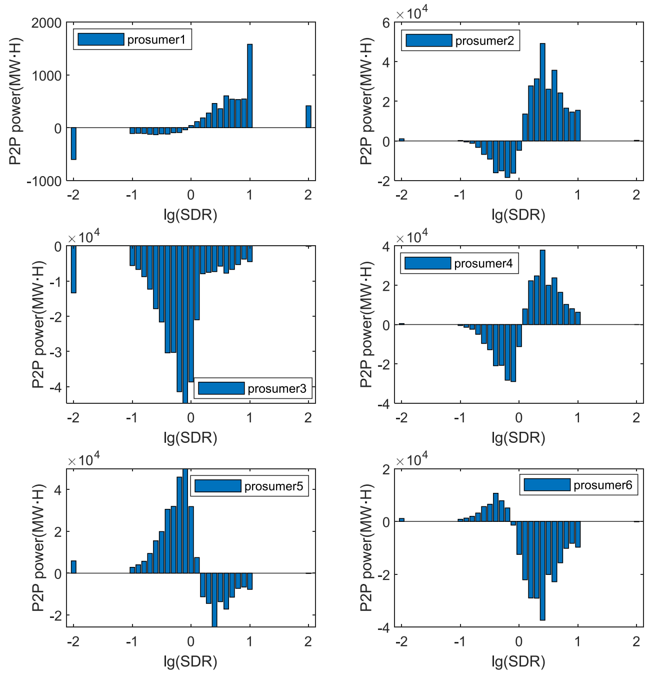

FIGURE 8 The trading power of P2P participated by different prosumers under supply and demand ratio (SDR)

demand ratio were analysed in Figure 8. The reasons for such a relationship between supply/demand ratio and transaction price are as follows: (1) the price of P2P transaction conforms to the transaction characteristics of the market. As the ratio of supply and demand increases, the price decreases. However, due to the limitation of power generation cost and electricity consumption cost, the curve shows an inverse S-shaped curve; (2) Prosumers have different expectations for P2P transaction when selling and supplying electricity. P2P transaction price is distributed around two transaction price curves. When the ratio of supply and demand is very small, most prosumers participate in P2P power to purchase, with prosumer three mainly selling electricity. At this time, the power available for purchase in the P2P market is less, and most prosumers expect to purchase electricity from the P2P market, so they may offer more aggressive prices to facilitate the transaction. With the increase of supply and demand ratio, the urgency of transaction of some prosumers is reduced, transaction prices will be relatively separated, and the expected separation of the two curve prices is more obvious. (3) The volatility of transaction price distribution is related to the supply and demand capacity and bargaining power of prosumers. The number of sellers affects the fluctuation of the upper curve, and the number of buyers affects the fluctuation of the lower volume curve. The volatility of transaction prices increases with the number of prosumers.

6.3 | Benefit analysis

Prosumers forecast P2P trading power and transaction price through the model, and adjust their electricity consumption plan in order to maximise their own income. The power consumption plans of the two methods are shown in Figure 9a,b respectively. In the Figure 9, the blue bar refers to the whole electricity purchased from the grid by prosumers, and the yellow bar refers to the P2P transaction electricity traded between prosumers.

The comparison of income and expenditure under the two methods can be seen from Figure 9 and Table 4 that the overall income of prosumers increases from the original $14,122.8 thousand dollars to $14,334.8 thousand dollars, with an increase of 1.5%. The overall electricity cost of prosumers decreased from $89.7 thousand dollars to $71.0 thousand dollars, and the electricity cost decreased by 20.9%. The number of iterations required by P2P exchange, the maximum amount of electricity purchased from the grid by prosumers decreased from 2024–1643 MW, decreased by 18.8%. Our calculations are based on Intel(R) Core(TM) i7-8700 CPU @ 3.20 GHz and the calculation time using the two methods to optimise the P2P result of one day is 82.5 and 39.6s, respectively.

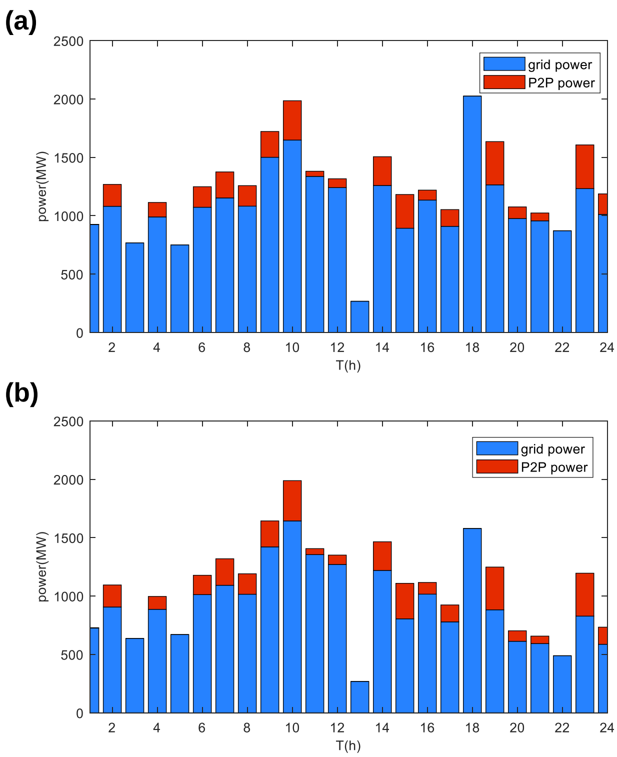

FIGURE 9 Power supplied by P2P and grid under two methods. (a) Traditional P2P, (b) Deep learning based P2P

TABLE 4 The benefits and expenses under two methods

Methods	Traditional P2P	Deep learning based P2P
Electricity revenue (thousand $)	14,122.8	14,334.8
P2P amount (MW·h)	153,563.6	153,726.6
Electricity expenditure (thousand $)	89.7	71.0
Computing time (s/1 day)	82.48	39.55

7 | CONCLUSION

This paper proposes a novel deep learning based P2P transaction method for prosumer under two-stage market environment. The main conclusions are as follows:

1. The method of deep LSTM model to describe prosumers P2P transaction features has excellent protection for user privacy. This approach is based on the ability to fully exploit hidden information in public data and model based on it, rather than on private parameters. This method can construct the deep LSTM P2P model of P2P interaction between prosumers under the condition of taking user privacy protection into account.
2. The prosumers P2P transaction deep neural network model based on LSTM has excellent representation accuracy. The selective forgetting of time sequence information of LSTM method fits well with the inter-day correlation coupling of prosumers in P2P transactions and decision-making. The RMSE of the model in convergence is 0.0486, which is less than 5% and meets the accuracy requirement.
3. P2P transactions based on a deep learning model can improve the income of prosumers and accelerate the P2P bidding process. Compared with the traditional P2P bidding method, the P2P bidding process based on LSTM has higher precision. Based on this, prosumers can adjust the electricity consumption plan and optimise the revenue. Simulations show a 20.9% reduction in electricity bills. In addition, more accurate P2P forecasting reduces the exploratory process of P2P bidding and speeds up the P2P bidding process. The simulation shows that the interaction times are reduced by 67.09%.
4. The relationship between P2P transaction price and supply/demand ratio presents an inverse S-shaped curve. The different price expectations of prosumers will lead to the separation of P2P transaction prices.

In the future, we will further discuss P2P transaction methods from the perspective of the cooperative game.

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CONFLICT OF INTEREST

The author declares that there is no conflict of interest that could be perceived as prejudicing the impartiality of the research reported.

PERMISSION TO REPRODUCE MATERIALS FROM OTHER SOURCES

None.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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