P2P energy Trading Based on power generation and Load forecasting of Prosumers

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Abstract. With the development of distributed power sources for the community microgrid, an increasing number of energy consumers possessing local power generation abilities will gradually transform into prosumers, balancing the dual identities of power producers and consumers. Peer-to-peer (P2P) energy trading has the potential to reduce the total cost of prosumers in community microgrids. A P2P energy trading scenario with photovoltaic (PV) systems is designed in this paper. To substantiate the effects of accurate power generation and load forecasts on this scenario, an ensemble method integrating forecasting and P2P trading is proposed. Finally, as the accuracy of power generation and load forecasts improves, bills for individual prosumer and total cost within community microgrid will approach reality. The results of proposed method can be followed by participants within community microgrid.

Keywords: P2P energy trading; combination of forecasts; prosumers; power generation and load forecasting

1 Introduction

The reform of the electricity market has diminished barriers for distributed energy to be integrated into the grid, escalated the investment proportion of local power grids in

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wind power, photovoltaic (PV), energy storage, etc., and incrementally increased the number of prosumers with power generation and consumption capabilities [1].

The accuracy of power generation and load forecasting of prosumers is the fundamental basis for enhancing the utilization of renewable energy. In power load forecasting, current popular artificial intelligence methods include artificial neural network (ANN) [2], support vector machine (SVM) [3], deep learning (DL) [4], etc. The main methods for power generation forecasting include Markov chain model [5], hybrid model [6], fuzzy logic [7], etc. Nonetheless, given the restricted information leveraged by a single forecasting method, an erroneous forecasting model can introduce substantial inaccuracies to the forecasts of power generation and load. Therefore, reference [8] proposed a combination of forecasting methods, with the objective of comprehensively exploiting the valuable data offered by various individual methods, in order to heighten the accuracy.

In community microgrids, peer-to-peer (P2P) energy trading encourages flexible trading of excess energy amongst peers [9]. Prosumers can achieve on-site consumption of distributed renewable energy through P2P energy trading diminishing carbon emissions generated by fossil energy and long-distance transmission [10]. Reference [8] constructed an energy-sharing model with price-based demand response. Reference [11] proposed three different market paradigms for P2P energy trading. Reference [12] investigated game theory to describe the decision-making process of prosumers participating in P2P energy trading.

For the purpose of maximizing the benefits of power trading within community microgrids, this paper proposes an ensemble method for power generation and load forecasting of prosumers and P2P energy trading. Methods such as extreme gradient boosting (XGB), random forest (RF), DL and the combination of forecasts (CoF) are applied to power generation and load forecasting for reducing information uncertainty and increasing accuracy. Meanwhile, the results of power generation and load forecasting are utilized as input for the P2P energy trading to optimize transaction prices. Ultimately, the feasibility and effectiveness of the proposed method are verified through numerical experimen

2 scenario of the P2P energy trading

The focus of this study is to explore a novel community microgrid based on P2P energy trading (Fig. 1). Within the community microgrid, each prosumer operates independent PV systems, while power generation and consumption are considered collectively as a single community entity, rather than on a per prosumer basis. Prosumers engage in power transactions via P2P energy trading system when purchase or sale demands emerge. After P2P trading, the entire community needs to interact with the grid to achieve power supply equilibrium. Surplus power generated by the community can be sold to the grid, and in the meanwhile when the community's power generation falls short, additional power needs to be procured from the grid.

It should be noted that power prices of purchase and sale for the grid differ from the ones of P2P power trading in community microgrid. Power prices of purchase and sale in microgrid are provided by energy trading system. A framework consisting of two main components is devised for the P2P energy trading scenario (Fig. 2).

- Forecast power generation and load of each prosumer with three models each and comprehensively analyze these results to increase forecasting accuracy.
- Implement a P2P transaction strategy in the microgrid to decrease the aggregate cost of power consumption.

In the first stage, we gather and analyze data from the distributed PV system, including power generation, load, weather, and obtain the forecasted power generation and load. In the second stage, based on predicted results from stage one, the price of P2P power trading is determined through the development of reasonable trading strategies. The entire framework is designed to not only optimize and obtain the most suitable prices of power trading, but also ensure fairness and rationality of transactions.

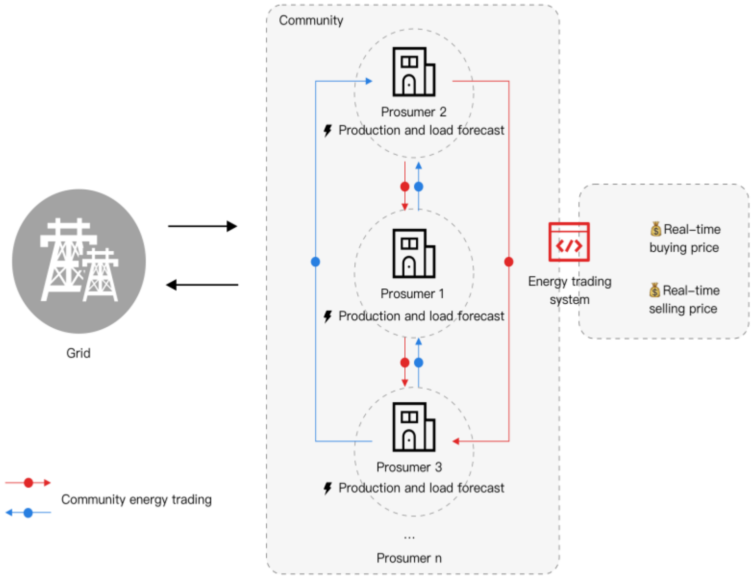

Fig. 1. The scenario of energy trading in community microgrid

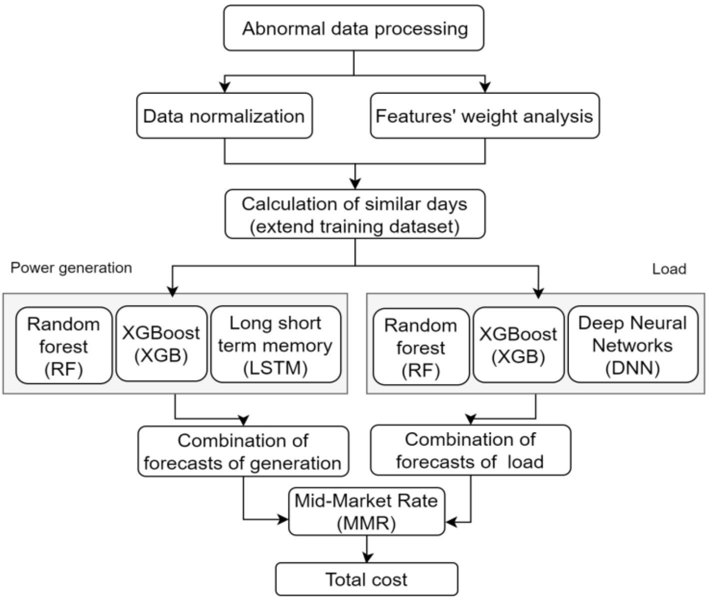

Fig. 2. Flowchart of the proposed framework

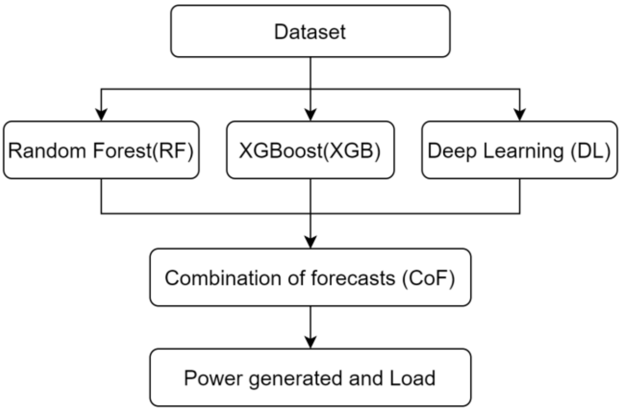

Fig. 3. Flowchart of forecasting

3 method

3.1 Method of power generation and load forecasting

Four models are applied to power generation and load forecasting, as in the flowchart (Fig. 3).

- RF, also known as the Random Decision Forest, is a machine learning algorithm commonly used for classification and regression analysis (Fig. 4) [13, 14]. It is an ensemble learning method that builds multiple decision trees at training time, and outputs classes or forecasts. RF adds variability and robustness to each tree by randomly subsampling the data and features for each tree. This reduces overfitting and improves generalization performance by making the individual trees more diverse and uncorrelated.
- XGB is an efficient gradient boosting decision tree algorithm that is optimized based on the gradient boosting decision tree (GBDT) to significantly improve the model's performance [14-16]. The XGB model uses a series of regularization techniques and model combination strategies to avoid problems such as overfitting and underfitting. Loss function is shown as the second-order Taylor series (1), where f_t represents the t-th tree and $\Omega(f_t)$ is a regularized term. g_i, h_i are the first and second order gradients.

$$L^{(t)} \simeq \sum_{i=1}^{k}\left[l(y_i, {y_i}^{(t-1)}) + g_i f_t(x_i) + \frac{1}{2}h_i {f_t}^2(x)\right] + \Omega(f_t) \tag{1}$$

- Deep Neural Networks (DNNs) are artificial architectures composed of multi-layered nodes (Fig. 5), capable of modeling complex data representations [17]. These nodes, interconnected in diverse layers, receive weighted inputs and produce outputs through nonlinear activation functions. During the training process, the weights are optimized employing the gradient-based techniques to minimize the loss function.

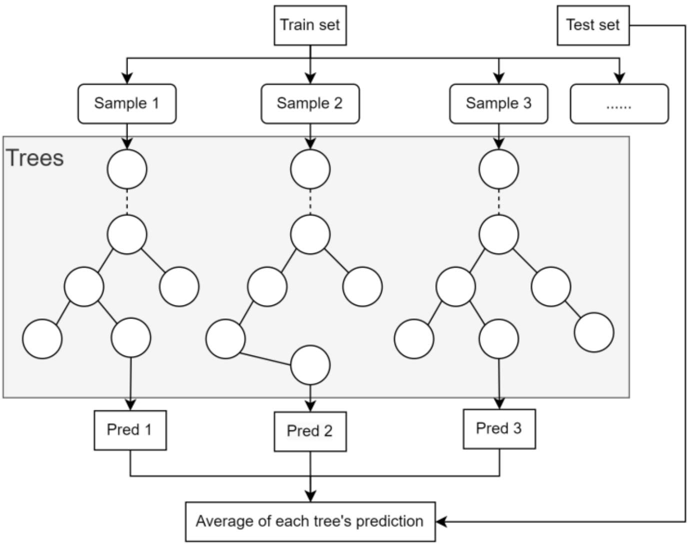

Fig. 4. Schematic view of RF

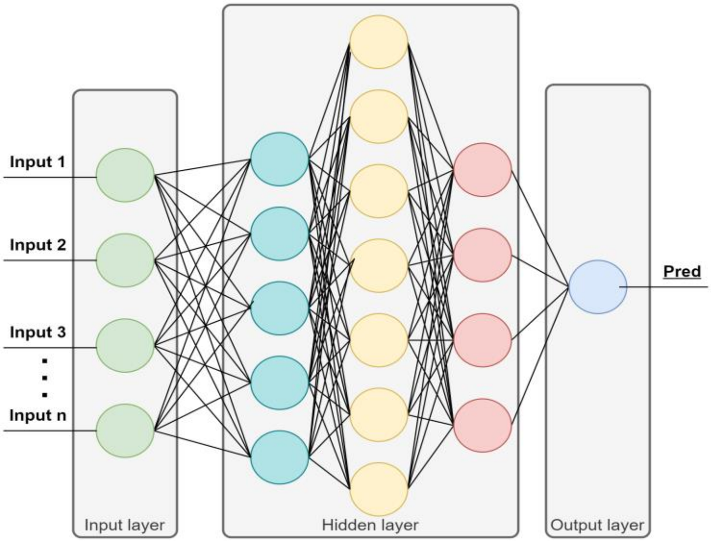

Fig. 5. Schematic view of DNN

- Long short-term Memory (LSTM) is a type of recurrent neural network that is mainly used for processing sequence and time series data [18, 19]. The core idea of the LSTM model is to selectively forget certain information to quickly learn and process long-term sequence information. In LSTM, there are three gate controllers for each time step (Fig. 6): input gate, forget gate, and output gate. Input gate controls the amount of new information. Forget gate controls how much of the previous state is forgotten. Output gate controls the output amount for each time step.

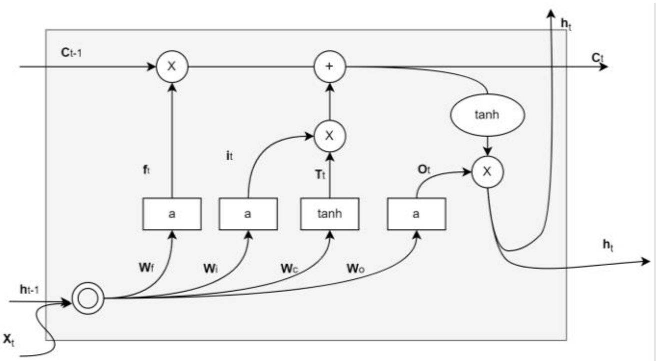

Fig. 6. Schematic view of LSTM model unit

- The CoF model is a combination of multiple prediction models, with an appropriate weighted form [8]. In order to make the combination of forecasting models more effective, the core problem is to find the weight coefficients. S in (2) is the sum of squared errors, where E_r is the error information matrix of each prediction and W is the weight vector of predictive models with w_i as the weight of each model. When W is calculated by (3), S is the smallest, R_r is a unit vector with r dimensions.

$$S = \sum_{t=1}^{n} e_t^2 = \sum_{t=1}^{n}(\sum_{i=1}^{r} w_i e_{i,t})^2 = W^T E_r W \tag{2}$$

$$W = \frac{E_r^{-1} R_r}{R_r^T E_r^{-1} R_r} \tag{3}$$

3.2 Method of P2P power trading

The energy exchange price in community microgrid is considered as the mid-value between the power price of purchase and sales. The Mid-Market Rate (MMR) method assumes that the exchange price is the midpoint of these two prices as (4) [11].

$$P_{p2p} = \frac{P_B + P_S}{2} \tag{4}$$

where P_{p2p} denotes the price of PV power when the demand equals the generation, P_B is the purchase price from grid, P_S is the sales price to grid.

Due to difference between local PV generation and load demand, there are three possible situations that can occur (Fig. 7-9).

- PV power generation equals to demand

$$P_{im}(t) = P_{P2P} \tag{5}$$

$$P_{ex}(t) = P_{P2P} \tag{6}$$

where $P_{im}(t)$ denotes the actual purchasing price at time t, $P_{ex}(t)$ is the actual selling price.

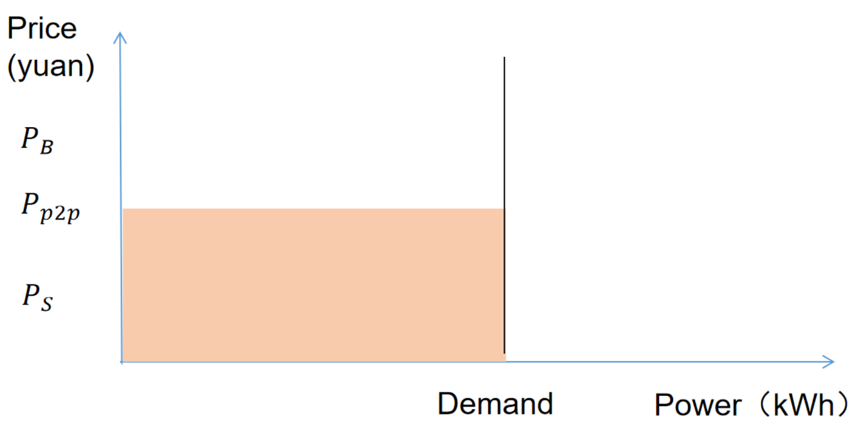

Fig. 7. Total cost when PV generation equals to load

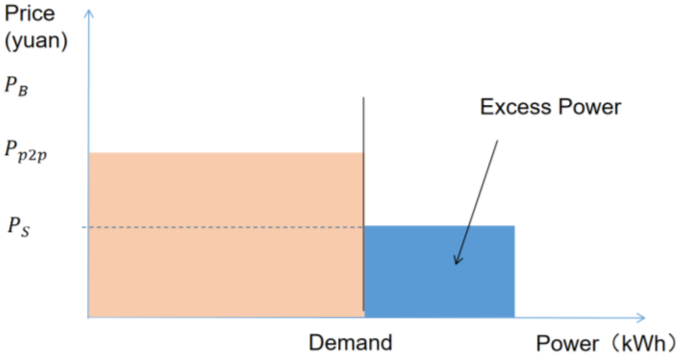

Fig. 8. Total cost when PV generation is larger than load

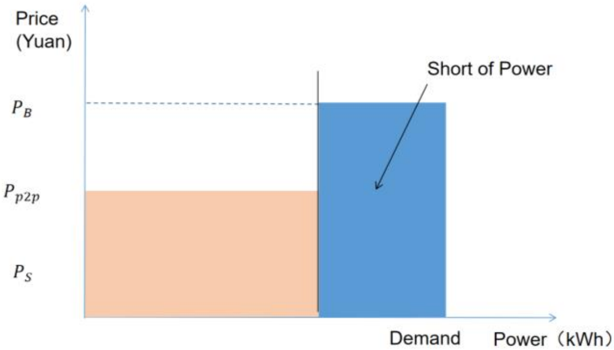

Fig. 9. Total cost when PV generation is less than load

- PV power generation is larger than demand

$$P_{im}(t) = P_{P2P} \tag{7}$$

$$P_{ex}(t) = \frac{\sum_{n=1}^{N} D^n(t) * P_{P2P} + \left(\sum_{n=1}^{N} G_{PV}^n(t) - \sum_{n=1}^{N} D^n(t)\right) * P_S}{\sum_{n=1}^{N} G_{PV}^n(t)} \tag{8}$$

where the load demand of prosumer n at time t is denoted by $D^n(t)$, and the on-site PV generation is denoted by $G_{PV}^n(t)$.

- PV power generation is less than demand

$$P_{im}(t) = \frac{\sum_{n=1}^{N} G_{PV}^n(t) * P_{P2P} + \left(\sum_{n=1}^{N} D^n(t) - \sum_{n=1}^{N} G_{PV}^n(t)\right) * P_B}{\sum_{n=1}^{N} D^n(t)} \tag{9}$$

$$P_{ex}(t) = \mathrm{P}_{P2P} \tag{10}$$

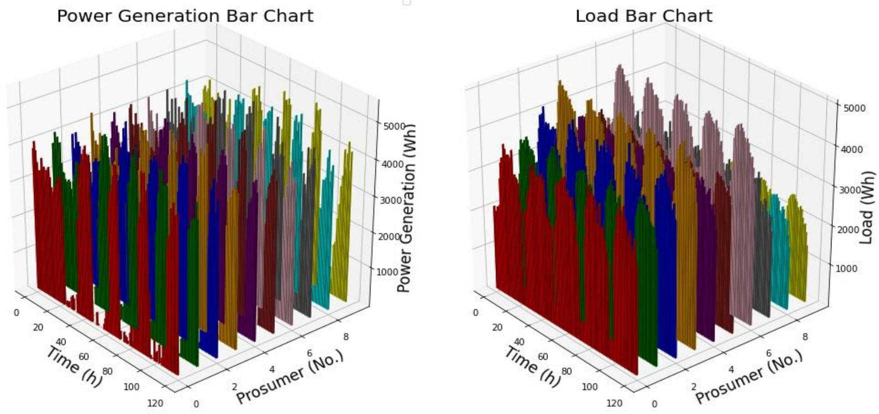

Fig. 10. Power generation and load dataset

- The power bill of individual prosumer when MMR is applied

$$PB_n = \sum_{t=0}^{T}(E_B^n(t) * P_{\mathrm{im}}(t)) - \sum_{t=0}^{T}(E_S^n(t) * P_{\mathrm{ex}}(t)) \tag{11}$$

where $E_B^n(t)$ denotes the amount of electricity that can be bought by prosumer$n$, $E_S^n(t)$ represents the amount of electricity that can be sold.

4 experiment results

4.1 Data acquisition

The power generation data are acquired from a PV power station in Gansu, China. The load data are acquired from residents in Gansu, China. These selected data have already been desensitized and preprocessed (Fig. 10).

4.2 Feature selection

In order to enhance the accuracy of forecasting models, it is essential to consider the temporal shifts in PV power output and the closely associated meteorological data when constructing the training dataset. Various meteorological factors such as irradiance, temperature, relative humidity, cloud cover, and atmospheric pressure, can induce variations in PV power generation.

The residential power demand is similarly influenced by meteorological factors such as temperature, precipitation, and atmospheric pressure. In addition, non-working days, encompassing weekends and holidays, contribute significantly to fluctuations in power load. The interrelationships among these parameters are evaluated by using Pearson correlation analysis [20].

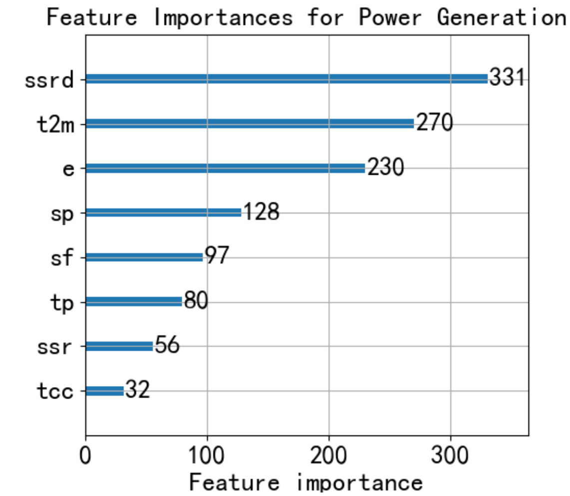

Fig. 11. Feature importances of weather for power generation

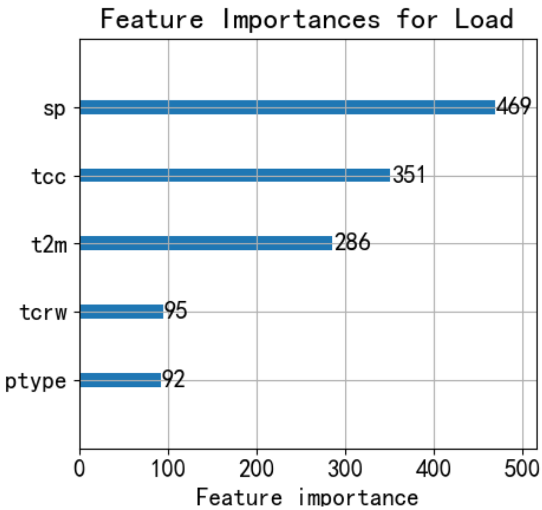

Fig. 12. Feature importances of weather for load

After initial training of models with the weather data and corresponding power, the models can generate its own feature weights, which are shown in Fig. 11. It can be observed that, in terms of power forecasting, the most impactful feature is surface solar radiation downwards, followed by 2-meter temperature, evaporation, surface pressure, and snowfall.

In terms of load forecasting, Fig. 12 shows the most influential feature is the surface pressure, followed by cloud cover, 2-meter temperature and column rain water.

4.3 Data pre-processing

PV power generation data and power load data are recorded separately by different devices. During the operation of these devices, data distortions or omissions may occur due to issues like signal interference and equipment malfunction.

For data distortion, such as sudden spikes or drops in power load data due to short-circuit current and similar situations, the moving average method is employed to average the data within a certain time window to obtain smoother data.

The training process of neural networks may be slow or fail to achieve convergence if the input data are not on the same scale. To address this, the normalization is adopted to pre-process the training set into an appropriate scale. The specific normalization calculation formula is (12).

$$X_{i\_G} = \frac{X_i - X_{i\_min}}{X_{i\_max} - X_{i\_min}} \tag{12}$$

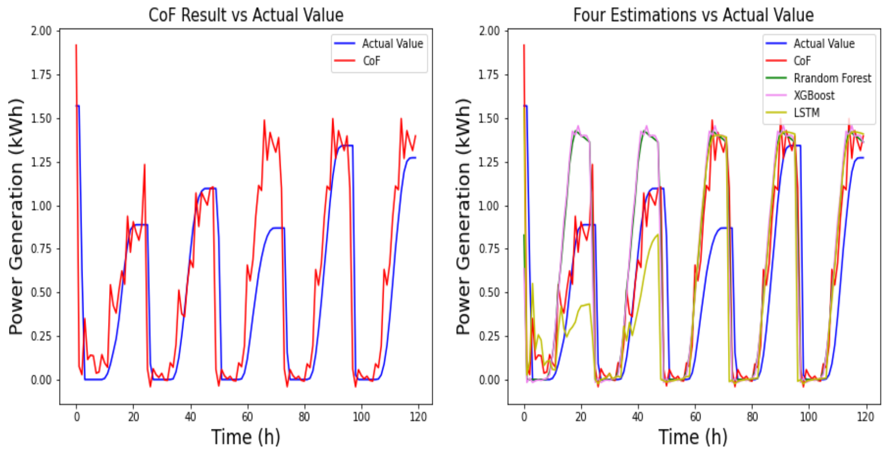

Fig. 13. Estimations of power generation given by RF, LSTM, XGB and CoF methods

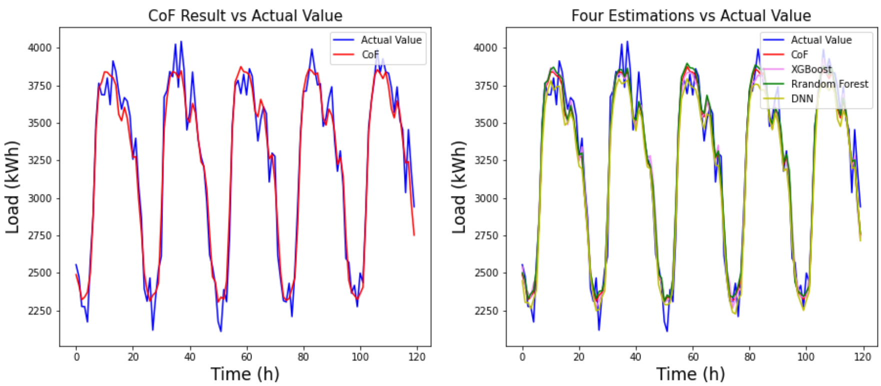

Fig. 14. Estimations of load given by RF, LSTM, XGB and CoF methods

X_{i_G} is the normalized array of the i-th input variable, where X_i is the original array and X_{i_max} and X_{i_min} are the maximum and minimum values of the array.

Through the execution of data preprocessing, the days exhibiting the highest similarity to the forecasted date are ascertained by implementing Pearson's correlation analysis

4.4 Experiment results and discussions

CoF method is applied to forecast power generation and compared with RF, LSTM and XGB methods. Results are shown in Table I. Fig. 13 is the plot of forecasted generated power of a randomly chosen prosumer in the community.

Regarding to load forecasting, the results of the selected prosumer are shown in Table II and Fig. 14.

By applying the aforementioned results as input parameters to the MMR method, four sets of total cost and power prices of purchase and sale in community microgrid are calculated. These calculated cost and prices are compared with actual total cost and actual prices corresponding to the identical day (Table III-IV).

Table 1. Model performance comparison of power generation estimations

Performance of power generation estimation	**Model**			
	RF	***LSTM***	***XGB***	***CoF***
MAE	0.301	0.288	0.320	0.210

Table 2. Model performance comparison of load estimations

Performance of load estimation	**Model**			
	RF	***DNN***	***XGB***	***CoF***
MAE	0.921	1.098	0.938	0.833

Table 3. Model performance comparison

Model accuracy comparison	**Model**			
	CoF	***XGB***	***RF***	***DL***
Buying price (MAE)	0.004	0.025	0.0164	0.0163
Selling price (MAE)	0.003	0.024	0.0184	0.0184

Table 4. Total cost given by different models

Trading method	**MMR method**					**Conventional method**
Input given by model/ actual value	***CoF***	***XGB***	***RF***	***DL***	***Actual value***	***Actual value***
Total cost (yuan)	78536	71091	74583	72717	79272	96064

Two significant observations can be drawn from the data presented these tables and figures. Firstly, the MMR method can effectively reduce the total cost associated with power trading within the community microgrid, by comparing ‘actual value using conventional method’ and ‘actual value using strategy’. Secondly, the estimation error derived from CoF method is the lowest among all the methods. Moreover, the total cost and the power prices of purchasing and sales are the closest to ‘actual value using strategy’. It is observed, the mean absolute error (MAE) of forecasting decreases, the total cost and power prices of purchasing and sales are closer to the actual value. Therefore, when the forecasted power prices of purchasing and sales approach the actual value more closely, more effective and efficient trading strategies for P2P trading within the community microgrid can be derived.

5 Conclusions

This paper proposes an ensemble method for P2P energy trading, consisting of two components. The first part is the power generation and load forecasts based on the multiple methods, encompassing both machine learning (XGB, RF) and deep learning (DNN, LSTM), following with the CoF method to synthetically optimize these estimation results. The second part is P2P trading strategy, specifically MMR, which reduces approximately 20% of total cost if compared with the one directly purchases and sales with the grid. Moreover, the total cost and power prices of purchasing and sales estimated by applying the estimation results is close to the result calculated by actual values, which confirms the effectiveness of the method. Meanwhile, there is strong flexibility for this method, which specifically manifested as follows. The models in the first stage can be changed to other suitable ones if results of higher accuracy are provided. In the second stage, MMR method is also replaceable if some other P2P power trading strategies show superior performance.

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