Double-layer Electricity Market Trading Strategy for Microgrids Based on Multi-agent System

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Abstract. Aiming at the power generation and consumption of microgrid, this paper proposes a double-layer electricity market trading model for microgrids (MGs) based on multi-agent system (MAS). In the upper level, MG conducts power transactions with other MGs and grid companies in the electricity market. In the lower layer, the various components within the MG coordinate and cooperate to obtain the maximum profit. In order to the uncertainty problem in power forecasting, a rolling optimization model based on chance constrained programming is established by combining interruptible load and demand response in the real-time market. And the consequence of the case analyses by MATLAB simulation proves the rationality and validity of the model for optimal dispatch of virtual power plants given by this paper.

1. Introduction
Microgrids are small power systems that can more flexibly and reliably distribute energy over small geographic areas [1-3], typically using distributed energy resources (DERs), including distributed generator sets and energy storage facilities to meet local demand [4]. In addition to the environmental benefits of utilizing locally available renewable energy sources, MGs can also reduce transmission and distribution losses due to the physical proximity of DERs and loads. Therefore, microgrids play a dual role in the electricity market, depending on the amount of internal power generation and load demand [5]. When MGs generate more power than the load, the excess power is delivered to the large grid. And in the opposite case, they purchase electricity from the electricity market.

A number of novel models have been proposed methods and optimization techniques for improving electricity prices, regional bid strategies and RESs integration in the electricity trading market. Several game theory methods for microgrid energy trading are mentioned in [6-8]. These articles focus on solving the maximum profit problem of the microgrid using various game models, while ignoring internal optimization adjustments.

In addition, the uncertainty of power production and load forecasting in the microgrid also brings difficulties to the electricity market trading. Various forms of demand and supply issues have been studied in the literature to optimize the operation of MG in consideration of load demand forecasting, power generation forecasting and/or energy storage capacity [9,10]. However, due to the intermittent and large variability of renewable energy such as wind and solar energy, distributed generation using this unpredictable energy source is difficult to control. Especially with the large-scale deployment of renewable energy, it will be a huge challenge to balance the energy demand and supply while leveraging the capabilities of renewable energy.
To solve these problem above, this paper proposes a double-layer electricity market trading strategy for microgrids based on MAS, taking microgrids consisting of photovoltaic cell(PV), wind turbines(WT), load and other distributed power generation resources(DR) as an example. The innovative model of the trading strategy is reflected in the following aspects:
1). Improved electricity market trading methods. Combined with multi-agent system, rationally distributes the power of the microgrid and eliminates fluctuations in electrical energy by means of grid companies. 2). Through the double-layer bidding model, the bidding and optimization process MG is realized, and the maximum profit is realized. 3). Reduce the impact of prediction errors through rolling optimization and improve the ability to absorb clean energy.

2. Double-layer electricity market trading model for microgrids based on MAS

2.1. Electricity market architecture for microgrids based on MAS

As a branch of artificial intelligence technology, MAS is a distributed autonomous system composed of multiple agents[11]. With the improvement of interaction, MAS provides a unified model and framework for various practical systems, which can well solve the communication problems of complex systems[12]. The MAS-based power market trading framework for MGs constructed in this paper is shown in Figure 1. It consists of the electricity market agent, microgrid agents and equipment agents. The layers are optimized and coordinated through information and energy exchange[13].

![Figure 1. Microgrid structure diagram in the electricity market based on MAS.](image)

1)Electricity Market Agent. Summarize the information of the purchase and sale of electricity and output range reported by the lower-level agent, consider the system security, calculate the electricity price decision, and send the electricity price and the transaction power result information to each MG agent, and monitor the MG agent's power status to judge Nash. Whether the condition of the equilibrium point is satisfied, and if it is satisfied, the process of the game is stopped.

2)Microgrid Agent. Combine the information of self-generation forecasting and internal load power forecasting to adjust the operation plan of the lower-level agent; electricity generation microgrid submits its bidding strategy, including bidding electricity price and power, while electricity purchase microgrid submits load demand; receive the clearing price and the bidding power issued by the power market agent and the trading strategy information of other MG agents; adjust the power generation/purchasing strategy with the goal of maximizing their own benefits, and finally determine the transaction amount of electricity to the micro grid and the sale/purchase amount to the grid company, and feedback the strategy to the superior agent.

3)Equipment Agent. PV Agent and WT Agent provide the prediction information of the clean energy generation to Microgrid Agent; DG Agent is responsible for providing MG Agent with information such as the operating status, output range, and power generation cost; Load Agent prioritizes according to the importance of the load, which will be different. And the type of load information will be sent to the upper agent. The equipment agent dynamically adjusts the power generation/load...
amount according to the control instructions of the upper Agent and its own constraint conditions, and feeds back its own power information to the upper-layer agent in time.

2.2. Uncertainty characterization

Wind and photovoltaic generation predictions can usually be described using Weibull distribution models[14] and Beta distribution models[15], and load prediction data is obtained through artificial neural networks[16]. Assuming that the prediction error of wind and solar power generation and load fluctuation are characterized by independent normal distribution with zero mean value, i.e.

\[
\begin{align*}
\delta_{W_{i_{-}T}} &\sim N(0, \sigma_{W_{i_{-}T}}^2) \\
\delta_{P_{i_{-}V}} &\sim N(0, \sigma_{P_{i_{-}V}}^2) \\
\delta_{L_{i}} &\sim N(0, \sigma_{L_{i}}^2)
\end{align*}
\]

(1)

\(\delta_{W_{i_{-}T}}, \delta_{P_{i_{-}V}}, \) and \(\delta_{L_{i}}\) represent wind power output fluctuations and load fluctuations at time \(t\), respectively. As the prediction accuracy increases with the decrease of the prediction time scale, this paper studies the optimal trading and real-time rolling optimization strategy to maximize the profit of microgrid power trading and balance the impact of prediction error.

2.3. Double-layer bidding strategy for MGs

The benefits of the MG \(W_{i_{-}t}^t\) are mainly composed of two parts: the upper benefits \(W_{i{-}ext}^t\) from trading with other MGs or grid companies and the bottom revenue \(W_{i{-}inner}^t\) determined by the internal benefits of the sale to the load and the cost of each power generation component.

\[\max W_{i_{-}t}^t = \max(W_{i{-}ext}^t + W_{i{-}inner}^t)\]  

(2)

2.3.1. Microgrid profit in the upper layer. The upper layer income function of the MG in the electricity market \(W_{i{-}ext}^t\) can be expressed as:

\[W_{i{-}ext}^t = \left\{ \begin{array}{l}
\rho f_i^{q_{i-M}^t} + P_{i-PGS}(q_{i-M}^t - q_{i-M}^t) - e_{i-loss}^t(q_{i-M}^t)^2, \quad i \in n_a \\
\rho f_i^{q_{i-M}^t} + P_{i-PGB}(q_{i-M}^t - q_{i-M}^t), \quad i \in n_b \\
C_{i}^f(q_{i-M}^t) = 2a_i^t q_{i-M}^t + b_i^t \\
\rho_i^t = (1 + \mu_i)C_{i}^f(q_{i-M}^t), \quad i \in n_a \\
\rho^t = \max(\rho_i^t, \rho_{i+1}^t, \ldots, \rho_{n_a}^t) \\
\rho^t \in [P_i^{t-PGS}, P_i^{t-PGB}]
\end{array} \right.\]  

(3)

(4)

(5)

(6)

(7)

In the formula 3, \(q_{i-M}^t\) is the total amount of bid for the \(i\)-th MG, taking positive and negative respectively to represent the microgrid to sell and purchase electricity. \(q_{i-M}^t\) refers to the amount of electricity submitted to the power market. \(P_{i-PGS}\) and \(P_{i-PGB}\) represent the price of electricity absorbed and sold by the company. \(e_{i-loss}^t\) is the cost factor, which is converted from the network loss cost. \(n_a\) and \(n_b\) represent the number of power purchasers sellers in the microgrids. Equation 4 shows the marginal cost of MG \(C_{i}^f(q_{i-M}^t)\), and \(a_i^t\) and \(b_i^t\) are their cost factors. \(\rho^t\) is the electricity clearing price.

To prevent the scalping behavior, MG only has one authority in the sale of electricity or electricity purchase at the same time and not allowed to purchase electricity with low electricity price and resell it with high electricity price. The following constraints(8-11) were proposed to achieve this condition.

\[q_{i-M}^t \in [q_{i-M}^{min}, q_{i-M}^{max}]\]  

(8)

\[q_{i-M}^t \in [0, q_{i-M}^t]\]  

(9)

\[q_{i-M}^t \in [q_{i-M}^t, 0]\]  

(10)

\[\sum_{i=1}^{n_a} \rho_i^t = |\sum_{i=1}^{n_b} \rho_i^t|\]  

(11)

2.3.2. Microgrid profit in the upper layer. Ignoring the cost of PV and WT generation, the objective function of the \(i\)-th MG \(W_{i{-}inner}^t\) is:

\[W_{i{-}inner}^t = W_{i-L} - C_{i-DG}(q_{i-DG}^t) - C_{i-L}(q_{i-L}^t) = P_{i-L}(q_{i-L}^t - q_{i-L}^t) - (a_{DG}(q_{i-DG}^t)^2 +\]
\[ b_{DG} q_{L-DG}^i + d_{DG} ) - (a_{IL}(q_{IL})^2 + b_{IL}q_{IL} + d_{IL} ) \]  

Equation 12

In the formula, \( q_{L}^i, q_{IL}^i, \) and \( q_{L-DG}^i \) represent the power generation of L, IL, and DG respectively. The cost of IL includes the sales revenue and compensation cost of the cutting load. \( p_{IL}^i \) is the internal selling electricity price. \( a_{DG}, b_{DG}, \) and \( d_{DG} \) are the power generation cost coefficients of DG. \( a_{IL}, b_{IL}, \) and \( d_{IL} \) are the interrupt cost coefficients of IL.

The reserve price \( p_{IL}^i \) for selling its own load is defined and the actual load price \( p_{IL}^i \) is considered a more favorable price. Besides, Equation 14 guarantees that the microgrid will not lose money. And Equation 15 is the power balance constraint. It is worth mentioning that \( q_{L}^i, q_{PV}^i, \) and \( q_{WT}^i \) here refer to the predicted values of load power, PV and WT power generation.

\[ p_{IL}^i = \min (p_{IL}^i, \rho_i^f) \]  

Equation 13

\[ p_{IL}^i \geq c_i^l(q_i^l) / q_i^l \]  

Equation 14

\[ q_i^l + q_{IL}^i - q_{IL}^i = q_{PV}^i + q_{WT}^i + q_{L-DG}^i \]  

Equation 15

Considering the actual load and power generation, the electricity market transactions for MGs should also meet the following constraints. \( q_{L-DG}^i, q_{IL}^i, R_{DG}^i, \) and \( R_{DG}^i \) are the Upper and lower sections of power generation and climbing rate of DG. \( \eta \) is the maximum call rate of IL.

\[ q_{min-DG}^i \leq q_{DG}^i \leq q_{max-DG}^i \]  

Equation 16

\[ -R_{DG}^i \Delta t \leq q_{DG}^i - q_{DG}^{i-1} \leq -R_{DG}^i \Delta t \]  

Equation 17

\[ 0 \leq q_{IL}^i \leq \eta q_{IL}^i \]  

Equation 18

2.4. Real-time rolling optimization strategy

During the rolling optimization process, the MG performs direct load control by adjusting the output of the controllable unit DG and the price-based demand response DR to correct the error between the operational plan and the expected result. The objective function is

\[ \min F = a_{DG}(q_{L-DG}^i)^2 + b_{DG}q_{L-DG}^i + d_{DG} + a_{PV}q_{PV}^i + a_{WT}q_{WT}^i + a_{IL}q_{IL}^i + b_{IL}q_{IL}^i + a_{DG}(q_{L-DG}^i)^2 + b_{DG}q_{L-DG}^i - W_{l-ext} \]  

Equation 19

\[ W_{l-ext} = \rho_i^f q_{IL}^i + p_{l-PV}^f (q_i^l - q_{IL}^i) - \rho_i^f q_{IL}^i + p_{l-PV}^f (q_i^l - q_{IL}^i) \]  

Equation 20

\( q_{i-P}, q_{i-W} \) is the amount of abandoned wind and abandoned light generated by PV and WT. \( a_{PV} \) and \( a_{WT} \) are the cost coefficients of abandoning light and wind. \( W_{l-ext} \) is the revenue of microgrids in the current power market transactions, including revenue from participating in the electricity market and internal load sales. \( q_{IL}^i \) is the actual winning power of MG in the market in the past few days. The constraints(8-11,13-18) are also required.

In addition, in order to achieve the dual goals of reliability and economy, it is also necessary to meet the opportunity constraint planning(set \( \delta = 0.95 \) in this paper).

\[ P_i \left( q_{WT}^i + \delta_{WT}^i - q_{WT}^i \right) + \left( q_{PV}^i + \delta_{PV}^i - q_{PV}^i \right) + q_{DG}^i + q_{IL}^i + q_{DR}^i = \delta \]  

Equation 21

In some cases, adjusting the output of components such as DG and DR through real-time scrolling optimization still cannot meet the day-ahead interactive power limit. At this point, it is necessary to update the day-to-day trading model and dynamically correct the trading power with other microgrids and grid company according to the forecasted data of wind and photovoltaic power output and load.

The tasks of the real-time rolling phase include: adjusting the MT output, determining the amount of abandoned wind and IL removal, and determining the total trading power and DR.

3. Optimization process and solution

The Nash equilibrium game strategy of the upper and lower layers of the microgrid can be expressed as

\[ W_i^f(S_{L}^f, S_{IL}^f) \geq W_i^f(S_{L}^f, S_{IL}^f), i \in U(n, n) \]  

Equation 22

\[ q_i^l = \arg \max W_i^l_{inner}(q_i) \]  

Equation 23
In the electricity market, the bidding strategy for each microgrid is $S_i^t(q_i^t, p_i^t)$ (sufficient power) or $S_i^t(q_i^t)$ (lack of power). Use $S_i^{t,*}$ to represent the optimal strategy of the microgrid $i$, and $-i$ denotes other MGs apart from microgrid $i$. $q_i$ represents the power generation strategy of the internal controllable components, including the output of PV, WT and DG and the power consumption of L and IL. $n$ is the total number of internal controllable components inside the microgrid.

Since the above model involves the random variable prediction and the opportunity constraints of the rolling optimization stage, it is a solution to convert it into an equivalent determination form and reuse the linear/nonlinear programming problem. However, in practical applications, especially when there are many random variables, this conversion is more difficult. Therefore, this paper uses a genetic algorithm to solve.

For the microgrid in the electricity market and the internal game model, the equilibrium can be achieved through a finite number of games, so a nested genetic algorithm is used to solve the problem and the game flow chart is shown in Figure 2.

4. Case Analysis
This part simulates the trading strategy of the electricity market. Assume that there are five microgrids in the area. Each MG consists of PV, WT, DG, L and IL, as is shown in Figure 3.
The cost parameters of each DG are shown in Table 1. The maximum call rate of IL is 10%, $a_{IL} = 0.005$, $b_{IL} = 0.06$, and $d_{IL} = 1.32$. DDR accounts for 5% of the total load, $a_{DR} = 0.006$, $b_{DR} = 0.06$, and $d_{DR} = 1.38$. The electricity sale and purchase price of the electricity market are 0.4 yuan and 0.7 yuan, and the load standby electricity price $p_{i-load}^t$ is 0.55 yuan. The daily and real-time predicted fluctuation variances of WT, PV output and load demand are 0.3, 0.3 and 0.05.

|          | a   | b   | d   | Pmin | Pmax | RmtU | RmtD |
|----------|-----|-----|-----|------|------|------|------|
| DG1      | 0.63| 0.103| 4.02| 100  | 300  | 80   | 80   |
| DG2      | 0.724| 0.176| 3.03| 60   | 180  | 60   | 60   |
| DG3      | 1.11| 0.215| 4.03| 0    | 120  | 40   | 40   |
| DG4      | 0.984| 0.167| 2.27| 80   | 200  | 60   | 60   |
| DG5      | 1.304| 0.329| 4.03| 0    | 90   | 30   | 30   |

4.1. Day-ahead double-layer trading strategy

The bidding power and real winning power of MGs result are shown in the figure4.

|          | a   | b   | d   | Pmin | Pmax | RmtU | RmtD |
|----------|-----|-----|-----|------|------|------|------|
| MG1      |      |     |     |      |      |      |      |
| MG2      |      |     |     |      |      |      |      |
| MG3      |      |     |     |      |      |      |      |
| MG4      |      |     |     |      |      |      |      |
| MG5      |      |     |     |      |      |      |      |

Figure 3. structure chart of of the power market

Figure 4. Comparison chart of bidding power and real winning power of MGs

MG1 and MG2 always sell electric energy while MG5 always purchases electrical energy in the electricity market. MG3 and MG4 sell or purchase electric energy at different times according to the internal load power consumption. And the bidding power is slightly different from the actual winning bid for MGs.

For convenience of comparison, this paper considers two trading strategies: microgrids operate independently and directly cooperate with the grid company to purchase/sell electricity for maximum profit or microgrids trade with others and grid companies. The cost and benefits of each microgrid are shown in Table 2.
Table 2. Cost and income statement for each MG

| Index | Cost  | Income |
|-------|-------|--------|
|       | Strategy 1 | Strategy 2 | Strategy 3 | Strategy 1 | Strategy 2 | Strategy 3 |
| MG1   | 1246.76   | 1308.01    | 2002.58    | 2246.97    |
| MG2   | 1054.55   | 973.07     | 1491.78    | 1477.69    |
| MG3   | 736.73    | 689.61     | 952.21     | 956.79     |
| MG4   | 1401.56   | 1259.03    | 2065.3     | 1983.41    |
| MG5   | 789.26    | 709.75     | 869.13     | 996.83     |
| Total | 5228.86   | 4939.47    | 7381       | 7661.69    |

It can be seen from the table that the cost coefficients of MG1, MG2 and MG4 are small, the profit is relatively high, and the profit of MG3 and MG5 is small. Besides, the income of the three microgrids using the microgrid trading model proposed in this paper is higher than the respective revenues under the individual operating conditions, which is an effective way of income distribution and can improve the economic benefits of VPP operation.

4.2. Real-time scrolling optimization results

This section is the result of verifying real-time scrolling optimization. Considering the MG scheduling results directly determined by daily optimization and or by rolling optimization proposed in this paper two modes. The results of the two modes of scheduling and the required spare capacity for rotation are shown in Figure 9, using MG3 as an example.

As can be seen from Figure 6, when using the forecast data of the day before, the running result is smoother than Strategy 2 because there are fewer sampling points (24 data points in 24 hours). In real-time rolling optimization, the microgrid can dynamically correct the amount of distributed power and removable load based on current forecast data while satisfying operational constraints. The specific power purchase and power sales strategies also change.

5. Conclusion

The double-layer electricity market trading strategy for microgrids proposed in this paper shows that,

1) The two-layer optimization model can make the microgrid more profitable.

2) The appropriate economic load reduction during peak hours or insufficient power generation can improve the overall economic benefits of the system and adding certain economic compensation to users can increase the enthusiasm of users.

3) Consider rolling optimization strategy and opportunity constrained planning, which can more accurately coordinate the distributed power output and improve system reliability.

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