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Optimal Time-of-Use Electricity Price for a Microgrid System Considering Profit of Power Company and Demand Users

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Abstract: With high proportions of renewable energy generation in power systems, the power system dispatch with renewable energy generation has currently become a popular research direction. In our study, we propose a multi-objective dispatch model for a hybrid microgrid comprising a wind generator, photovoltaic (PV) generator, and an energy storage system to optimize the time-of-use (TOU) electricity price. The objective of the proposed multi-objective dispatch model is to maximize the profit of the power company and demand users, and minimize the proportion of users abandoning PV power and wind power. The elastic price of the load demand with a linear function is employed to optimize the TOU electricity price. Finally, we applied five test cases to validate the practicability of the multi-objective dispatch model.

Keywords: photovoltaic power; wind power; energy storage system; time-of-use electricity



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1. Introduction

1.1. Background

In recent years, the use of conventional energy sources has gradually decreased. However, environmental pollution remains extremely serious. Many countries have vigorously promoted the generation of renewable energy [1]. Renewable energy generation, including wind power [2], photovoltaic (PV) power [3], pumped hydro storage [4], and geothermal power [5], among others, have been widely utilized in power systems.

Due to the uncertainty of wind speed and solar radiation, the wind output power and PV output power are uncertain and random. This poses serious challenges to economic dispatch [6]. With the increasing power generation capacities of wind turbines and PV panels, the problems in power dispatching and power system reliability will become increasingly serious.

1.2. Literature Reviews

For the problems mentioned above, some studies have proposed various solutions, such as utilizing the demand response (DR) and energy storage system (ESS). The ESS is a great tool for solving the above problem owing to its flexible charging–discharging characteristics [7]. DR is another effective tool for improving the economic dispatch problem by guiding consumers to change their electricity costs through a series of measures. For DR, there are two parts: incentive-based programs—for example, emergency DR programs—and time-based rate programs—for example, time-of-use (TOU) pricing [8].

In [9], a critical peak electricity pricing model based on load control was investigated for the multi-objective function of the cost and emissions of the microgrid. Mixed-integer linear programming is applied to solve the multi-objective optimal problem. In [10], a

real-time electricity price model was proposed to adjust the proportion of each stage in load demand through DR management. A price control algorithm based on simulated annealing was utilized to solve the nonconvex electricity price dispatch problem. In [11], the concept of exergy was used to evaluate each energy carrier, and an economic–exergetic optimal scheduling model, with the implementation of a real-time pricing-based DR program, was proposed and formulated into a mixed-integer linear programming problem. In [12], an optimization framework was proposed for DR aggregation. Optimal contracts were offered to users by DR aggregators using the self-scheduling optimization model based on electricity price. In [13], bilateral contracting and selling prices were determined by considering the uncertainty characteristics of the demand load and the output power of renewable resources. Fixed pricing, TOU pricing, and real-time pricing (RTP) are compared to determine selling prices. In [14], a demand elasticity model was developed to determine the optimal electricity price signal for RTP. The rationality of the proposed model was verified using the six-bus test system. In [15], a robust optimization model was proposed to obtain the optimal decision for electricity retailers. In addition, an optimal bidding model using the time-based DR program model was proposed. The effect of the DR program on the total procurement cost was also considered. In [16], a short-term decision model was established to determine the electricity procurement and retail prices in the electricity retailer. In addition, the DR was established using a price elasticity matrix. A robust optimization approach was applied to model the uncertainty in spot prices. Price elasticity coefficients are divided into commercial, residential, and industrial. In [17], a DR scheme was proposed based on an adaptive consumption-level pricing scheme. It not only encourages customers to manage their energy consumption and consequently lower their energy bill, but also allows for utilities to manage aggregate consumption and predict load requirements. In [18], an optimal energy management was proposed in a grid-connected PV–battery hybrid system to explore solar energy and benefit customers on the demand side. In addition, an optimal control method is developed to schedule the power flow of a hybrid system. To solve the uncertain disturbances, model predictive control as a closed-loop method was used to dispatch the power flow in real time.

1.3. Aim and Contributions

In this study, we propose a multi-objective dispatch model to determine the optimal TOU electricity price by utilizing the DR. Unlike other studies that use the electricity price elasticity matrix for the DR model, the elastic price of load demand with a linear function is applied to the model for optimizing the TOU electricity price herein. The purpose of the multi-objective function in the proposed dispatch model is to minimize the rate of abandoning renewable power and maximize the profit of the power company and demand users. However, the multi-objective function, including economic cost and pollution emission, is the relevant dispatch model.

1.4. Paper Organization

The remainder of this paper proceeds as follows. The price elasticity of the load demand with a linear function is described in Section 2. In Section 3, a stochastic problem is presented to solve the uncertainty of PV power, wind power, and demand loads. The problem formulations, including the multi-objective function and constraints, are described in Section 4. Section 5 proposes a comprehensive weighting-factor-based method for the multi-objective function. In Section 6, the test cases and results are presented and analyzed to demonstrate the proposed dispatch model. Finally, we present the conclusions in Section 7.

2. Price Elasticity of Load

From an economic perspective, the load is closely related to electricity price. Therefore, under the base of meeting the most basic load, users adjust the load demand depending on the TOU electricity price to minimize their electricity cost [19]. In addition to the

basic load demand of the user's life and work, the user may adjust the daily load curve according to the electricity price. For example, users may charge electric vehicles, increase the charging time at the lower electricity price period, and reduce the charging time at the higher electricity price period.

The correlation between the electricity price and load demand is shown in Figure 1. The demand for user load decreases as the electricity price increases, as illustrated in Figure 1. Four different representations of load demand against electricity price were proposed—linear, potential, logarithmic, and exponential representation functions—in [20]. The price elasticity of a load with a linear function was applied herein to optimize the TOU electricity price.

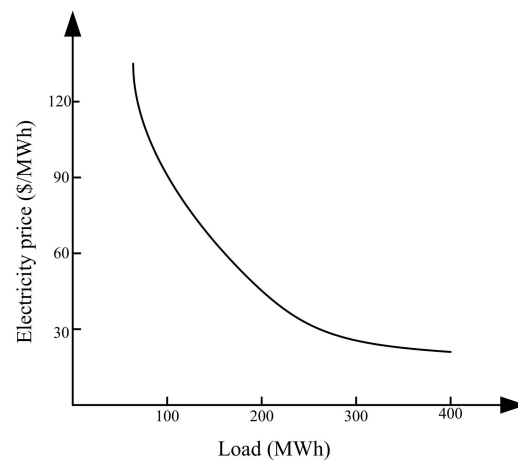


Figure 1. Electricity price against load demand.

The price elasticity of the load is defined as the sensitive response of the load to the electricity price [19]. The price elasticity of demand is calculated as follows:

$$E(t) = \frac{P_0(t)}{\Delta P(t)} \cdot \frac{\Delta L(t)}{L_0(t)} \quad (1)$$

where $L_0(t)$ is the initial load demand at time t , and $P_0(t)$ is the initial electricity price at time t .

The linear function for the price elasticity of the load can be illustrated as [20]

$$L(t) = a + b \cdot P(t) \quad (2)$$

where a and b denote the coefficients of the linear function of the load demand against the electricity price.

On the basis of Equations (1) and (2), the price elasticity of load demand can be calculated as follows:

$$E(t) = \frac{\Delta L(t)}{\Delta P(t)} \cdot \frac{P_0(t)}{L_0(t)} = b \cdot \frac{P_0(t)}{a + bP_0(t)} \quad (3)$$

Subsequently, the increased load demand can be expressed as

$$\Delta L(t) = b \cdot \frac{\Delta P(t)L_0(t)}{a + bP_0(t)} \quad (4)$$

Therefore, the load demand after modifying electricity price can be expressed as

$$L_1(t) = L_0(t) + \Delta L(t) = L_0(t) + b \cdot \frac{L_0(t)\Delta P(t)}{a + bP_0(t)} \quad (5)$$

3. Stochastic Problem

The randomness of PV power, wind power, and load demand may significantly affect the dispatch of power systems. The multi-scenario simulation technology is implemented to select several typical system operation states in the proposed dispatch model by using the uncertainty information of the load demand, PV power, and wind power. The discrete probability distribution set of the load, wind power, and PV power is described as follows [13]:

$$\left\{ \begin{array}{l} D_L = \{ (L, \beta_L^1); \dots (L \pm i\Delta L, \beta_L^i); \dots (L \pm n\Delta L, \beta_L^{N_L}) \} \\ D_{PV} = \left\{ \begin{array}{l} (P_{PV}, \beta_{PV}^1); \dots (P_{PV} \pm i\Delta P_{PV}, \beta_{PV}^i); \dots \\ (P_{PV} \pm n\Delta P_{PV}, \beta_{PV}^{N_{PV}}) \end{array} \right\} \\ D_{wind} = \left\{ \begin{array}{l} (P_{wind}, \beta_{wind}^1); \dots (P_{wind} \pm i\Delta P_{wind}, \beta_{wind}^i); \dots \\ (P_{wind} \pm n\Delta P_{wind}, \beta_{wind}^{N_{wind}}) \end{array} \right\} \end{array} \right. \quad (6)$$

where D_L , D_{wind} , and D_{PV} are the sets of load, wind power, and PV power, respectively; N_L is the number of scenarios of load demand; N_{PV} is the number scenarios of PV power; N_{wind} is the number scenarios of wind power; β_L^i is the probability of load demand in the i -th scenario; β_{PV}^i is the probability of PV power in the i -th scenario; β_{wind}^i is the probability of wind power in the i -th scenario; ΔL is the base deviation of load demand; ΔP_{PV} is the base deviation of PV power; and ΔP_{wind} is the base deviation of wind power.

The probabilities of wind power, load demand, and PV power satisfy the following:

$$\left\{ \begin{array}{l} \beta_L^1 + \beta_L^2 + \dots + \beta_L^{N_L} = 1 \\ \beta_{PV}^1 + \beta_{PV}^2 + \dots + \beta_{PV}^{N_{PV}} = 1 \\ \beta_{wind}^1 + \beta_{wind}^2 + \dots + \beta_{wind}^{N_{wind}} = 1 \end{array} \right. \quad (7)$$

$$\sum_i^{N_L} \sum_j^{N_{PV}} \sum_k^{N_{wind}} \beta_L^i \beta_{PV}^j \beta_{wind}^k = 1 \quad (8)$$

The total set D of scenarios for load demand, PV power, and wind power can be calculated as follows:

$$D = D_L \times D_{PV} \times D_{wind} \quad (9)$$

4. Problem Formulation

In this study, the utilization rate of renewable energy and the economy are two important indices for power system scheduling. The multi-objective function of the proposed dispatch model includes the profit of the power company and demand users, and the rate of abandoning the output power of wind turbines and PV panels.

The relation between the TOU electricity price and the cost of the power company and demand users is analyzed. However, there is no correlation between TOU electricity price and renewable energy power. The cost of the wind generator and PV generator were disregarded, and the cost of the ESS was also ignored in our study. The hybrid microgrid used herein is only composed of solar power generation, wind power generation, and ESS, excluding traditional energy generation.

4.1. Multi-Objective Dispatch Model

In our work, the multi-objective dispatch model is aimed at determining the optimal TOU electricity price. The multi-objective function established in this section includes the following: (1) maximization of the profit of the power company and the demand users, and (2) minimization of the rate of abandoning the total output power of wind panels and PV turbines.

4.1.1. Maximizing the Profit of Power Company and Demand Users

For the economic dispatch of power systems, the profits of the power company and demand users are both considered herein. However, the profits of the power company and demand users may have less or more of an effect on the optimal TOU electricity price, depending on the case. The profit of the power company comprises the income of selling electricity and the penalty cost of power supply shortage. The profit of demand users is to reduce electricity costs after implementing the optimal TOU electricity price. The profit of the demand users is the electricity cost at the initial electricity price minus the electricity cost at the optimal TOU electricity price.

Therefore, the first function (f_1) for the power company's profit and demand users is expressed as follows:

$$\max f_1 = \alpha \text{Pro}_{\text{company}} + \beta \text{Pro}_{\text{user}} \quad (10)$$

where $\text{Pro}_{\text{company}}$ is the profit of the power company, Pro_{user} is the profit of demand users, and α and β are the weight coefficients of the profit of the power company and demand users, respectively. In this study, the relation between them is $\alpha + \beta = 1$.

(1) Profit of the power company

For the power company, the profit mainly comprises selling electricity to demand users, the generation cost, and the penalty cost for the power supply shortage. In our study, the renewable generation cost was not considered. Therefore, in this study, the profit of the power company includes the penalty cost of power supply shortage and the income of selling electricity to demand users, expressed as

$$\text{Pro}_{\text{company}} = \sum_{t=1}^T P(t)(L(t)u_1(t) + (P_{\text{gen}}(t) + P_{\text{dis}}(t))u_2(t)) - a_{\text{punish}} \sum_{t=1}^T d_{\text{short}}(t) \quad (11)$$

where $P_{\text{gen}}(t)$ is the output power of renewable energy at time t ; $P_{\text{dis}}(t)$ is the discharge power of the ESS at time t ; $u_1(t)$ and $u_2(t)$ are binary numbers: $u_1(t) = 0$ and $u_2(t) = 1$ indicates that the load demand exceeds the total renewable energy power at time t ; $u_1(t) = 1$ and $u_2(t) = 0$ indicates that the renewable energy power exceeds the load demand at time t ; a_{punish} is the penalty coefficient of power supply shortage; and $d_{\text{short}}(t)$ is the shortage of power supply at time t .

(2) Profit of the demand users

For demand users, electricity cost is the first consideration. However, the electricity cost of demand users is mainly affected by the electricity price and load demand. In this study, the profit of the demand users is given by reducing electricity costs after implementing the optimal TOU electricity price. This can be expressed as follows:

$$\text{Pro}_{\text{user}} = C_0 - C_{\text{TOU}} = \sum_{t=1}^T P_0(t)L_0(t) - \sum_{t=1}^T (\Delta P(t) + P_0(t))L_1(t) \quad (12)$$

where C_0 denotes the electricity cost of demand users with the initial electricity price, and C_{TOU} is the electricity cost of demand users with TOU electricity price.

4.1.2. Minimizing the Rate of Abandoning PV Power and Wind Power

Owing to the uncontrollable characteristic of the renewable energy power, when the sum output power of renewable energy exceeds the load demand, the extra output power of wind turbines and PV panels will be abandoned. By optimizing the TOU electricity price,

the load curve comes close to the renewable energy power to reduce the rate of abandoning PV power and wind power. The second objective is expressed as follows:

$$\min f_2 = 1 - \frac{\sum_{t=1}^T (L(t) + P_{\text{char}}(t))}{\sum_{t=1}^T (P_{\text{PV,upper}}(t) + P_{\text{wind,upper}}(t))} \quad (13)$$

where $P_{\text{char}}(t)$ is the charge power of the ESS at time t ; and $P_{\text{PV,upper}}(t)$ and $P_{\text{wind,upper}}(t)$ are the upper PV power and the upper wind power at time t , respectively.

4.2. Constraints

The multi-objective dispatch model proposed herein meets the following equality and inequality constraints (14)–(21).

4.2.1. Power Balance Constraint

For power system scheduling, the output power, charge power, and discharge power of the ESS should be equal to the power supply and charge power of the ESS, which can be expressed as

$$L_1(t) + P_{\text{char}}(t) = P_{\text{PV}}(t) + P_{\text{wind}}(t) + P_{\text{dis}}(t) + d_{\text{short}}(t) \quad (14)$$

4.2.2. PV Power and Wind Power Constraints

The wind power and PV power utilized in the hybrid microgrid were mainly determined by the maximum and minimum values of the output power. The utilization of PV power and wind power should satisfy the following constraints:

$$0 \leq P_{\text{PV}}(t) \leq P_{\text{PV,upper}}(t) \quad (15)$$

$$0 \leq P_{\text{wind}}(t) \leq P_{\text{wind,upper}}(t) \quad (16)$$

4.2.3. ESS Constraint

When the ESS is operated during the charging process, battery banks are charged with renewable energy power. The stored energy of the battery is determined by the charge power and stored energy of the previous hour. It is calculated as [21]:

$$E(t) = E(t-1) + P_{\text{char}}(t) \cdot \eta_{\text{char}} \quad (17)$$

where $E(t)$ is the stored energy of the battery at time t and η_{char} is the battery charge efficiency.

When the ESS is operated during the discharging process, the battery banks discharge power to load demand. The stored energy of the battery is determined by the discharge power and stored energy of the previous hour. It can be calculated as [21]:

$$E(t) = E(t-1) - P_{\text{dis}}(t) / \eta_{\text{dis}} \quad (18)$$

where P_{dis} is the battery discharge efficiency.

Herein, the self-discharge of the ESS is negligible in our work. The state of charge (SOC) constraint is expressed as [22]:

$$S_{\text{OC,lower}} \leq S_{\text{OC}}(t) \leq S_{\text{OC,upper}} \quad (19)$$

where $S_{\text{OC}}(t)$ is the SOC of the ESS at time t , $S_{\text{OC,lower}}$ is the lower SOC of the ESS, and $S_{\text{OC,upper}}$ is the upper SOC of the ESS.

The constraint of the discharged power for the ESS is expressed as

$$0 \leq P_{\text{dis}}(t) \leq \min(P_{\text{dis,upper}}, (S_{\text{OC}}(t-1) - S_{\text{OC,lower}})E_{\text{ESS}}) \quad (20)$$

The constraint of the charging power for the ESS is expressed as

$$0 \leq P_{\text{char}}(t) \leq \min(P_{\text{char.upper}}, (S_{\text{OC.upper}} - S_{\text{OC}}(t-1))E_{\text{ESS}}) \quad (21)$$

where $P_{\text{char.upper}}$ and $P_{\text{dis.upper}}$ are the upper charging power and discharged power of the battery banks, respectively, and E_{ESS} is the rated capacity of the battery banks.

4.2.4. Optimization Variables

In the multi-objective dispatch model proposed herein, the TOU electricity price is the optimization variable. According to the hourly load data, the hours of one day were divided into three parts: peak period, off-peak period, and valley period. The initial electricity prices were all set to 75 USD/MWh. The three periods in the TOU electricity prices are listed in Table 1. In the electricity market of power systems, to maintain the stability of the electricity price, the electricity price of the power company should be adjusted within a fixed range. The constraints of the TOU electricity price are limited, as shown in Table 2.

Table 1. Three periods in the TOU electricity price.

	Time (h)	Initial Electricity Price (USD/MWh)
Off-peak	7–9, 14–19, 22	75
Peak	10–13, 20–21	75
Valley	1–6, 23–24	75

Table 2. Constraint of TOU electricity price.

	Lower Limit (USD/MWh)	Upper Limit (USD/MWh)
Peak	90	153
Off-peak	60	90
Valley	15	60

5. Multi-Objective Algorithm

The multi-objective genetic algorithm (GA) [23] and particle swarm optimization (MOPSO) [24], as mature optimization algorithms, have been applied by many scholars. In our work, the optimal solution of the multi-objective dispatch mode is determined using MOPSO. A satisfactory solution is selected from the Pareto optimal solution set [25]. The standardized objective function for each solution is expressed as [26]:

$$\begin{cases} \sigma_1(x) = \frac{f_1(x) - f_{1,\min}}{f_{1,\max} - f_{1,\min}} \\ \sigma_2(x) = \frac{f_2(x) - f_{2,\min}}{f_{2,\max} - f_{2,\min}} \end{cases} \quad (22)$$

where $s(x) = [f_1(x), f_2(x)]$ is the standardized objective function of the objective function $f = [f_1, f_2]$; $f_{1,\max}$ and $f_{2,\max}$ are the maxima of the objective functions f_1 and f_2 , respectively; $f_{1,\min}$ and $f_{2,\min}$ are the minimum values of the objective functions f_1 and f_2 , respectively.

The normalized function value of the nondominated solution can be calculated as [26]:

$$N_{\sigma,i} = \frac{\sum_{m=1}^N \sigma_m(i)}{\sum_{m=1}^N \sum_{i=1}^M \sigma_m(i)} \quad (23)$$

where $N_{\sigma,i}$ is the normalized function value with i nondominated solution, N is the number of objective functions, and M is the number of nondominated solutions. The maximum value of $N_{\sigma,i}$ determines the optimal solutions of the multi-objective function.

The flowchart shown in Figure 2 presents the step procedure for the multi-objective dispatch model.

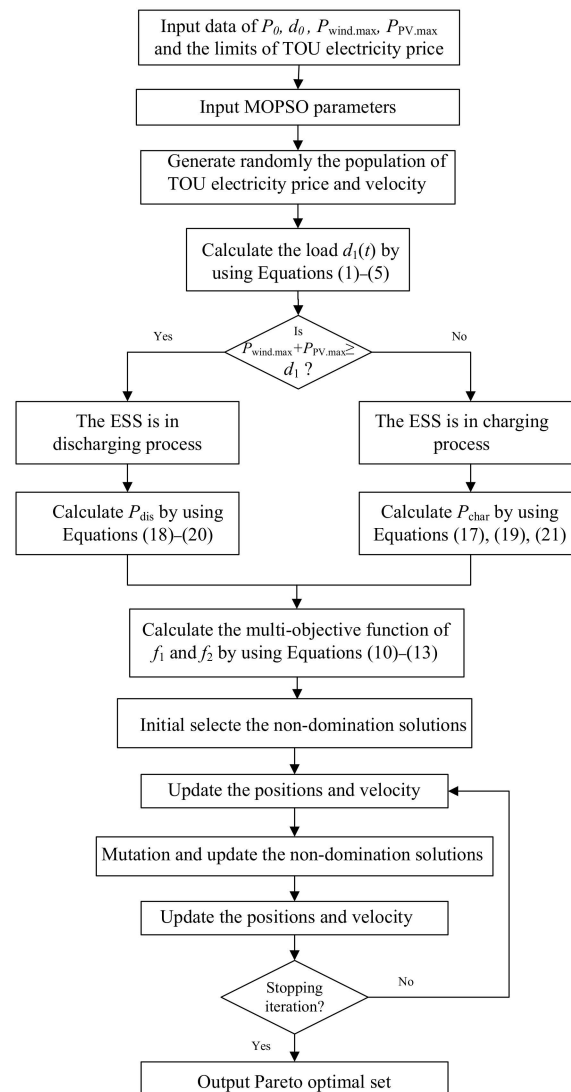


Figure 2. Flowchart of the optimization calculation.

- (1) The initial data of the load demand, electricity price, wind power, and PV power are input.
- (2) The populations of the variables (TOU electricity price) are randomly generated within the limits of TOU electricity price.
- (3) The loads that carry out the random TOU electricity price are calculated by Equations (1)–(5).
- (4) The load demand and output power of renewable energy are compared to determine the charging or discharging processes of the ESS. If the output power of renewable energy can satisfy the load demand, the ESS is operated during the charging process. If the output power of renewable energy cannot satisfy the load demand, then the ESS is operated during the discharging process. The multi-objective functions of f_1 and f_2 are calculated using Equations (10)–(13).
- (5) The non-dominant solution set is obtained from Step (4).
- (6) Update the TOU electricity price and velocity.
- (7) Update the new solutions by mutating the solutions of Step (6) and determining the new non-dominant solution.
- (8) Stop criterion. When the number of iterations is less than the number parameters set herein, go to Step (6); otherwise, stop criterion.
- (9) The Pareto optimal set was obtained by applying multi-objective particle swarm optimization.
- (10) The satisfactory solution is obtained by Equations (22) and (23).

6. Case Study

In this section, a hybrid microgrid composed of PV power plants, wind power plants, and ESSs is used to test the multi-objective dispatch model proposed herein. The ESS parameters are presented in Table 3. The coefficients of the linear function for the price elasticity of load demand a and b are 300 and -1.5 , respectively, extracted from [20] with some modifications. The penalty coefficient of the power supply shortage was 70 USD/MWh.

Table 3. Parameters of ESS.

Parameters	
Power capacity (MW)	1000
$S_{OC,upper}$	0.9
$S_{OC,lower}$	0.1
$S_{OC}(1)$	0.1
η_{dis}	1
η_{char}	1

The proposed multi-objective dispatch model was solved using MOPSO in this section. In our MOPSO work, the population size was 20, the number of iterations was 100, and the repository size was 100. The proposed algorithm was implemented in the software package MATLAB 2015 on a PC with an M1 CPU and 8 GB of RAM.

In our work, the number scenarios of load demand, wind power, and PV power were set to 5. We assume that the deviations of wind power, PV power, and load demand obey the standard normal distribution. The base deviation of the load demand, output power of the wind, and PV panels is 15% of the load demand, and the output power of the wind and PV panels. The discrete probability of the output power of the wind and PV panels and the load demand are shown in Table 4, which is from [13] with some modifications. The total number of scenarios was $5 \times 5 \times 5 = 125$. The hourly wind power, PV power, and load demand data for one day are shown in Table 5.

Table 4. Probability of PV power, wind power, and load demand.

Wind Power	PV Power	Load Demand	Probability
$0.7 p^{wind}$	$0.7 p^{PV}$	0.7 L	0.05
$0.85 p^{wind}$	$0.85 p^{PV}$	0.85 L	0.15
p^{wind}	p^{PV}	L	0.5
$1.15 p^{wind}$	$1.15 p^{PV}$	1.15 L	0.15
$1.3 p^{wind}$	$1.3 p^{PV}$	1.3 L	0.05

Table 5. Hourly data of PV power, wind power, and load demand in one day.

Time (h)	1	2	3	4	5	6	7	8	9	10	11	12
Load (MW)	700	750	850	950	100	1100	1150	1200	1300	1400	1450	1500
PV (MW)	0	0	0	0	0	0	120	180	360	420	550	430
Wind (MW)	1430	1300	1235	1105	975	910	1087	1080	1005	560	465	620
Time (h)	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	1400	1300	1200	1050	1000	1100	1200	1400	1300	1100	900	800
PV (MW)	370	300	255	200	100	0	0	0	0	0	0	0
Wind (MW)	610	1065	1005	902	950	1155	1260	980	910	1155	1170	1040

Subsequently, Equation (6) can be expressed as

$$\left\{ \begin{array}{l} D_L = \{(L, 0.5); (L \pm 0.15L, 0.15); (L \pm 0.3L, 0.05)\} \\ D_{PV} = \left\{ \begin{array}{l} (P^{PV}, 0.5); (P^{PV} \pm 0.15P^{PV}, 0.15); \\ (P^{PV} \pm 0.3P^{PV}, 0.05) \end{array} \right\} \\ D_{wind} = \left\{ \begin{array}{l} (P^{wind}, \beta_{wind}^1); (P^{wind} \pm 0.15P^{wind}, 0.15); \\ (P^{wind} \pm 0.3P^{wind}, 0.05) \end{array} \right\} \end{array} \right. \quad (24)$$

Five cases were simulated by applying MOPSO to verify the multi-objective dispatch model proposed herein. These five cases were proposed with different profit coefficients. The optimization results were analyzed and compared. The simulation results for these five cases are listed in Tables 6 and 7. Table 6 illustrates the optimal TOU electricity price, multi-objective function, and profit of the power company and demand users. Table 7 illustrates the proportion of load demand at the three-part period for these five cases.

Table 6. Simulation results of five cases.

α	β	TOU Price (USD/MWh)			Objective Function		Profit of the Power Company and Demand Users				
		Valley	Off-Peak	Peak	f_1 (USD)	f_2 (%)	Pro _{company} (USD)	Pro _{users} (USD)	Income of Selling Electricity	Penalty Cost of Power Supply Shortage	
Base	×	×	75.0	75.0	75.0	×	6.82	1,692,909.1	0	1,856,849.5	163,940.4
Case 1	0.3	0.7	15.0	60.0	111.0	698,347.0	5.33	1,287,124.6	377,918.7	1,471,612.6	184,488.0
Case 2	0.4	0.6	15.0	60.0	140.0	792,943.3	4.74	1,458,766.9	349,061.0	1,584,055.2	125,288.2
Case 3	0.5	0.5	15.0	62.6	153.0	928,014.4	5.51	1,519,936.6	336,092.2	1,624,858.3	10,492.7
Case 4	0.6	0.4	37.9	88.7	112.5	1,102,424.1	6.54	1,846,779.9	−14,109.5	1,934,830.9	88,051.0
Case 5	0.7	0.3	51.2	85.4	110.6	1,315,901.6	7.06	1,913,492.7	−78,477.3	1,997,332.4	83,839.7

Table 7. Proportion of load demand in each period.

Load Distribution						
	Valley (MW)	Proportion of Valley %	Off-Peak (MW)	Proportion of Off-Peak %	Peak (MW)	Proportion of Peak %
Base case	7050	26.0	11,600	42.8	8450	31.2
Case 1	9170	32.1	12,472	43.7	6925	24.2
Case 2	9170	33.5	12,472	45.6	5696	20.8
Case 3	9170	34.4	12,320	46.3	5146	19.3
Case 4	8362	32.1	10,805	41.5	6863	26.4
Case 5	7891	30.6	10,995	42.6	6941	26.9

Figure 3 shows the simulation results for the multi-objective dispatch model solved by MOPSO. The profit of the power company and demand users, and the rate of abandoning PV power and wind power, may conflict.

6.1. Base Case

To analyze the economic and the rate of abandoning PV power and wind power, the base case was set to an initial electricity price of 75 USD/MWh in the hybrid microgrid. The proportion of the load in the base case is shown in the first row of Table 6. The multi-objective function of f_2 was 6.82%. The profit of the power company and demand users cannot be calculated as the weight coefficients of the power company's profit and demand users are not set in this case. The proportions of demand load at peak, off-peak, and valley periods were 31.2%, 42.8%, and 26%, respectively.

6.2. Analysis of the Profit of the Power Company and Demand Users

For the profit of demand users, minimizing the electricity price is the optimal solution, as it can obtain the minimum electricity cost of demand users. The weight coefficients of the profit of demand users are higher than those of the power company in Cases 1 and 2. Therefore, in the two cases, the optimal electricity prices of the valley and off-peak periods

are 15 USD/MWh and 60 USD/MWh, respectively, which are the lower limits of the TOU electricity price. For Cases 1–3, the weight coefficients of the profit of demand users are progressively reduced. In Cases 1–3, the optimal electricity prices at the peak period are 110 USD/MWh, 114 USD/MWh, and 153 USD/MWh, respectively. In Cases 4 and 5, the weight coefficients of the power company are higher than those of demand users. From the simulation results in Cases 4 and 5, the profits for demand users are –14,109.5 USD and –78,477.3 USD, respectively. Therefore, the profit of the power company increases, and the profit of users is less than zero.

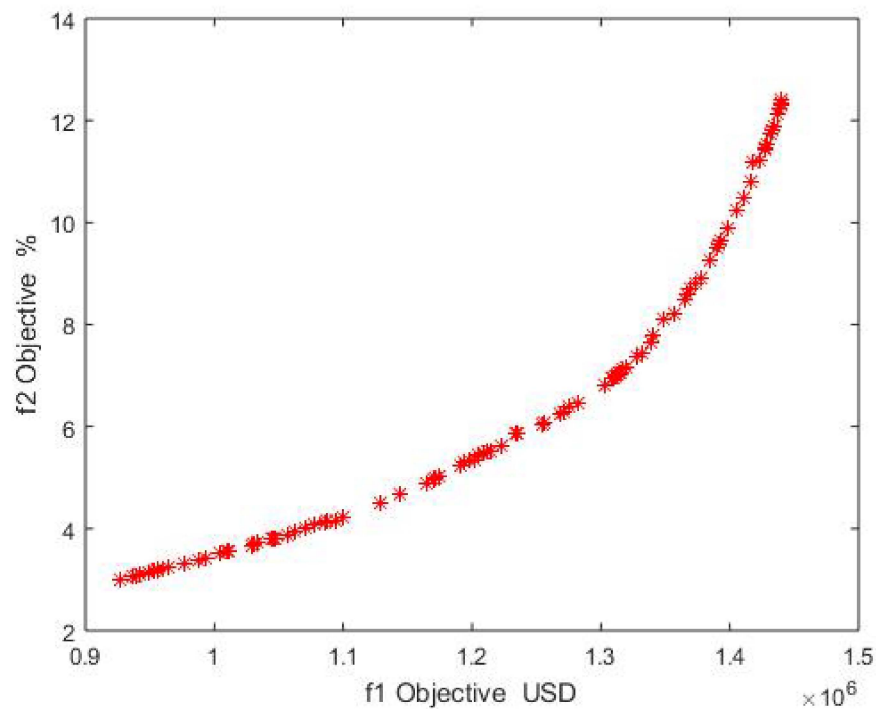


Figure 3. MOPSO simulation results for the multi-objective dispatch model.

For the profit of the power company, maximizing the electricity price is the optimal solution that can maximize the income of selling electricity for the power company. As shown in Table 5, the off-peak electricity prices of Cases 4 and 5 are 88.7 USD/MWh and 85.4 USD/MWh, respectively. The electricity prices are close to the upper limit of the off-peak electricity price. The valley electricity prices of Cases 4 and 5 are 37.9 USD/MWh and 51.2 USD/MWh, respectively, obviously exceeding those of Case 1 and Case 2. The weight coefficients of the profit of the power company exceed those of demand users in Cases 3 and 4.

In Case 3, the weight coefficients of the profit of demand users and the power company are equal to 0.5. Compared with the results of Cases 1 and 2, the off-peak electricity price is increased by 2.6 USD/MWh as the weight coefficient of the profit of the power company in Case 3 exceeds that in Cases 1 and 2. Moreover, the electricity prices of the valley and off-peak periods in Case 3 are smaller than those in Cases 4 and 5 as the weight coefficient of the profit of users in Case 3 exceeds that in Cases 4 and 5.

6.3. Analysis of the Rate of Abandoning Output Power of Renewable Energy

To minimize the rate of abandoning the output power of renewable energy, the excess output power of renewable energy should be minimized. The hours of exceeding the total output power of renewable energy may occur during the valley period. The sum of the output power of the renewable energy exceeds the load demand.

As shown in Table 6, compared with the base case data, the valley period loads in Cases 1, 2, and 3 are all increased by 2120 MW as the valley electricity price in these three

cases was 15 USD/MWh. The valley electricity prices in Cases 4 and 5 are 37.9 USD/MWh and 51.2 USD/MWh, respectively, which are higher than those of the three cases. Therefore, the loads at the valley period in Cases 4 and 5 only increased by 1312 MW and 841 MW, respectively. During the valley period, the loads in Cases 4 and 5 were less than those in the three cases.

From the above simulation results, the weight coefficients of the profit of demand users gradually decrease. The weight coefficients of the profit of the power company gradually increase from the results of Cases 1–5. With the increasing weight coefficients of the power company profit, the electricity price and the rate of abandoning PV power and wind power increased.

The load demand of the valley period increases, and the load demand of the peak period is reduced. The results of the first three cases were similar. This is as the TOU electricity prices of these three cases are close to the lower limit of the electricity price. The TOU electricity price in Case 3 was the upper limit of the electricity price.

7. Conclusions

DR plays a significant role in power system scheduling. As one of the methods for the DR, the price elasticity of load demands was applied herein to establish a multi-objective dispatch model for integration to minimize the rate of abandoning renewable energy generation power and maximize the profit of the power company and demand users. The hybrid microgrid comprises renewable generation and an ESS. The uncertainty problem of renewable generation is considered in this study. MOPSO was applied to obtain the solutions for the optimal TOU electricity price for the proposed multi-objective model.

The simulation results of five cases with different profit weight coefficients were analyzed and compared to prove the feasibility of the proposed multi-objective dispatch model. The results listed in Table 6 show that, with the increasing weight coefficients of the power company profit, electricity price, and the rate of abandoning PV power and wind power are increased. The results in Figure 3 show that with an increase in the profit of the power company and demand users, the rate of abandoning PV power and wind power correspondingly decrease. We can draw the conclusion that the profits of power companies and demand users, and the rate of abandoning PV power and wind power, are conflicting. With an increase in the profit weight coefficient, the optimal electricity price increases. Simultaneously, the rate of abandoning PV power and wind power increased. In our work, the elastic price of the load demand with a linear function is employed to optimize the TOU electricity price. However, the coefficients of the linear function for the price elasticity of load demand should be more accurate, which could form the basis for the next research topic.

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