Research Article

Multiobjective Optimization Model considering Demand Response and Uncertainty of Generation Side of Microgrid

Hanfang Li,1 Huaqing Wang,1 Jinghan Zhou,1 Zhongfu Tan,1 Jiacheng Yang,1 and Puyu He2

1North China Electric Power University, Beijing 102206, China
2State Grid Sichuan Economic Research, Chengdu 610041, China

Correspondence should be addressed to Puyu He; hepuyunceu@163.com

Received 16 July 2020; Revised 5 September 2020; Accepted 26 September 2020; Published 9 October 2020

1.Introduction

Due to the overuse of traditional fossil energy, the utilization of renewable power has received considerable attention. Distributed renewable power, because of its clean and efficient form of power generation, plays an important role in energy supplies [1] and is an effective way to solve the energy shortage. The microgrid system (MS), as a key pathway for renewable power integration, is an appropriate complement to the distribution grid, facilitating renewable energy access and consumption and avoiding the disruption of distributed generation to the public grid [2]. With the orderly development and application of energy storage, electric vehicle charging-discharging technology, and demand response, the flexibility and reliability of the power supply for microgrids have been further improved [3–5]. The MS effectively solves the problem of integrated application of large-scale renewable energy, but owing to limited capacity, there are few effective methods in dealing with the instability of renewable power generation, so solving the uncertainty in the MS to achieve its economical and reliable operation is a popular research topic in this field [6].

To date, considerable research has been concerned with optimizing microgrid system, mainly focusing on operational scheduling and economical operation, but various deficiencies remain. Tsalaklis and Hatzigraphiou [7] considered the fuel and environmental costs of distributed generation and established an islanded microgrid operation optimization model with minimum operation cost of distributed power generation as the objective function. Ross et al. [8] proposed a method of calculating multiobjective optimization that quantifies the objective according to the evaluation function of each microgrid system. To make better economic operation of microgrid, the impact of consumer side costs and consumer satisfaction is also considered. Bracale et al. [9] used the hybrid coding method of matrix real numbers and 0-1 integers to solve the demand side power consumption optimization model of microgrids, but only considered a single objective function that was insufficient to manage wind and light abandonment in...
microgrids. Mayank et al. [10] designed a multiobjective optimization algorithm for microgrid systems that mainly considered economic and environmental benefits. Based on the multistrategy fusion particle swarm optimization algorithm, Ramadan et al. [11], respectively, applied the weighting method, membership function technique, and Pareto principle to implement multiobjective processing. Based on particle swarm optimization algorithm, Mohamad and Ahad [12] solved the problem of the lack of an accurate mathematical description between optimization variables and performance indicators. Zeng B et al. [13] established a bi-level optimization model, and the resulting bi-level robust optimization model is transformed into an equivalent single-level optimization problem by replacing the lower-level problem with Karush-Kuhn-Tucker optimality conditions. Research on introducing electric vehicles into microgrid operation, Zeng B et al. [14] studied the impact of incentive policies on the behavior of electric vehicles and the impact on microgrid planning. These scholars studied the operation and optimal scheduling model of microgrids but did not analyze the impact of WPP and PV output instability on system operation.

As renewable energy generation increases, studying the impact of output uncertainty on the grid has become a popular topic. Peik Herfeh et al. [15] constructed a two-point evaluation model to obtain different values on both sides of the output value to represent the output fluctuation. Yang et al. [16] applied Weibull distribution to predict real-time wind speed and used maximum likelihood estimation to calculate a wind turbine’s output. Yang et al. [17] constructed a robust optimization model, and the optimization scheme is adjusted by processing its coefficients to obtain a scheme cluster, but the robust stochastic optimization could only consider the constraints and was unable to analyze the stochastic planning function. Duhee and Ross [18] constructed a wind power forecast using the power spectrum density to regressionly analyze on the previous data, which maximized local historical and environmental information. Considering the efficiency problem caused by the scale of sample scene sets, many studies also proposed scene abatement algorithms, such as backward abatement [19], fast-forward selection [20], and scene tree construction [21], but the current scene abatement algorithm uses serial iterative search; that is, for each scene abatement, all of the possible combinations must be compared in the preselection set, and the time complexity increases with the scene set size by a squared exponential, affecting the processing scale.

Adding demand response to microgrid systems can mobilize end-users to participate in grid peak load regulation and reduce load peak-valley differences. Abdul Latif et al. [22, 23] proposed using demand response to analyze a microgrid integrated with photovoltaics, wind turbines, fuel cells, diesel generators, and energy storage systems and established an optimal energy distribution strategy, but did not consider how demand response affected the scheduling of various parts of the microgrid. To compensate for the output fluctuation of renewable power at the lowest costs, F. Sheidaei [24] added two demand response methods, including real-time pricing and key peak pricing, to the microgrid to compensate for the WPP and PV’s fluctuations with minimal cost. Sahbasadat [25] analyzed three simulation results and studied the impact of DR on the cost of microgrids. Tan et al. [26] proposed a single-objective optimization model of demand response based on preference to solve the problem of user participation in virtual power plants. Seyed and Navid [27] introduced a new microgrid pricing model using marginal pricing technology that considered step-by-step demand response plans to achieve co-operation. To minimize the operating costs of smart MS, with less voltage fluctuations and power loss as the goal, Mostafa et al. [28] introduced demand response subdivided into hours and analyzed the improvement of the time-of-use (TOU) price on the application for maintaining efficiency management. Zeng B et al. [29, 30] applied generation capacity credit to DR and proposed a new framework of distribution network reliability evaluation method. The above scholars mainly studied how to introduce DR into microgrid, and seldom considered the impact of DR on microgrid dispatching.

First, robust optimization methods are used in many studies to analysis of the instability and uncertainty of WPP and PV’s output on the optimal dispatch of MS. However, the aim of this method is to optimize the worst-case objective function when all of the constraints are satisfied. This optimization method is conservative. Nevertheless, the scenario analysis method can clearly reflect the probabilistic features of uncertainty and describe the traits of many complex scenarios using a few representative examples. Therefore, the scenario reduction method is adopted in this paper to overcome the uncertainties and manage the constraints and random variables in the objective function.

Second, DR can avoid users’ unreasonable power consumption behavior; for example, users will balance the power consumption, improving the operation efficiency of microgrid systems after implementing DR. When there is too much power demand to meet the power capacity, users can reduce their power consumption to compensate for the microgrid’s power output. WPP and PV can obtain reverse capacity from the virtual output power of DR to optimize the results of microgrid scheduling. However, previous studies have rarely discussed the impact of integrating demand response to microgrids. In this paper, IBDR and PBDR blocks are integrated into a microgrid system, and the impact of demand response on microgrid operation is discussed. Third, because the microgrid’s operating target is not single, the microgrid scheduling model also needs multiple targets, as a reasonable mathematical model is the capital method to the MS’s optimal operation. The contributions of this study are as follows:

(1) A multitarget model of grid-connected MS is proposed, including WPP, PV, GT, ESS, and EV. From the perspective of MS differential cost, power abandonment costs, and operating income of each block, three optimization objective functions are set: a minimum MS differential cost, minimum power abandonment cost, and maximum operating income. The effectiveness of the model is verified by the case analysis.
(2) To enable end-users to participate in microgrid peaking and scheduling, two demand response methods, PBDR and IBDR, increase DR’s quantitative effect on MS containing renewable power generation.

(3) To weaken the impact of WPP and PV’s uncertainty, possible WPP and PV output scenarios are generated randomly, and then the scene reduction technology is applied, aiming at the minimum Kantorovich distance between the initial scenario and the post-reduced scenario, to avoid scenarios with high repetitiveness, and the output of each power generation unit is analyzed considering uncertainty.

(4) The decision attribute analysis table of the multiobjective optimization model is constructed, and dimensionless processing of the cost objective and income objective is implemented. In addition, the weight of the multiobjective function is calculated via the rough set theory, and the multiobjective optimization algorithm is set up, which converts the multitarget model to the comprehensive single target optimization model.

The rest of this article is arranged as follows. Section 2 proposes the structure of the microgrid in this paper. Section 3 establishes a microgrid system model containing WPP, PV, GT, ESS, and EV components, and two demand response models, PBDR and IBDR, are integrated. Section 4 establishes a multiobjective optimal model of MS differential cost, power abandonment cost, and operating income, analyzes WPP and PV’s uncertainty, and increases the stability of MS via scenario reduction to remove very similar scenarios. Section 5 uses the rough set theory to solve the multitarget optimization scheduling model. Section 6 provides an example of the proposed model and an analysis of the study’s results. Section 7 describes the study’s main conclusions.

2. Microgrid System

In this paper’s MS structure, renewable energy includes WPP and PV. The normal power supply includes a GT unit. EVs are regarded as the energy storage modules that together with the energy storage system form the energy storage part of the MS. The MS has a multienergy storage structure and multitype load coupling system regulated by a microgrid dispatch center (MDC). According to the microgrid’s internal energy consumption and demand response implementation, the microgrid exchanges power with the external grid. The microgrid’s demand resource providers (DRPs) are composed of controllable and uncontrollable loads. The controllable load carries out demand response (DR) by signing an advanced contract with the microgrid and obtains corresponding subsidy revenues. Price-based demand response, PBDR, and incentive-based demand response, IBDR, affect the microgrid’s load via price stimulation and excitation, respectively. In this paper, to ensure the energy supply of the microgrid, energy transmission is performed with the external grid through the junction. The structure of the MS is shown in Figure 1.

3. Microgrid System and Demand Response Models

3.1. Microgrid System Model

3.1.1. GT

\[ P_{GT,t} = V_{GT,t} H_{ng} \eta_{GT,t} \]  

where \( P_{GT,t} \) represents the GT’s power supply at time \( t \); \( V_{GT,t} \) represents the GT’s gas consumption; \( H_{ng} \) represents the thermal value of natural gas; and \( \eta_{GT,t} \) represents the GT’s power efficiency.

3.1.2. WPP. Due to the wind speed’s uncertainty, the WPP’s output is also uncertain. However, a large amount of historical data show that the Weibull function can approximate wind speed as shown in formula (2):

\[ f(v) = \frac{\phi \left( \frac{v}{\nu} \right)^{\nu-1} e^{-ab^c \left( \frac{v}{\nu} \right)^c}}{\nu^c} \]  

where \( v \) represents the wind speed and \( \phi \) and \( \nu \) represent the form and size parameters of the probability density function, respectively. The WPP’s power generation is affected by the entering wind. When the wind speed is above or below the tolerance, the WPP cannot generate power. The relationship between the WPP’s output power and wind speed is as follows:

\[ P_{WPP,t} = \begin{cases} 0, & 0 \leq v_t < v_{in}, v_t > v_{out}, \\ \frac{v_t^3 - v_{in}^3}{v_{rated}^3 - v_m^3} P_{WPP}^R, & v_{in} \leq v_t \leq v_{rated}, \\ \frac{v_t - v_{rated}}{v_{rated} - v_m} P_{WPP}^R, & v_{rated} \leq v_t \leq v_{out}, \\ \end{cases} \]  

where \( P_{WPP,t} \) represents the WPP’s available power at time \( t \), \( P_{WPP}^R \) represents the rated output power, \( v_t \) represents the...
actual wind speed at time $t$, and $v_{in}$, $v_{out}$, and $v_{rated}$ represent the cut-in, cut-out, and rated speeds, respectively.

$$f(\theta) = \begin{cases} \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha + \beta)}(\beta \theta^{\alpha-1}) (1 - \theta)^{\beta-1}, & 0 \leq \theta \leq 1, \alpha \geq 0, \beta \geq 0, \\ 0, & \text{else}, \end{cases}$$

(4)

where $\alpha$ and $\beta$, respectively, represent the shape parameters of the $\beta$ distribution and $\theta$ represents the radiation intensity. $\alpha$ and $\beta$ are calculated by formulas (5) and (6):

$$\beta = (1 - \mu) \times \left( \frac{\mu \times (1 + \mu)}{\delta^2} - 1 \right),$$

(5)

$$\alpha = \frac{\mu \times \beta}{1 - \mu},$$

(6)

where $\mu$ and $\delta$ represent the average value and standard normal distribution values of sun’s power radiation, respectively. The probability of sun’s irradiance state $\theta$ is calculated by formula (7):

$$P(\theta) = \int_{\theta_0}^{\theta} f(\theta)d\theta.$$  

(7)

The photovoltaic output power is calculated using formula (8):

$$P_{PV,t} = \eta_{PV} \times S_{PV} \times \theta_t,$$

(8)

where $\eta_{PV}$ is the PV’s conversion efficiency, $S_{PV}$ is the sunshine received by the area, and $\theta_t$ is the sunshine intensity at time $t$.

3.1.3. PV. The function of the PV’s generating power generally satisfies the $\Gamma$ distribution as shown in formula (4):

3.1.4. ESS. Energy storage technology can solve the WPP and PV’s randomness and volatility to a large extent. The ESS can smooth the renewable energy output curve through its own charge or discharge state.

When the ESS is in a charge state,

$$SOC_{ESS,t} = SOC_{ESS,t-1} + \frac{\eta_{chr} P_{ESS,t}^{chr}}{C_{ESS}}.$$  

(9)

When the ESS is in a discharge state,

$$SOC_{ESS,t} = SOC_{ESS,t-1} - \frac{P_{ESS,t}^{dis}}{\left( \eta_{dis} C_{ESS} \right)},$$

(10)

where $SOC_{ESS,t}$ is the energy storage device’s energy state; $\eta_{chr}$ and $\eta_{dis}$, respectively, represent the storage and release efficiency; $P_{ESS,t}^{chr}$ and $P_{ESS,t}^{dis}$, respectively, represent the energy power of storage and release; and $C_{ESS}$ is the ESS’s capacity. At time $t$, the ESS’s output power is expressed by formula (11):

$$P_{ESS,t} = u_{chr} P_{ESS,t}^{chr} - u_{dis} P_{ESS,t}^{dis},$$

(11)

3.2. Demand Response Model. There are two kinds of demand response: price-based demand response (PBDR) and incentive-based demand response (IBDR). In PBDR, the user changes the way of using electricity according to the electricity price; that is, as the MS load approaches peak, power prices will rise, users will reduce the power demand or transfer it to the off-peak time, which helps MS operate stably. In IBDR, users need to sign a response contract with the DRPs, and the DRPs will carry out corresponding rewards and punishments according to the performance of the users’ contract.

3.2.1. Price-Based DR Model. The PBDR can reduce load demand at peak time and shift it to valley time and smooth the load curve by implementing time-sharing power price. The PBDR’s post-load demand is calculated as follows:

$$L_t = L^0_t \times \left[ 1 + \frac{\sum_{s=1}^{24} e_s (P_t - P_s^0)}{P_t^0} \right] + \sum_{s=1}^{24} e_s \left( \frac{P_s - P_s^0}{P_s^0} \right),$$

(12)

$$e_s = \frac{\Delta L_t / L^0_t}{\Delta P_t / P_t^0} \begin{cases} e_s < 0, & \text{if } s = t, \\ e_s \geq 0, & \text{if } s \neq t, \end{cases}$$

where $L^0_t$ and $L_t$, respectively, represent the load demand before and after implementing PBDR; $P_t^0$ and $P_t$, respectively, represent the electricity price before and after PBDR; $s$ and $t$ represent time $s$ and time $t$, respectively, $s, t = 1, 2, \ldots, T$; and $e_s$ is the price elasticity for power demand. $P_t^0$ refers to the price before PBDR in time $t$; $L^0_t$ refers to the users’ demand in time $s$. $\Delta L_t$ represent the price change at time $s$ and $\Delta P_t$ represents the demand change at time $t$ after PBDR, respectively.

The PBDR’s implementation cost is determined by the change in sales revenue before and after implementation:

$$C_{PBDR} = P_t^0 L^0_t - P_t L_t.$$  

(13)

3.2.2. Incentive-Based DR Model. IBDR provides incentives to increase customer participation in the MS market, thereby maintaining a balance between system supply and demand.
Customers can provide MS upstream and downstream reservations. The load reduction and cost of IBDR can be calculated using equations (14) and (15):

$$\Delta L^I = \sum_{t=1}^{24} \Delta L^d + \sum_{t=1}^{24} \Delta L^u_s,$$

$$\bar{\omega}^j = \sum_{t=1}^{24} \delta P_s \Delta L^d + \sum_{t=1}^{24} (1 - \eta) P_s \Delta L^u_s,$$

where $\Delta L^I$ is the load and $\bar{\omega}^j$ is the revenue of participating IBDR customers, respectively. $\delta$ is the compensation rate. $\eta$ is the incentive discount ratio. $\Delta L^d$ is the upstream standby load at time $t$ and $\Delta L^u_s$ is the downstream standby load of customers at time $s$.

4. Multiobjective Optimization Model for MS

4.1. Objective Function

4.1.1. MS Differential Cost. After implementing DR in the microgrid system, the peak and valley can be cut so that the microgrid’s load curve can be smoother and its operation improved [31]. However, it will also affect the system’s economic benefits. The introduction of DR can promote the transfer of peak loads and reduce demand loads during peak hours. The change in power sales revenue calculated using formula (13) can be regarded as the DR’s implementation cost. This study considers combining the power shortage cost and DR implementation cost, called MS differential cost, considering the minimum value as the objective function:

$$f_1 = \sum_{t=1}^{T} \left[ (C_t^p + C_t^i) + \rho_s \Delta L^u_s \right],$$

where $C_t^p$ is the difference in the power sales revenue before and after the PBDR’s implementation; $C_t^i$ is the cost increment for implementing the IBDR; $\rho_s$ is the compensation price per unit for power shortage; and $\Delta L^u_s$ is the power shortage at time $t$.

4.1.2. Power Abandonment Cost. This section considers the minimum power abandonment cost of the MS as another objective function, including the waste of WPP and PV’s power generation:

$$f_2 = \sum_{t=1}^{T} \left[ \rho_{WPP} (P_{WPP}^* - P_{WPP}^t) + \rho_{PV} (P_{PV}^* - P_{PV}^t) \right],$$

where $P_{WPP}^*$ and $P_{PV}^*$ are, respectively, WPP and PV’s actual output power. $\rho_{WPP}$ and $\rho_{PV}$, respectively, refer to power price of WPP and PV purchased by general grid.

4.1.3. Operating Income. This section considers the maximum operating income of the MS as the objective function, including the generation income and the spread benefits of the EV and ESS:

$$f_3 = \sum_{t=1}^{T} \left[ \omega_{\text{WPP},t} + \omega_{\text{PV},t} + \omega_{\text{GT},t} + \omega_{\text{ESS},t} \right],$$

where $\omega_{\text{WPP},t}$, $\omega_{\text{PV},t}$, and $\omega_{\text{GT},t}$, and $\omega_{\text{ESS},t}$ are, respectively, the generation income of the WPP, PV, and GT. $\omega_{\text{EV},t}$ and $\omega_{\text{ESS},t}$ are, respectively, the spread benefits of the EV and ESS. $\rho_{\text{WPP},t}$, $\rho_{\text{PV},t}$, and $\rho_{\text{GT},t}$ are, respectively, the power generation prices of the TG, WPP, PV, and GT at time $t$. $N_t^{\text{dis}}$ and $N_t^{\text{chr}}$ are the number of electric vehicles discharging and charging at time $t$, respectively. $P_{\text{EV},t}^{\text{dis}}$ and $P_{\text{EV},t}^{\text{chr}}$ are, respectively, the charge-discharge power of the EV at time $t$. $P_{\text{ESS},t}^{\text{dis}}$ and $P_{\text{ESS},t}^{\text{chr}}$ are, respectively, the charge-discharge power of the energy storage device at time $t$. $P_{\text{GRID},t}^{\text{chr}}$, and $P_{\text{GRID},t}^{\text{dis}}$ are, respectively, the charge-discharge power of the energy storage device at time $t$. $P_{\text{GRID},t}^{\text{ Chr}}$, and $P_{\text{GRID},t}^{\text{Dis}}$ are, respectively, the charge-discharge power of the energy storage device at time $t$.

4.2. Constraint Condition

4.2.1. Power Balance Constraints.

$$P_{\text{GRID},t} + P_{\text{WPP},t} + P_{\text{PV},t} + P_{\text{GT},t} + P_{\text{ESS},t} + P_{\text{EV},t}^{\text{dis}} - P_{\text{EV},t}^{\text{chr}} = L_t - P_{\text{GRID},\text{max}} \leq P_{\text{GRID}} \leq P_{\text{GRID},\text{max}},$$

where $P_{\text{GRID}}$ is the interactive power value between the MS and the external grid in time period $t$, and $P_{\text{GRID},\text{max}}$ is the microgrid output/input interactive power upper limit. $P_{\text{ESS}}$ is the charge-discharge power of the ESS.

4.2.2. GT Operating Constraints. The power generation power and climbing power constraints of the GT are as follows:

$$\delta_{\text{GT}} (t) P_{\text{GT},t}^{\text{min}} \leq P_{\text{GT},t} \leq \delta_{\text{GT}} (t) P_{\text{GT},t}^{\text{max}} - \Delta P_{\text{GT,D}},$$

where $\delta_{\text{GT}} (t)$ is the GT’s start-stop state parameter at time $t$. $P_{\text{GT},t}^{\text{min}}$ and $P_{\text{GT},t}^{\text{max}}$ are the GT’s minimum and maximum output power, respectively. $\Delta P_{\text{GT,L}}$ and $\Delta P_{\text{GT,D}}$ are the threshold of the GT’s climbing rate, respectively.

The GT should also meet the minimum start and stop time constraints:

$$\left( T_{\text{GT, on}} (t - 1) - T_{\text{GT}} \right) (\delta_{\text{GT}} (t) - \delta_{\text{GT}} (t - 1)) \geq 0,$$

$$\left( T_{\text{GT, off}} (t - 1) - T_{\text{GT}} \right) (\delta_{\text{GT}} (t) - \delta_{\text{GT}} (t - 1)) \geq 0,$$

where $T_{\text{GT, on}}$, and $T_{\text{GT, off}}$ are the start and stop time of the GT.
where $T_{\text{GT,on}}$ and $T_{\text{GT,off}}$ are the GT’s accumulated operation and downtime in period $t$, and $T_{\text{GT,on}}$ and $T_{\text{GT,off}}$ are the GT’s minimum start-up and stop times, respectively.

### 4.2.3. WPP Operating Constraints.

\[ 0 \leq P_{\text{WPP},t} \leq P_{\text{WPP}}^{\text{max}} \]  
\[ (22) \]

where $P_{\text{WPP},t}$ and $P_{\text{WPP}}^{\text{max}}$ are the output and upper limit of the WPP’s output in time period $t$, respectively.

### 4.2.4. DR Operating Constraints. DR main constraints include the maximum load reduction constraint, the climb constraint, and the minimum start-stop time constraint.

1. **Load reduction constraint**
   The microgrid has the lowest load demand, and the load after DR reduction should not be lower than the minimum value:
   \[ |L_t - L_t^{\text{DR}}| \leq \Delta L_t^{\text{max}} . \]  
   \[ (23) \]

2. **Climb constraint**
   To better meet the peak-valley load adjustment, the load change caused by DR should meet the climbing constraint:
   \[ S_t^{L,\text{DR}} - L_t^{\text{DR}} \leq L_{t-1}^{\text{DR}} - S_{t-1}^{L,\text{DR}} \leq S_{t}^{L,\text{DR}} - L_{t}^{\text{DR}} , \]  
   \[ (24) \]

   where $S_t^{L}$ and $S_{t}^{L}$ are the operation states of the PBDR and IBDR, respectively, both of which are 0-1 variables. $L_{t}^{\text{DR}}$ and $L_{t}^{\text{DR}}$, respectively, represent the lower and upper limits of the PBDR’s load climbing rate. $L_{t}^{\text{DR}}$ and $L_{t}^{\text{DR}}$, respectively, represent the lower and upper limits of the IBDR’s load climbing rate. $L_{t}^{\text{DR}}$ and $L_{t}^{\text{DR}}$ are, respectively, the loads of the PBDR and IBDR in period $t$.

3. **Start-stop time constraints**
   After the user receives the price signal from the dispatch center, it takes some time to change the electricity consumption behavior. Correspondingly, the load also needs to have a start and stop time limit:
   \[ |X_{t-1}^{\text{on}} - T_{t-1}^{\text{on}}| \leq (S_{t-1}^{L} - S_{t-1}^{L}) \geq 0 , \]
   \[ |X_{t}^{\text{off}} - T_{t}^{\text{off}}| \leq (S_{t}^{L} - S_{t}^{L}) \geq 0 , \]
   \[ |X_{t-1}^{\text{on}} - T_{t}^{\text{on}}| \leq (S_{t-1}^{L} - S_{t-1}^{L}) \geq 0 , \]
   \[ |X_{t}^{\text{off}} - T_{t}^{\text{off}}| \leq (S_{t}^{L} - S_{t}^{L}) \geq 0 , \]  
   \[ (25) \]

   where $T_{t-1}^{\text{on}}$ and $T_{t}^{\text{on}}$ are the PBDR’s minimum load operation time and minimum load downtime. $T_{t}^{\text{on}}$ and $T_{t}^{\text{off}}$ are the IBDR’s minimum running time and minimum load downtime. $X_{t-1}^{\text{on}}$ and $X_{t}^{\text{on}}$ are the PBDR’s continuous running time and continuous downtime, respectively. $X_{t}^{\text{on}}$ and $X_{t}^{\text{on}}$ are the 0-1 state variables of the IBDR’s continuous running time and downtime, respectively. $S_{t}^{L}$ and $S_{t}^{L}$, respectively, represent 0-1 state variables for the PBDR and IBDR, where 1 represents planned and 0 represents unplanned.

### 4.2.5. ESS Operating Constraints.

\[ P_{\text{ESS}}^{\text{min}} \leq P_{\text{ESS},t} \leq P_{\text{ESS}}^{\text{max}} , \]  
\[ (26) \]

where $P_{\text{ESS}}^{\text{min}}$ and $P_{\text{ESS}}^{\text{max}}$ are the threshold of the ESS power, respectively.

The state of charge (SOC) reflects the residual capacity of the ESS, and the change in the SOC is expressed by the following formulas during charge and discharge:

\[ \text{SOC}_{\text{ESS},t+1} = \text{SOC}_{\text{ESS},t} + \frac{\eta_{\text{ch}}P_{\text{ESS},t}^{\text{ch}}}{E_{\text{ESS}}} - \frac{\eta_{\text{dis}}P_{\text{ESS},t}^{\text{dis}}}{E_{\text{ESS}}} , \]  
\[ (27) \]

where $\text{SOC}_{\text{ESS},t}$ and $\text{SOC}_{\text{ESS},t+1}$ are the state of charge of the ESS in $t$ and $t+1$ periods, respectively; $\eta_{\text{ch}}$ and $\eta_{\text{dis}}$ are the charge and discharge efficiency of the ESS, respectively; $P_{\text{ESS},t}^{\text{ch}}$ and $P_{\text{ESS},t}^{\text{dis}}$ are the charge and discharge power of the ESS in $t$ period, respectively; $E_{\text{ESS}}$ represents the rated capacity of the ESS; and $\text{SOC}_{\text{ESS}}^{\text{min}}$ and $\text{SOC}_{\text{ESS}}^{\text{max}}$, respectively, represent threshold of the state of charge of the ESS.

### 4.2.6. EV Constraints.

\[ \begin{cases} -P_{\text{EV}}^{\text{min}} \leq P_{\text{EV},t} \leq P_{\text{EV}}^{\text{max}}, & t_{\text{start}} < t < t_{\text{end}}, \\ P_{\text{EV},t} = 0, & \text{else,} \end{cases} \]  
\[ (28) \]

where $t_{\text{start}}$ is the time when the EV is connected to the grid and $t_{\text{end}}$ is the time when the EV leaves.

Battery capacity of EV is limited, in order to avoid the damage to the battery caused by overcharge or over-discharge, battery storage capacity needs to be limited. The lower limit should take into account the power required for emergency travel. The constraints are as follows:

\[ \text{SOC}_{\text{EV},t}^{\text{min}} \leq \text{SOC}_{\text{EV},t} \leq \text{SOC}_{\text{EV},t}^{\text{max}}, \]  
\[ \text{SOC}_{\text{EV},t} = \text{SOC}_{\text{EV},t-1} + P_{\text{EV},t} \Delta T, \]  
\[ (29) \]

where $\text{SOC}_{\text{EV},t}$ and $\text{SOC}_{\text{EV},t-1}$ are the EV charge capacity, $\text{SOC}_{\text{EV},t}$ is the EV charge capacity at time $t$, and $\text{SOC}_{\text{EV},t-1}$ is the charge capacity at time $t-1$.

### 4.2.7. Rotation Reserve Constraint.

\[ r_{t}^{\text{MS}} = r_{1} \cdot P_{\text{WPP},t} + r_{2} \cdot P_{\text{PV},t} + r_{3} \cdot P_{\text{EV},t}, \]  
\[ (30) \]

where $r_{t}^{\text{MS}}$ is MS’s reserve capacity requirement and $r_{1}$, $r_{2}$ and $r_{3}$ are the reserve capacity coefficients of the WPP, PV, and EV, respectively.

### 4.3. Uncertainty Handling.

The scenario analysis is introduced to deal with the output uncertainty of WPP and PV in this study. The larger the scenario’s scale, the more typical it
is and the more accurate the simulation results are, but large-scale scenarios will increase the running time of target and constraint functions. Therefore, after WPP and PV’s outputs are generated, the scenarios are reduced to an appropriate number by scenario reduction. In this study, the Kantorovich distance is introduced to calculate the distance

$$D_K(P', Q') = \min \left\{ \sum_{s \in P', u \in Q'} c(s, u)\omega(s, u) \big| \omega(s, u) \geq 0, \forall s \in P', \forall u \in Q'; \sum_{u \in Q'} \omega(s, u) = p_s, \forall s \in P'; \sum_{s \in P'} \omega(s, u) = p_u, \forall u \in Q' \right\}$$

(31)

where $s$ and $u$ are the scenarios in the scenario sets $P'$ and $Q'$, $p_s$ and $p_u$ are the probabilities of scenarios $s$ and $u$ in $P'$ and $Q'$, respectively; $c(s, u)$ is a nonnegative, continuous, and symmetrical distance function; and $\omega(s, u)$ is the probability of scenarios $s$ and $u$. If $P'$ is the original scenario set, $Q'$ indicates the target scenario set, and formula (32) is equivalently expressed as

$$D_K(P', Q') = \sum_{s \in P', u \in Q'} p_s \min_{u \in Q'} c(s, u),$$

(32)

$$c(s, u) = \sum_{i=1}^{T} |P_{PV,i} - P_{PV,i}|,$$

(33)

where $T$ is the scheduling period and $P_{PV,i}$ and $P_{PV,i}'$ are the output power in period $t$ of scenarios $s$ and $u$, respectively. By presetting the required number of target scenarios according to the iteration of formula (33), the reduced output scenario is obtained.

The number of deleted scenarios will affect the results of scenario reduction. To make the number of deleted schemes appropriate, the maximum reduction limit of scenarios is proposed:

$$\sum_{u \in Q'} p_u \min_{j} c_{f_j}(\xi_{it}^u, \tilde{F}_j) \leq \vartheta,$$

(34)

where $\vartheta$ is the precision of the reduction of the pre-determined scenario to ensure the similarity between the reduced WPP or PV scenario and the initial scenario.

5. Solving Algorithm

This paper uses rough set theory to solve the multiobjective model. The calculation steps are as follows: (1) calculate the decision attribute analysis table of the system’s multi-objective scheduling model; (2) based on decision attribute analysis table, use the rough set theory to determine each objective’s weighted coefficient; and (3) convert into a single objective optimization model.

5.1. Decision Analysis Table of the Multiple Objective Function. Using the objective function as the optimization object, the model is solved, and the relationship between the objective functions is represented by a two-dimensional table. First, calculate the optimal objective $F_i (i = 1, 2, \ldots, I)$ of the objective function $i$ and then calculate the optimal objective of the $i$ objective function. The optimal objective of the $1-1$ objective function $F_i (i = 1, 2, \ldots, I - 1, I + 1, \ldots, I)$ obtains the following relationship as shown in Table 1, where $F_i$ is the value under the optimal condition $F_i$.

The maximum and minimum values of the function are calculated according to Table 1, which in turn determines the weight factor of the objective function to form the system scheduling composite objective function. As the objective functions, the system compensation and power abandonment costs are cost-based objective functions, the operating income is a benefit-type objective function, and different objective functions are not the same quantitative outline, which must be processed without a quantitative outline.

Dimensionless treatment of the benefit-type objective function:

$$F_{ij} = \frac{\max_{i} F_{ij} - F_{ij}}{\max_{i} F_{ij} - \min_{i} F_{ij}}, \quad j = 1, 2, \ldots, n.$$  \hspace{1cm} (35)

Dimensionless treatment of the cost-type objective function:

$$F_{ij} = \frac{F_{ij} - \min_{i} F_{ij}}{\max_{i} F_{ij} - \min_{i} F_{ij}}, \quad j = 1, 2, \ldots, n.$$  \hspace{1cm} (36)

5.2. Weighted Coefficient Calculation. After dimensionless processing, the objective function’s weighted coefficients must be determined according to the system optimization information of different objective functions. In this study, rough set theory is used to calculate the weight and transform it into the importance evaluation problem.

5.2.1. Model Building. Set the weight of $F_i$ as 1/1 and calculate the comprehensive target value $\tilde{F}$ when $D = \{\tilde{F}\}$ is the decision attribute set. $U = \{u_1, u_2, \ldots, u_n\}$ is the sample set, $u_j = (f_{i1}, f_{i2}, \ldots, f_{nj})$ is the sample, and $u_i$ is the optimal value of the comprehensive objective, and the attribute of $u_j$ is $F_i(u_j) = v_{ij}, F_i(u_j) = \tilde{F}$.
5.2.2. Calculate RV’s Dependence on RD.

\[
r_{R_{v_i}}(R_D) = \frac{\sum \rho[R_{v_i}(U_{R_{v_i}})]}{\rho(U)}
\]

(37)

where \( R_{v_i} \) is the knowledge base of \( R_{v_i} \), \( r_{R_{v_i}}(R_D) \) is \( R_{v_i} \)’s dependence on \( R_{v_i} \); \( \rho(U) \) is \( R_{v_i} \)’s set base; and \( \rho[R_{v_i}(U_{R_{v_i}})] \) represents all of the knowledge in \( U \) using the U/C classification that can determine the target set equivalent classification in U/D.

5.2.3. Calculate RV’s Dependence on \( R_{v_i}^{-|v_i|} \).

\[
r_{R_{v_i}^{-|v_i|}}(R_D) = \frac{\sum \rho[R_{v_i}^{-|v_i|}(U_{R_{v_i}^{-|v_i|}})]}{\rho(U)}
\]

(38)

where \( r_{R_{v_i}^{-|v_i|}}(R_D) \) refers to the degree of \( R_{v_i} \)’s dependence on \( R_{v_i}^{-|v_i|} \) and \( \rho[R_{v_i}^{-|v_i|}(U_{R_{v_i}^{-|v_i|}})] \) refers to all of the knowledge of the U/C classification in the whole U domain after removing the indicator \( v_i \).

5.2.4. Calculate the Weight Value of \( |i| \).

\[
\sigma_D(D) = r_{R_{v_i}}(D) - r_{R_{v_i}^{-|v_i|}}(D),
\]

\[
\lambda_i = \frac{\sigma_D(v_i)}{\sum_{i=1}^{\pi} \sigma_D(v_j)}
\]

(39)

where \( \sigma_D(D) \) represents the importance of objective \( i \) and \( \lambda_i \) is the weight coefficient of target \( i \). After calculating the weighting function, the optimal satisfactory solution of the microgrid system scheduling that takes into account each objective function can be solved.

6. Case Study

6.1. Basic Data. A microgrid system is designed to analyze the proposed model. The MS consists of four 100 MW wind turbines, a 10 x 20 MW energy storage system, 15 x 10 MW photovoltaic generators, and 30 x 20 MW gas turbines. The rated output power of the GT is 20.5 MW, the start-stop time is 0.1 h and 0.2 h, and the start-stop costs are 0.2 yuan/kW and 0.25 yuan/kW, respectively [32]. The cut-in wind speed, rated design wind speed, and cut-out wind speed of the wind turbine are 2.8 m/s, 13 m/s, and 23 m/s [33]. The shape parameter \( \phi = 2 \) and the scale parameter \( \nu = 2\pi \sqrt{\nu} \). The shape parameter sums of the PV distribution functions \( \alpha \) and \( \beta \) are 0.32 and 9.45, respectively [34]. Figure 2 shows the typical daily power load demand with a period length of \( \Delta t = 1 \) h. Before demand response, the microgrid’s purchase and sale prices are 0.49 yuan/kWh and 0.38 yuan/kWh [35, 36], respectively. After DR is designed, the purchase and sale prices of the microgrid are divided into peak, valley, and flat periods. The prices are shown in Table 2. The charge and discharge prices of the ESS are the peak valley TOU prices.

6.2. Scenario Settings. This section sets four scenarios to compare the effectiveness of the proposed model:

Scenario 1 is the basic scenario regardless of the uncertainty and demand response.
Scenario 2 only considers the uncertainty.
Scenario 3 only considers the demand response.
Scenario 4 takes into account both the uncertainty and demand response.

6.2.1. Basic Scenario. To analyze the effect of the uncertainty and demand response, the basic scenario without considering uncertainty and demand response is set. The simulation results show that due to the constraints and influence of the purchase and sale prices of the MS, its operation mode is generally the power output in the priority microgrid. The power is transmitted to the public network when the load is low, and the power is supplemented by the power purchase to the public network when the load is high. The ESS can effectively absorb the renewable power generation when the load is low to realize the effective use of power. Each unit’s output in the basic scenario is shown in Figure 2.

In the basic scenario shown in Figure 3, electric vehicles do not participate in the microgrid’s peak load regulation scheduling, but charge only according to the power demand. While the WPP and PV are fully absorbed in the microgrid, the power load is supplemented by the public grid and GT. Because uncertainty is not considered, the WPP and PV output fluctuate considerably. Although renewable energy can be consumed to a greater extent, they need to face the risk and power shortage costs caused by uncertainty. The ESS can increase the microgrid’s flexibility because it does not consider demand response, but it cannot obtain the income of the peak valley price difference and only plays a role in regulating the MS load.
6.2.2. Considering the Uncertainty Scenario. According to the WPP and PV scenario simulation and reduction methods proposed in this study, 20 typical scenarios are obtained. Scenario 1 with the largest probability of occurrence (0.295) and scenario 10 with the largest wind wave dynamics are selected as the results of the day ahead prediction and day ahead prediction of wind power, respectively, as shown in Figure 4. Similar to the WPP output, the PV output curve also uses the maximum probability scenario (scenario (2)) and maximum fluctuation scenario (scenario (5)) as the prediction results as demonstrated in Figure 5.

Considering the uncertainty of WPP and PV’s output will reduce the operation income, the unstable scheduling of wind power and photovoltaic is reduced, greater losses caused by wind and light abandonment is effectively avoided, and the reduced power generation of renewable energy will be supplemented by the GT and public grid power purchase. The microgrid’s power output considering the uncertainty is shown in Figure 6.

In the scenario considering uncertainty, as shown in Figure 7, due to the target control of the power shortage costs, the WPP and PV output is less than that of the basic scenario, but the system is more stable. A comparison of the two scenarios’ wind power and photovoltaic output is shown in the figure. Accordingly, as the load demand is basically unchanged, the reduction of the WPP and PV output leads to an increase in the public grid and gas turbine output.

6.2.3. Considering the Demand Response Scenarios. Figure 8 shows that the addition of demand response mainly affects the MS’s external power purchase and the GT’s output during peak and valley periods. Under the constraint conditions, the higher power sales revenue during peak hours increases the GT’s output and reduces the external power purchase. Compared with scenario 1, part of the load during the peak period is transferred to the period with lower external power prices, and the original load curve is
effectively reduced in the two peak periods 13:00–15:00 and 21:00–24:00. The ESS unit also makes full use of the advantages of the power price, charges during the period of low power price, and power releases during the period of peak power price, realizing energy conversion and time-sharing utilization and providing more power to the microgrid during peak hours. The load peak value of the microgrid with DR decreases from 943.05 MW to 928.08 MW, and the load valley value increases from 667.44 MW to 722.49 MW, which fully reduces the peak valley difference, causing peak cutting and valley filling, and improving the overall economy.

As shown in Figure 9, the implementation of demand response mainly affects the ESS and GT output and power purchase and sale of the public grid. The WPP and PV will also increase part of the output during peak hours, while the valley time does not decrease due to the impact of the energy abandonment cost. The EV charging load will also be affected by demand response, but due to travel time constraints and the necessity of charging at night, the change in the electric vehicle load with the demand response is not obvious most of the time. From 19:00 to 22:00, the external power supply revenue is high due to the peak time, the electric vehicle load changes from charging in the basic time to discharging, and from 0:00 to 7:00, more charging is used for power replenishment.

6.2.4. Integrated Scenario. Scenario 4 comprehensively considers the influence of the wind and light output uncertainty and demand response to ensure the stability of the MS while implementing the demand response. The specific output is shown in Figure 10.

Figure 10 shows the output of each unit in the composite scenario, and Figure 11 compares the composite scenario with the basic scenario. As shown in Figures 10 and 11, the uncertainty and demand response are considered in the comprehensive scenario. The WPP output is more stable than in the basic scenario. The power supply from the public grid to the MS is the most affected. Power output decreases during peak periods and increases significantly during trough periods. The output change of ESS is affected by the coupling of uncertainty and demand response. It is necessary to coordinate the change in the WPP and PV output and charge and discharge with the ESS’s price fluctuations. The nighttime load of the EV has no obvious fluctuation in the basic scenario. Under the comprehensive scenario, the load during the 19:00–22:00 peak period moves to the 0:00–7:00 valley period, which plays an important role in the peak load reduction and valley filling of the MS.

6.3. Analysis of Optimization Results. Table 3 shows the comparison of optimization results of each scheme. In terms of operating income and MS’s output risk, in scenario 2, due to WPP and PV power generation, the cost of microgrid energy abandonment increases by 194,200 yuan, and the net operating income decreases by 80,900 yuan, but the operating risk also declines accordingly, which demonstrates that decision-makers need to bear the reduction of part of
operating income to avoid risk loss; otherwise, to pursue excess income, they will bear the corresponding insurance. Demand response will greatly affect the revenue of MS, in scenario 3, the microgrid revenue increases by 67,100 yuan. The reason is that the micro-grid increases the electricity sales to the public grid during the peak period. The ESS and EV obtain the price difference income of the valley storage and peak discharge, and the WPP and PV abandon less energy and reach the maximum output under the constraints.
In terms of power generation capacity of the MS, in scenario 2, WPP and PV power generation capacity decline and the GT power generation capacity increases. Especially during the peak period, to make up for the reduction in renewable energy generation, the GT units increase from 511 MW to 542 MW. During the valley period, due to the low load demand, the GT power generation slightly increases, while during the normal period, GT power generation remains basically unchanged. In scenario 3, the peak period of the output equivalent curve shifts from 21:00–24:00 to 1:00–5:00 because the difference between the purchase and sale prices (including the difference between the charge and discharge price of the ESS) affects the decision-making of each unit during the peak and valley periods.

In terms of MS’s load demand, when the uncertainty is not taken into account, WPP and PV have the largest output in this scenario and MS bears a larger peak-to-valley ratio and more serious risks. Considering the uncertainty, due to the limited power output of the WPP and PV and the high transfer degree of the EV and ESS, the load curve’s peak valley ratio is 1.79 and the operation risk of the MS is minimal. Considering uncertainty can significantly improve the stability of the MS, and considering DR can significantly improve the economy of the MS and the benefits of internal agents.

7. Conclusions

The uncertainty of WPP and PV power generation is the main factor that affects power grid to absorb their power generation. In addition, the implementation of DR can guide users to use power reasonably and provide capacity space for MS. In this study, PBDR and IBDR models are introduced to solve these problems, and a multiobjective optimal microgrid scheduling model considering WPP and PVS uncertainties is constructed. The results of this study are as follows:

(1) Scenario reduction can overcome the influence of WPP and PV’s uncertainty; considering uncertainty, to reduce the penalty cost of power shortage and control the risk to the system by WPP and PV uncertainty, the system will reduce part of the renewable energy power generation capacity to improve the micro-grid’s stability.

(2) Considering the uncertainty will affect the scope of micro-grid scheduling, and the reduction of dispatching range corresponds to the improvement of micro-grid stability. Therefore, the impact of uncertainty on Microgrid scheduling should be given priority.

(3) Demand response can stimulate users to participate in the system’s peak load regulation to obtain intuitive economic benefits, which is conducive to mobilizing users to participate in the optimization of generation side dispatching to solve the problem of poor matching between the power and load sides.

(4) Under the effect of ESS and DR, WPP and PV’s uncertainty can be better suppressed, and the renewable energy utilization efficiency and operation stability of MS can be improved. The overall benefits are significant.

(5) The operation benefit of the optimized micro-grid system is higher than that of the basic scenario. The energy abandonment cost increases by a small margin because the system’s stability is obtained at the expense of some renewable energy generation benefits. In summary, the overall system benefits prove that the optimization model has better feasibility.

Data Availability

The basic data used to support the findings of this study have been deposited in the DOI repository.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

This study was supported by the National Science Foundation of China (grant no: 71573084) and the 2018 Key Projects of Philosophy and Social Sciences Research, Ministry of Education, China (grant no: 18JZD032).

References

[1] H. B. Julio, R. W. Josh, and J. R. Luke, “Optimal distributed energy resources and the cost of reduced greenhouse gas emissions in a large retail shopping center,” Applied Energy, vol. 155, pp. 120–130, 2015.

[2] A. Chatterjee and A. Keyhani, “Netural network estimation of microgrid maximum solar power,” IEEE Transactions on Power Electronics, vol. 26, no. 7, pp. 1913–1919, 2011.

[3] N. Gilles, “Importance of islands in renewable energy production and storage: the situation of the French islands”
Renewable and Sustainable Energy Reviews, vol. 47, no. 7, pp. 260–269, 2015.
[4] J.-H. Teng, S.-H. Liao, and C.-K. Wen, “Design of a fully decentralized controlled electric vehicle charger for mitigating charging impact on power grids,” IEEE Transactions on Industry Applications, vol. 53, no. 2, pp. 1497–1505, 2017.
[5] Q. Wang, C. Zhang, Y. Ding, G. Xydias, J. Wang, and J. Østergaard, “Review of real-time electricity markets for integrating distributed energy resources and demand response,” Applied Energy, vol. 138, pp. 695–706, 2015.
[6] Y. Zhang, H. F. Zhang, Y. Wang, and J. Wu, “Optimized scheduling model for isolated microgrid of wind-photo-voltaic-thermal-energy storage system with demand response,” in Proceedings of the IEEE Congress on Evolutionary Computation, pp. 1170–1175, Wellington, New Zealand, May 2019.
[7] A. G. Tskalakis and N. D. Hatziargyriou, “Centralized control for optimizing micro-grids operation,” IEEE Transactions on Energy Conversion, vol. 23, no. 1, pp. 241–248, 2008.
[8] M. Ross, C. Abbey, F. Boulfard, and G. Joos, “Multiobjective optimization dispatch for microgrids with a high penetration of renewable generation,” IEEE Transactions on Sustainable Energy, vol. 6, no. 4, pp. 1306–1314, 2015.
[9] A. Bracale, P. Caramia, G. Carpinelli, E. Mancini, and F. Mottola, “Optimal control strategy of a DC micro grid,” International Journal of Electrical Power & Energy Systems, vol. 67, pp. 25–38, 2015.
[10] P. Mayank, S. Siddharth, and H. Rob, “A multi-criteria decision analysis-based approach for dispatch of electric microgrids,” International Journal of Electrical Power & Energy System, vol. 88, pp. 99–107, 2017.
[11] H. S. Ramadand, A. F. Bendary, and S. Nagy, “Particle swarm optimization algorithm for capacitor allocation problem in distribution systems with wind turbine generators,” International Journal of Electrical Power & Energy Systems, vol. 84, pp. 143–152, 2017.
[12] M. J. Mohammad and K. Ahad, “Demand side management in a smart grid with multiple electricity suppliers,” Energy, vol. 81, pp. 766–776, 2015.
[13] B. Zeng, H. Q. Dong, S. Ramteen et al., “Bi-level robust optimization of electric vehicle charging stations with distributed energy resources,” IEEE Transactions on Industry Applications, vol. 56, no. 5, pp. 5836–5847, 2020.
[14] B. Zeng, Z. H. Feng, N. Liu et al., “Co-optimized public parking lot allocation and incentive design for efficient PEV integration considering decision-dependent uncertainties,” IEEE Transactions on Industrial Informatics, vol. 20, p. 1, 2020.
[15] M. Peik-Herfeh, H. Seifi, and M. K. Sheikh-El-Eslami, “Decision making of a virtual power plant under uncertainties for bidding in a day-ahead market using point estimate method,” International Journal of Electrical Power & Energy Systems, vol. 44, no. 1, pp. 88–98, 2013.
[16] H. Yang, D. X. Yi, D. Yi, J. Zhao, F. Luo, and Z. Dong, “ Distributed optimal dispatch of virtual power plant based on ELM transformation,” Journal of Industrial & Management Optimization, vol. 10, no. 4, pp. 1297–1318, 2014.
[17] J. J. Yang, J. H. Zhao, F. S. Wen et al., “Development of bidding strategies for virtual power plants considering uncertain outputs from plug-in electric vehicles and wind generators,” Automation of Electric Power Systems, vol. 38, no. 22, pp. 92–102, 2014.
[18] L. Duehee and B. Ross, “Future wind power scenario synthesis through power spectral density analysis,” IEEE Transactions on Smart Grid, vol. 5, no. 1, pp. 490–500, 2014.
[19] G. K. Nicole, H. Holger, and R. Werner, ”Scenario reduction and scenario tree construction for power management problems,” in IEEE Bologna PowerTech Conference, IEEE, Bologna, Italy, June 2003.
[20] H. Holger and R. Werner, “Scenario reduction algorithms in stochastic programming,” Computational Optimization and Applications, vol. 24, no. 2-3, pp. 187–206, 2003.
[21] J. Growe-Kuska and N. W. Romisch, “Scenario reduction in stochastic programming: an approach using probability metrics,” Mathematical Programming, vol. 95, no. 3, pp. 493–511, 2003.
[22] V. V. S. N. Murty Vallem and K. Ashwani, “Optimal energy dispatch in microgrids with renewable energy sources and demand response,” International Transactions on Electrical Energy Systems, vol. 30, no. 5, 2020.
[23] L. Abdul, C. D. Dulal, K. B. Amar, and R. Sudhanshu, “Illumination of demand response supported co-ordinated system performance evaluation of YSGA optimized dual stage PIFOD-(1+ P1) controller employed with wind-tidal-biodiesel based independent two-area interconnected microgrid system,” IET Renewable Power Generation, vol. 14, no. 6, 2020.
[24] A. Sheidai, “Multi-stage stochastic framework for energy management of virtual power plants considering electric vehicles and demand response programs,” International Journal of Electrical Power and Energy Systems, vol. 120, Article ID 106047, 2020.
[25] R. Sahbasadat, “Cost reduction in microgrid using demand response program of loads and uncertainty modeling with point estimation method,” International Transactions on Electrical Energy Systems, vol. 30, no. 4, 2020.
[26] Z. Tan, W. Fan, H. Li et al., “Dispatching optimization model of gas-electricity virtual power plant considering uncertainty based on robust stochastic optimization theory,” Journal of Cleaner Production, vol. 247, Article ID 119106, 2020.
[27] E. A. Seyed and R. Navid, “A new isolated renewable based multi-microgrid optimal energy management system considering uncertainty and demand response,” International Journal of Electrical Power and Energy Systems, vol. 118, 2020.
[28] R. Mostafā, E. Mohsen, H. A. Mohammad, H. M. Mohammad, and S. Pierluigi, “A Bi-layer multi-objective techno-economical optimization model for optimal integration of distributed energy resources into smart/microgrids,” Energies, vol. 13, no. 7, 2020.
[29] B. Zeng, X. Wei, B. Sun, F. Qiu, J. Zhang, and X. Quan, “Assessing capacity credit of demand response in smart distribution grids with behavior-driven modeling framework,” International Journal of Electrical Power & Energy Systems, vol. 118, no. 118, Article ID 105745, 2020.
[30] B. Zeng, J. Zhang, X. Yang, J. Wang, J. Dong, and Y. Zhang, “Integrated planning for transition to low-carbon distribution system with renewable energy generation and demand response,” IEEE Transactions on Power Systems, vol. 29, no. 3, pp. 1153–1165, 2014.
[31] Y. Kong, W. Wang, L. Yang, and X. Du, “Energy efficient strategies for anti-freezing of air-cooled heat exchanger,” Applied Energy, vol. 261, no. 261, Article ID 114468, 2020.
[32] S. Yu, Z. H. Wei, G. Q. Sun et al., “A bidding model for a virtual power plant considering uncertainties,” Automation of Electric Power Systems, vol. 38, no. 22, pp. 44–49, 2014.
[33] L. Ju, Z. Tan, J. Yuan, Q. Tan, H. Li, and F. Dong, “A bi-level stochastic scheduling optimization model for a virtual power plant connected to a wind–photovoltaic–energy storage system considering the uncertainty and demand response,” Applied Energy, vol. 171, pp. 184–199, 2016.
[34] N. Amjady, J. Aghaei, and H. A. Shayanfar, “Stochastic multiobjective market clearing of joint energy and reserves auctions ensuring power system security,” IEEE Transactions on Power Systems, vol. 24, no. 4, pp. 1841–1854, 2009.

[35] L. Pu, X. Wang, Z. Tan, J. Wu, C. Long, and W. Kong, “Feasible electricity price calculation and environmental benefits analysis of the regional nighttime wind power utilization in electric heating in Beijing,” Journal of Cleaner Production, vol. 212, no. 212, pp. 1434–1445, 2019.

[36] L. Pu, X. Wang, Z. Tan, H. Wang, J. Yang, and J. Wu, “Is China’s electricity price cross-subsidy policy reasonable? Comparative analysis of eastern, central, and western regions,” Energy Policy, vol. 138, no. 138, Article ID 111250, 2020.