Economic Dispatch of Energy System With Uncertain Renewable Energy Sources

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Abstract*—This work proposes an economic dispatch scheme for the energy robust optimal in microgrid. This scheme includes a two-stage robust optimization model which accounts for the uncertainties in the renewable energy source (RES) generation and the load demand using extreme scenarios strategy produced by the rules. The result of the inner function in the two-stage robust optimization is to generate extreme scenarios, and the result of the outer function is to optimize the system in the scenarios. The optimization model could be transformed into a single layer nonlinear mathematical structure through the above strategy. Moreover, the relationship between the cost and the demand response load adjustment factor is also analyzed. Finally, the impact of different purchase and sale price on system cost is analyzed. Numercial cases show the effectiveness of the model and solution strategy. In addition, the results also indicate that the demand response load adjustment factor affects the cost of the system and the satisfaction of users, which can provide references to microgrid investors and distribution system operator for energy planning and the design of incentive mechanism, respectively.

Keywords-component; economic dispatch; two-stage robust optimization; uncertainty set; extreme scenarios

I. INTRODUCTION

A variety of distributed energy, energy storage and load are integrated into the energy node, and its highly autonomous nature and connection to the distribution network is accomplished through coordinated internal operations[1-3]. Furthermore, an increasing number of renewable energy is connected to the grid for improving the environmental problems and energy crisis. However, the uncertainty of renewable energy increases the risk of system scheduling. Therefore, ensuring the minimum operating cost of energy system is widely referred to as the difficulty of energy management optimization problem with the uncertainties of renewable energy[4]. The microgrid economic operation model with multiple distributed energy sources is established in [5]. Energy storage system and rotating reserve method are used for economic dispatch of energy system, in which the dispatch results are more realistic due to the increase of multiple system constraints[6]. Distributed energy, load and energy storage units have contributed to the construction of microgrid operation optimization framework, in which energy storage units are regarded as generalized demand side resources[7]. In the aforementioned energy economic dispatch Currently, energy robust optimization considering uncertain factors is mainly as follows. A microgrid stochastic optimization model for electric vehicles and renewable energy is established in [8]. An adaptive algorithm that takes into account the uncertainty of load, electricity price and renewable energy is proposed in [9]. A method using Monte Carlo simulation to solve the problem of uncertainty scenarios and using mixed integer linear programming to solve the model is proposed in [10]. The power flow constraints in the microgrid are further considered in [11]. By combining the stochastic programming method with the conditional risk constraint method, the expected return under the corresponding scenario can be no less than a given confidence level. This method can achieve the purpose of reducing risk[12]. Among the above research methods, whether random planning or scenario analysis, it would lead to inaccuracy of the model. Robust optimization[13] is used as a common method for dealing with uncertain optimization problems. It is not necessary to know the probability distribution of uncertain data, and the purpose of reducing risk is achieved by establishing a set.

A two-stage robust optimization model and an extreme scenario solving strategy are established in this paper. Extreme scenarios will be solved in the first-stage of optimization. The optimal economic energy scheduling scheme under extreme scenarios is obtained by the second-stage optimization. The demand response load adjustment factor is added to the model, which can provide reference for the regulation of the microgrid dispatcher. In addition, through comparative analysis, the impact of electricity price on system operating costs is obtained.

II. MATHEMATICAL MODELING OF ENERGY SYSTEM

In this section, we formulate models for the energy system in which the total operational cost is considered.

A. Controllable distributed generators(CDG)

It is assumed that CDG owns MTs here. The objective of CDG can be formulated as follows[14].

$$C_{MG}(t) = n_{MG} P_{MG}(t) \bullet \Delta t \qquad (1)$$

$$P_{MG}^{\min} \le P_{MG}(t) \le P_{MG}^{\max} \qquad (2)$$

where $C_{MG}(t)$ is the operational cost of MT at time t, represented as the linear function. n_{MG} is the coefficient of the operational cost. $P_{MG}(t)$ is the power out of MT, Δt is the time interval of operation, which equals to 1. $P_{MG}^{\min} / P_{MG}^{\max}$ are the min/max generation of MT. The power out of MT in rach time period should satisfy the power and ramp constrains as (2).

B. Energy storages(ESS)

The schematic diagram of charging and discharging of energy storage unit is shown in "Fig.1", $E(t)$ is the current status of ESS. $P_E(t)$ is the charge and discharge power. $E^{\min} / E^{\max}$ is the min/max power of ESS. The charging and discharging process is satisfied:

$$E(t) = E(t-1) + P_E(t)\Delta t \tag{3}$$

The cost function of ESS in this chapter as follows:

$$C_E(t) = n_E[\eta_{ch} P_E^{ch}(t) + (1/\eta_{dis}) P_E^{dis}(t)]\Delta t \tag{4}$$

where $C_E(t)$ is the operational cost of ESS. n_E is the coefficient of the cost in ESS. η_{ch} is the efficiency of charging. $1/\eta_{dis}$ is the efficiency of discharging. $P_E^{ch}(t)$ / $P_E^{dis}(t)$ is the power of charging and discharging. Then equation (4) can be described as:

$$E(t) = E(t-1) + \eta_{ch} P_E^{ch}(t)\Delta t - 1/\eta_{dis} P_E^{dis}(t)\Delta t \tag{5}$$

The constraints of the cost function can be shown as:

$$E^{\min} < E(t) < E^{\max} \tag{6}$$

$$0 \le P_E^{dis}(t) \le U_s(t) P_E^{\max}, 0 \le P_E^{ch}(t) \le [1 - U_s(t)] P_E^{\max} \tag{7}$$

$$E(0) = E(T) \tag{8}$$

where $U_s(t)$ indicates the state of the ESS at time t. $U_s(t) = 1$ indicates that the ESS is charging. On the contrary, $U_s(t) = 0$ indicates that the ESS is discharging. $P_E^{\max}$ is the maximum charging/discharging power allowed by ESS.

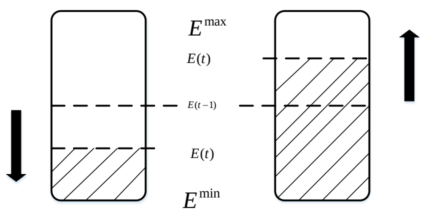

Figure 1. Schematic diagram of charging and discharging of energy storage unit

C. Load modeling

In this section, the full-time demand response load(FDR) is taken as the object of optimal scheduling based on the existence of the translatable load in the system. The operational cost of full-time demand response load is given by:

$$C_D(t) = n_D P_D(t) \times \Delta t \tag{9}$$

$$\sum_{t=1}^{N_T} P_D(t)\Delta t - DR = 0 \tag{10}$$

$$[1 - \delta_D(t)] P_D^*(t) \le P_D(t)\Delta t \le [1 + \delta_D(t)] P_D^*(t) \tag{11}$$

where $C_D(t)$ is the cost of FDR. $P_D(t)$ is the actual operational power. n_D is the coefficient of the FDR operational cost. $P_D^*(t)$ is the expected operational power. The coefficient of the operational full-time demand response load is δ_D, represented as consumer satisfaction.

D. Exchanged power model

The exchange cost is defined as the sum of expenditure and income produced by the power exchange with the main grid. The following model can be written as[15]:

$$C_M(t) = n_M(t)\Delta P_M(t)\Delta t \tag{12}$$

$$\Delta P_M(t) = P_b(t) - P_s(t) \tag{13}$$

$$\Delta P_M(t) = P_E^{ch}(t) + P_H(t) - P_{MG}(t) - P_E^{dis}(t) - P_{PV}(t) \tag{14}$$

$$0 \le P_b(t) \le U_M(t) P_M^{\max}, 0 \le P_s(t) \le [1 - U_M(t)] P_M^{\max} \tag{15}$$

where $\Delta P_M(t)$ is the power exchanged with the distribution network. $P_{PV}(t)$ is the power out of photovoltaic units (PV). $P_b(t)$ / $P_s(t)$ is the power that the system buys/sells from the distribution network. $n_M(t)$ is electricity price.

III. MATHEMATICAL MODELING OF ROBUST ENERGY MANAGEMENT

In this section, we formulate a two-sage robust model for energy optimization in which the uncertainties of PV and load demand are simultaneously considered.

A two-stage energy robust optimization model considering the uncertainty sets of PV and load is as follows[16]:

$$C_1 = \max_{u \in \boldsymbol{U}} \min_{y \in (x,u)} C \tag{16}$$

$$C = \min \sum_{t=1}^{N_T} [C_{MG}(t) + C_E(t) + C_D(t) + C_M(t)] \tag{17}$$

$$C_2 = \min_{y \in (x,u)} (C_1) \tag{18}$$

where x is a collection of binary variables for (7), (15). y is output variable in the optimization result, $P_L(t)$ is conventional load. C_1 is the first-stage of optimization. C is deterministic optimization function. C_2 is the second-stage of optimization.

Considering the actual operation of the power grid and the constraints of the comprehensive supply and demand balance (14), it can be seen that each of the PV units is taken as the lower bound of the fluctuation interval, and when the load unit is taken as the upper bound of the fluctuation interval, the system can better conform to the characteristics of the extreme scenarios. The uncertainty set can be rewritten as follows:

$$U = \begin{cases} u = [u_{PV}(t), u_H(t)] \quad , \quad t = 1,2,3 \ldots N_T \\ u_{PV}(t) = \hat{u}_{PV}(t) - \xi_{PV}^{\max}(t) \\ u_H(t) = \hat{u}_H(t) + \xi_H^{\max}(t) \\ \xi_{PV}^{\max}(t) \in [\xi_{PV}^{\max}(1), \xi_{PV}^{\max}(2), \xi_{PV}^{\max}(3) \ldots \xi_{PV}^{\max}(B_{PV})] \\ \xi_H^{\max}(t) \in [\xi_H^{\max}(1), \xi_H^{\max}(2), \xi_H^{\max}(3) \ldots \xi_H^{\max}(B_L)] \\ B_{PV} = 1,2,3 \ldots N_T \\ B_H = 1,2,3 \ldots N_T \\ \sum B_{PV} \le \Gamma_{PV} \\ \sum B_H \le \Gamma_H \\ \upsilon_{PV} = \dfrac{\hat{u}_{PV}(t) - \xi_{PV}^{\max}(t)}{\hat{u}_{PV}(t)} \\ \upsilon_H = \dfrac{\hat{u}_H(t) + \xi_H^{\max}(t)}{\hat{u}_H(t)} \end{cases} \tag{19}$$

where B_{PV} , B_H is represented as the feature of selected scenario. $\xi_{PV}(t)$, $\xi_H(t)$ is the error of uncertain value. Γ_{PV} , Γ_H represents the adjustable selection coefficients of uncertain scenario in the day-ahead scheduling scheme and the number of uncertain scenarios selected in the total time period. υ_{PV} , υ_H represent the error proportionality coefficients of uncertain sets, respectively. Redefining the uncertain scenario set by selecting the upper and lower bounds of variables can greatly reduce the number of scenario traversal.

IV. SOLUTION STRATEGY

A solution strategy to obtain the extreme scenario sequence by traversing the comparison cost will be presented in this section. The specific solution process is as "Fig.2":

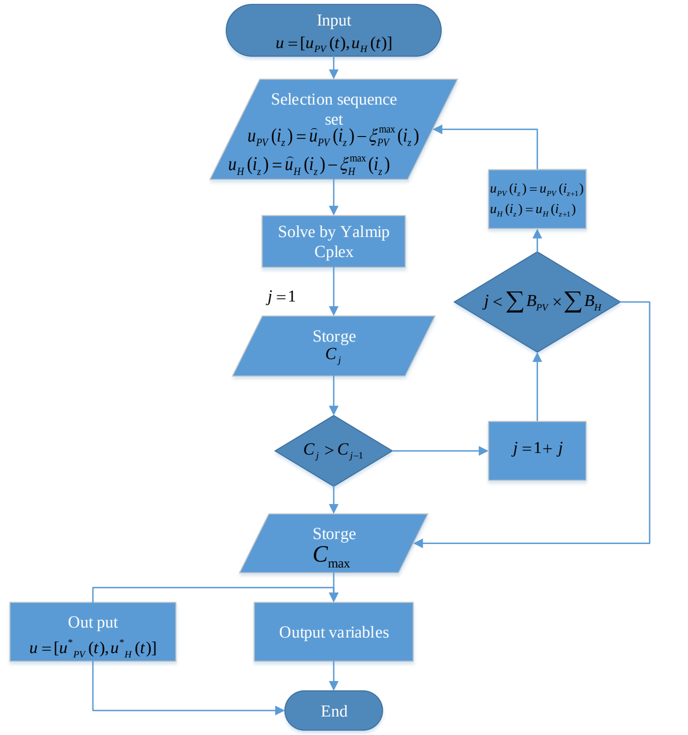

Figure 2. Algorithm flowchart

where $\{u_{PV}(i_z), u_H(i_z)\}$ represents each time the sequence set of PV and load unit which are selected, i_z represents the sequence combination from 1 to N^T, and the size of the sequence is equal to $\sum B_{PV}$ and $\sum B_H$ respectively. By comparing the sequence sets corresponding to the maximum cost stored at each time, when the sequence sets get the regulated parameters of the specified uncertain sets, the qualified sequence sets and the optimal solution of the corresponding objective function can be solved and the optimal coordination scheme in the extreme scenario can be obtained.

V. EXAMPLE ANALYSIS

Taking the system structure diagram shown in "Fig.3" as an example.

A. Economic Optimal Scheduling Scheme Simulation Analysis

The system operation parameters are from [15], the other parameters are shown in Table 1.

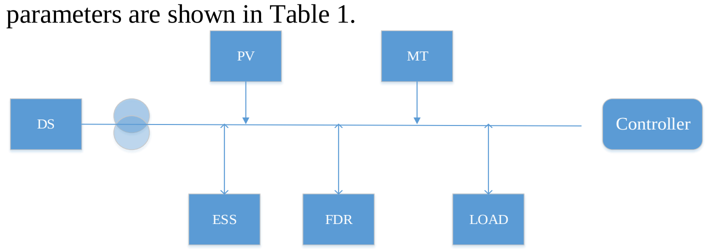

Figure 3. System structure diagram

TABLE I   OPERATIONG PARAMETERES

Untis	Parameter	Value
FDR	δ_{P_D}	20%
Uncertain set adjustment parameter	Γ_{PV}	6
	Γ_{H}	12
Uncertain set error scale factor	υ_{PV}	0.9
	υ_{H}	1.5

The price of a city day-ahead distribution network and the day-ahead demand response load power of each period are shown in [15]. The day ahead predicted power of PV and load unit is also shown in [15]. The simulation results are as follows:

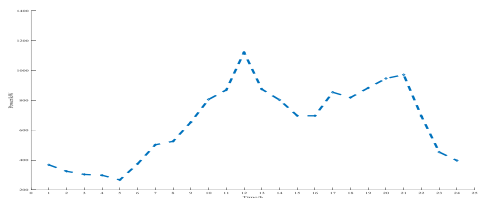

Figure 4. Actual dispatch load power curve

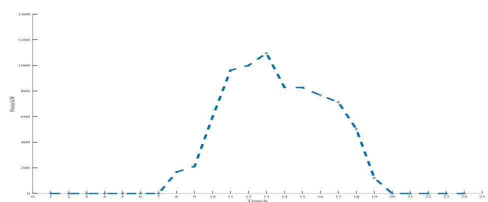

Figure 5. Actual dispatching photovoltaic power generation curve

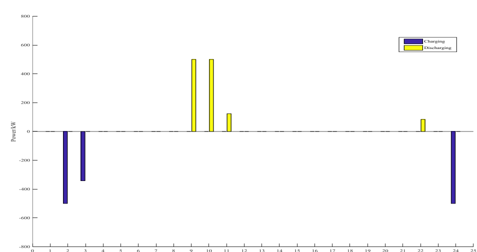

Figure 6. Energy storage unit charging / discharging power

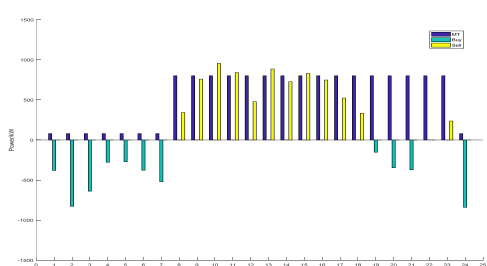

Figure 7. Output power of micro turbine & the change power of grid distribution net work

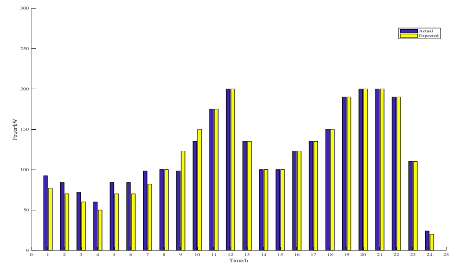

Figure 8. Planned power of actual / expected demand response load dispatch

From the simulation results, it can be seen that the minimum power output of micro-gas turbine is 80kW, the maximum power output is 800KW from 8 to 23, and the minimum power output is from 24. The output power of PV unit is zero from 1 to 7 and 24, and according to the price data, it can be seen that the electricity price is lower than the operation cost of MT at this time. During this period, MT operate with minimum power to meet the objective of optimal operating costs. During the period of 8-23, PV units began to produce power, and the increase of electricity price during this period made MT output the maximum power to sell power to the distribution network for earning revenue and achieve the purpose of reducing operating costs. As can be seen in "Fig.6", charging in period 2, 3 and 24 and discharging in period 9 to 11 can also be carried out according to the electricity price, so that the electricity in the lower period can be stored in the energy storage unit to meet the demand of the system during the peak period of the load. In " Fig.8", it can be seen that the demand load response adjustment coefficient exists, which makes it possible to adjust the load to a lower demand period while satisfying the user satisfaction and the total demand response load constraints, so as to meet the optimization purpose. The effectiveness of the optimization model and the solution strategy proposed in this chapter is verified by simulation.

B. Simulation comparison and analysis of the impact of demand load response coefficient on the system

In this section, different demand load response coefficients are adopted to analyze the impact on the system through simulation results

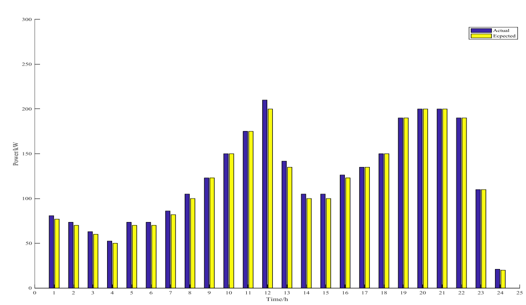

Figure 9. Optimized scheduling results when the demand response load adjustment factor is 0.05

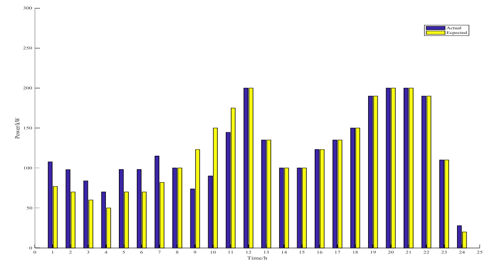

Figure 10. Optimized scheduling results when the demand response load adjustment factor is 0.4

In "Fig.10", the actual demand response dispatch load and the expected demand response load in periods 1 to 7 and 9 to 11 are quite different. Same in "Fig.10", when the demand response adjustment coefficient increasing, the system optimization process allocates the demand response load in high load period to low demand period. When the coefficient value is 0.05, the adjusted power is small. The simulation results of the two cases can also observe that the change of other variables is small.

C. *Simulation and Analysis of the Impact of Electricity Price on Operation Cost*

The same period price for convenience comparison is adopted in this case, but the simulation conditions of purchase and sale price are different. The simulation results are shown in "Fig.11". Compared with the consideration of uncertainty and only relying on interactive power to balance costs, the optimization result in this chapter is more stable.

VI. SUMMARY

This paper aims to solve the economic dispatch problem for energy node with uncertainties. The main advantages of these strategies include the following.

1) The designed extreme scenario solving strategy can effectively obtain the required scenario values in the two-side robust optimization. Compared with the dual programming method, the solution dimension is reduced.

2) The adjustment factor of the demand response load is introduced, and the commonly used upper and lower bounds are replaced by the coefficient, which can provide a reference for the operator.

3) The characteristics of purchasing electricity price and selling electricity price are introduced into the model. By comparing with other optimization models, the cost change is more gradual in our model.

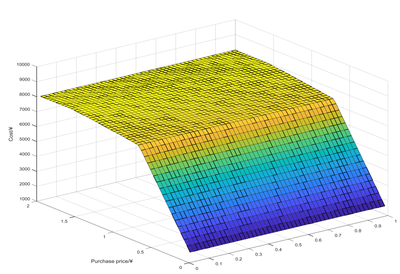

Figure.11 Size and proportion analysis of electricity price

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