Distributed Robust Optimization of Integrated Energy System Considering Integrated Demand Response

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Abstract. Integrated energy system is receiving extensive attention. In order to solve the problem of economic operation caused by uncertainty of renewable energy generation in integrated energy system, a distributed robust optimization method considering integrated demand response is proposed. Firstly, the optimization model of integrated energy system is established by taking the minimum total cost of system operation as the objective function. Secondly, the probability distribution of the random vector of power prediction error is described in the form of set, which does not need to limit the probability distribution form of the random vector, but describes all possible probability distribution of the random variable by moment uncertainty ambiguity sets. Thirdly, the demand response is considered to alleviate the economic growth of integrated energy system in response to uncertainty. Finally, the effectiveness of proposed method is proved by a simple integrated energy system.

1. Introduction
Energy Internet (EI) is an inevitable choice to solve the contradiction between the growing energy demand of human society and the increasingly serious energy shortage and environmental pollution. As the physical carrier of energy Internet, integrated energy system (IES) is receiving extensive attention [1]. Compared with electricity, gas, heat, cold and other independent energy supply systems, IES can convert fossil energy and renewable energy of different quality and characteristics into a variety of energy that meet the needs of users, including cold, heat, electricity and so on. Therefore, IES optimizes the use of different energy sources, improves the utilization rate of renewable energy, and has good development and application prospects [2].

Increasing the proportion of renewable energy to achieve energy transformation is the only way for sustainable development [3]. However, with the participation of large-scale renewable energy in the operation of integrated energy system, the uncertainty of its prediction error increases the difficulty and challenge of system economic dispatch [4]. The most direct performance is how to describe the uncertain factors reasonably and accurately with mathematical methods and how to alleviate the uncertainty and get the optimal decision results.

At present, stochastic optimization (SO) and robust optimization (RO) are widely used to build uncertain models of renewable energy output. SO transforms the uncertain problem into the
deterministic problem by assuming the probability distribution of data and then sampling or analytical derivation [5], which requires that the probability distribution of random variables with high accuracy be obtained first. RO deals with the worst scenario in the uncertain set of random variables to obtain the optimal decision that can deal with all uncertain scenarios [6]. But it is precisely because RO does not need uncertain probability information that its decision results tend to be conservative. Therefore, in order to better balance the economy and the ability to deal with uncertainty, a compromise method, namely distributed robust optimization (DRO), has received widespread attention. DRO is based on RO, changing the uncertain set describing the value of random variables into ambiguity set describing the uncertain probability distribution of random variables, and optimizing the worst probability distribution scenario in ambiguity set. DRO method considering the uncertainty of wind power is proposed for unit commitment optimization in [7]; the ambiguity sets of wind power output and reserve capacity are constructed based on the moment information of uncertainty in [8]; the uncertainty of wind power in electricity-gas system is described by DRO method, and it is proved that DRO has better economy than RO in [9]. At the same time, literature [10] has proved that demand response can reduce electricity price by reducing network congestion in the field of dispatching; literature [11] has proved that in view of the need to deal with uncertain renewable energy output, demand response (DR) resources can gradually highlight its potential value through flexible participation in the system scheduling process.

In conclusion, considering the uncertainty of renewable energy output is one of the important research directions for the optimization of IES with renewable energy system. At the same time, the important value of integrated demand response for improving system economy needs to be further studied in the field of IES. Therefore, this paper proposes a DRO method of IES considering integrated demand response. The DRO method is used to deal with the uncertainty of renewable energy output, and the demand response resources are used to mitigate the uncertainty of the system. The effectiveness of the proposed model is verified by several groups of numerical examples.

2. The construction of IES model

2.1. Constraints of IES considering integrated demand response

The IES includes gas turbine (GT), gas boiler (GB), absorption chiller (ABSC), air conditioner (AC), electric energy storage equipment (EES) and cold energy storage equipment (CES). In addition, IES achieves power balance by interacting with power grid and heating network. In order to ensure the safety of system operation, the formula (1) - (27) should be satisfied.

\[ H'_{GB} = N'_{GB} \eta_{GB} \lambda_{gas} \]  \hspace{1cm} (1)

\[ P'_{GT} = N'_{GT} \eta_{GT} \lambda_{gas} \]  \hspace{1cm} (2)

\[ H'_{GT} = P'_{GT} R_{GT}^{he} \]  \hspace{1cm} (3)

\[ R_{GT}^{he} = \frac{H'_{GT}}{P'_{GT}} \]  \hspace{1cm} (4)

\[ Q'_{ABSC} = COP_{ABSC} H'_{ABSC} \]  \hspace{1cm} (5)

\[ P'_{ABSC} = \eta_{ABSC} H'_{ABSC} \]  \hspace{1cm} (6)

\[ Q'_{AC} = COP_{AC}^e P'_{AC,e} \]  \hspace{1cm} (7)

\[ H'_{AC} = COP_{AC}^h P'_{AC,h} \]  \hspace{1cm} (8)
\[ S_{ES,j}^{t+1} = (1 - \alpha_{ES,j}) S_{ES,j}^{t} + \eta_{ES,j}^c P_{ES,dis,j}^{t} - \frac{P_{ES,dis,j}^{t}}{\eta_{ES,j}^{dis}} \] (9)

Formula (1) shows energy conversion relationship of GB. Where, \( N_{GB}^t \), \( H_{GB}' \) represents natural gas consumption rate and thermal power output of GB in the t-th scheduling time respectively; \( \eta_{GB} \) is heat generation efficiency of GB; \( \lambda_{gas} \) is calorific value of natural gas. Formulas (2) - (4) show energy conversion relationship of GT. Where, \( N_{GT}^t \), \( P_{GT}^t \), \( H_{GT}' \) represent natural gas consumption rate, output electric power and thermal power of GT in the t-th dispatching time respectively; \( \eta_{GT}^c \), \( \eta_{GT}^e \) are generation efficiency and thermal power ratio of GT. Formulas (5) - (6) show energy conversion relationship of ABSC. Where, \( H_{ABSC}' \), \( P_{ABSC}^t \), \( Q_{ABSC}^t \) are heat consumption power, power consumption power and cooling power of ABSC in the t-th scheduling time; \( COP_{ABSC}^c \), \( \eta_{ABSC} \) are refrigeration energy efficiency ratio and power consumption coefficient of ABSC. Formulas (7) - (8) show energy conversion relationship of AC. Where, \( H_{AC}' \), \( Q_{AC}^t \), \( P_{AC,h}^t \), \( P_{AC,c}^t \) are heating power, cooling power, heating power and cooling power of AC in the t-th scheduling time respectively; \( COP_{AC}^c \), \( COP_{AC}^e \) represent heating energy efficiency ratio and heating energy efficiency ratio of AC respectively. Formula (9) shows the relationship between the capacity of energy storage equipment and the charging or discharging power, and \( \alpha_{ES,j} \) represents the self-loss coefficient of the i-th energy storage device.

\[ P_{buy}^t - P_{sell}^t + P_{GT}^t + P_{PV}^t = P_{ABSC}^t + P_{AC}^t + \eta_{ES,j}^{ch} P_{ES,dis,j}^t - \frac{P_{ES,dis,j}^t}{\eta_{ES,j}^{dis}} + P_{EES}^t \] (10)
\[ H_{buy}^t - H_{sell}^t + H_{GB}' + H_{GT}' = H_{ABSC}' + H_{AC}' + H_{L}' \] (11)
\[ Q_{ABSC}^t + Q_{AC}^t = \eta_{CES,j}^{ch} P_{CES,dis,j}^t - \frac{P_{CES,dis,j}^t}{\eta_{CES,j}^{dis}} + Q_{L}^t \] (12)

Formulas (10) - (12) represent energy balance constraints of IES. Formula (10) represents the balance of electric power, where, \( P_{buy}^t \), \( P_{sell}^t \) represent power purchased from the external network and the power sold to the external network in the t-th dispatching time respectively; \( P_{AC}^t \) represent electrical consumption of AC in the t-th scheduling time, when AC is in cooling status, \( P_{AC}^t = P_{AC,c}^t \), \( P_{PV}^t \) represents photovoltaic output of the t-th dispatching time; \( P_{LC}^t \) represents the electrical load of the t-th dispatching time. Formula (11) denotes the thermal power balance, where, \( H_{buy}^t \), \( H_{sell}^t \) denote thermal power purchased by the IES from the external network and the thermal power sold by IES to the external network in the t-th dispatching time respectively; \( H_{AC}' \) only exists when the air conditioner is in heating state, \( H_{L}' \) is heating load of the t-th scheduling time. Formula (12) represents cold power balance, where, \( Q_{AC}^t \) exists only when the air conditioner is in the cooling state, \( Q_{L}^t \) represents the cooling load of the t-th scheduling time.

In order to ensure the normal operation of IES, it is also necessary to meet the operation constraints of the equipment, as shown in (13) - (27).
Formulas (13) - (24) indicate the upper and lower limits of equipment operation. Where, $P_{buy}^t$, $P_{sell}^t$, $H_{buy}^t$, $H_{sell}^t$, $P_{GT}^t$, $P_{AC}^t$, $P_{ES,ch,i}^t$, $P_{ES,div,i}^t$, $S_{ES,i}^t$, represent state variables of power purchase, power sale, heat purchase, heat sale and energy charging and discharging. For example, when IES purchases power from the external power grid, $P_{buy}^t = 1$, otherwise, $P_{buy}^t = 0$; Formula (25) shows at the last time of the scheduling period, the stored energy of the energy storage equipment is equal to the energy at the first time, so as to ensure the normal operation of the later scheduling time. Formulas (26) - (27) represent the climbing constraints of GT and GB respectively.

Load can be composed of fixed load and translatable load. The fixed load requires high reliability, and the energy consumption time is determined to ensure normal production and life. The translatable load allows the user to adjust consumption power and time independently according to the energy price, which needs to meet the following constraints:

$$L_i = L_{f,i} + L_{t,i}$$
$$0 \leq L_{t,i} \leq L_{t,i}^\text{max}$$
$$\sum_i L_{t,i} \Delta t = V_{t,j}$$

Where, $i = \{1,2,3\}$ refers different kinds of loads of electricity, heat and cold, and $L_i$, $L_{f,i}$, $L_{t,i}$, $L_{t,i}^\text{max}$, $L_{t,i}^\text{max}$ refer load value, fixed load, translatable load and maximum translatable load of the i-th load of users in the t-th dispatching time respectively, for example $L_i = \{P_L^t, H_L^t, Q_L^t\}$; $V_{t,j}$ represents the total
amount of translatable load in the whole dispatching time, formula (30) denotes that the total amount of translatable load before and after demand response is required to remain unchanged.

2.2. Objective function

The objective function of deterministic optimization consists of operating cost $C_{om}$, energy purchase cost $C_{buy}$, and fuel cost $C_{fuel}$, as shown in formulas (31) - (34). Where, $c_{om}^{ES,i,j}, c_{om}^{ABSC}, c_{om}^{GB}, c_{om}^{AC}$ respectively, represents the unit operation cost of the i-th type of energy storage equipment, ABSC, GB and AC; $c_{grid}^{t}, c_{heat}^{t}, c_{gas}^{t}$ represent the price of electricity, heat and natural gas in the t-th dispatching time.

$$C = C_{om} + C_{buy} + C_{fuel}$$ (31)

$$C_{om} = \sum_{i}^{T} \left( \sum_{j}^{y} c_{om}^{ES,i,j} (P_{ES,dis,j}^{t'} + P_{ES,ch,j}^{t'}) + c_{om}^{ABSC} H_{ABSC}^{t'} + c_{om}^{GB} H_{GB}^{t'} + c_{om}^{AC} P_{AC}^{t'} \right) \Delta t$$ (32)

$$C_{buy} = \sum_{i}^{T} \left( c_{grid}^{t'} (P_{buy}^{t'} - P_{sell}^{t'}) + c_{heat}^{t'} (H_{buy}^{t'} - H_{sell}^{t'}) \right) \Delta t$$ (33)

$$C_{fuel} = \sum_{i}^{T} \left( c_{gas}^{t'} H_{GB}^{t'} + c_{gas}^{t'} P_{GT}^{t'} \right) \eta_{GB} + \eta_{GT} \Delta t$$ (34)

2.3. Ambiguity set

The DRO of IES considering demand response proposed in this paper is shown in (35) with the form of matrix.

$$\min \{ c_{h}^{T} x + \sup_{\xi \in \Omega} E_{p} \{ L(x, \xi) \} \}$$

s.t. $Ax \leq c$

$$Cx + D\xi = h$$ (35)

Where, $x$ represents decision variables in deterministic optimization model. $E_{p} \{ L(x, y, \xi) \}$ represents the expectation of discarded PV generation in the distribution P of uncertain variables $\xi$, $\Omega$, $\Xi$ are ambiguity set and extended ambiguity set of the uncertainty of $\xi$ respectively, as shown in formulas (36)-(37).

$$\Omega = \left\{ p \in P(R) \left| \begin{array}{l} \xi \in R \\ E_{p}(\xi) = \mu \\ E_{p}(\xi^{2}) = \sigma^{2} \\ p(\xi \leq \xi \leq \xi) = 1 \end{array} \right\} \right\}$$ (36)

$$\Xi = \left\{ Q \in P(R^{2}) \left| \begin{array}{l} \xi \in R, u \in R^{2} \\ E_{Q}(\xi) = \mu \\ E_{Q}(\xi^{2}) = u \\ Q(\xi \leq \xi \leq \xi) = 1 \end{array} \right\} \right\}$$ (37)
3. Case Analysis

In order to verify the effectiveness of the proposed method in the paper, the IES of an industrial park is analysis. Four scenarios are set in this part to fully verify the influence of DRO and demand response in IES.

- Case 1: Optimization of IES in deterministic scenario;
- Case 2: On the basis of case 1, the integrated demand response is considered;
- Case 3: On the basis of case 1, the DRO method is used to deal with the uncertainty of photovoltaic prediction error;
- Case 4: On the basis of case 3, the integrated demand response is considered.

The optimization results of case 1 are shown in Figure 1-3, which respectively show the equipment output and corresponding load curves in electric balance, heat balance and cold balance. From the figure, it can be seen that the power balance at each time is realized through energy interconnection and complementation. Taking electricity balance as an example, when the electricity price is lower, the power of GT is 0 and system purchases electricity from the grid to meet the electricity load, at the same time, the surplus electric energy is used to charge the battery. When the electricity price is higher, GT, which is more economical than direct power purchase, is used to generate electricity and discharge the battery, so as to improve the economy of the system.

![Figure 1. Electrical load and electrical power balance of optimization results.](image1)

![Figure 2. Heating load and heat power balance of optimization results.](image2)

![Figure 3. Cooling load and cool power balance of optimization results.](image3)
Figure 4-6 show the operation results of the integrated demand response of case 2. It can be seen that, compared with the original load curve, the peak of electrical load, heating load and cooling load curves are cut to fill the valley in case 2 with the comprehensive demand response is considered, the translatable load at the peak time of electricity price is transferred to the lower time, which is of great significance to the safety and economic operation in IES.

Table 1 shows the operation cost of the system with different operation modes of case 1-4. It can be seen from the table that the total daily operation cost of IES in the four operation modes are 126300, 125180, 126610, 125490 yuan respectively. By comparing case 1 and case 2, it can be seen that daily operation cost of IES is reduced by 1120 yuan through users' participation in demand response. By comparing case 1 and case 3, it can be seen that daily operating cost of IES increases by 310 yuan when considering the uncertainty of photovoltaic output. By comparing case 3 and case 4, it can be seen that considering the integrated demand response of users can offset some of the costs used to deal with the uncertainty of photovoltaic output.

| Case | Cost   |
|------|--------|
| Case1| 126300 |
| Case2| 125180 |
| Case3| 126610 |
| Case4| 125490 |
4. Conclusion
In this paper, a DRO model of IES considering integrated demand response is constructed, and the effectiveness of the proposed method is verified by a numerical example. It can be concluded that the IES can realize multi-energy interconnection and complementarity. When considering the uncertainty of photovoltaic output, it will increase some cost to ensure the system can still operate safely and economically even in the possible worse scenario. At the same time, if integrated demand response is considered, the effect of peak load reduction and valley filling can alleviate the cost increase caused by the uncertainty of renewable energy to a certain extent.

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