Robust day-ahead dispatch for combined heat and power microgrid considering wind-solar power uncertainty

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Abstract. Due to the energy crisis and environment pollution, small-scale wind power and photovoltaics have been widely deployed in power system using microgrid (MG). Moreover, several researches have focused on incorporating various energy forms into MG. However, the uncertainties of wind power and photovoltaics may significantly impact the security and economy of the MG operation. To deal with this issue, this paper presents a two-stage robust model to achieve the optimal day-ahead economic dispatch strategy involving uncertain wind power and photovoltaics. The first stage decides the initial day-ahead dispatch strategy before the realization of uncertain wind power and photovoltaics. The additional adjustment action is made in the second stage as long as the uncertainties are observed. The column and constraint generation (C&CG) decomposition is employed to decompose the original model into the day-ahead dispatch master problem and the additional adjustment sub-problem. Based on the duality theory and Big-M approach, the sub-problem with complex max-min structure can be converted into a tractable mixed-integer linear programming (MILP) problem. Therefore, C&CG iteration algorithm can be further implemented to achieve the optimal day-ahead economic dispatch strategy for the MG. The experimental results of the comparisons to the deterministic optimization demonstrate the effectiveness of the presented optimization.

1. Introduction
Currently, due to the energy crisis and environment pollution, the intermittent energy resources (IER) generations have been widely deployed in modern power system using microgrid (MG). In researches [4, 5], MG has been proven to be an effective way to integrate wind power and photovoltaics. Moreover, along with the developments of energy technologies, several researches have focused on incorporating various energy forms into MG for example heating and electricity. As a result, combined heat and power system-based MG (CHP-MG) shows remarkable effectiveness in terms of satisfying multiple load demands and accommodation of IER [6, 7].

However, the uncertainties of IER, especially the uncertainties of wind power and photovoltaics, challenge the economy of the system operations [8-13]. Among the operations, day-ahead economic dispatch (ED) [14] determines the optimal allocation of the outputs of the controllable generators (CG), which is widely admitted as an underlying fundamental. Therefore, it is necessary to implement the MG operation involving uncertain wind power and photovoltaics. In this regard, several researches have presented various heuristic algorithms and mathematic approaches to achieve the optimal ED strategy. However, two main disadvantages prevent the heuristic algorithms from being effectively employed [15, 16]. The first one is that the heuristic algorithms are often trapped in computationally
intensive issues. The second one is that the algorithms usually converge into the locally optimum solution. Consequently, the mathematical optimization approaches, especially deterministic optimization (DO), stochastic optimization (SO), and robust optimization (RO) have been widely researched to figure out the optimal ED strategy.

Research [17] presented deterministic optimal ED model for power-gas system. Their experimental results demonstrated the practicality of DO. However, researches [18-20] pointed out that the uncertainties of wind power and photovoltaics are not considered in DO, which may result in sub-optimal issue of the DO-based optimal economic dispatch strategies. Furthermore, SO has been presented to solve the power flow [18], unit commitment [19], and energy management optimizations problems [20] involving the uncertainties. However, research [21] pointed out that SO requires accurate distribution of the uncertainties, which is a huge challenge for the current wind prediction technology. Therefore, RO has been gradually studied in several researches. The objective of RO is to immunize the operation strategy against the worst-case scenarios over a set of all possible scenarios, which does not require the accurate distribution. A single-stage robust optimization model was introduced in research [22] to deal with the uncertainties of wind power and load demand. However, researches [23, 24] pointed out that the single-stage robust optimization tends to be over-conservative. In this regard, the two-stage robust optimization model with min-max-min structure was studied in researches [23, 24]. Furthermore, Ben-Tal et al. [25] introduced a budget parameter in RO to adjust the pessimistic degree of the worst-case scenarios. By applying budget parameter, RO is upgraded into the adjustable RO (ARO), which has great potential to balance the economy and robustness of the optimization.

Motivated by the aforementioned researches, this paper employs ARO as the underlying approach to achieve the optimal day-ahead ED strategy for the CHP-MG involving uncertain wind power and photovoltaics. Firstly, a two-stage ED model is presented for CHP-MG. In the first stage, the initial day-ahead strategy is decided before observing the uncertain wind power and photovoltaics. As long as the uncertainties are observed in the second stage, the additional adjustment decision is made to correct the day-ahead strategy. Secondly, based on ARO, the uncertainty set is constructed to describe the uncertainties of wind power and photovoltaics. Thirdly, by applying C&CG algorithm, the original model with complex min-max-min structure is effectively decomposed into a master problem (MP) and a sub problem (SP). Based on the duality theory and Big-M approach, SP with min-max structure is then converted into a tractable MILP. As a result, the original model is able to be solved directly by iterations between MP and SP.

The rest of the paper is organized as: section 2 constructs the two-stage ARO ED model for CHP-MG with involving uncertain wind power and photovoltaics; section 3 presents the model solution; section 4 shows and discusses the experiment results; section 5 concludes paper.

2. Two-stage day-ahead ED for CHP-MG

2.1. Objective function

The two-stage ARO model can be presented by Eq. (1) [21].

\[
\begin{align*}
\min_x \{ C_{DA}(x) + \max_u \min_y C_{AA}(u, y) \} \\
\end{align*}
\]  

(1)

where \(x\) denotes the first-stage dispatch strategy, \(x\) includes output of the fuel cell \(P_{FC}\), output of the microturbine \(P_{MT}\), sold power with the grid \(P_{sold}\) and purchased power with the grid \(P_{purchased}\). \(C_{DA}\) is the conventional day-ahead operation cost of CHP-MG. The details of \(C_{DA}\) are expressed by Eq. (2).

\[
C_{DA} = \sum_{t=1}^{T} \left( a_{FC} \cdot P_{FC}(t) + b_{FC} + a_{MT} \cdot P_{MT}(t) + b_{MT} - \lambda_{Grid}^{sold}(t) P_{Grid}^{sold}(t) + \lambda_{Grid}^{purchased}(t) P_{Grid}^{purchased}(t) \right)
\]  

(2)

where \(a_{FC}\) and \(b_{FC}\) are the coefficients of the fuel cell; \(a_{MT}\) and \(b_{MT}\) are the coefficients of the microturbine; \(\lambda_{Grid}^{sold}\) and \(\lambda_{Grid}^{purchased}\) are the sold and purchased prices with the grid; \(P_{Grid}^{sold}\) and \(P_{Grid}^{purchased}\) are the sold and purchased power.
The first-stage makes initial day-ahead ED strategy only based on the predicted values of the wind power and photovoltaics. However, the imprecise prediction may result in power imbalance in CHP-MG. Therefore, the additional adjustment action \( C_{AA} \) is made in the second stage once the wind power and photovoltaics uncertainties are observed, which can compensate power imbalance.

Consequently, in Eq. (1), the second-stage max function is adopted to identify the worst-case scenarios. The inner layer min function is adopted to figure out additional adjustment cost under the worst-case scenarios. \( w \) stands for the uncertain wind power and photovoltaics. \( y \) includes up-regulation of CG \( P_{CG}^{up} \), down-regulation of CG \( P_{CG}^{down} \), adjustment of sold power \( P_{Balance}^{sold} \), adjustment of purchased power \( P_{Balance}^{purchased} \), actual wind power \( P_{wind} \), and photovoltaics \( P_{solar} \). \( C_{AA} \) is shown by Eq. (3).

\[
C_{AA} = \sum_{i=1}^{T} (\lambda_{CG}^{upt} \cdot P_{CG}^{up}(t) + \lambda_{CG}^{down}(t) \cdot P_{CG}^{down}(t) + \lambda_{Balance}^{sold}(t) \cdot P_{Balance}^{sold}(t) - \lambda_{Balance}^{purchased}(t) \cdot P_{Balance}^{purchased}(t))
\]

where \( \lambda_{CG}^{up} \) and \( \lambda_{CG}^{down} \) are the prices of the up/down-regulation of CG; \( \lambda_{Balance}^{sold} \) and \( \lambda_{Balance}^{purchased} \) are the prices of the up/down-regulation of the natural gas supply; \( P_{wind} \) and \( P_{solar} \) are the uncertain wind power and photovoltaics; \( \lambda_{wind}^{loss} \) and \( \lambda_{solar}^{loss} \) are the penalty costs of the wind power and photovoltaics curtailment.

### 2.2. Constraints

#### 2.2.1. Day-ahead dispatch constraints

Constraints include power balance constraints, CG constraints, storage system constraints, and interaction constraints. Power balance constraints are shown by Eq. (4).

\[
P_{CG}^{dis}(t) + P_{ESS}^{dis}(t) + P_{P_T}^{dis}(t) + P_{solar}^{dis}(t) + P_{Grid}^{dis}(t) = P_{load}(t) + P_{EB}(t) + P_{Grid}^{sold}(t) + P_{ESS}^{sold}(t)
\]

where \( P_{ESS}^{dis} \) and \( P_{SS}^{dis} \) are the discharging/charging power of energy storage system (ESS); \( Q_{ESS}^{dis} \) and \( Q_{HSS}^{dis} \) are the discharging/charging power of heat storage system (HSS); \( P_{load} \) and \( Q_{load} \) are the electricity and heat demands; \( P_{wind}^{dis} \) and \( P_{solar}^{dis} \) are forecasted wind power and photovoltaics; electric boiler (EB) generates heat energy \( Q_{EB} \) by consuming electricity energy \( P_{EB} \); \( Q_{MT} \) is the heat energy generated by microturbine; \( Q_{EB} \) and \( Q_{MT} \) can be presented by Eq. (5).

\[
Q_{MT}(t) = \eta_{MT} \cdot P_{MT}(t), \quad Q_{EB}(t) = \eta_{EB} \cdot P_{EB}(t)
\]

In this paper, \( \eta_{MT} \) and \( \eta_{EB} \) equal to 0.9 and 0.85 respectively.

CG stands for fuel cell, microturbine and EB. Constraints of these components are shown in Eq. (6).

\[
0 \leq P_{CG,i}(t) \leq P_{CG,i}^{max}, \quad -R_{CG,i} \leq P_{CG,i}(t) - P_{CG_i}(t-1) \leq R_{CG,i}
\]

where \( P_{CG,i}^{max} \) is the permissible maximum output of the \( i \)th CG; \( R_{CG,i} \) is the allowable maximum ramping rate of the \( i \)th CG.

Storage system (SS) includes ESS and HSS. Constraints of these components are represented by Eqs. (7-9) [26-28].

\[
E_{SS_{i},j}(t) = E_{SS_{i},j}(t-1) + P_{SS_{j}}^{dis}(t) \cdot \eta_{SS_{i},j}^{dis} - P_{SS_{j}}^{dis}(t) / \eta_{SS_{i},j}^{dis}
\]

\[
0 \leq P_{SS_{j}}^{dis}(t) \leq P_{SS_{j}}^{max} \cdot \eta_{SS_{i},j}^{dis}(t), \quad 0 \leq P_{SS_{j}}^{solar}(t) \leq P_{SS_{j}}^{max} \cdot \eta_{SS_{i},j}^{solar}(t)
\]

\[
E_{SS_{i},j}(T) = E_{SS_{i},j}(0)
\]

where \( E_{SS_{i},j} \) is the energy stored in the \( i \)th SS; \( \eta_{SS_{i},j}^{dis} \) and \( \eta_{SS_{i},j}^{solar} \) are the charging and discharging rates; \( P_{SS_{j}}^{max} \) and \( P_{SS_{j}}^{max} \) are maximum discharging/discharging power of the \( i \)th SS; \( \eta_{SS_{i},j}^{ON/OFF} \) represents the ON/OFF status of charging mode.

The maximum exchange power with the power grid should be limited by Eq. (10).

\[
\text{Maximum exchange power with the power grid should be limited by Eq. (10).}
\]
\[ 0 \leq P_{\text{purchased}}^{\text{Grid}}(t) \leq P_{\text{Grid}}^{\text{max}} \cdot S_{\text{purchased}}^{\text{Grid}}(t), \quad 0 \leq P_{\text{sold}}^{\text{Grid}}(t) \leq P_{\text{Grid}}^{\text{max}} \cdot (1 - S_{\text{purchased}}^{\text{Grid}}(t)) \]  

where \( P_{\text{Grid}}^{\text{max}} \) is the maximum exchange power with the grid; \( S_{\text{purchased}}^{\text{Grid}} \) represents the selling/purchasing mode.

It should be pointed out that the lifetime loss cost during the charging/discharging process is negligible compared to the total operational cost. Therefore, it is acceptable to neglect the lifetime loss in our model.

2.2.2. Additional adjustment constraints. As long as uncertain wind power and photovoltaics are revealed, the additional adjustment action should be made to compensate the power imbalance. The constraints consist of power balance constraints, CG constraints, storage system constraints, interaction constraints, and wind power/photovoltaics curtailment constraints. Power balance constraints are shown by Eq. (11).

\[
\begin{align*}
Q_{\text{MT}}(t) + Q_{\text{FC}}(t) - Q_{\text{EB}}(t) &= Q_{\text{dis,adjust}}^{\text{ESS}}(t) + Q_{\text{ch,adjust}}^{\text{ESS}}(t) \\
Q_{\text{MT}}(t) - Q_{\text{FC}}(t) - Q_{\text{EB}}(t) &= Q_{\text{up,adjust}}^{\text{ESS}}(t) + Q_{\text{dis,adjust}}^{\text{ESS}}(t) \\
P_{\text{up,MT}}(t) + P_{\text{up,FC}}(t) - P_{\text{down,MT}}(t) - P_{\text{down,FC}}(t) &= P_{\text{wind}}(t) + P_{\text{solar}}(t) + P_{\text{Grid}}^{\text{purchased}}(t) \\
-\Delta P_{\text{CG}}(t) &\leq P_{\text{CG},i}^{\text{up}}(t) + P_{\text{CG},i}^{\text{down}}(t) - P_{\text{CG},i}^{\text{max}} - P_{\text{CG},i}^{\text{min}} \leq \Delta P_{\text{CG}}(t) \\
0 &\leq P_{\text{up,CG},i}(t) \leq S_{\text{CG},i}(t) \cdot P_{\text{CG},i}^{\text{max}}, \quad 0 \leq P_{\text{down,CG},i}(t) \leq (1 - S_{\text{CG},i}(t)) \cdot P_{\text{CG},i}^{\text{max}} \\
0 &\leq P_{\text{ch,adjust}}^{\text{ESS},i}(t) \leq P_{\text{ch,max}}^{\text{ESS},i}(t) = S_{\text{ESS},i}(t) \cdot P_{\text{ESS},i}^{\text{max}}(t) \\
0 &\leq P_{\text{dis,adjust}}^{\text{ESS},i}(t) \leq P_{\text{dis,max}}^{\text{ESS},i}(t) = (1 - S_{\text{ESS},i}(t)) \cdot P_{\text{ESS},i}^{\text{max}}(t) \\
0 &\leq P_{\text{Grid}}^{\text{sold}}(t) \leq P_{\text{Grid}}^{\text{max}} \cdot (1 - S_{\text{Grid}}^{\text{purchased}}(t)) \leq P_{\text{Grid}}^{\text{sold}}(t) \leq P_{\text{Grid}}^{\text{max}} \cdot S_{\text{Grid}}^{\text{purchased}}(t) \\
0 &\leq P_{\text{solar}}(t) \leq P_{\text{Solar}}^{\text{max}}(t) \leq P_{\text{solar}}(t) \leq P_{\text{solar}}^{\text{max}}(t) \leq P_{\text{solar}}^{\text{max}}(t)
\end{align*}
\]

where \( S_{\text{CG},i} \) represents the ON/OFF status of the \( i \)th CG.

SS constraints include the limits of charging/discharging power and stored energy, which are expressed by Eqs. (15-16).

\[
\begin{align*}
E_{\text{SS},i}^{\text{adjust}}(t) &= E_{\text{SS},i}^{\text{max}}(t) - E_{\text{SS},i}(t) - E_{\text{SS},i}^{\text{adjust}}(t) / \eta_{\text{SS}}^{\text{dis}} \\
0 &\leq P_{\text{ch,adjust}}^{\text{SS},i}(t) \leq P_{\text{ch,max}}^{\text{SS},i}(t) = S_{\text{SS},i}(t) \cdot P_{\text{SS},i}^{\text{max}}(t) \\
0 &\leq P_{\text{dis,adjust}}^{\text{SS},i}(t) \leq P_{\text{dis,max}}^{\text{SS},i}(t) = (1 - S_{\text{SS},i}(t)) \cdot P_{\text{SS},i}^{\text{max}}(t)
\end{align*}
\]

where \( P_{\text{ch,adjust}}^{\text{SS},i} \) and \( P_{\text{dis,adjust}}^{\text{SS},i} \) are the charging/discharging power of the \( i \)th SS; \( E_{\text{SS},i}^{\text{adjust}} \) is the stored energy.

The maximum exchange power with the power grid should be limited after adjustment, which is expressed by Eqs. (17-18).

\[
\begin{align*}
0 &\leq P_{\text{Grid}}^{\text{purchased}}(t) \leq P_{\text{Grid}}^{\text{max}} \cdot (1 - S_{\text{Grid}}^{\text{purchased}}(t)) \leq P_{\text{Grid}}^{\text{purchased}}(t) \leq P_{\text{Grid}}^{\text{max}} \cdot S_{\text{Grid}}^{\text{purchased}}(t) \\
0 &\leq P_{\text{Grid}}^{\text{sold}}(t) \leq P_{\text{Grid}}^{\text{max}} \cdot (1 - S_{\text{Grid}}^{\text{purchased}}(t)) \leq P_{\text{Grid}}^{\text{sold}}(t) \leq P_{\text{Grid}}^{\text{max}} \cdot S_{\text{Grid}}^{\text{purchased}}(t)
\end{align*}
\]

where \( P_{\text{Grid}}^{\text{max}} \) is the maximum power with the grid after adjustment.

The wind power and photovoltaics should be limited in the allowable range, which is shown by Eq. (19).

\[
0 \leq P_{\text{solar}}(t) \leq P_{\text{solar}}^{\text{max}}(t), \quad 0 \leq P_{\text{solar}}(t) \leq P_{\text{solar}}^{\text{max}}(t)
\]

3. Uncertainty set and solution algorithm

3.1. Uncertainty set

Uncertainty set \( U \) is constructed to characterize the uncertainties of wind power and photovoltaics, which is shown by Eq. (20).
where $P^\text{err}_{\text{wind}}$ and $P^\text{err}_{\text{solar}}$ are the predicted errors of the wind power and photovoltaics respectively; $\Gamma_{\text{wind}}$ and $\Gamma_{\text{solar}}$ are uncertain budgets to control the times of worst-case scenarios of wind power and photovoltaics respectively. It is worth to point out that the prediction errors are provided by local weather department, which have a significant impact on the performance of our model. How to obtain accurate prediction belongs to the other research field. Therefore, we will not discuss the specific way to obtain the prediction.

3.2. Compact form
For simplicity, the abovementioned objective functions Eqs. (1-3) and the constraints Eqs. (4-20) can be rewritten into a compact form Eq. (21) [29]:

$$
U = \begin{cases}
    P^\text{pre}_{\text{wind}} - P^\text{err}_{\text{wind}}(t) & \in [P^\text{pre}_{\text{wind}}(t) - P^\text{err}_{\text{wind}}(t), P^\text{pre}_{\text{wind}}(t) + P^\text{err}_{\text{wind}}(t)], \\
    P^\text{pre}_{\text{solar}} - P^\text{err}_{\text{solar}}(t) & \in [P^\text{pre}_{\text{solar}}(t) - P^\text{err}_{\text{solar}}(t), P^\text{pre}_{\text{solar}}(t) + P^\text{err}_{\text{solar}}(t)], \\
    \sum_{t=1}^{T} \frac{P^\text{pre}_{\text{wind}}(t) - P^\text{err}_{\text{wind}}(t)}{P^\text{err}_{\text{wind}}(t)} \leq \Gamma_{\text{wind}}, \\
    \sum_{t=1}^{T} \frac{P^\text{pre}_{\text{solar}}(t) - P^\text{err}_{\text{solar}}(t)}{P^\text{pre}_{\text{solar}}(t)} \leq \Gamma_{\text{solar}}
\end{cases}
$$

(20)

3.3. Model decomposition
The presented model has a complicated three level min-max-min structure, which is difficult to be solved. Therefore, C&CG [30] is employed to decompose the model into MP (Eq. (22)) and SP (Eq. (23)).

$$
\begin{align*}
\min_{x, y} & \quad d^T x + \max_{u \in U} \min_y (e^T y + f^T u) \\
\text{s.t.} & \quad Dx \leq g, Fx + Gy \leq h, I_u y \leq u
\end{align*}
$$

(21)

where $d, e, f, D, F, G,$ and $I_u$ are the constant matrices; $g$ and $h$ represent vectors.

3.4. Transformation of SP
SP contains a max-min structure, which is difficult to be solved. Therefore, strong duality theory is applied to transform SP into an equivalent single-stage problem. And then Big-M method is applied to linearize the nonlinear terms in the dual problem. Consequently, the transformed SP1 can be expressed by Eq. (24).

$$
\begin{align*}
\max & \quad h^T \alpha - x^T F^T \alpha + u^T \theta^+ + u^T \theta^- + u^0 (1 - \theta^+ - \theta^-) \\
\text{s.t.} & \quad G^T \alpha + I_u^T \beta = e, \alpha \leq 0, \beta \leq 0, \theta = f + \beta \\
& \quad -M(1 - \mu^+_c) + \theta^+ \leq \theta^+ \leq M(1 - \mu^+_c) + \theta^+ \\
& \quad -M(1 - \mu^-_c) + \theta^- \leq \theta^- \leq M(1 - \mu^-_c) + \theta^- \\
& \quad -M \mu^+_c \leq \theta^+ \leq M \mu^-_c, -M \mu^+_c \leq \theta^- \leq M \mu^-_c \\
& \quad \mu^+_c + \mu^-_c \leq 1, \sum \mu^+_c + \mu^-_c \leq 1
\end{align*}
$$

(24)
where \( \alpha, \beta, \) and \( \theta \) are dual variables; \( \theta^+ \) and \( \theta^- \) represent the positive and negative values of \( \theta \). \( M \) is a large-enough constant. \( u^+ \) and \( u^- \) are the upper and lower limits of uncertain variables; \( \mu^+, \mu^- \) are the binary variables introduced by the Big-M approach; the uncertain budgets include \( \Gamma_{\text{wind}} \) and \( \Gamma_{\text{solar}} \).

3.5. Model solution using C&CG iteration algorithm

The solution of the model using the C&CG iteration algorithm includes the following major steps:

Step 1: Initialize the worst-case scenario \( u_1 \). Set the upper bound \( U = +\infty \), the lower bound \( L = -\infty \), the iteration number \( k = 1 \), and the convergence gap \( \lambda > 0 \);

Step 2: Given the scenarios \((u_1, \ldots, u_k)\), solve the MP and achieve the optimal solution \((x_k, \eta, y_1, \ldots, y_k)\). Update \( L = \eta \);

Step 3: Given the solution \( x_k \), solve the SP and obtain the optimal solution \((u^+_k, y^+_k)\). Update \( u_{k+1} = u^+_k, U = e^T y^- + f^T u^- \);

Step 4: If \( U - L \leq \lambda \), return the solution \( x = x_k \) and terminate the algorithm. Otherwise add the new variable \( y_{k+1} \) and constraint Eq. (25). Update \( k = k+1 \) and return to Step 2.

\[
\begin{align*}
\eta & \geq e^T y_{k+1} + f^T u_{k+1} \\
Fx + Gy_{k+1} & \leq h, I_{\eta} y_{k+1} \leq u_{k+1}
\end{align*}
\]

4. Experimental results

This section carries out the experiments to verify the effectiveness of the presented model. The model is constructed under MATLAB R2016b and solved by CPLEX. The experimental environment is Intel Core I3 CPU, 2.80 GHz, 4 GB memory, Win10 64 bit.

4.1. Robust dispatch strategy

Set the adjustable robust parameter \( \Gamma = 10 \). C&CC approach convergences after 8 iterations, whose process is listed in Table 1. In the optimized strategy, the day-ahead outputs of MT, FC, EB, and HSS, as well as purchased and sold electricity, are shown in Figure 1. The day-ahead charge and discharge power of ESS are shown in Figure 2. In these figures, positive power of the CG indicates that it supplies power to MG, while negative power power means power consumption; positive power of storage system means charging, and negative power means discharging; the positive interactive power indicates that CHP-MG purchases electricity, and negative power means selling electricity.

| Iteration number | Upper bound/CNY | Lower bound/CNY | Gap/CNY |
|------------------|-----------------|-----------------|---------|
| 1                | 7621.7          | 5170.2          | 2151.5  |
| 2                | 7025.3          | 6861.5          | 163.8   |
| 3                | 6995.5          | 6908.9          | 86.6    |
| 4                | 6992.9          | 6918.9          | 74.0    |
| 5                | 6926.4          | 6920.0          | 6.4     |
| 6                | 6926.1          | 6921.7          | 4.4     |
| 7                | 6922.3          | 6922.0          | 0.3     |
| 8                | 6922.0          | 6922.0          | 0       |

According to the figures, conclusions can be made as following:

1) Figure 1 indicates that at night when the wind power is sufficient and the electric load and solar power are small, EB starts up to increase the electric load. As a result, excess electric energy is converted into heat energy, which greatly reduces the wind curtailment and increases the wind power consumption.
Figure 1. The details of day-ahead dispatch strategy. Figure 2. The charge/discharge power of ESS.

To demonstrate the robustness of the presented RO-based model, robustness analysis is provided. The day-ahead cost of the dispatch is 5370.8 CNY while the real-time cost of the dispatch is 1551.2 CNY. Monte Carlo method generates 1000 real-time scenarios that include 10 extreme scenarios. And then the real-time cost of each scenario under the day-ahead dispatch is calculated. The results are compared with the real-time cost of the worst-case scenario considered in the presented robust optimization. The results are shown in Figure 3.

Figure 3 shows that the real-time cost of every generated scenario is less than that of the worst-case scenario of the robust optimization. This point proves that the presented model can evaluate and further consider the worst-case scenario. So that the provided day-ahead dispatch can involve the worst-case scenario to improve the robustness.

4.2. Comparison of different dispatch models
In order to reveal the effectiveness of the presented model, Monte Carlo method is employed to generate 1000 random real-time scenarios for comparing the economy of the RO-based model and the DO-based model. The total costs of all scenarios are shown as Figure 4 and Table 2.
Table 2. Comparison for operation costs between RO-based model and traditional DO-based model.

| Adjustment cost /$       | RO-based model  | DO-based model |
|--------------------------|-----------------|----------------|
| Day-ahead operation cost /$ | 5370.8          | 5170.3         |
| Unit operation cost       | 422.2           | 531.2          |
| Wind power curtailment cost | 0              | 314.9          |
| Solar power curtailment cost | 0              | 205.2          |
| Total adjustment cost     | 422.2           | 951.3          |
| Total cost /$             | 5793.0          | 6121.6         |

Figure 4 reveals that the scatters of the RO-based strategy are dense, and the distribution interval of the scatters is small. However, the distribution interval of the DO-based strategy is generally larger. Meanwhile, scatters of DO-based strategy are generally higher than that of the RO-based strategy. This is because the RO-based strategy focuses on the worst-case scenario when optimizing the dispatch. Therefore, real-time adjustment cost of RO-based strategy is much less than that of the DO-based strategy, so that the scatters of the total cost are dense. This point also demonstrates the robustness feature of the presented model.

Table 2 further indicates the details of the costs. Two points can be clearly seen in the table:

a) although the RO-based day-ahead cost is higher than that of the DO-based model, the total cost has been significantly reduced compared to that of the DO-based model (no cost for wind-solar power curtailment);

b) Based on the RO-based model, neither wind power curtailment nor solar power curtailment occurs, which considerably improves the utilization of the wind-solar power. This is because RO considers the wind-solar power output uncertainty when optimizing the day-ahead strategy.

Due to the fact that the RO-based day-ahead dispatch generally results in more feasible and economic real-time dispatch, it can be concluded that RO-based model has great potential to handle the uncertainty in a robust and economic way.

4.3. Comparison of models with different adjustable robust parameters

In order to reveal the adjustable ability of the model in handling uncertainties, different adjustable robust parameters ($\Gamma = 0$, $\Gamma = 24$) are selected for optimization. Similarly, Monte Carlo method is employed to generate scenarios for economic analysis. The results of optimization are listed in Table 3.

It can be seen from Table 3 that the robust optimization results are equivalent to deterministic optimization when $\Gamma = 0$ is configured. The total operating cost of the dispatch is 6120.0 CNY. In addition, it should be pointed out that the randomness of scenarios selection results in certain deviation from the deterministic optimization in the previous section.

In addition, the table also shows that the optimization achieves the most conservativeness when $\Gamma = 24$. This is because that with the increase of $\Gamma$, more wind-solar power uncertainties will be considered in the day-ahead dispatch, which leads to the increase of the day-ahead cost. In addition, it can be clearly seen that the economy performance of $\Gamma = 24$ is worse than that of $\Gamma = 10$. This is due to the fact that relatively conservative configuration of the adjustable robust parameters $\Gamma$. In generally, although higher $\Gamma$ can lead to more robust day-ahead dispatch, it is necessary to select a suitable $\Gamma$ to balance the robustness and economy.
Table 3. Optimization results and economic efficiency in different budget of uncertainty.

| Parameter | Day-ahead cost/CNY | Real-time cost/CNY | Total cost/CNY |
|-----------|--------------------|--------------------|---------------|
| $\Gamma = 0$ | 5170.2             | 949.8              | 6120.0        |
| $\Gamma = 10$ | 5370.8            | 422.2              | 5793.0        |
| $\Gamma = 24$ | 5650.4             | 386.5              | 6036.9        |

5. Conclusions

In this paper, a two-stage adjustable robust optimization model for CHP-MG dispatch considering wind-solar power uncertainty is constructed. The model is decomposed into a day-ahead dispatch problem and a real-time adjustment dispatch problem, which makes the model suitable for the actual situation. Using Big-M method, duality theory, and C&CG iteration, the optimal day-ahead dispatch considering the worst-case real-time scenario is figured out. Experiments demonstrate that the MT, EB, ESS, HSS and other units in the CHP-MG can collaboratively operate. Our experiments also demonstrate that compared to DO-based model, the RO-based model has better ability to improve wind-solar power utilization and further achieve better economy and robustness. Moreover, the introduction of adjustable robust parameters enables operators to flexibly balance robustness and economy in the day-ahead dispatch. In our future work, uncertain load demand will be further considered.

Acknowledgement

This paper is supported by project from State Grid Sichuan Economic Research Institute, Chengdu, China.

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