A Two-Stage Distributionally Robust Coordinated Dispatch for Integrated Electricity and Natural-gas Energy Systems Considering Uncertainty of Wind Power

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Abstract. Application of gas-fired units and power-to-gas devices promotes coupling between power system and natural gas system, and hence provides an alternative solution for the wind power integration. Also, the traditional stochastic optimization and robust optimization methods may result in uneconomic or conservative decisions in dealing with the uncertain problems. Thus, a data-driven based distributionally robust dispatch model for the integrated electricity and natural gas system is proposed in this paper, which is constructed in a two-stage optimization fashion. The day-ahead total cost for the integrated system is regarded as the optimization objective in the first stage where the forecast wind power information is also taken into consideration while the output adjustment of thermal generation units and the supply regulation of natural gas source are included in the real-time dispatch (second stage in this study). Besides, the norm-1 and norm-inf are simultaneously combined to constrain the confidence set of wind power probability distribution. Then the model is solved by the Column-and-Constraint Generation algorithm. Finally, numerical results verify the effectiveness of the proposed model.

1. Introduction
In order to improve the efficiency of energy, the “Energy Internet” concept has been proposed recently which aims to promote coupling among different networks [1]. Compared with other energy, natural gas keeps a rising integration in electricity system, owing to low cost, low carbon emission, so it is vital to research the coupling between power system and natural gas system. Moreover, the dispatch of the integrated system is regarded as an efficient way to promote the use of wind power.

Currently, the gas-fired unit servers as a linkage between the electricity and natural gas system. The reference [2] introduced a carbon trading mechanism to study the economic operation of the integrated system. The reference [3] made the optimal operation decisions of the integrated system considering security of the electricity and natural gas networks. However, the gas-fired units only convert the natural gas into electricity, extensive researches consider the Power-To-Gas (P2G) devices which could convert the energy in a contrary direction and thus make the energy flow in the integrated system run in a closed loop [4-6]. In [7], the author conducted a dispatch model for integrated electricity-gas-heating system with P2G devices, and discussed the accommodation of the wind power.
In [8], the authors proposed a two-stage economic dispatch model for integrated electricity and natural gas system. However, the uncertainty of the wind power was not considered in the previous research. Generally, stochastic optimization and robust optimization methods were used in dealing with the uncertainties of the wind power. In [9], an optimization method based on the scenario of wind power output is proposed to make the day-ahead dispatch of the integrated system. Paper [10] conduct a robust optimization dispatch model of the electricity and natural gas system considered the security of integrated system and the dynamic characteristics of the natural gas system. However, the stochastic optimization method needs to obtain the accurate probability distribution function[11] while the robust optimization may result in over-conservative decisions[12]. Based on the known problems, recent researches combine the two existing methods and propose a distributionally robust optimization (DRO)[13-15] methods to deal with the uncertainties. In this paper, a data-driven distributionally robust optimization dispatch model based on the historical wind power output data is proposed. In the model, norm-1 and norm-inf constraints are simultaneously included to constrain the confidence set of wind power probability distribution in order to find the optimal solution under the worst probability distribution. The paper [16] and [17] apply the DRO method into the reactive optimization problem and the unit commitment respectively, but these researches only consider the norm-1 or norm-inf constraint which could make the decisions more uneconomic. We apply the DRO method which considers the norm-1 and norm-inf simultaneously to the integrated electricity and natural gas system coupled with gas-fired unit and P2G devices for the first time.

2. Integrated electricity and natural gas system modeling

The proposed model of the integrated system can be illustrated in Fig. 1. The system includes electricity transmission system, gas supply system, electricity load, gas load, gas-fired units and P2G devices. The electricity and natural gas system are closely interconnected by the gas-fired units and P2G devices which can be treated as energy converters among these two energy networks. As we can see, the wind power can be accommodated by the decrease output of gas-fired units and the increase usage of P2G devices.

![Figure 1. The structure of the integrated system](image)

2.1. Objective Function

The integrated systems set the day-ahead dispatch cost and the real-time adjustment cost as the optimization targets which is represented in (1):
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\[
\begin{align*}
\min & \sum_{t=1}^{T} \sum_{i=1}^{N_{s}} S_{i}^{s} I_{i,t} (1-I_{i,t-1}) + S_{D_{i}} I_{i,t-1} (1-I_{i,t}) + (a_{i} P_{i}^{2} + b_{i} P_{i} + c_{i} I_{i,t}) \\
+ & \sum_{t=1}^{T} \sum_{i=1}^{N_{s}} S_{i}^{g} I_{i,t} (1-I_{i,t-1}) + S_{D_{i}} I_{i,t-1} (1-I_{i,t}) + (a_{i} P_{i}^{2} + b_{i} P_{i} + c_{i} I_{i,t}) + \sum_{t=1}^{T} \sum_{i=1}^{N_{w}} \delta (P_{i,t}^{w} - P_{i,t}^{w}) \\
+ & \max \sum_{k=1}^{K} p_{k} \left[ \min \sum_{t=1}^{T} \sum_{i=1}^{N_{s}} c_{i} \Delta P_{i,k} + \sum_{t=1}^{T} \sum_{i=1}^{N_{s}} c_{i} \Delta P_{i,k} + \sum_{t=1}^{T} \sum_{i=1}^{N_{w}} c_{i} \Delta P_{i,k} \right] + \sum_{t=1}^{T} \sum_{i=1}^{N_{w}} c_{i} \Delta P_{i,k} (P_{i,t}^{w} - P_{i,t}^{w}) \right] 
\end{align*}
\]  

(1)

The first part of (1) represents the day-ahead dispatch cost of the integrated system, which includes the start-up and shut-down cost, the generation cost of traditional units and gas-fired units, and the curtailment cost of wind power, where \( T \) represents the total scheduling time; \( N_{s} \) represents the number of the traditional units; \( S_{i}^{s} \) and \( S_{D_{i}} \) represents the start-up and shut-down cost of traditional units; \( I_{i,t} \) represents the status indicator of traditional units; \( a_{i} \), \( b_{i} \), \( c_{i} \) is the cost coefficient; \( P_{i,t} \) is the power output of traditional units; \( N_{s} \) represents the number of gas-fired units; \( S_{i}^{g} \) and \( S_{D_{i}} \) represents the startup and shutdown cost of gas-fired units; \( I_{i,t} \) represents the status indicator of gas-fired units; \( a_{i}^{g} \), \( b_{i}^{g} \), \( c_{i}^{g} \) is the cost coefficient of gas-fired units; \( P_{i,t}^{g} \) is the power output of gas-fired units; \( N_{w} \) is the number of wind plant; \( \delta \) is the penalty coefficient of wind power curtailment; \( P_{i,t}^{w} \) and \( P_{i,t}^{w} \) represent the forecast output and the actual output of wind power, respectively.

The second part of (1) represents the real-time adjustment cost of the integrated system, which includes the adjustment cost of the power unit and gas supplier. Based on the historical data, this paper construct \( K \) scenarios to describe possible wind power output realizations. The basic empirical probability in each given scenario \( k \) can correspondingly be obtained, which is denoted as \( p_{k}^{s} \); \( p_{k} \) represents the probability of each scenario; \( \Delta P_{i,k}^{s} \) and \( \Delta P_{i,k}^{g} \) represent the adjustment of traditional units and gas-fired units respectively; \( P_{i,t}^{w} \) and \( P_{i,t}^{w} \) represent the forecast output and the actual output of wind power in scenario \( k \); \( c_{i} \), \( c_{i}^{g} \) and \( c_{i}^{w} \) represent the adjustment penalty coefficient in real-time dispatch.

2.2. Day-ahead Dispatch Constraints

In the day-ahead dispatch, for each period \( t \), the electricity, natural gas system and the coupling devices constraints are expressed as follows:

2.2.1 Power System Constraints

1) Power Balance

\[
\sum_{i=1}^{N_{s}} P_{i}^{s} + \sum_{i=1}^{N_{s}} P_{i}^{w} + \sum_{i=1}^{N_{s}} P_{i}^{g} = P_{l}^{L} + \sum_{i=1}^{N_{s}} P_{i}^{P2G}
\]

(2)

where \( P_{l}^{L} \) is the total electricity load; \( N_{P2G} \) is the number of P2G devices; \( P_{i}^{P2G} \) is the power usage of P2G devices.

3) Wind power output Constraints

\[
0 \leq P_{i,t}^{w} \leq P_{i,t}^{w}
\]

(3)

2.2.2 Natural Gas System Constraints

1) Node Pressure Constraints

In the gas networks, each gas node has the upper and lower pressure limit, which is denoted as follows:

\[
\pi_{i,min} \leq \pi_{i} \leq \pi_{i,max}
\]

(4)

where \( \pi_{i} \) is the pressure of the gas node; \( \pi_{i,min} \) and \( \pi_{i,max} \) is the minimum and maximum of the node pressure respectively.

2) Gas Balance Constraints

The steady-state natural gas injection at each node is equal to flow extracted from the node. The (5) ensures the nodal balance at the natural gas transmission system:

\[
\sum_{i=1}^{N_{w}} \Delta P_{i} + \sum_{i=1}^{N_{w}} P_{i} = \sum_{i=1}^{N_{w}} P_{i}
\]

(5)
$Q_{i}^g + Q_{i}^{P2G} - Q_{j}^g - Q_{j}^\text{pipe} = Q_{i,j}^{\text{pipe}}$  \hfill (5)

where $Q_{i}^g$, $Q_{i}^{P2G}$, $Q_{j}^g$ is the gas injection of the corresponding devices; $Q_{i,j}^{\text{pipe}}$ is the gas flow of the gas pipeline.

3) Flow Conservation Constraints

Natural gas is delivered to customers via pipelines. The pipelines include passive pipeline and active pipeline. In this paper, we consider the gas flow between nodes $i$ and $j$ is a quadratic function of the pressure at the two end nodes:

$$Q_{i,j}^{\text{pipe}} = \text{sgn}(\pi_i, \pi_j) \cdot C_{i,j} \sqrt{|\pi_i - \pi_j|}$$  \hfill (6)

where $C_{i,j}$ is the pipeline constant that depends on the temperature, length, friction and natural gas compositions.

$$\text{sgn}(\pi_i, \pi_j) = \begin{cases} 1, & \pi_i \geq \pi_j \\ -1, & \pi_j \geq \pi_i \end{cases}$$  \hfill (7)

4) Gas Supplier Constraints

The gas is usually supplied by the gas well, and the gas supplier has the limitation which is denoted as follows:

$$Q_{i}^g_{\text{min}} \leq Q_{i}^g \leq Q_{i}^g_{\text{max}}$$  \hfill (8)

2.2.3 Coupling Devices Constraints

The integrated system is coupled by gas-fired units and P2G devices.

1) Gas-fired Units Constraints

$$Q_{i}^\text{min} \leq Q_{i}^{f,i} \leq Q_{i}^\text{max}$$  \hfill (9)

$$Q_{i}^{f,i} = \frac{P_{i}^{f,i}}{\eta}$$  \hfill (10)

where $\eta$ is the efficiency of gas-fired units, which equals to 40%.

2) P2G Constraints

$$Q_{i}^{P2G} = \eta^{\text{P2G}} \cdot P_{i}^{P2G}$$  \hfill (11)

$$P_{i}^{\text{min},P2G} \leq P_{i}^{P2G} \leq P_{i}^{\text{max},P2G}$$  \hfill (12)

where $\eta^{\text{P2G}}$ is the convert efficiency of P2G devices, which equals to 80%.

2.3. Real-time Dispatch Constraints

The generation units and gas suppliers have to adjust their outputs when the wind power is revealed in the real-time dispatch model. The constraint in each scenario $k$ is denoted as follows:

2.3.1 Power System Constraints

1) Power Balance

$$\sum_{\nu=1}^{N_{\nu}} (P_{\nu} + \Delta P_{\nu,k}) + \sum_{\nu=1}^{N_{\nu}} P_{\nu,k} + \sum_{\nu=1}^{N_{\nu}} (P_{\nu}^\text{w} + \Delta P_{\nu,k}^\text{w}) = P_{i}^L + \sum_{\nu=1}^{N_{\nu}} P_{\nu,k}^{\text{P2G}}$$  \hfill (13)

3) Wind power output Constraints

$$0 \leq P_{\nu,k}^w \leq P_{\nu,k}^{w,0}$$  \hfill (14)

2.3.2 Natural Gas System Constraints

1) Node Pressure Constraints

$$\pi_{i,j,k} \leq \pi_{i,j} + \Delta \pi_{i,j,k} \leq \pi_{i,j,max}$$  \hfill (15)

where $\Delta \pi_{i,j,k}$ is the pressure change of the gas node.

2) Gas Balance Constraints
\[ (Q_{t,j}^{mp} + \Delta Q_{t,j,k}^{mp}) + (Q_{t,j}^{pc} + \Delta Q_{t,j,k}^{pc}) - (Q_{t,j}^{mp} + \Delta Q_{t,j,k}^{mp}) = -Q_{t,j}^{p} + \Delta Q_{t,j,k}^{p} \] 

where \( \Delta Q_{t,j,k}^{mp} \), \( \Delta Q_{t,j,k}^{pc} \), \( \Delta Q_{t,j,k}^{pp} \) is the gas injection change of the corresponding devices.

3) Flow Conservation Constraints

\[ Q_{t,j}^{mp} + \Delta Q_{t,j,k}^{mp} = \text{sgn}(\pi_{i,j}, \pi_{i,j}) C_{\theta} \sqrt{(\pi_{i,j} + \Delta \pi_{i,j})^2 - (\pi_{j} + \Delta \pi_{j})^2} \] 

4) Gas Supplier Constraints

\[ Q_{t,j}^{mp} \leq Q_{t,j}^{mp} + \Delta Q_{t,j,k}^{mp} \leq Q_{t,j}^{max} \] 

where \( \Delta Q_{t,j}^{p} \) is the gas injection change of the gas supplier.

2.3.3 Coupling Devices Constraints. There is no adjustment power of P2G devices, so we only consider the regulation of the gas-fired units in the real-time dispatch:

\[ Q_{t,j}^{min} \leq Q_{t,j}^{mp} + \Delta Q_{t,j,k}^{mp} \leq Q_{t,j}^{max} \] 

\[ Q_{t,j}^{mp} + \Delta Q_{t,j,k}^{mp} = (P_{t,j}^{mp} + \Delta P_{t,j,k}^{mp}) / \eta \] 

In the two-stage of the model, we also consider the constraints of the traditional generation units which include ramping rate, minimum/maximum power output, and minimum ON/OFF time. Besides, the reserve rate of integrated system which is used to handle the uncertainties is also considered (which is set to 10% of the wind power forecast value). In this paper, we apply the DC power flow model which is proposed in paper [18].

3. Solution Algorithm

3.1. Linearization of the Norm Constraints

In the two-stage DRO model, we propose to use the norm-1 and norm-inf simultaneously to constrain the probability distribution of the wind power in order to find optimal solution under the worst distribution. The constraints can be expressed by follows:

\[ \Omega = \{ p_{i} \} = \left\{ \begin{array}{l} p_{i} \geq 0, k = 1, \ldots, K \\ \sum_{k=1}^{K} p_{i} = 1 \\ \sum_{k=1}^{K} |p_{i} - p_{i}^{0}| \leq \theta_{i} \\ \max_{i+k \in k} |p_{i} - p_{i}^{0}| \leq \theta_{w} \end{array} \right\} \] 

where \( \theta_{i} \) and \( \theta_{w} \) are norm-1 and norm-inf tolerance value, which becomes smaller when more statistic historical data are provided. Supposing K scenarios from M historical samples.

3.2. Solution of The Two-Stage DRO Model

The two-stage DRO model is a three-level min-max-min optimization problem, which is usually solved by Benders decomposition algorithm or CCG algorithm [16]. The CCG algorithm divides the model into two problems that are the master problem (MP) and the sub-problem (SP). The iteration would stop until the difference of optimization results between MP and SP meet the predefined tolerance requirement. In this model, the master problem aims to find the optimal robust first-stage solution under some given finite worst-case probability distributions (possible realizations obtained from sub-problem). The MP provides a lower bound for model.
\[
(MP) \min_{x \in X, y \in F(x), \xi \in F(x)} a^T x + b^T y + c^T \xi + L
\]

\[
L \geq \sum_{k=1}^{K} p_k^m (b^T y^m + c^T \xi), \forall m = 1, \ldots, n
\]

The equation (22b) is the second part of (1).

The sub-problem gives an upper bound for model by optimizing the worst probability distribution after first-stage variables \(x^*\) are given. The SP can be described in (23):

\[
(SP) \quad L(x^*) = \max_{(x_k, \xi_k) \in \Omega} \sum_{k=1}^{K} p_k \min_{y \in F(x_k)} (b^T y + c^T \xi_k)
\]

The inner min model can be decoupled into \(K\) small independent problems that are suitable to be solved in parallel and be expressed into (24):

\[
L(x^*) = \max_{(x_k, \xi_k) \in \Omega} \sum_{k=1}^{K} f(x_k, \xi_k) p_k
\]

4. Numerical Simulation

4.1. System Description

In this part, we use a case study consisting of a 6-bus natural gas system and the IEEE39 power system to test the proposed model. The 6-bus natural gas system is illustrated in Fig. 2. The specific data of the 6-bus system can be seen in [7]. In the IEEE39 system, the gas-fired units are connected to nodes 30-32. The traditional generation units are connected to nodes 33-39. Three wind plants are connected to nodes 37-39. The electricity load and gas load are shown in Fig. 3.

![Fig 2. 6-node natural gas system](image_url)

![Fig 3. The daily curves of Electricity load, Gas load and wind power](image_url)

4.2. Results Comparisons
The DRO model proposed in this paper is used to obtain the worst probability distribution wind power. We give the following comparisons to verify the efficiency of the model.

4.2.1 Results Comparisons under different number of historical data. We set different number of historical data to compare the results, which are shown in Table 1.

| Historical Data | norm-1 | Proposed model | norm-∞ | Stochastic model |
|-----------------|--------|----------------|--------|------------------|
| 100             | 2.3538 | 2.2995         | 2.3190 | 1.1422           |
| 500             | 1.6071 | 1.5052         | 1.6003 | 1.1422           |
| 1000            | 1.5411 | 1.4419         | 1.5311 | 1.1422           |
| 2000            | 1.5185 | 1.3073         | 1.4073 | 1.1422           |
| 5000            | 1.4603 | 1.2783         | 1.3620 | 1.1422           |
| 10000           | 1.1446 | 1.1431         | 1.1445 | 1.1422           |

As we can see in Table 1, when the number of historical data increases, the total cost of the integrated system decreases, that is because when the historical data number increases, the tolerance value decreases so the conservatism of the model decreases. Also, we can conclude that under the same number of historical data, the model proposed in this paper is more economic than the others. Comparing with the stochastic optimization method, the proposed model becomes more economic when the number of historical data increases, and the results are much closer to stochastic method. So we choose 1000 historical data in the following calculation in order to guarantee the conservatism of the model.

4.2.2 Results Comparisons under different confidence set. In this part, we set different confidence set value to analysis the results, which are shown in Table 2.

| \( \alpha_i \) | \( \alpha_\infty \) | 0.5  | 0.9  | 0.99 |
|----------------|------------------|------|------|------|
| 0.2            |                  | 1.4412 | 1.4414 | 1.4420 |
| 0.5            |                  | 1.4419 | 1.4427 | 1.4429 |
| 0.9            |                  | 1.4419 | 1.4429 | 1.4431 |

We can conclude from Table 2 that when the confidence set increases, the total cost of the integrated system increases simultaneously. The reason is that when the confidence set increases, the uncertainty of the wind power output increases as well, the integrated system has to adjust more units and gas supplier to deal with the uncertainty which means more cost. Moreover, we set the \( \alpha_\infty \) as 0.99, the range of \( \alpha_i \) as [0.2, 0.9] to compare with the model only considering the norm-\( \infty \). The results are shown in Table 3.
Table 3. Comparison between comprehensive norm and ∞-norm

| αₙ | Cost($×10^6$) | Proposed model | norm-∞ |
|-----|----------------|----------------|--------|
| 0.2 | 1.4420         | 1.4436         |
| 0.5 | 1.4429         | 1.4436         |
| 0.99| 1.4431         | 1.4436         |

Then we set α₁ as 0.5, the range of α₂ as [0.5, 0.99] to compare with the model only considering the norm-1. The results are shown in Table 4.

Table 4. Comparison between comprehensive norm and 1-norm

| α₁ | Cost($×10^6$) | Proposed model | norm-1 |
|-----|----------------|----------------|--------|
| 0.5 | 1.4419         | 1.5411         |
| 0.8 | 1.4427         | 1.5411         |
| 0.99| 1.4429         | 1.5411         |

4.2.3 Results Comparisons under different methods. We also analyze the optimization results among traditional stochastic optimization (SO), robust optimization (RO), and distributionally robust optimization methods under 1,000,000 test probability distributions generated by Monte Carlo simulation, as shown in Table 5.

Table 5. The results comparison between different algorithms

| α₂ | DRO($×10^6$) | SO($×10^6$) | RO($×10^6$) |
|-----|--------------|-------------|-------------|
|     | First Stage  | Test        | First Stage |
|     | Cost         | Distributions | Cost       | Distributions |
|     | Mean         | Max         | Mean        | Max          | Mean         | Max          |
| 0.5 | 1.4419       | 0.6194      | 1.1422      | 1.1453       | 2.6665       | 7.1693       |
| 0.9 | 1.4427       | 0.9541      | 1.1422      | 1.1453       | 2.6665       | 7.1693       |
| 0.99| 1.4429       | 1.1225      | 1.1422      | 1.1453       | 2.6665       | 7.1693       |

We can conclude from the Table 8 that the DRO method can obtain a balanced dispatch solution in robustness and economic perspectives compared with the traditional SO and RO methods. The first stage results of the DRO method is smaller than that of the RO and larger than that of SO. Under the second-stage simulation results, the DRO shows a better expected performance in both averaged and worst-case probability distribution scenarios compared with the SO and RO methods.

5. Conclusions
From the simulation results above, we can draw the following conclusions: 1) By simultaneously considering norm-1 and norm-inf, the proposed model exhibits an economic advantage with the lowest total cost. The total cost becomes larger with the increase of the amount of available historical data. 2)
The decisions are more conservative and the total cost increases when the confidence level settings \( \alpha_l \) and \( \alpha_w \) increase. 3) Compared with SO and RO, the DRO approach can obtain a balanced dispatch solution in robustness and economic perspectives. The first-stage cost of DRO is smaller than that of RO and larger than that of SO. Also, DRO shows a better expected performance in both averaged and worst-case probability distribution scenarios.

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