Electrical Power and Energy Systems 104 (2019) 255–258

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

A data-driven distributionally robust coordinated dispatch model for integrated power and heating systems considering wind power uncertainties

Yue Shui[a], Hongjun Gao[a,*], Lingfeng Wang[b], Zhenbo Wei[a], Junyong Liu[a]

[a] College of Electrical Engineering and Information Technology, Sichuan University, 610065 Chengdu, China
[b] Department of Electrical Engineering and Computer Science, University of Wisconsin- Milwaukee, 53211 Milwaukee, WI, USA

ARTICLE INFO

Keywords:
Integrated power and heating systems
Coordinated dispatch
Wind power
Distributionally robust
Uncertainties

ABSTRACT

When dealing with the practical wind power uncertainties in integrated power and heating systems, stochastic optimization is not feasible due to the unavailable accurate probability distribution function while robust optimization may result in over-conservative decisions. Based on the known historical data, a data-driven two-stage distributionally robust dispatch method is proposed in this study with the electric boiler, heating storage device, power storage device and combined heat and power (CHP) units considered in the model, which is then solved by a column and constraint generation (CCG) algorithm. The effectiveness of the proposed method is verified based on a modified IEEE 39-bus system.

1. Introduction

With coupling elements such as combined heat and power (CHP) units, electric boilers, and heating storage devices being integrated, the power and heating systems become interdependent and thus influence each other significantly. In this context, coordinated dispatch of integrated systems is regarded as an efficient way to promote the use of clean energies [1]. In this dispatch topic, the key challenge is the modeling of associated uncertainties. Currently, existing methods on this issue are stochastic optimization (SO) [2] and robust optimization (RO) [3]. Stochastic optimization is usually based on the known probability distribution, which is, however, difficult to obtain in practical applications. Meanwhile, robust optimization may result in over-conservative or risky decisions that are easily influenced by the uncertainty set manually and subjectively configured when dealing with the wind power uncertainties.

To overcome the difficulties mentioned above, we propose to combine these two existing methods and present a data-driven two-stage distributionally robust dispatch model [3] that is developed on the basis of the known historical data available in the supervisory control and data acquisition (SCADA) system and energy management systems (EMS). In the first stage of the model, the objective function includes not only the startup and shutdown cost of the traditional generation units but also the corresponding cost associated with the forecast wind power scenario, which can enable a more economical dispatch planning strategy [5]. The parameters for the heating and the power storage device are used as the first stage decision variables due to the multi-time coupling characteristic [6]. In the second stage of the model, norm-1 (absolute deviation summation constraints) and norm-inf (absolute deviation maximum 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. Finally, the distributionally robust model is solved by a column and constraint generation (CCG) algorithm. Moreover, a small transformation from absolute constraints of the feasible region of probability distribution to linear ones is devised in the solution method section to efficiently solve the model.

2. Distributionally robust coordinated dispatch model

The coordinated dispatch model treats the startup and shutdown cost, the generation cost of traditional units, the CHP units' operation cost, and the curtailment cost of wind power as its optimization targets while satisfying the power network constraints, heating network constraints, and power-heating coupling constraints. The power network constraints contain the generation limits, ramp limits and minimum ON/OFF time limits for the traditional generation units, the thermal generation units, the power storage devices and the electric boilers, the wind power curtailment limits and the DC power flow equations. The heating network constraints contain the heating balance, the heat limits of the CHP units, and the limits of the heating storage devices. The coupling constraints consider the coupling between the power and

* Corresponding author.
E-mail address: gaohongjun@scu.edu.cn (H. Gao).

https://doi.org/10.1016/j.ijepes.2018.07.008
Received 6 February 2018; Received in revised form 4 April 2018; Accepted 5 July 2018

heating for the electric boiler and the CHP units. For subsequent analysis, in this study the ON/OFF and startup/shutdown status of traditional generation units, the power storage and the heat storage are seen as the robust decision variables ($\boldsymbol{x}$) that cannot be adjusted after the uncertainties are revealed. The ON/OFF and startup/shutdown status are set as the day-ahead variables to instruct the dispatch scheduling. And in consideration of the multi-time coupling characteristic of the storage devices, the corresponding variables of the power storage and heat storage are set as the first-stage variable as well. Meanwhile, the corresponding operation variables ($\boldsymbol{y}_0$) associated with the forecast wind power scenario (ξ_0) are also included in the first stage for economic purpose. The continuous second-stage variables ($\boldsymbol{y}_k$) represent the real-time operation decisions as "wait-and-see" recourses. We apply a data-driven distributionally robust optimization (DRO) approach to describe the wind power uncertainties in this study. After a set of historical data is given, it is easy for us to construct K scenarios (ξ_k) 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^0. Nevertheless, the actual distribution (p_k) may usually be different from the above empirical one. All the existing works construct two types of confidence sets based on norm-1 and norm-inf, respectively. The two different sets may result in different dispatch schemes – it will be hard for the dispatcher to decide which one is superior. This study simultaneously considers these two norms to generate a single confidence set (Ω), which is more convenient for the dispatcher to make informed decisions quickly. The general structure of the data-driven distributionally robust coordinated dispatch model can be expressed in the following two-stage compact matrix form [7]:

$$\min_{x\in \mathrm{X}, \boldsymbol{y}_0\in \mathrm{Y}(\boldsymbol{x},\xi_0)} \boldsymbol{a}^{\mathrm{T}}\boldsymbol{x} + \boldsymbol{b}^{\mathrm{T}}\boldsymbol{y}_0 + \boldsymbol{c}^{\mathrm{T}}\boldsymbol{\xi}_0 + \left[\max_{\{p_k\}\in\Omega} \sum_{k=1}^{\mathrm{K}} p_k \min_{\boldsymbol{y}_k\in Y(\boldsymbol{x},\xi_k)} (\boldsymbol{b}^{\mathrm{T}}\boldsymbol{y}_k + \boldsymbol{c}^{\mathrm{T}}\xi_k)\right] \tag{1}$$

$$\text{s.t.} \quad \boldsymbol{Ax} \leqslant \boldsymbol{d} \tag{2}$$

$$\boldsymbol{Bx} = \boldsymbol{e} \tag{3}$$

$$\boldsymbol{Cy}_k \leqslant \boldsymbol{D}\xi_k, \forall\ k = 0,\ \ldots, \mathrm{K} \tag{4}$$

$$\boldsymbol{Gx} + \boldsymbol{Hy}_k \leqslant \boldsymbol{g}, \forall\ k = 0,\ \ldots, \mathrm{K} \tag{5}$$

$$\boldsymbol{Jx} + \boldsymbol{Ky}_k = \boldsymbol{h}, \forall\ k = 0,\ \ldots, \mathrm{K} \tag{6}$$

where $\boldsymbol{a}^{\mathrm{T}}\boldsymbol{x}$ is the startup/shutdown cost of the traditional generation units; and $\boldsymbol{b}^{\mathrm{T}}\boldsymbol{y} + \boldsymbol{c}^{\mathrm{T}}\boldsymbol{\xi}$ is the operational cost, including the generation cost of the traditional units and CHP units, and the curtailment cost of wind power. From the above formulation, the physical meaning of the distributionally robust model is to derive the robust optimal first-stage solution that minimizes the total cost, including the startup/shutdown cost of the traditional generation units and the corresponding operation cost under the forecast scenario in the first stage, and the expected operation cost under the worst-case wind power distribution in the second stage. The inner max-min model is to identify the worst-case probability distribution with the maximum expected operation cost for all K scenarios. Expression (2) denotes the first-stage inequality constraints such as the minimum up-time and down-time restrictions, and the storage charge/discharge limitations. Eq. (3) represents the first-stage equality constraints such as the relationship between the ON/OFF status and the startup/shutdown status of traditional units. Constraints (4) representing the dispatched wind power in each scenario are restricted by the forecast amount. Constraints (5) and (6) represent the coupling relationship between the first-stage variables and the second-stage variables. Next, the confidence set is constructed as follows within which the probability distribution can be arbitrary:

$$\Omega = \left\{ \{p_k\} \left| \begin{array}{l} p_k \geqslant 0,\ k = 1, \ldots, K \\ \sum_{k=1}^{\mathrm{K}} p_k = 1 \\ \sum_{k=1}^{\mathrm{K}} |p_k - p_k^0| \leqslant \theta_1 \\ \max_{1\leqslant k\leqslant \mathrm{K}} |p_k - p_k^0| \leqslant \theta_\infty \end{array} \right. \right\} \tag{7}$$

where θ_1 and θ_∞ are norm-1 and norm-inf tolerance value, which becomes smaller when more statistic historical data are provided. From (7), it can be found out that norm-1 and norm-inf are simultaneously used to constrain the confidence set of wind power probability distribution. And we suppose to find the worst wind power distribution probability in this model from (7). Supposing K scenarios from M historical samples, and the probability p_k^0 of each scenario k can be obtained as well, which is set as the basic empirical probability distribution, the following relationship can easily be obtained [4,7].

$$\Pr\left\{\sum_{k=1}^{\mathrm{K}} |p_k - p_k^0| \leqslant \theta_1\right\} \geqslant 1 - 2\mathrm{K}e^{-2\mathrm{M}\theta_1/\mathrm{K}} \tag{8}$$

$$\Pr\{\max_{1\leqslant k\leqslant \mathrm{K}} |p_k - p_k^0| \leqslant \theta_\infty\} \geqslant 1 - 2\mathrm{K}e^{-2\mathrm{M}\theta_\infty} \tag{9}$$

The right-hand side expressions of (8) and (9) are actually the confidence levels (e.g., 95%). They can be denoted as α_1 and α_∞, respectively. Then we can have (10) that enables the dispatcher to set a reasonable norm-1 and norm-inf tolerance value for the distributionally robust optimization model.

$$\begin{aligned} \theta_1 &= \frac{\mathrm{K}}{2\mathrm{M}}\ln\frac{2K}{1-\alpha_1} \\ \theta_\infty &= \frac{1}{2\mathrm{M}}\ln\frac{2K}{1-\alpha_\infty} \end{aligned} \tag{10}$$

3. Solution methods

The model (1)–(6) is a three-level min-max-min optimization problem, which is solved by the CCG algorithm in this study. The CCG algorithm divides the model into two problems that are the master problem (MP) and the sub-problem (SP). The repeated 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 (including $\boldsymbol{x}$ and $\boldsymbol{y}_0$) under some given finite worst-case probability distributions (possible realizations obtained from sub-problem). The MP provides a lower bound for model (1)–(6). After n iterations have been executed, the master problem can be expressed as follows:

$$(MP) \quad \min_{x\in \mathrm{X}, \boldsymbol{y}_0\in Y(\boldsymbol{x},\xi_0), \boldsymbol{y}_k^m\in Y(\boldsymbol{x},\xi_k), L} \boldsymbol{a}^{\mathrm{T}}\boldsymbol{x} + \boldsymbol{b}^{\mathrm{T}}\boldsymbol{y}_0 + \boldsymbol{c}^{\mathrm{T}}\boldsymbol{\xi}_0 + L \tag{11a}$$

$$L \geqslant \sum_{k=1}^{\mathrm{K}} \boldsymbol{p}_k^m(\boldsymbol{b}^{\mathrm{T}}\boldsymbol{y}_k^m + \boldsymbol{c}^{\mathrm{T}}\xi_k), \forall\ m = 1,\ \ldots, n \tag{11b}$$

The sub-problem gives an upper bound for model (1)–(6) by optimizing the worst probability distribution after first-stage variables $\boldsymbol{x}^*$ are given. The SP can be described in (12).

$$(\mathrm{SP}) \quad L(\boldsymbol{x}^*) = \max_{\{p_k\}\in\Omega} \sum_{k=1}^{\mathrm{K}} p_k \min_{\boldsymbol{y}_k\in \boldsymbol{Y}(\boldsymbol{x}^*,\xi_k)} \left(\boldsymbol{b}^{\mathrm{T}}\boldsymbol{y}_k + \boldsymbol{c}^{\mathrm{T}}\xi_k\right) \tag{12}$$

Because of the facts that the feasible region Ω and $\boldsymbol{Y}$ are absolutely disjoint and the feasible region $\boldsymbol{Y}$ for each scenario k is independent and separable, the outer max model and the inner min model can separately be solved. That is to say, the inner model can first be solved and the outer model is subsequently handled. Moreover, the inner min model can be decoupled into K small independent problems that are suitable