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Adaptive robust unit commitment considering distributional uncertainty

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ABSTRACT

To reduce the conservativeness of robust optimization-based unit commitment methods, an uncertainty set is usually prespecified with respect to the distributions of uncertain renewable resources, i.e., wind power. However, since the law of large numbers does not always work in practice, the obtained probability distribution may be unreliable. In this paper, a data-driven adaptive robust optimization method for the unit commitment of bulk power systems with high-level wind power integration is proposed. Different from the conventional robust unit commitment methods, the distributional uncertainty of wind power is well respected in the proposed approach. An imprecise-Dirichlet-model-based method is developed to construct the ambiguity set of wind power, which incorporates all possible probability distributions confirmed by historical data. The set can dynamically change with the data, i.e., the more valid data we have, the smaller the ambiguity set will become. With respect to the bounds of the ambiguity set, a polyhedron uncertainty set of wind power is constructed. By tuning the parameters of the uncertainty set, a balance between operational efficiency and risk can be achieved. An adaptive, robust unit commitment model is constructed based on the uncertainty set. By using the duality principle and big-M method, the formulations are converted into a mixed integer linear programming problem and solved using a column and constraint generation algorithm. Case studies on two benchmark systems illustrate the effectiveness and efficiency of the proposed method.

1. Introduction

The increasing integration of large-scale wind power has made achieving the unit commitment (UC) of bulk power systems a challenging task [1]. The UC module determines the online units and their dispatch strategies. Meanwhile, it is responsible for assigning a sufficient number of flexible resources to accommodate the uncertainty of wind power [2]. When these flexible resources cannot address the uncertainty, load shedding or wind spillage are implemented [3]. Therefore, finding an optimal approach to assign a sufficient number of flexible resources for wind power accommodation while maintaining high operational efficiency is important.

A variety of optimization technologies have been proposed to address the uncertainties in UC. These technologies can be roughly categorized into three types: deterministic optimization (DO) methods, stochastic optimization (SO) methods and robust optimization (RO) methods. The DO methods assign a spinning reserve (SR) according to deterministic rules [4,5]. Although these methods are easy to implement, they can hardly capture the varying characteristics of wind power, thereby potentially yielding suboptimal solutions [6,7]. The SO methods manage the uncertainties of wind power according to the probability distributions learned from historical data (HD) [8,9]. Theoretically, the SO methods can improve the expected performance of UC under uncertainties, but this improvement is highly dependent on the accuracy of the estimated probability distributions. In fact, the distributions of wind power can hardly be estimated precisely in practice; thus, satisfactory SO performance cannot always be guaranteed. In addition, the SO methods are usually time-consuming, and they are usually intractable even for moderate power systems [10]. The RO methods can optimize system operation in the worst case of a predetermined uncertainty set [11,12]. During optimization, the RO methods do not require any probabilistic information regarding the uncertainties and can usually converge quickly. However, RO-based UC methods may make over-conservative decisions as a result of ignoring the underlying statistical regularity, and the considered worst-case scenario may not always actually occur [13].

Note that the stochastic programming assumes the underlying probability distribution of uncertainties to be precisely known [8–10], whereas the conventional robust optimization ignores the probabilistic information [11–13]. In practice, the probability distribution truly

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Nomenclature

Sets

B	set of all buses
D	set of loads
D_b	set of loads in bus b
G	set of thermal units
G_b	set of thermal units in bus b
L	set of transmission lines
L_b^{in}	$l \in L \quad l = (k, b), k \in B$
L_b^{out}	$l \in L \quad l = (b, k), k \in B$
S	set of segments
T	set of scheduling periods
W	set of wind farms
W_b	set of wind farms in bus b

Indices

b	index for buses
d	index for loads
g	index for thermal units
l	index for transmission lines
s	index for segments
t	index for time periods
w	index for wind farms

Parameters

a_g, b_g, c_g	coefficients of the quadratic production cost function of unit g
B_{ij}	element in row i and column j of DC power flow matrix
c_{dt}	price of load shedding of load d in period t, c_{dt} = 1000$/MWh
c_{wt}	price of wind spillage of wind farm w in period t, c_{wt} = 10 $/MWh
D_{dt}	the electricity demand of load d in period t (MW)
$F_l^{\max}$	maximum power flow on transmission line l (MW)
M_{big}	big M: a very large number $M_{\text{big}} = 10^6$
$P_g^{\min}$, $P_g^{\max}$	minimal/maximum power output of thermal unit g (MW)
r_g^{up}, r_g^{dn}	ramp-up/ramp-down rate of thermal unit g
T_g^{on}, T_g^{off}	minimal on/off hour of thermal unit g
W_{wt}^{f}	forecasted output of wind farm w in period t (MW)
$W_w^{\max}$	installed capacity of wind farm w (MW)
X_g^{on}, X_g^{off}	number of periods unit g has been online/offline prior to the first period of the time span (end of period 0)
Γ^S/Γ^T	uncertain budget over spatial/temporal scale
β^T/β^S	confidence level of Γ^T/Γ^S
Φ	cumulative distribution function of the standard normal distribution

Variables

$f_{ij,t}$	flow on transmission line ij
P_{gt}	real-time power output of thermal unit g in period t (MW)
ΔW_{wt}	wind spillage power of wind farm w in period t (MW)
ΔD_{dt}	load shedding power of load d in period t (MW)
u_{gt}	binary decision variable: on/off status of unit g in period t. “1” if generator is on; “0” otherwise
v_{gt}	binary decision variable indicating whether generator g shuts down at the beginning of period t. “1” if generator shuts down; “0” otherwise
z_{gt}	binary decision variable indicating whether generator g starts up at the beginning of period t. “1” if generator starts up; “0” otherwise
W_{wt}	actual power output of wind farm w in period t (MW)
W_{wt}^{l}	lower output bound of wind power, determined by the IDM method (MW)
W_{wt}^{u}	upper output bound of wind power, determined by the IDM method (MW)
θ_{bt}	phase angle of bus b in period t

Functions

C_g	production cost function for thermal unit g
$S_g^{\text{u}}/S_g^{\text{d}}$	start-up/shut-down costs of thermal unit g (In this paper, the same letter symbol with different fonts represents different meanings. The common fonts have been assigned to specific meanings, which have been given in the nomenclature section. The bold and black fonts in the solution method parts are used to represent matrices or vectors.)

exists but must be estimated from historical data and is, therefore, itself uncertain. To better modeling and tackling uncertainties, the distributionally robust optimization (DRO) proposed in [14–17] offers an appealing decision-making paradigm for power system optimization without assuming the existence of precise probability distributions. DRO assumes that the true probability distribution of uncertain parameters lies in an ambiguity set (of probability distributions) and immunizes the operation strategies against all distributions in the ambiguity set. The objective of distributional robust is to optimize a problem under the worst case of the distributions in a set (the so-called ambiguity set). The DRO methods have been applied in UC [14,15], energy and reserve dispatch [16] and optimal power flow [17]. Typically, the DRO methods are developed from the SO methods, but they make decisions based on the worst distribution in a possible distribution set, namely, the ambiguous set, instead of an assumed precise distribution.

Different ways of constructing the ambiguity set lead to different DRO approaches with different degrees of conservativeness and computational efficiency. The ambiguity set is a family of possible distributions that can be formulated in terms of moments (the expectation, variance or both of distributions) [14–20] or distance from a known distribution [21]. In [14], the support of a one-dimensional random variable is partitioned into several segments, and an ambiguity set imposes the lower and upper bounds for the expectation of each segment. As the number of segments increases, the probability distribution can be characterized in more detail. Ref. [15] adopts the L_1 norm and L_∞ norm to construct the ambiguity sets, where the wind power is assumed to have finite samples. Refs. [16–20] construct ambiguity sets with a given expectation and covariance. The main shortcoming of the moment-based methods is that only part of the available statistical information is used in the optimization, which may worsen the conservativeness of the result. In this regard, Ref. [22] provides an ambiguity set based on the non-parametric confidence band estimation of the cumulative distribution function (CDF), with the assumption that random variables have continuous distributions. Ref. [23] employs a statistical inference technique to construct the ambiguity sets of discrete distributions. This work illustrates that more data will lead to less conservative solutions. The aforementioned studies well demonstrate that extracting reliable statistical information from available data is crucial for making a robust and less conservative UC decision. However, the existing methods either assume an affine recourse process to simplify the model or approximately convert the DRO model into a semi-definite programming (SDP) problem or a second-order conic programming (SOCP) problem to improve the numerical tractability, which may lead to a suboptimal solution.