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Bi-level robust dynamic economic emission dispatch considering wind power uncertainty



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Zhijian Hu^a, Menglin Zhang^{a,*}, Xiaofei Wang^a, Chen Li^b, Mengyue Hu^a

^a School of Electrical Engineering, Wuhan University, Wuhan City, Hubei Province, China ^b Wuhan Institute of Marine Electric Propulsion, Wuhan City, Hubei Province, China

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ABSTRACT

This paper presents a new formulation for the dynamic economic emission dispatch (DEED) based on robust optimizaiton (RO) and bi-level programming (BLP) in the background of large-scale wind power connected into power grid. RO is adopted to model the uncertainty of wind power output which varies within a bounded interval obtained by prediction. Considering that the feasible region of the optimization problem is likely to be empty due to the high uncertainty of wind power output, a slack varible - the reduction of the upper bound of the predicted wind power output interval - is introduced into the model to guarantee the security of the power system. To reflect the premise that the renewable energy should be fully utilized, the proposed model presents a BLP framework, in which the leader level pursuits the minimal fuel cost and emission simultaneously, and the follower level seeks for the minimal interval reduction of wind power output. A solution methodology in a nested framework based on the improved teaching-learning-based optimization (TLBO) algorithm and linear programming (LP) is proposed to solve the nonlinear BLP problem. In addition, a constraint handling technique is introduced to enforce the feasiblity of solutions. The proposed model and the solution methodology are applied to three cases with different ratios of wind power to evaluate their efficiency and feasibility.

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1. Introduction

Dynamic economic dispatch (DED) plays an important role in electric power system operation, it deals with determining the optimal output levels of the committed units over a dispatching horizon so as to minimize the fuel cost [1]. Recently, the increasing concern over the environment has led to the society demanding electricity not only at the cheapest price but also at minimum level of gas emission pollution [2]. The emission reduction measures for electric utilities include installing post-combustion cleaning systems, switching to fuels with low emission potential, emission dispatch, and so on[3]. However, emission dispatch is the most preferred measure as its ease of implementation. The method of extending the DED problem by incorporating emission dispatch is known as the dynamic economic emission dispatch (DEED) problem [4]. DEED is a multi-objective optimization problem and it is desirable to minimize the fuel cost and the emission simultaneously over

* Corresponding author. *E-mail address:* 951057354@qq.com (M. Zhang).

http://dx.doi.org/10.1016/j.epsr.2016.03.010 0378-7796/© 2016 Elsevier B.V. All rights reserved. a dispatching horizon, while satisfying load demands constraint, ramp rate constraint, etc.

This paper aims to present a new framework for integrating DEED with wind power generation in the background of large-scale wind power connected into power grid. Wind power generation can reduce fuel cost and carbon emission for electricity generation. However, due to the inherent uncertainty, the fluctuation of wind power may result in uneconomic or even unsecure operation conditions for power system operation. Therefore, uncertain modeling methods for wind power are required in the power system dispatching.

In previously published works on DEED or DED considering wind power, most research adopted stochastic programming to model the uncertainty of wind power. In Bahmani-Firouzi et al. [5], researchers used stochastic approach based on scenarios to model the uncertainty of wind power output, yet each scenario corresponded to a scheduling solution, which solution should be adopted was a problem. In Yuan et al. [6], the authors used chance constrained programming to simulate the impacts of wind power fluctuation on system operation, however, only the power balance constraints considered the impacts of wind power, neglecting

Nomenclature	
Abbreviat	ions
BLP	Bi-level programming
DCC	Dispatching control center
DED	Dynamic economic dispatch
DEED	Dynamic economic emission dispatch
LP	Linear programming
RO	Robust optimization
TLBO	Teaching-learning-based optimization algorithm
Indices i.j t	Unit index. Time interval index.
Constants a_i, b_i, c_i, d_i, e_i Fuel cost coefficients of unit i . $\alpha_i, \beta_i, \gamma_i, \zeta_i, \lambda_i$ Emission cost coefficients of unit i . N/T Total number of units/intervals. $p_{i,\min/p_{i,\max}}$ Minimum/maximum power output of unit i . $p_{load,t}$ System demand at time t . ur_i/dr_i Ramp up/down rates of unit i . B_{00}, B_{0i}, B_{ij} Loss coefficients. ε_i Scale factor of unit i for bearing wind power fluctuations. \bar{w}_t/Ψ_t Upper/lower bound of forecasted wind power output interval at time t . rd Random number of interval (0,1).	
General ve	ariables
$p_{t,i}$	Power output of unit <i>i</i> at time <i>t</i> .
$loss_t$	Active power losses at time <i>t</i> .
w_t	Dispatched wind power output at time <i>t</i> .
Δw_t	Wind power curtailment at time <i>t</i> .
Uncertain	<i>ty variables</i>
P̃ _{t,i}	Actual power output of unit <i>i</i> at time <i>t</i> .
ŵ _t	Actual wind power output at time <i>t</i> .

whether the ramping capacity constraint was still satisfied in actual scenario.

As an alternative way to cope with uncertain optimization problems, the robust optimization (RO) approach has received growing attention. RO is a set-based approach, in which the uncertain parameter belongs to a predetermined uncertainty set. This approach is attractive in two aspects. First, it is much easier to construct a bounded uncertain set for decision makers, compared with betting on the probability distribution function in the stochastic programming. Second, the optimal solution obtained by RO can satisfy all constraints for all data from the uncertainty set. RO has been extended to unit commitment and economic dispatch problems in recent years. Bertsimas et al. [7] proposed a two-stage adaptive robust unit commitment model with a bi-level mixedinteger optimization form, in which the uncertain parameter was the nodal net injection. Zhao et al. [8] proposed a robust unit commitment approach that considered wind power output and demand response information uncertainty together, assuming that both the wind power output and the price-elastic load curve were within a given interval or range. A robust interval wind power optimal method for look-ahead dispatch was presented in Wu et al. [9]. On the basis of [9], uncertainty set constructing strategies were proposed to reduce the conservativeness in [10].

In this paper, the actual wind power output is an uncertain parameter, and it is likely to be arbitrary value within the bounded interval obtained by prediction. As the actual wind power output deviates from the dispatched wind power output, the fluctuation happens. In such case, the original constraint balance between supply and demand is broken. To regain the balance between supply and demand, the thermal power units need to regulate their outputs in time to realize the transition of their outputs from the dispatched scenario to the actual scenario. It is assumed that the fluctuation is mainly undertaken by the committed thermal power units. It should be noted that due to the low accuracy of day-ahead wind power forecasting, the predicted interval of wind power output is very wide, which implies that the fluctuation at some extreme scenarios may be very large. As the extreme scenarios happen, if the system has no ability to provide sufficient generation capacity or ramping reserve to regain the power balance, the secure operation of the power system cannot be guaranteed. However, most research on DEED considering wind power has neglected the feasibility of the transition from the dispatched scenario to the actual scenario. Given that, we introduce a slack variable in the optimization problem to guarantee the feasible region nonempty when the system fails to provide sufficient regulating capacity to cope with all possible wind power fluctuations. As it is the high uncertainty of wind power output that lead to the large demand for regulating capacity, the reduction of the upper bound of the predicted wind power output interval is selected as the slack variable. By interval reduction, a new safe interval for wind power output is obtained. Here, the "safe" means as long as the actual wind power does not exceed the safe interval, the system can always provide sufficient regulating capacity to regain the power balance in the actual scenario. As stated above, the slack variable "reduction of the forecasted interval" is mainly used to guarantee the feasible region nonempty. However, from the perspective of full use of clean energy, a small interval reduction implies that the power system can accommodate more wind power, which is encouraged by the government, especially in countries like China where the phenomenon of wind curtailment is very serious. Therefore, the total minimum of interval reduction was chosen as a new objective to response to the government's appeal. To reflect the premise that the renewable energy should be fully used in DEED, the new objective should be included into the constraints. To this end, we introduce a new model to combine the DEED and the minimal interval reduction well by adopting a BLP framework. The BLP problem includes two levels: the upper level and the lower level, in the upper level, we minimize the fuel cost and emission; and in the lower level, we minimize the total interval reduction. In BLP, the upper level minimizes its objectives with the lower level problem as its constraint. This feature is exactly consistent with the idea of our scheduling. However, it should be noted why this paper did not adopt a threeobjective model like other references that try to achieve something similar as DEED. For example, in Nwulu and Xia [4], the authors combined the DEED with demand response program using a threeobjective model and each objective had the same weighting factor with the assuming that three objectives had the same status. Unlike Nwulu and Xia [4], if we adopt a three-objective model with the minimal interval reduction as the third objective, the premise that the renewable energy should be fully used cannot be well reflected as it is hard to set a suitable weight value for the third objective.

A BLP problem with nonlinear characteristic is usually hard to solve due to its intrinsic complexity [11]. The traditional methods for solving BLP problems are mainly focused on transforming the bi-level problem into a single level problem, but these methods usually require that both the upper and lower level problems are differentiable. Thereupon, many heuristic algorithms have been developed to solve the BLP problems with nonlinear characteristic, such as genetic algorithm [12], particle swarm optimization algorithm [13], and evolutionary algorithm [14]. The main advantage of heuristic algorithms is that it can solve optimization problems Download English Version:

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