Contents lists available at [ScienceDirect](http://www.sciencedirect.com/science/journal/03787796)

Electric Power Systems Research

iournal homepage: www.elsevier.com/locate/epsr

CrossMark

Robust unit commitment with dispatchable wind power

Germán Morales-España^{a,∗}, Álvaro Lorca^b, Mathijs M. de Weerdt^a

a Algorithmics Group, Department of Software Technology, Delft University of Technology, 2628 CD Delft, The Netherlands **b** Department of Electrical Engineering, Department of Industrial and Systems Engineering, UC Energy Research Center, Pontificia Universidad Católica de Chile, Vicuña Mackenna 4860, Macul, Santiago, Chile

a r t i c l e i n f o

Article history: Received 25 January 2017 Received in revised form 4 September 2017 Accepted 1 October 2017

Keywords: Stochastic optimization Robust optimization Dispatchable wind Wind curtailment Unit commitment

a b s t r a c t

The increasing penetration of uncertain generation such as wind and solar in power systems imposes new challenges to the unit commitment (UC) problem, one of the most critical tasks in power systems operations. The two most common approaches to address these challenges — stochastic and robust optimization – have drawbacks that restrict their application to real-world systems. This paper demonstrates that, by considering dispatchable wind and a box uncertainty set for wind availability, a fully adaptive two-stage robust UC formulation, which is typically a bi-level problem with outer mixed-integer program (MIP) and inner bilinear program, can be translated into an equivalent single-level MIP. Experiments on the IEEE 118-bus test system show that computation time, wind curtailment, and operational costs can be significantly reduced in the proposed unified stochastic–robust approach compared to both pure stochastic approach and pure robust approach, including budget of uncertainty.

© 2017 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license [\(http://creativecommons.org/licenses/by/4.0/](http://creativecommons.org/licenses/by/4.0/)).

1. Introduction

In recent years, higher penetration of variable and uncertain generation(e.g., windandsolarpower)has challengedindependent system operators (ISOs) to maintain a reliable and still economical operation of power systems. To achieve this and to be prepared for future demand, ISOs decide about startup and shutdown schedules of generating units some time (typically a day) up front by solving the so-called unit commitment (UC) problem, whose main objective is to minimize operational costs while meeting power system constraints. These operational costs are commitment-related costs, and dispatch costs of both thermal and wind generating units, where the latter can present negative cost (or bids) [\[1\].](#page--1-0) High levels of variable and uncertain generation significantly increase the uncertainty in the net forecasted future demand, increasing the difference between a fail-safe solution and an economical solution, and this dilemma thereby increases the complexity of the UC optimization problem [\[2\].](#page--1-0)

The two main approaches for dealing with the uncertainty in UC problems are stochastic and robust optimization. Stochastic optimization (SO) $[2-5]$ typically consists of minimizing expected costs over a set of possible scenarios for uncertain parameters. However, SO can become impractical under high-dimensional problems

mainly because of a heavy computational burden [\[2\].](#page--1-0) Additionally, the main goal for ISOs is to ensure a safe operation of the system, and SO does not give sufficient guarantees on meeting the constraints in realizations of the uncertainty. Moreover, SO requires a large number of scenarios to be reliable and their associated probability distribution is hard to obtain.

In robust optimization (RO) $[6-10]$ the costs are minimized maintaining feasibility under all possible realizations of uncertain parameters within some specified uncertainty set. Consequently, the resulting schedules could turn out to be over-conservative under a large uncertainty set: although the probability of the worst-case event is virtually nil, the chosen schedule is robust for this event, and hence much more costly than what is actually required. One way to reduce over-conservatism is to use a budget of uncertainty, which models a smaller uncertainty set in a flexible way $[6]$. A robust UC typically requires solving a bilevel optimization problem, where the outer level is a mixed-integer linear program (MIP), and the inner level is usually a bilinear program, which is non-deterministic polynomial-time hard (NP-hard) [\[6\].](#page--1-0) Finding optimal robust solutions in time for large-scale systems is still a major challenge; in particular, solving the respective bilinear problems usually requires sub-optimal heuristic methods or computationally expensive exact methods $[6,11-14]$. Further, this bilinear problem is typically solved multiple times as part of an iterative algorithm such as column-and-constraint generation [\[11\],](#page--1-0) which also requires solving a difficult master problem multi-

∗ Corresponding author.

<https://doi.org/10.1016/j.epsr.2017.10.002>

0378-7796/© 2017 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license [\(http://creativecommons.org/licenses/by/4.0/](http://creativecommons.org/licenses/by/4.0/)).

E-mail address: g.a.moralesespana@tudelft.nl (G. Morales-España).

ple times. This computational difficulty highlights the challenge of creating efficient methods to find effective robust UC solutions.

Recently, the so-called unified stochastic–robust (SR) optimization approach has been proposed to strike a very good balance between robustness and efficiency [\[7\].](#page--1-0) This approach increases safe operation of the system while mitigating the over-conservatism of robust optimization. However, since this formulation combines the stochastic formulation (which requires optimization over many scenarios) with the bilinear robust formulation, the computational challenge is even stronger.

This paper considers wind dispatch flexibility by allowing curtailment in the UC formulation. In various previous works, wind power has also been modeled as dispatchable by allowing wind curtailment in UC or expansion planning models [\[1,12,15–19\].](#page--1-0) In this paper we will exploit some consequences that are obtained in the robust UC problem when wind power is dispatchable, which will lead to very computationally efficient formulations.

This paper rises up to various current challenges in the UC problem by providing the following contributions:

- 1. Under the case in which wind power availability is modeled through a box uncertainty set, and assuming that wind power can be curtailed, we prove that the usually non-linear and NP-hard [\[6\]](#page--1-0) second stage of a fully adaptive robust UC problem has an equivalent linear program (LP) representation, which solves in polynomial time. Consequently, in this case the fully adaptive two-stage robust UC formulation can be translated into an equivalent single-level MIP problem. This allows solving realistically-sized problem instances very close to global optimality significantly faster than the traditional bi-level robust UC. When compared with a typical robust formulation based on budget of uncertainty, the proposed formulation provides similar results but solves significantly faster.
- 2. We also show that considering dispatchable wind can contribute to efficiently solving a unified stochastic–robust optimization problem [\[7\]](#page--1-0) by linking the wind dispatch between the stochastic and the robust parts. Thus, the proposed SR formulation provides a cheaper operation, higher robustness, less wind curtailment, while simultaneously having lower computational burden than a typical RO formulation based on budget of uncertainty. Also, the SR needs very few scenarios to provide very similar results to a scenario-rich SO, hence naturally avoiding the high computational burden associated to considering a large number of scenarios.

The remainder of this paper is organized as follows. Section 2 details the proposed robust UC reformulation with dispatchable wind, and shows how to complement stochastic UC by incorporating the robust part. Section [3](#page--1-0) provides and discusses results from several experiments, where a comparison between robust, stochastic and unified UC formulations is made. Finally, main conclusions are drawn in Section [4.](#page--1-0)

2. Mathematical models and structural results

This section formulates the mathematical models and presents a set of results that exploit the structure of the robust UC with dispatchable wind. Section 2.1 defines this problem, and Section 2.2 presents a general structural result that characterizes the subset of elements of the uncertainty set that can achieve the worst case. Section [2.3](#page--1-0) studies this structural result under the widely used budget and box uncertainty sets. Finally, Section [2.4](#page--1-0) studies the consequences of these structural results in the unified stochastic–robust UC.

2.1. Robust UC with dispatchable wind

We extend the 3-binary setting UC formulation [\[20\]](#page--1-0) to a robust UC with dispatchable wind. The compact form of this robust UC is expressed as

$$
\min_{\mathbf{x} \in X} \left\{ \boldsymbol{b}^{\top} \mathbf{x} + \max_{\boldsymbol{\xi} \in \varXi} \min_{(\boldsymbol{p}, \boldsymbol{w}) \in \varOmega(\mathbf{x}, \boldsymbol{\xi})} \left(\boldsymbol{c}^{\top} \boldsymbol{p} + \boldsymbol{d}^{\top} \boldsymbol{w} \right) \right\}
$$
(1)

where

$$
X = \left\{ \boldsymbol{x} \in \{0, 1\}^{3|\mathcal{G}||T|} : \boldsymbol{A}\boldsymbol{x} \leq \boldsymbol{a} \right\}
$$
 (2)

and

$$
\Omega(\mathbf{x},\boldsymbol{\xi}) = \{(\mathbf{p},\mathbf{w}): \mathbf{E}\mathbf{p} + \mathbf{F}\mathbf{w} \leq \mathbf{g} + \mathbf{G}\mathbf{x} \tag{3a}
$$

$$
w \leq \xi \tag{3b}
$$

Here, **x** is a vector of first-stage decisions including the binary on/off, start-up and shut-down decisions of conventional generators. These decisions are constrained through set X defined in (2), which includes the logical relations between on/off, start-up and shut-down variables, as well as minimum up and down times. In (2), $\mathcal G$ is the set of conventional generators and T is the set of time periods. Vector ξ contains all uncertain parameters in the problem, corresponding to the availability of wind power at all wind farms and time periods, i.e., $\xi = (\xi_{it} : i \in \mathcal{W}, t \in \mathcal{T})$, where ξ_{it} is the available wind power at bus i and time t, and W is the set of buses containing wind production. The closed set E is an uncertainty set that describes the realizations of **ξ**. Vectors **p**, **w** are second-stage power dispatch decisions for conventional generators and wind farms, respectively, i.e., $\boldsymbol{p} = (p_{gt} : g \in \mathcal{G}, t \in \mathcal{T})$ and $\mathbf{w} = (w_{it} : i \in \mathcal{W}, t \in \mathcal{T})$, where p_{gt} and w_{it} are the power output of conventional generator g and of wind farms at bus i, at time t, respectively. These power dispatch decisions are constrained through set $\Omega(x, \xi)$ defined in (3). In $\Omega(x, \xi)$, Eq. (3a) involves dispatch-related constraints such as power output bounds for conventional generators, nonnegativity of power output at wind farms, ramping constraints, transmission line capacity constraints and energy balance constraints. Eq. $(3b)$ represents the upper bound for power output at wind farms, depending on available wind power, that is, $w_{it} \leq \xi_{it}$ for all *i*, *t*. Finally, the objective function of problem (1) consists of minimizing the sum of no-load, start-up and shutdown costs, given by $\mathbf{b}^\top \mathbf{x}$, and worst-case dispatch costs, given by the inner max-min problem, where **c** contains the production costs of conventional generators and where **d** is the production costs of wind farms, which is usually zero or negative representing negative bids (resulting in wind curtailment penalization) [\[1\].](#page--1-0)

The robust UC problem (1) is an adaptive robust optimization problem [\[21\].](#page--1-0) In this problem, **p** and **w** are adaptive decision variables whose values can depend on the realization of the vector of uncertain parameters ξ , while **x** is a "here-and-now" decision that is taken before **&** is realized. This adaptive robust framework for the UC problem was first proposed in [\[6,22,23\].](#page--1-0) This section focuses on studying the consequences of considering wind power to be dispatchable, that is, that wind power output w_{it} can take any value between 0 MW and its availability ξ_{it} . In what follows, we provide a general result that characterizes a subset of the uncertainty set that necessarily contains the worst-case realization of ξ .

2.2. Worst-case is achieved in the set of minimal elements

The inner max–min problem in the robust $UC(1)$

$$
\max_{\xi \in \mathcal{Z}} \min_{(\boldsymbol{p}, \boldsymbol{w}) \in \mathcal{Q}(\boldsymbol{x}, \xi)} (\boldsymbol{c}^{\top} \boldsymbol{p} + \boldsymbol{d}^{\top} \boldsymbol{w})
$$
\n(4)

has a special structure: the only dependence of $\Omega(\mathbf{x}, \xi)$ on ξ is through constraint (3b), namely, $w \leq \xi$. We can use this structure Download English Version:

<https://daneshyari.com/en/article/5000868>

Download Persian Version:

<https://daneshyari.com/article/5000868>

[Daneshyari.com](https://daneshyari.com)