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Integration of renewable generation uncertainties into stochastic unit commitment considering reserve and risk: A comparative study

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ABSTRACT

The uncertainties of renewable energy have brought great challenges to power system commitment, dispatches and reserve requirement. This paper presents a comparative study on integration of renewable generation uncertainties into SCUC (stochastic security-constrained unit commitment) considering reserve and risk. Renewable forecast uncertainties are captured by a list of PIs (prediction intervals). A new scenario generation method is proposed to generate scenarios from these PIs. Different system uncertainties are considered as scenarios in the stochastic SCUC problem formulation. Two comparative simulations with single (E1: wind only) and multiple sources of uncertainty (E2: load, wind, solar and generation outages) are investigated. Five deterministic and four stochastic case studies are performed. Different generation costs, reserve strategies and associated risks are compared under various scenarios. Demonstrated results indicate the overall costs of E2 is lower than E1 due to penetration of solar power and the associated risk in deterministic cases of E2 is higher than E1. It implies the superimposed effect of uncertainties during uncertainty integration. The results also demonstrate that power systems run a higher level of risk during peak load hours, and that stochastic models are more robust than deterministic ones.

1. Introduction

The large-scale penetration of IRESs (intermittent renewable energy sources), such as wind and solar, into traditional power systems has significant impacts on system commitment, dispatches and reserve requirements [1]. There are generally two approaches to manage and mitigate uncertainties from IRESs. One approach is to improve the forecast accuracy as much as possible, using point forecasting or probabilistic forecasting methods [2–4]. Another approach is to develop advanced methodologies to effectively manage these uncertainties [5,6] while realizing that forecast errors will always exist to a certain degree. This research combines these two approaches and integrates IRES uncertainties from probabilistic forecasting into power system operations for UC (unit commitment) scheduling and ED (economic dispatch).

Recent works in the field of renewable energy forecasting indicate a shift from traditional point forecast methods towards probabilistic forecasting [7]. This is due to the limitations of point forecasting methods in adequately representing uncertainty. As opposed to point forecasts, probabilistic forecasting quantifies uncertainty in the form of quantiles, intervals, scenarios or density prediction [7]. Despite significant progress in the field of probabilistic forecasting, literature is quite weak in terms of embedding these forecasts into optimization and decision-making processes [6]. Probabilistic forecasting encounters the multivalued problem when used for decision-making. Taking the PIs (prediction intervals) as an example, a single level of PI consists of three components: the upper bound, the lower bound and the corresponding confidence level $(1-\alpha)\%$ [8]. Compared to the single value of point forecasts, the multiple values of PIs become a barrier to the computation and decision-making [6]. This becomes even more challenging if PIs with different significance levels are constructed.

To manage the uncertainties during renewable energy integration to the gird, fuzzy logic models [9–11], robust optimization [12–14], CCP (chance-constrained programming) [15–17] and stochastic programming models [18,19] address the problem in different perspectives. In fuzzy logic models, fuzzy sets and membership functions are used to represent the variability of IRESs. In

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Nomenclature

i	index of generators, i = 1, …, N
t	index of scheduled hours, t = 1, …, H
s	index of scenarios, s = 1, …, S
p_s	the probability of scenario s
$X_{i,t}$	the scheduled state (on/off) of unit i at time t
$P_{i,t}$	the output power of unit i at time t
$E(X,P)$	objective function: the expected product costs
$F_i(P_{i,t})$	fuel cost of unit i when its output power is $P_{i,t}$
a_i, b_i, c_i	coefficients for quadratic cost curve of unit i
$SU_{i,t}$	startup cost of unit i at time t
$CSU_{i,t}$	cold startup cost of unit i at time t
$HSU_{i,t}$	hot startup cost of unit i at time t
R_t^s	the spinning reserve at time t in scenario s
D_t	the system demand at time t
ENS_t^s	the energy not served at time t in scenario s
RNS_t^s	the reserve not served at time t in scenario s
C_{ens}	the cost of energy not served
C_{rns}	the cost of reserve not served
W_t^s	wind generation at time t in scenario s
PV_t^s	solar generation at time t in scenario s
FO_t^s	generator forced outage at time t in scenario s
$P_{i,max}$	maximum real power generation of unit i
$P_{i,min}$	minimum real power generation of unit i
$T_{i,t}^{off}$	the continuously off time of unit i at time t
$T_{i,t}^{on}$	the continuously on time of unit i at time t
T_i^{Up}	the minimum up time of unit i
T_i^{Down}	the minimum down time of unit i
T_i^{cold}	the cold start hours of unit i
α	the significance level, and $(1-\alpha)$% is the nominal confidence level of prediction intervals
A	a system-dependent constant in fitness function

Ref. [9], fuzzy-optimization was proposed for solving the generation scheduling problem. Hourly load, available water, wind speed and solar radiation forecast errors were taken into account using fuzzy sets. Robust optimization-based methods model the randomness using an uncertainty set which includes the worst-case scenario. The uncertainty set can be constructed from the PIs or quantiles of IRES forecasting. In Ref. [12], Jiang et al. studied the robust UC with wind power and pumped storage hydro, and developed an algorithm to automatically simulate the worst-case scenario where the wind power output changes between upper and lower bounds. An extension of robust optimization was derived in Ref. [13] as adjustable robust optimization. CCP describes uncertainty in the form of probability attainment [15], implying that one or a set of constraints has a desired probability of satisfaction. However, CCP problems are usually computational intractable because the feasibility region defined by chance constraints is generally not convex, or multi-integration is required to calculate probability indices.

The cornerstone of stochastic programming models is the probability and scenarios. In these models, each scenario represents one possible realization of the renewable power, and the expected value is further calculated to make operational decisions. In Ref. [19], Wu et al. implemented a SCUC (stochastic security-constrained UC) study in which the scenario-based stochastic SCUC was compared with the optimistic and pessimistic solutions obtained from the interval optimization [19]. Wang et al. in Ref. [20] emphasized the aspects of intermittence and volatility of wind power in SCUC. Wind power was assumed to follow a normal distribution and Monte Carlo simulation was used to generate scenarios. In Ref. [21], Ortega-Vazquez et al. considered wind power generation as a negative load to estimate the spinning reserve requirements in systems with significant wind power penetration. The net demand forecast error was generated using a Gaussian cumulative probability distribution. In Ref. [22], a stochastic programming framework was built as a multi-objective problem and different sources of uncertainties were taken into consideration for optimal operation of micro-grids.

It is noted that most of the previous studies make special assumptions on wind speed distributions, either a normal distribution [21] or a Weibull (Rayleigh) probability distribution [18]. The robust UC needs to predefine the uncertainty set and find the worst-case scenario [14]. To generate wind power scenarios, in Refs. [23,24] the complex covariance matrix needs to be calculated based on a multivariate Gaussian distribution assumption. Although the works highlighted above have focused on integration of IRESs into UC, very few have conducted an extensive comparative study. They either consider only wind uncertainty [19,20] or integrate some uncertainties together [22,25]. Moreover, these studies are conducted in a separate manner.

The main goal of this paper is to conduct a comparative study on integration of renewable generation into grid scheduling from the uncertainty management and risk assessment points of view. Our main contributions are summarized below:

(1) An extensive comparative study has been conducted, and the case with wind-only uncertainty is compared to the case with multiple uncertainties arising from load, wind, solar and generator outages.
(2) A novel scenario generation method is proposed to capture renewable uncertainties from PIs without making specific assumptions about data distributions.
(3) Five deterministic and four stochastic UC strategies are implemented and compared under various scenarios.
(4) Different reserve strategies are investigated, and the scheduled reserve and real time ED reserve are compared.
(5) The conclusion derived from these studies can serve to provide some guidelines for system operators from the reserve and risk assessment perspectives.

The rest of this paper is organized as follows. Uncertainty representation with renewable generation is introduced in Section 2. Problem formulation and the GA (genetic algorithm)-based solution method are described in Section 3. Sections 4 and 5 describe case studies and discuss simulation results. Finally, Section 6 concludes the paper.

2. Uncertainty representation with renewable generation

2.1. Load uncertainty representation

Although the load forecasting errors, such as MAPE (mean absolute percentage errors), are much smaller than the errors associated with IRESs, the MW value of load forecasting error is typically large. A common method is to model the load uncertainty as normal distribution [6,26]. In this paper, load forecast errors are assumed to follow the normal distribution, and load uncertainty is