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A computational framework for uncertainty integration in stochastic unit commitment with intermittent renewable energy sources

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HIGHLIGHTS

- A computational framework is proposed for uncertainty integration.
- A new scenario generation method is proposed for renewable energy.
- Prediction intervals are used to capture uncertainties of wind and solar power.
- Load, wind, solar and generator outage uncertainties are integrated together.
- Different generation costs and reserves are discussed for decision making.

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ABSTRACT

The penetration of intermittent renewable energy sources (IRESs) into power grids has increased in the last decade. Integration of wind farms and solar systems as the major IRESs have significantly boosted the level of uncertainty in operation of power systems. This paper proposes a comprehensive computational framework for quantification and integration of uncertainties in distributed power systems (DPSs) with IRESs. Different sources of uncertainties in DPSs such as electrical load, wind and solar power forecasts and generator outages are covered by the proposed framework. Load forecast uncertainty is assumed to follow a normal distribution. Wind and solar forecast are implemented by a list of prediction intervals (PIs) ranging from 5% to 95%. Their uncertainties are further represented as scenarios using a scenario generation method. Generator outage uncertainty is modeled as discrete scenarios. The integrated uncertainties are further incorporated into a stochastic security-constrained unit commitment (SCUC) problem and a heuristic genetic algorithm is utilized to solve this stochastic SCUC problem. To demonstrate the effectiveness of the proposed method, five deterministic and four stochastic case studies are implemented. Generation costs as well as different reserve strategies are discussed from the perspectives of system economics and reliability. Comparative results indicate that the planned generation costs and reserves are different from the realized ones. The stochastic models show better robustness than deterministic ones. Power systems run a higher level of risk during peak load hours.

1. Introduction

Renewable energy resources such as wind and solar power have several major benefits including low economic costs and zero environmental footprints. That is why their deployment has sustained a high growth rate in many countries worldwide [1]. However, the level of uncertainties associated with operation of intermittent renewable energy sources (IRESs) is high. In addition, uncertainties do exist in other parts and components of power systems including but not limited to consumers (load demands), generators (shutdowns), and transmission lines (faults and leakages).

Uncertainties in forecasting the output of IRESs such as wind and solar generation, as well as system loads, are not incorporated into existing energy management systems (EMSs) and tools used for generation commitment, dispatch, and market operation. With the growing penetration of intermittent resources, these uncertainties could result in significant unexpected load following and dispatch problems and pose serious risks to control and

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Nomenclature

Mathematical symbols

i	index of generators, $i = 1, \ldots, N$
t	index of scheduled hours, $t = 1, \ldots, H$
s	index of scenarios, $s = 1, \ldots, S$
α	$(1-\alpha)\%$ is the confidence level of PIs
p_s	the probability of scenario s
$(.)^s$	variable related to 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
$E(X,P)$	the objective function, the expected product costs.
$F_i(P_{i,t})$	the fuel cost of unit i when its output power is $P_{i,t}$
$SU_{i,t}$	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^s	the system demand at time t in scenario s
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
a_i, b_i, c_i	coefficients for the quadratic cost curve of unit i
$FLAC(i)$	the full load average cost of unit i
A	the system-dependent constant in the fitness function
q	the parameter in the q-tournament selection

Abbreviations

IRES	intermittent renewable energy source
DPS	distributed power system
PI	prediction interval
ECDF	empirical cumulative distribution function
SCUC	security-constrained unit commitment
UC	unit commitment
ED	economic dispatch
PL	priority listing
LR	Lagrangian relaxation
GA	genetic algorithm
PSO	particle swarm optimization
DE	differential evolution
NN	neural network

operation of the grid and its reliability. Without quantifying prevailing risks, system operators have limited means to assess the likelihood of occurrence of problems and take actions to mitigate them [2]. Hence, there is a real business need to develop and deploy a computational framework to integrate these uncertainties together and mitigate the potential risks for the system.

To account for the variability and intermittence of IRESs during renewable energy integration to the grid, fuzzy mathematical programming models [3,4], stochastic programming models [5,6] and robust optimization approaches [7–10] are popular in literature. Probabilistic forecasts of IRESs, such as prediction intervals (PIs), quantiles or scenarios, are optimal inputs to the integration framework [11]. A comprehensive review of probabilistic forecasting of wind power generation can be found in [11]. Fuzzy mathematical programming models represent uncertainty through fuzzy set and membership functions. In [4], a fuzzy-optimization approach was proposed for solving the generation scheduling problem with consideration of wind and solar energy systems. Hourly load, available water, wind speed and solar radiation forecast errors were taken into account using fuzzy sets. Stochastic programming models quantify uncertainties of IRESs by probability and scenarios, and the expected value is provided. A stochastic programming framework [5] was built as a multi-objective problem. Different sources of uncertainties were considered for optimal operation of micro-grids. Wu et al. [6] implemented and compared the stochastic models and interval optimization approaches for security-constrained unit commitment (SCUC). Wind power scenarios were generated from a Weibull probability distribution. Robust optimization approaches predefine the uncertainties in an uncertainty set and the worst case scenario is considered. An integrated framework [7] was proposed based on multi-agent modeling and robust optimization for microgrid energy management.

Some recent publications [12–14,7] investigated the influence of IRES uncertainties on grid operations. These uncertain factors include but not limited to extreme weather conditions [12], operation reserves [13], generator ramp rate and the power market behavior [14]. A methodology to set operating reserve considering load forecast uncertainty, conventional generation outages and wind power forecast uncertainty was described in [13]. Makarov et al. in [15] proposed an approach to integrate the uncertainty model with an existing EMS. Different levels of integration such as passive, active and proactive integrations were presented. However, only load and wind power forecasting uncertainties were considered and the solar power uncertainty was not involved. In [16], intermittent wind units were integrated into a generating company's generation assets. The hourly wind generation schedule was coordinated with that of natural gas units and hydro units for maximizing the generating company's payoff.

Previous studies mainly focus on one or two aspects of the uncertainties, such as the load and/or wind power forecast uncertainties [6,17–19,8,9]. It is very important to address this problem comprehensively by including all sources of uncertainty (load, wind and solar power generation, forced generator outages, etc.). In [20,21], the influence of wind power forecast uncertainties on generation costs and different reserves have been investigated. In order to focus on wind power uncertainties, other uncertainties such as load and forced generator outages were temporarily ignored. Moreover, the scenario generation methods of previous stochastic models suffer from either the specific data distribution assumptions [6,18] or implementation difficulties [22,23]. For example, wind speed was usually assumed to follow the Weibull [6] or Normal distributions [18]. To generate wind power scenarios, the complex covariance matrix needs to be calculated based on a multivariate Gaussian distribution assumption [22,23]. The robust UC needs to predefine the uncertainty set. It is also difficult to find and prove the worst case scenario [7–10]. In this paper, a computational framework is proposed to consider various uncertainties together. It avoids making assumptions about specific data distributions and can be easily implemented. A preliminary research has been conducted to investigate the framework for uncertainty integration.