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Two-stage stochastic unit commitment model including non-generation resources with conditional value-at-risk constraints

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ABSTRACT

This paper presents a two-stage stochastic unit commitment (UC) model, which integrates non-generation resources such as demand response (DR) and energy storage (ES) while including risk constraints to balance between cost and system reliability due to the fluctuation of variable generation such as wind and solar power. This paper uses conditional value-at-risk (CVaR) measures to model risks associated with the decisions in a stochastic environment. In contrast to chance-constrained models requiring extra binary variables, risk constraints based on CVaR only involve linear constraints and continuous variables, making it more computationally attractive. The proposed models with risk constraints are able to avoid over-conservative solutions but still ensure system reliability represented by loss of loads. Then numerical experiments are conducted to study the effects of non-generation resources on generator schedules and the difference of total expected generation costs with risk consideration. Sensitivity analysis based on reliability parameters is also performed to test the decision preferences of confidence levels and load-shedding loss allowances on generation cost reduction.

1. Introduction

Stochastic unit commitment (SUC) is an effective modeling technique and it has been introduced as a promising tool to deal with power generation problems involving uncertainties [1–6]. SUC assumes scenario-based uncertainty in unit commitment problems, i.e., it captures the uncertainty and variability of the underlying factors by simulating a large number of scenarios. One of prominent factors is the high penetration of renewable energy to current power systems, which brings a lot of uncertainties on energy supply and transmission. Considering one of renewable energy resources like wind energy, the forecasting errors or intermittent energy supply in net load will cause conventional power plants to ramp up/down frequently to ensure their energy outputs satisfy real-time demand levels. Therefore, on one side, non-generation resources, e.g., demand response (DR) and energy storage (ES), have been well developed and facilitate the expansion of renewable energy's usage. On the other side, management techniques for energy systems can be used effectively to ensure the smooth integration of existing power plants with renewable energy outputs [7] as well as power system reliability. This paper aims to investigate the unit commitment scheduling cooperated with non-generation resources and risk control so as to improve power system reliability and reduce cost. The main uncertainties in consideration of this paper include renewable energy output and demand response. This real-world problem is formulated through a two-stage stochastic mixed integer program.

On one hand, energy storage is one of typical non-generation resources and a feasible solution to facilitate the integration of wind power generation. The main advantage is that it is able to provide electricity supply when the peak demands occur to be greater than generation capacities in a power system, or the generation costs are extremely high. Since the storage devices can store or release energy based on operations and demands, the incorporation of ES can increase the flexibility of power supply systems and decrease total costs at the same time. Some literature has discussed the economic value of ES investments, system-economic evaluations [8], optimal size and capacity for ES systems [9,10], and stochastic operation management with ES on micro grid [11]. Recently, there are three main large-scale energy storage technologies, including pumped hydro accumulation storage (PAC), underground PAC and compressed air energy storage (CAES). Most studies of energy storage focus on CAES in the areas of economic value of investments, system-economic perspectives, technical challenges to the integration of wind power with power systems, and production planning [12,13]. In most of the optimization models, energy storage is

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Nomenclature

A. Sets and Indices

A	Set of transmission lines
G	Set of all generators
G_i	Set of electrical power generators at bus i
N	Set of locations (buses)
T	Length of planning horizon
g	Indices of generators
i, j	Indices of buses
t	Time period
Ξ	The set of all possible scenarios
ξ	Indices of scenarios

B. Parameters

SU_{gt}	start-up cost of unit g in period t
SD_{gt}	shut-down cost of unit g in period t
$Prob^{\xi}$	probability of scenario ξ
L_g	minimum ON time of unit g
l_g	minimum OFF time of unit g
$P_g^{\max}$	maximum power generation of unit g
$P_g^{\min}$	minimum power generation of unit g
RU_g	ramping up limit of unit g
RD_g	ramping down limit of unit g
RS_{it}	spinning reserve requirement at bus i in period t
$S_g^{\max}$	maximum spinning reserve of unit g
R_{it}^{ξ}	renewable energy at bus i in period t of scenario ξ
D_{it}	forecasted demand at bus i in period t
E_{it}^{ξ}	price elasticity at bus i in period t of scenario ξ
ρ_i	storage efficiency at bus i
B_{ijt}	susceptance in branch $i-j$ in period t;
θ	confidence level
β_{it}^{ξ}	voltage angle at bus i
$\overline{\phi}$	maximum load-shedding loss allowance
α, γ	price velocity indicators
κ_i	maximum storage capacity at bus i

C. Variables

u_{gt}	commitment decision of unit g at period t
v_{gt}	startup action of unit g at period t
w_{gt}	shutdown action of unit g at period t
p_{gt}^{ξ}	power generation of unit g in period t of scenario ξ
s_{gt}^{ξ}	spinning reserve of unit g in period t of scenario ξ
f_{ijt}^{ξ}	power transmission from bus i to bus j in period t of scenario ξ
q_{it}^{ξ}	electricity price at bus i in period t of scenario ξ
r_{it}^{ξ}	remaining power at bus i in period t of scenario ξ
v_{it}^{ξ}	power saving at bus i in period t of scenario ξ
x_{it}^{ξ}	renewable energy dispatch amount at bus i in period t of scenario ξ
y_{it}^{ξ}	shifted demand at bus i in period t of scenario ξ
η_t	value-at-risk at period t (VaR)
ζ_t^{ξ}	the loss exceeding VaR in period t of scenario ξ

introduced as time-dependent multi-period storage constraints. Senjyu et al. [14] discuss the thermal UC problem consisting of generalized energy storage systems (ESS) and solve the model by extended priority list. Daneshi and Srivastva [8] develop enhanced security-constrained UC with wind generation and CAES, and conduct the comprehensive analysis of CAES on economics, peak-load shaving and wind curtailment. Except to the function of peak shaving provided by ESS, the primary reserve requirements and their combined provision are investigated via economic assessment [15].

On the other hand, demand response mechanisms have been proposed and practiced for several years to encourage consumers to reduce power consumption during on-peak hours and increase uses at off-peak hours or the times of high production. Since there exist unavoidable forecast errors for day-ahead wind resource, this increases re-dispatch costs and loss of load events. Sioshansi [16] discusses the introduction of demand response by real-time pricing in order to mitigate these wind integration costs. Zhao and Zeng [17] also proposed a two-stage robust optimization model for UC with DR in the integration of wind energy and solved the problem by a novel cutting plane algorithm. On one hand, the effect of demand response in an isolated system with wind integration has been studied in [18]. DR-based reserve capacity has also been proved to be an effective mechanism to accommodate the uncertainty of wind generation, which has been studied by the extension of security-constrained unit commitment model with DR and performing simulation tests [19]. On the other hand, deterministic and stochastic security approaches were compared for energy and spinning reserve scheduling in presence of DR, where stochastic approach was shown to achieve a lower system cost and load shedding [20]. Later, Madaeni and Sioshansi [21] examined the effectiveness of stochastic programming and demand response on the reductions of wind uncertainty costs. Their empirical studies showed a stochastic program with DR brings more benefits significantly. Of the many modeling approaches of demand response, the method based on price elasticity matrix (PEM) will be utilized in our study. Although there are possibly some forecast errors existing in PEM, it is relatively easy to forecast loads which follow a specific end-user type. It is a good approximation for demand response and has been studied in [22]. The other benefit of this method offers easy incorporation with optimization models and produces sufficient results as well.

To limit the likelihood of load losses due to uncertainties, risk management has been merging to daily operations of power generation. Chance-constrained optimization models have been developed to deal with uncertain wind power output [23], uncertain load [24] and transmission network expansion planning [25]. Chance constraints are equivalent to constraints that bound the risk measure value-at-risk (VaR). Another tighter risk measure defined upon VaR is conditional value-at-risk (CVaR). As popular risk measures, VaR and CVaR have been widely used in financial risk management [26–28]. Compared to VaR based models, CVaR based models are less computationally demanding due to the fact that modeling CVaR only requires linear constraints and continuous variables. We thus introduce CVaR to our SUC model to maintain system reliability at various levels.

Compared to the recent works of stochastic programming approaches on unit commitment problems (e.g., [29–31,21]), the main contributions of this study are summarized as follow:

1. A comprehensive two-stage stochastic mixed intger programming model for unit commitment with risk constraints based on CVaR is developed to control risk of loss of loads while including non-generation resources. The proposed optimization model helps to satisfy real-time demands and minimize the total operation costs with the support of non-generation resources. The model can help balance between expected cost and risks of load losses.
2. A modified Benders' decomposition algorithm is applied to solve for this CVaR-based model and reduce computation times.
3. Numerical experiments are conducted to find out optimal unit commitment solutions and compare the effects of the risk resilience of non-generation resources on power generation.