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New probabilistic method for solving economic dispatch and unit commitment problems incorporating uncertainty due to renewable energy integration

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ABSTRACT

In this paper, a methodology to solve Unit Commitment (UC) problem from a probabilistic perspective is developed and illustrated. The method presented is based on solving the Economic Dispatch (ED) problem describing the Probability Distribution Function (PDF) of the output power of thermal generators, energy not supplied, excess of electricity, Generation Cost (GC), and Spinning Reserve (SR). The obtained ED solution is combined with Priority List (PL) method in order to solve UC problem probabilistically, giving especial attention to the probability of providing a determined amount of SR at each time step. Three case studies are analysed; the first case study explains how PDF of SR can be used as a metric to decide the amount of power that should be committed; while in the second and third case studies, two systems of 10-units and 110-units are analysed in order to evaluate the quality of the obtained solution from the proposed approach. Results are thoroughly compared to those offered by a stochastic programming approach based on mixed-integer linear programming formulation, observing a difference on GCs between 1.41% and 1.43% for the 10-units system, and between 3.75% and 4.5% for the 110-units system, depending on the chosen significance level of the probabilistic analysis.

Introduction

During many years, wind energy has experienced a relevant development from a technological and economic point of views, incrementing its participation and importance to supply energetic requirements in many countries around the world in order to reduce oil consumption and consequently the emission of Green-House Gases (GHG) [1]. However, the variability of wind resources is an aspect that limits the integration of wind power at high penetration due that the variability of wind power generation introduces uncertainty into the scheduling problem, which makes difficult determining the optimal amount of power that should be committed in order to compensate the variability with the lowest Generation Cost (GC). In fact, this problem has inter-temporal characteristics that depends on the integration level; according to the analysis of Electric Reliability Council of Texas (ERCOT) data [2], GC related to the variability of wind generation in the interval from 15 min to 1 h decreases as capacity factor increases; or in other words, those wind farms installed in places with high wind resources has a low integration cost; however, the benefit obtained from the integration of an additional wind farm reduces suddenly. Regarding the emissions of GHG, wind power variability can impact their emissions in a negative way due that cycling units are partially loaded so that their efficiency is reduced while GHG emissions are increased; besides of this, a recent analysis of Spanish power system [3] suggests that reduction of CO_2 emissions and their corresponding benefits are still important.

Nowadays, solving Economic Dispatch (ED) and Unit Commitment (UC) problems considering uncertainty of wind power generation have been extensively analysed by many authors. This problem could be solved by applying scenario generation/reduction methods as well as probabilistic methods. Scenario generation/reduction methods have been widely suggested in the technical literature due to extreme operating conditions can be easily represented in order to obtain a robust and cost-effective schedule; for this reason, it is likely that this methodology being adopted and implemented by the power industry. Other approaches, still under development, are those based on

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Nomenclature

Sets

j	index for conventional generators $(j = 1,\ldots,J)$
t	index for time step $(t = 1,\ldots,T)$
i	index for the discrete states of discrete distribution $G_j^t(i = 1,\ldots,I)$
q	index for discrete states of forecasted wind power distribution $(q = 1,\ldots,Q)$
r	index for sampling point of output power at $t-1(r = 1,\ldots,R)$
l	discretization state (bin) of forecasted wind generation $(l = 1,\ldots,L)$

Parameters

$A_j,\ B_j,\ C_j$	parameters of fuel consumption cost of unit j
UR_j	ramp up rate limit of unit j
DR_j	ramp down rate limit of unit j
SUR_j	start-up ramp rate limit of unit j
SDR_j	shut-down ramp rate limit of unit j
HSU_j	hot start-up cost of unit j
CSU_j	cold start-up cost of unit j
CST_j	cold start-up time of unit j
MDT_j	minimum down time of unit j
MUT_j	minimum up time of unit j
AWG^t	discretized distribution of forecasted wind generation at time t
$AWG^t_{\max}$	maximum forecasted wind generation at time t
$AWG^t_{\min}$	minimum forecasted wind generation at time t
α^t, β^t	parameters of beta distribution at time t
BWC	battery wear cost
$VOLL$	value of lost load
γ	significance level of the probabilistic analysis
SR^t_{req}	spinning reserve requirements at time t
δ	discretization parameter of beta distribution

Variables

G_j^t	output power of unit j at time t
$G_j^{\min}$	minimum power generation of unit j
$G_j^{\max}$	maximum power generation of unit j
$g_{j,r}^{t-1}$	power generation for unit j and sampling point r at time $t-1$
$g_{j,r}^{t,\max}$	maximum power of unit j at time t (limited by ramp constraint and rated capacity)
$G^{\max}$	maximum value of power to be represented on discrete distribution G_j^t
ΔG	discretization step of discrete distribution G_j^t
$G_{pdf}(i,j)$	tabular representation of G_j^t for discrete state i and unit j
SUC_j^t	start-up cost of unit j at time t
CWG^t	discretized distribution of consumed wind generation at time t
awg_l^t	forecasted wind generation for the state (bin) l at time t
cwg_l^t	consumed wind generation for the state (bin) l at time t
G_i	power value of the bin i
μ_r	sampling point of the interval [0, 1]
$\mu^{\max}$	maximum value of μ_r
$\mu^{\min}$	minimum value of μ_r
$\Delta\mu$	step used for sampling interval $[\mu^{\min},\ \mu^{\max}]$
$SP(j,r)$	tabular representation of sampled points of distribution G_j^{t-1}
n_q	values of the support over the interval [0, 1] of discretized beta distribution
Ω	discretized beta distribution (interval [0, 1])
φ	intermediate variable for discretization of beta discretization
$\overline{P_r}\{\cdot\}$	calculation of a normalized probability value
$P_r\{\cdot\}$	calculation of a probability value
$E\{\cdot\}$	calculation of an expected value
HL^t	hourly load at time t
HNL^t	hourly net load at time t
EE^t	discretized probability distribution of excess of electricity at time t
ENS^t	discretized probability distribution of energy not supplied at time t
K	discretized probability distribution of total generation cost
ΔK	difference between generation cost obtained from proposed approach and reference method
SR^t	discretized probability distribution of spinning reserve at time t
$k_{r,l}$	total generation cost for sampling point r and state (bin) l
ee_r^t	excess of electricity for sampling point r at time t
ens_r^t	energy not supplied for sampling point r at time t
sr_r^t	measurement of spinning reserve for sampling point r at time t
u_j^t	binary variable to represent offline $(u_j^t = 0)$ or online $(u_j^t = 1)$ conditions
$T_{o,j}^t$	amount of time that unit j has been online
$T_{f,j}^t$	amount of time that unit j has been offline
FCC_j^{avg}	average fuel consumption cost of unit j
G_j^{avg}	average power production of unit j
CP^t	cumulative committed capacity at time t
PUS_j^t	element that corresponds to unit j at time t of primary unit scheduling
ΔAWG^t	increment of committed capacity due to forecasting error
AWG_f^t	mode of forecasted wind-generation probability distribution at time t
S	intermediate variable of addition of power generation process

probabilistic analyses, which studies the probabilistic optimization problem since an analytical point of view; these methodologies have not been totally accepted because the reliability of the obtained results from their implementation has not been proved yet [4].

A representative methodology to solve stochastic UC problem by scenario generation/reduction method was proposed by Tuohy et al. [5] at which, correlated scenarios of wind generation and hourly load are generated by means of Monte Carlo Simulation (MCS) approach; more specifically, by evaluating an Autoregressive Moving Average (ARMA) model in order to describe the inter-temporal characteristics of wind power time series. The optimization model used to determine UC solution is based on a mixed-integer, stochastic optimization formulation. Additionally, an operation policy based on rolling planning is implemented in order to take advantage of wind generation and hourly load predictions with lower forecasting error; in consequence, a more robust solution could be obtained. However, this approach can be carried out only analysing a scenario set with a reduced number of trials, which could be a source of error. To solve this problem, Ruiz et al. [6] proposed the incorporation of Spinning Reserve (SR) requirements for each scenario to improve the robustness of the solution; this strategy compensates the problems related to consider a limited number of scenarios. Other important conclusion of this study is related to the computational time, which notably increases with the number of scenarios due that the solution of the corresponding stochastic optimization problem requires the solution of the