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A fast method for the unit scheduling problem with significant renewable power generation

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ABSTRACT

Optimal operation of power systems with high integration of renewable power sources has become difficult as a consequence of the random nature of some sources like wind energy and photovoltaic energy. Nowadays, this problem is solved using Monte Carlo Simulation (MCS) approach, which allows considering important statistical characteristics of wind and solar power production such as the correlation between consecutive observations, the diurnal profile of the forecasted power production, and the forecasting error. However, MCS method requires the analysis of a representative amount of trials, which is an intensive calculation task that increases considerably with the number of scenarios considered. In this paper, a model to the scheduling of power systems with significant renewable power generation based on scenario generation/reduction method, which establishes a proportional relationship between the number of scenarios and the computational time required to analyse them, is proposed. The methodology takes information from the analysis of each scenario separately to determine the probabilistic behaviour of each generator at each hour in the scheduling problem. Then, considering a determined significance level, the units to be committed are selected and the load dispatch is determined. The proposed technique was illustrated through a case study and the comparison with stochastic programming approach was carried out, concluding that the proposed methodology can provide an acceptable solution in a reduced computational time.

1. Introduction

The constant increment in the price of fossil fuel and the environmental impact of human activities has been the most relevant factors in the development of wind energy and solar energy. However, the main barrier in the successful integration of this type of sources is related to their intrinsic variability, which under high penetration, it is reflected as the increment in the operational costs of the power system. In fact, according to the analysis of the Belgian power system [1], if the wind power production is underestimated, approximately a third of the expected cost savings could be lost. On the contrary, if the wind power production is overestimated, cost savings are lost due that it is necessary to use open cycle gas generators in order to compensate the forecasting error.

In order to reduce the impacts of the wind power forecasting error, several techniques have been proposed: the integration of energy storage systems (EES) [2], the analysis of the wind power aggregation [3], the incorporation of demand response programs [4], and the analysis of the optimal scheduling under uncertainty or stochastic unit commitment (UC) problem.

This paper focus on the development of a methodology to solve the unit commitment (UC) problem considering the uncertainty related to the wind power generation. In this context, Tuohy et al. [5] developed a stochastic programming (SP) approach based on scenario generation of wind power production, failure events, and load demand. The scenarios used were randomly generated to take into account the autocorrelation of the analysed time series (wind power generation, load demand, etc.) by means of an autoregressive moving average (ARMA) model. In this framework two stages are considered: in stage one “here-and-now” decisions are taken; while in stage two “wait-and-see” decisions are incorporated. In other words, “here-and-now” decisions are taken assuming perfect forecasting and “wait-and-see” decisions are taken in the light of the different sources of uncertainty. The incorporation of wind power generation by means of a representative amount of realistic scenarios can provide a reasoning manner to determine

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Nomenclature

m	index for scenarios $(m = 1, 2, \ldots, M)$
n	index for generators $(n = 1, 2, \ldots, N)$
d	index for the interval in the discretization of PDF of load forecasting $(d = 1, 2, \ldots, D)$
j	index for the interval in the discretization of PDF of wind forecasting $(j = 1, 2, \ldots, J)$
t	index for time instant $(t = 1, 2, \ldots, H)$.
z	index for the interval in the discretization of start-up cost $(z = 1, 2, \ldots, Z)$
α	significance level used to determine the confidence interval
γ	significance level used to determine the definitive unit scheduling (U_n^t)
ARN_m^t	autoregressive time series for scenario m
Ø	one-lag autocorrelation parameter
ϵ	white noise of ARMA model
$NTWPG^t$	normalized total (forecasted) wind power generation at time t
$TWPG^t$	total (forecasted) wind power generation at time t (MW)
$NTWPG_m^t$	normalized total (synthetically generated) wind production at time t for scenario m
$TWPG_m^t$	total (synthetically generated) wind power production at time t for scenario m (MW)
β	limit to the outliers of the scenario generation process
IFE_m	vector that reflects the degree at which the hourly values of a determined scenario are within the corresponding forecasting error
FE_m^t	vector to represent if scenario m at time t is within the defined confidence interval according to the forecasting error.
$NP_r\{m\}$	normalized probability of scenario m of wind power generation
$P_r\{\cdot\}$	probability of occurrence of a determined event
$E\{\cdot\}$	expected value of a determined variable
$LB_{d,m}^t$	binary variable to represent the selection of the dth load interval of scenario m at time t
LP_d^t	probability of the dth load interval at time t
$WB_{j,m}^t$	binary variable to represent the selection of the jth wind power interval of scenario m at time t
WP_j^t	probability of the jth wind power interval at time t
R_m	total generation cost of scenario m ($)
R	total generation cost of the UC problem (h)
$FC_{n,m}^t$	fuel consumption cost of unit n at time t for scenario m ($/h)
$SUC_{n,m}^t$	start-up cost of unit n at time t for scenario m ($/h)
$SDC_{n,m}^t$	shutdown cost of unit n at time t for scenario m ($/h)
$P_{n,m}^t$	power generation of unit n at time t for scenario m (MW)
P_n^t	power generation of unit n at time t (MW)
P_n^{max}	maximum power generation of unit n (MW)
P_n^{min}	minimum power generation of unit n (MW)
$MP_{n,m}^t$	maximum available power of unit n at time t for scenario m (MW)
W_m^t	aggregated wind generation for scenario m at time t (MW)
L_m^t	load demand at time t for scenario m (MW)
SR	required spinning reserve
a_n, b_n	parameters of the fuel consumption cost of unit n ($/h, $/MWh)
$v_{n,m}^t$	binary variable to represent the commitment $(v_{n,m}^t = 1)$ or de-commitment $(v_{n,m}^t = 0)$ of unit n at time t for scenario m
U_n^t	definitive UC solution obtained from the proposed methodology, common to all scenarios considered
K_n^z	value of the interval z in the discretization of startup cost ($/h)
C_n	shutdown cost of unit n ($/h)
UR_n	ramp-up rate of unit n (MW/h)
DR_n	ramp-down rate of unit n (MW/h)
SUR_n	starting ramp rate of unit n (MW/h)
SDR_n	shutdown ramp rate of unit n (MW/h)
UP_n	amount of hours that generator n have to be initially committed in order to fulfil minimum up time constraint (h)
DW_n	amount of hours that generator n have to be initially de-committed in order to fulfil minimum down time constraint (h)
MUT_n	minimum up time of unit n (h)
MDT_n	minimum down time of unit n (h)
OFF_n^t	integer matrix that saves the cumulative account of the number of hours that generator n has been de-committed (h)
ON_n^t	integer matrix that saves the cumulative account of the number of hours that generator n has been committed (h)
μ_{WFE}^t	mean value of the discretized wind generation PDF at time t (MW)
μ_{LFE}^t	mean value of the discretized load demand PDF at time t (MW)
μ_{TWPG}	mean value of the time series $TWPG^t$ (MW)
σ_{WFE}^t	standard deviation of the discretized wind generation PDF at time t (MW)
σ_{LFE}^t	standard deviation of the discretized load demand PDF at time t (MW)
σ_{TWPG}	standard deviation of the time series $TWPG^t$ (MW)
$VOLL$	value of lost load ($/MWh)
$VRNS$	value of reserve not supplied ($/MWh)
ENS_m^t	energy not supplied of scenario m at time t (MWh)
RNS_m^t	reserve not supplied of scenario m at time t (MWh)

spinning reserve on an hourly basis [6]. However, this approach requires an important computational effort; according to the experiences of Ruiz et al. [7], the computational time could be until two or three orders of magnitude higher than those required for solving a deterministic UC problem. For this reason, improvements in the mathematical formulation of SP and decomposition techniques have been widely suggested in the literature.

Another approach proposed in the literature is based on chance-constrained programming (CCP). Ding et al. [8] have incorporated several uncertain variables, such as load demand, force outages, wind power, and energy prices in the UC problem using CCP. In this approach the stochastic constraints are substituted by their equivalent deterministic, in order to obtain a mathematical formulation that can be solved by using standard branch and bound algorithm. In a similar manner, Ji et al. [9] introduced a methodology based on CCP, where a combination of quantum-inspired binary gravitational search algorithm is used to determine the unit scheduling for several confidence levels and different forecasting errors.

Wang et al. [10] have developed a model that combines CCP and SP. Authors proposed a combined sample average approximation (SAA) algorithm that consists of three main processes: scenario generation, convergence analysis, and solution validation. The