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A probabilistic approach to solve the economic dispatch problem with intermittent renewable energy sources

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A B S T R A C T

In this paper, a methodology for solving the ED (economic dispatch) problem considering the uncertainty of wind power generation and generators reliability is presented. The corresponding PDF (probability distribution function) of available wind power generation is discretized and introduced in the optimization problem in order to probabilistically describe the power generation of each thermal unit, wind power curtailment, ENS (energy not supplied), excess of power generation, and total generation cost. The reliability of each unit is incorporated by estimating the joint PDF of power generation and failure events, while the PDF of ENS is incorporated by convoluting the PDF of ENS due to the forecasting error and any failure event. The performance of the proposed approach is analyzed by studying two power systems of 5 and 10 units. The proposed method is compared to MCS (Monte Carlo Simulation) approach, being able to reproduce the PDF in a reasonable manner, specifically when system reliability is not taken into account.

1. Introduction

Energy obtained from renewable energy sources has a key role to the sustainable development in the near future. Wind and solar energies have been continuously growing motivated by governmental incentives, the reduction in the operating and capital costs, and the increment in the revenue streams. Because of these conditions, the energetic policy is based on the increment of renewable power penetration. As a result, it is expected that in the year 2040, renewable generation is going to represent about 16% of total generation capacity in the United States.

Natural gas is going to be another important resource for power generation due to the expected reduction in market prices. In fact, it is likely that natural gas will become the main source of power generation in the United States in 2040, substituting the power capacity provided by coal-fired and nuclear power plants, sharing about 43% of the total generation capacity. This generation mix mainly composed by natural gas and renewable energies as the main power sources is going to lead to an important reduction in CO_2 emissions, reaching a decrease of about 11% from the emission levels of the year 2012 [1].

However, the variability related to the renewable energy sources and the difficulties related to storing energy represent important limitations in massive deployments of renewable sources to fully supply peak-load and base-load. To deal with the problems related to the stochastic nature of renewable energy sources, many approaches have been proposed, such as the analysis of geographic properties of aggregated wind power generation [2], the optimal management of ESSs (energy storage systems), implementation of DRPs (demand response programs) [3,4], and improvements in scheduling techniques in order to incorporate the wind power uncertainty by means of their corresponding forecasting error.

Analyzing the geographic characteristics of the place to locate a determined wind farm in order to connect it with other ones and smooth the aggregated power production could require an additional investment that affects the profitability of the project [5]. Moreover, economic viability of a determined technology of ESS depends on the renewable penetration level and its variability, the regulatory environment, and the revenues in yearly bases [6]. The main barrier for the implementation of DRPs is related to the uncertainty in people's behavior when the electricity prices are dynamically changed. This uncertainty is reflected in the estimation

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Nomenclature

AWP^k	discrete PDF of available wind power generation
A_m, B_m, C_m	parameters of cost curve of unit m
DL_i^k	value of the power consumed by the dump load at time k that corresponds to the sampling point i
DL^k	dump load at time k
DR_m	ramp down limit of unit m
D^k	load demand at time k
$E_{(l,m)}$	discrete PDF of power production when generators reliability is considered
ENS_i^k	value of energy not supplied at time k that corresponds to the sampling point i
F_h^m	discrete PDF of lack of power of unit m as a consequence of a failure event
FOR_m	forced outage rate of unit m
F_b^e	CDF of power loss as a consequence of a failure in the generator system
GHG_m	CO_2 emissions of unit m
$NP_r\{\cdot\}$	normalized probability of occurrence of a determined event
P_h	power value that corresponds to the discrete state h
P_b	power value that corresponds to the discrete state b
$P_{m,i}^{k-1}$	power production of unit m at time $k-1$ that corresponds to the sampling point i
P^{max}	maximum power value to be considered
P^{min}	minimum power value to be considered (assumed to be zero)
P_m^k	discrete PDF of power production of unit m at time k
P_m^{max}	maximum output power of unit m
P_m^{min}	minimum output power of unit m
$P_r\{\cdot\}$	probability of occurrence of a determined event
UR_m	ramp up limit of unit m
U_m, V_m	parameters of the CO_2 emission curve of unit m
W^k	discrete PDF of wind power generation
W_{max}^k	maximum value of available wind power generation at time k
W_{min}^k	minimum value of available wind power generation at time k
X_m	parameter of the CO_2 emission curve of unit m
a_0 to a_3	auxiliary variables
awp_j^k	value of available wind power generation of discrete state j at time k
b_m	discrete state that corresponds to the rated capacity of unit m
s_r	value that corresponds to the discrete state r
w_j^k	value of wind power generation of discrete state j at time k
$z_{i,j}$	total generation cost that corresponds to the sampling point i and the discrete state of available wind power generation j
θ_i	sampling point I of the interval $[\gamma, 1-\gamma]$
h	discrete state of power production $(h \in [0, H])$
B	total number of bins of discrete PDF of power production
H	last state of h $(H = B-1)$
I	total number of sampling points of interval $[\gamma, 1-\gamma]$
J	total number of bins of the discrete PDF of wind power generation
L	last state of l $(L = (H+1)^2 = B^2)$
M	total number of thermal units
R	last discrete state of beta PDF
$VOLL$	value of lost load
$VOWE$	value of wasted energy
b	discrete state of power production $b \in [1, B]$
i	index of sampling point θ_i, $i \in [1, I]$
j	discrete state of available wind power generation
l	discrete state of power production when generators reliability is considered
m	index for each generation unit
r	discrete state of beta PDF in the interval [0,1], $r \in [0, R]$
ΔP	discretization step of the power values P_b
$\Delta\theta$	sampling increment of interval $[\gamma, 1-\gamma]$
α, β	parameters of continuous beta PDF
γ	significance level
σ	parameter of the discretization process

Table of abbreviations

ESS	energy storage system
DRP	demand response program
ARMA	auto-regressive moving average
UC	unit commitment
ED	economic dispatch
PDF	probability distribution function
PSO	particle swarm optimization
ENS	energy not supplied
MCS	Monte Carlo simulation

of price elasticity, which is frequently used to decide the optimal use of demand response resources [7].

As a result, several approaches have been presented in the technical literature, such as stochastic programming, chance constrained programming, stochastic dynamic programming, robust optimization, and probabilistic approaches.

Stochastic programming approaches consist on carrying out the optimal management taking into account some possible situations or scenarios randomly generated. In our case, these scenarios represent the stochastic behavior of load demand, wind power generation and failure events.

In this regard, Tuohy et al. [8] introduced a methodology that employs scenarios randomly generated of load demand and wind power generation using an ARMA (autoregressive moving average) model combined with a reduction algorithm in order to select those representative scenarios. Then, power system management is carried out by solving a mixed integer programming optimization problem obtaining a feasible solution for the scenarios previously selected. However, in this approach a limited number of scenarios is analyzed, which represents an important source of error.

To overcome the aforementioned problem, Ruiz et al. [9] proposed the incorporation of spinning reserve requirements for each scenario, as well as the incorporation of extreme scenarios of failure events, such as single outage of the largest generation unit in order to provide a robust solution.

In other research work, Constantinescu et al. [10] paid special attention to the quality of scenarios used in stochastic programming optimization models. The authors have developed a model that joins a weather research and forecast model with a UC (unit commitment)/ED (economic dispatch) model in order to analyze the effects of wind power uncertainty on the scheduling problem. Among the most important findings, authors concluded that their