Energy 112 (2016) 408–419

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Evolutionary algorithms for power generation planning with uncertain renewable energy

Forhad Zaman [a,*], Saber M. Elsayed [a,b], Tapabrata Ray [a], Ruhul A. Sarker [a]

[a] School of Engineering and Information Technology, University of New South Wales, Canberra 2600, Australia
[b] Zagazig University, Zagazig, Egypt

ARTICLE INFO

Article history:
Received 18 November 2015
Received in revised form
28 March 2016
Accepted 17 June 2016

Keywords:
Economic dispatch
Uncertain wind energy
Variable load demand
Genetic algorithm
Differential evolution
Heuristic

ABSTRACT

To achieve optimal generation from a number of mixed power plants by minimizing the operational cost while meeting the electricity demand is a challenging optimization problem. When the system involves uncertain renewable energy, the problem has become harder with its operated generators may suffer a technical problem of ramp-rate violations during the periodic implementation in subsequent days. In this paper, a scenario-based dynamic economic dispatch model is proposed for periodically implementing its resources on successive days with uncertain wind speed and load demand. A set of scenarios is generated based on realistic data to characterize the random nature of load demand and wind forecast errors. In order to solve the uncertain dispatch problems, a self-adaptive differential evolution and real-coded genetic algorithm with a new heuristic are proposed. The heuristic is used to enhance the convergence rate by ensuring feasible load allocations for a given hour under the uncertain behavior of wind speed and load demand. The proposed frameworks are successfully applied to two deterministic and uncertain DED benchmarks, and their simulation results are compared with each other and state-of-the-art algorithms which reveal that the proposed method has merit in terms of solution quality and reliability.

1. Introduction

Over the past few decades, rapid increases in the use of fossil fuels and consequent increases in CO_2 emissions have introduced a new challenge to the power generation industry. In attempts to address this issue, the renewable sources, such as wind power, has been paid a great deal of attention. Although the operating costs and gas emissions of wind power generators (WPGs) are negligible, the uncertain nature of this resource presents a new challenge for their economical operation in the power generation industry. The scheduling of wind-thermal generators is described by two popular methods, unit commitment (UC) and economic dispatch (ED), where UC determines the startup and shutdown schedule of units to meet the required demand, and ED allocates the system demand among the committed units while minimizing the generation cost and satisfying system constraints [1].

The dynamic ED (DED) is an extension of the ED problem which has a more practical and complex formulation. It takes the ramp limits and schedules the generators for an operational cycle in a time horizon [2]. As the wind speed changes randomly, it is more appropriate to adopt a dynamic model in a wind-thermal power system, whereby the challenge is to determine the output from a wind farm 24 h before its day-ahead scheduling for operating with thermal generators as day-ahead forecast data may have significant deviations in magnitude which increases the difficulty of DED [3].

Therefore, researchers have incorporated uncertainty in the DED model using different approaches, such as neural network [4], fuzzy optimization [5], and Weibull distribution approach [6–9]. In the fuzzy method, the wind speed was considered as a fuzzy variable, and the fuzzy set theory was used to represent an ED problem, while in the Weibull distribution, two parameters, the scale and shape were determined from the historical data and then converted into a probability DED model [10]. A few authors, such as Mondal et al. [11] and Peng et al. [12] used penalty function approach to obtain the impacts of inaccurate estimations of wind energy caused by its uncertain nature, for example, a probabilistic analysis of cases in which wind power generation was over- and under-estimated from the expected value [13]. Although it is true that the penalty

* Corresponding author.
E-mail addresses: md.zaman@student.adfa.edu.au (F. Zaman), s.elsayed@adfa.edu.au (S.M. Elsayed), t.ray@adfa.edu.au (T. Ray), r.sarker@adfa.edu.au (R.A. Sarker).

http://dx.doi.org/10.1016/j.energy.2016.06.083
0360-5442/

Nomenclature

Variables

i,w,t,d,s indices of thermal-, wind- generator, time interval, day and scenario, respectively
F_{cd},F_{CT},F_T daily, weekly and overall costs, respectively
P_{CL} penalty cost due to load shedding
$P_{GT_{i,t,s}}$ ith plantâĂŹs output at tth time in sth scenario
$P^{min}_{i,t,s}, P^{max}_{i,t,s}$ possible increase and decrease in ith power plant at tth hour in sth scenario, respectively
$P^{min1}_{i,s}, P^{max1}_{i,s}$ possible increase and decrease limits of first and last hour in sth scenario, respectively
$P_{S_{t,s}}$ electricity shortfall at tth hour in sth scenario
G_i power generation from ith plant at T hour

Parameters

a_i,b_i,c_i cost coefficients of ith thermal unit
d_i,e_i valve point coefficients of ith power plant
B transmission loss coefficient
N_T,W numbers of thermal and wind power plants, respectively
N_S number of scenarios
N_P population size for EAs
N_G maximum number of generations for EAs
$P_{Dt,s}$ electricity demand at tth hour in sth scenario
P_{loss_t} transmission losses at tth time
$P^{min}_{GT_i}, P^{max}_{GT_i}$ minimum and maximum output power of unit ith plant, respectively
$P^r_{D_{t,s}}$ randomly generated load demand in sth scenario at tth time
$P^r_{W_{t,s}}$ randomly generated wind power in sth scenario at tth time
$S_{j,w,f}$ slope of segment j for wind farm f
T_R,T_O minimum on and off time of a generator, respectively
T, N_D total operational period and day, respectively
t_{start} random starting hour of the heuristic
UR_i,DR_i upper and lower ramp rate limits of ith plant, respectively
$V_{w,f},L_D$ forecast wind speeds and load demands
$V_{ci,w,f},V_{co,w,f}$ cut-in and cut-out wind speed, respectively of unit i in wind farm f
$V_{r,w,f}$ rated wind speed for wind farm f
$V_{j,w,f}$ breakpoints of segment j for wind farm f
λ penalty cost coefficient for unexpected electricity shortfall
$\varepsilon_0, \varepsilon_g$ relaxation factor of the equality constraints at the gth generation

function sometimes has a great impact on a system's operation, it is difficult to choose an appropriate one for a certain system.

To overcome the drawbacks researchers have recently used scenario based probabilistic DED model where the scenarios represent the stochastic behavior of load demand, wind power generation and failure events [14,15]. However, in the probabilistic method, the Monte Carlo (MC) sampling was often used to generate the scenarios of wind speeds, which was very expensive approach because of its heavy computational burden [16]. Hence, Markov chains [17] with a roulette wheel mechanism [5,18] was currently used to generate appropriate predictive values of the wind speeds and load demands for a 24-h time period. In this approach, large numbers of scenarios were initially generated using Markov transition matrix determined from the large amounts of historical data. Each scenario involved hourly wind speed and load demand data which had a one-to-one relationship with the time intervals. Moreover, each scenario had a certain normalized probability and those with lower probabilities were deleted based on a simultaneous backward scenario reduction technique because a large number of scenarios would increase the computational burden. Later, a probabilistic DED model was formulated, and each scenario under the model was solved using various optimization methods, such as mixed integer linear programming (MILP) [19], the branch and bound algorithm [20] and the 2 m point estimated method (PEM) [5]. However, although conventional algorithms were chosen due to their fast searching features, the valve-point effects (VPE) of their cost functions heightened the difficulties of solving the DED problem which has non-smooth, non-linear and non-convex characteristics [18,21]. For this kind of complex problem, solution approaches based on mathematical programming may fail to reach the global optimum, a shortcoming which motivates the need for alternative methods such as those based on evolutionary optimization [18].

In recent years, several meta-heuristic methods have been effectively used to solve deterministic DED problems because they are flexible, efficient and have a stochastic searching feature, for example genetic algorithm (GA) [22–24], simulated annealing (SA) [25], particle swarm optimization (PSO) [18], evolutionary programming (EP) [26], differential evolution (DE) [27] and harmony search algorithms [28,29]. Some hybrid methods that combine two or more approaches, such as EP and sequential quadratic programming (EP-SQP) [26], PSO-SQP [30], and modified hybrid EPâĂŞSQP (MHEP-SQP) [31], have also been applied to solve this problem. With integrating wind energy in the ED model, few authors although used some of these meta-heuristic algorithms, such as DE [12], SA [32], GA [33,34], and PSO [18], the problems were based on a single period of load demand. Work on applying these algorithms to solve the multi-period high dimensional complex uncertain wind-thermal DED problem is still limited. The major obstacle to successfully applying an evolutionary algorithm (EA) to such a problem is its poor diversity and premature convergence [17].

In reality the solutions of a DED problem are generated and implemented repeatedly over a one-day horizon with dividing it into multiple periods [35]. This periodicity assumption comes from the fact that the resources (generators) are fixed and demand is periodic due to the cyclic consumption and seasonal changes [35]. However, resources of a wind-thermal DED problem are fluctuating, depending on the weather conditions. As a result, for a periodic implementation of wind-thermal generators for a uncertain DED system, considering the scheduling approaches discussed above, there is a possibility for an unwanted electricity shortfall to appear between the last hour of a day and the first hour of the following one, which is also known as a transient ramp violation (TRV) [35]. To overcome this violation, some steps can be taken, such as: (i) committing additional generating units for the following day's scheduling; (ii) maintaining extra reserve requirements; (iii) facilitating energy storage approach; and (iv) designing an effective approach for scheduling. The first three approaches increase the operating cost as additional equipment to be