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Configuring two-algorithm-based evolutionary approach for solving dynamic economic dispatch problems

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ABSTRACT

A dynamic economic dispatch (DED) problem is a complex constrained optimization problem that has the objective of economically allocating power demands to the available generators for a certain period. Although, over the last few decades, different evolutionary algorithms (EAs) for solving different types of DED problems have been proposed, no single EA has consistently been the best for a wide range of them. In this paper, to solve a wide range of DED problems, a general EA framework which automatically configures the better EA from two considered during the evolutionary process is proposed. In it, a real-coded genetic algorithm and self-adaptive differential evolution are performed under two sub-populations, in which the number of individuals of a sub-population is dynamically varied in each generation based on each algorithm's performance during previous generations. Moreover, a heuristic technique is employed to repair infeasible solutions towards feasible ones to enhance the convergence rate of the proposed algorithm. The effectiveness of the proposed approach is demonstrated on a number of DED problems, with the simulation results, which are compared with those from recent state-of-the-art algorithms, revealing that it has merit in terms of solution quality and reliability.

1. Introduction

During the last few decades, the use of fossil fuels for power generation has significantly increased which has led to a consequential worldwide reduction in these resources. In attempts to address this issue, renewable sources, such as hydro, solar and wind power, have been paid a great deal of attention. However, despite its advantages for the environment and economy, the difficulties of renewable energy are the continuity and reliability of its operation. Therefore, scheduling the right mix of generation from a number of generating units to serve a particular load demand at minimum cost, which is known as an economic dispatch (ED) problem, is a challenging optimization problem (Zaman et al., 2016).

Previous efforts to solve ED problems have employed various conventional optimization methods, such as linear and quadratic programming, and the interior point and lambda iteration methods (Sun et al., 2014). Although their algorithms are usually computationally efficient, many approximate the cost function of each generator using a single quadratic function. However as, under a practical power system's operating conditions, many thermal units, especially those with valve point effects (VPE), have prohibited operating zones, a nonlinear and nonconvex ED problem is formed (Zaman et al., 2016). Also, in nature, the ED problem for a cycle of T hours with ramp limits, called a dynamic ED (DED) problem, involves many local optima and multiple constraints which prevent classical methods from obtaining global solutions (Secui, 2015).

As meta-heuristic-based optimization techniques, for example, a genetic algorithm (GA) (Elsayed et al., 2014a; Gjorgiev et al., 2015; Hemamalini and Simon, 2011a; Zaman et al., 2016), simulated annealing (SA) (Panigrahi et al., 2006; Po Wong, 1995), particle swarm optimization (PSO) (Neyestani et al., 2010; Panigrahi et al.; Wang and Singh, 2009), differential evolution (DE) (Lu et al., 2011; Zaman et al., 2016), evolutionary programming (EP) (Attaviriyanupap et al., 2002), harmony search (HS) (Manjarres et al., 2013), stochastic fractal search (SFS) (Li and Shao, 2016), and artificial bee colony (ABC) (Li et al., 2014; Li and Yao, 2014) do not require certain mathematical properties of the objective function to be satisfied, they have been successfully applied to solve different types of DED problems. Also, hybrid methods that combine two or more approaches, such as EP and sequential quadratic programming (EP-SQP) (Attaviriyanupap et al., 2002), PSO-SQP (Victoire and Jeyakumar, 2005c) and modified hybrid EP–SQP (MHEP–SQP) (Victoire and Jeyakumar, 2005b), have been used.

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Nomenclature

A. Thermal system

i, t indices of thermal plant and time period (in hours), respectively
N_T, number of thermal power plants
T total operational cycle
P_{T_i} output power from ith thermal power plant
F_{C_i} fuel cost of ith thermal power plant
a_i, b_i, c_i, d_i, e_i cost coefficients of ith thermal power plant
P_{loss},B power transmission loss and its coefficients, respectively
P_i^{min} P_i^{max} minimum and maximum output powers of ith unit, respectively
UR_i, DR_i upward and downward ramp limits of ith unit, respectively
SRS, SRS_m spinning reserves for 1 h and 10 min, respectively

B. Hydro-thermal system

j index of hydro power plant
N_H number of hydro power plants
P_{H_j}, X_j, V_j power output, water discharge rate and storage volume of jth hydro unit, respectively
$C_{k,j}$, hydro power generation coefficients of jth power plant, where k=1, 2, . . , 6
I_j, S_j water inflow rate and spillage water for jth reservoir, respectively
N_{up}, $t_{d_{r,j}}$ number of upstream plants and water transport delay from rth to jth reservoirs, respectively
$P_{H_j}^{min}$, $P_{H_j}^{max}$ minimum and maximum output powers of jth hydro power, respectively
V_j^{min}, V_j^{max} minimum and maximum water storage volumes of jth hydro reservoir, respectively
X_j^{min}, X_j^{max} minimum and maximum water discharge rates of jth hydro reservoir, respectively
V_j^{ini}, V_j^{end} initial and final water volumes of jth reservoir, respectively

C. Wind–thermal system

w index of wind power plant
N_W number of wind power plants
δ_w, $W_{w,t}$ cost coefficients of wth wind farm and its scheduled output time period t, respectively
F_{c_i}, F_{E_i} fuel cost and gas emission of ith thermal generator, respectively
F_{w_w}, F_{U_w}, F_{O_w} operating, and under- and overestimated costs of wth wind power plants, respectively
K_{U_w}, K_{Ow} under- and over-estimated penalty cost coefficients, respectively
W_{R_w}, v_{r_w} rated wind power and speed of wth wind farm, respectively
v_{in_w},v_{out_w}, cut-in and cut-out wind speeds of wth wind farm, respectively
Γ gamma function
μ_t, σ_t mean value and standard deviation of wind speeds for tth time period, respectively
k_t,c_t, ϕ, Ψ constants used to calculate F_{U_w} and F_{O_w}
S operational status of thermal generator, *i.e.*, 0 – unit off, 1 – unit on
T^{on},T_{min}^{on} continuous and minimum on-line times of thermal generator, respectively
T^{off}, and T_{min}^{off} continuous and minimum off-line times of thermal generator, respectively
DR^0 and UR^1 upper and lower ramp limits of thermal generator while unit in process of start-up or shutdown, respectively

D. Solar–thermal system

s index of solar plant
N_S number of solar power plants
α_i, β_i, γ_i,$\eta_i$$\lambda_i$ emission coefficients of ith thermal power plant
h_i constant used to normalize emission function to cost function
F_P operating cost of solar power generation
$P_{S_{s,t}}$ available output power of sth solar power plant at tth time period
$PU_{cos\ t_s}$ per unit cost of sth solar power plant
$U_{S_{s,t}}$ binary decision variable that determines whether sth solar unit turns on or off at tth time period
P_{r_s}, T_{ref_s} rated power and reference temperature of sth power plant, respectively
Ω temperature coefficient
$T_{amb_{s,t}}$, $Si_{s,t}$ ambient temperature and incident solar radiation, respectively, for sth solar power plant at tth time period

E. Algorithm

g index of number of current generation
N_G , N_P number of maximum generations and population size, respectively
N_{P1}, N_{P2} sub-population sizes of GA and DE, respectively
N_{gc} number of cut-off generations (or cycle)
N_{P1}^{min},N_{P1}^{max} minimum and maximum sub-population sizes, respectively
FV, CV fitness value and sum of constraint violations, respectively
$SR_{1,g}$,$SR_{2,g}$ success rates of GA and DE for gth number of generations, respectively
ASR_1,ASR_2 average success rates of GA and DE, respectively
$\vec{x}$, N_x decision variable's vector and number of decision variables, respectively
$\vec{x}^{min}$, $\vec{x}^{max}$ lower and upper bound vectors for $\vec{x}$, respectively
$\vec{y}$ offspring decision vector evaluated from $\vec{x}$
η_c pre-defined parameter of distribution index for simulated binary crossover
ε_g relaxation factor for equality constraints in gth generation
ε_0 CVs at initial generation
θ stopping criterion, *i.e.*, best fitness value no longer improved in θ generations