Chapter 2
Firefly Algorithm for Power Economic Emission Dispatch

Chao-Lung Chiang

Abstract This work proposes a firefly algorithm for the optimal economic emission dispatch (EED) of the hydrothermal power system (HPS), considering non-smooth fuel cost and emission level functions. The firefly algorithm (FA) can efficiently search and actively explore solutions. The multiplier updating (MU) is introduced to handle the equality and inequality constraints of the HPS, and the ε-constraint technique is employed to manage the multi-objective problem. To show the advantages of the proposed algorithm, one example addressing the best compromise is applied to test the EED problem of the HPS. The proposed approach integrates the FA, the MU, and the ε-constraint technique, revealing that the proposed approach has the following merits—ease of implementation; applicability to non-smooth fuel cost and emission level functions; better effectiveness than the previous method, and the requirement for only a small population in applying the optimal EED problem of the HPS.

Keywords Firefly algorithm • Multiplier updating • Economic emission dispatch

2.1 Introduction

Traditionally, in the short-term scheduling of a fixed water head, the variation of the net head can be ignored only for relatively large reservoirs, in which case power generation depends only on the discharge of water [1]. Recently, Basu [2] modeled the HPS problem as a multi-objective problem and solved it using a weighted combination. Nevertheless, the weighting method linearly combined the objectives as a weighted sum. The objective function thus formed may lose significance because the various multiple noncommensurable factors are incorporated into a single function. This study employs the ε-constraint technique [3] to handle the multi-objective problem.

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Firefly algorithm (FA) was developed by Yang [4]. It is a new metaheuristic nature-inspired algorithm, based on the flashing light of fireflies has been successfully applied to solve different engineering problems [5–7]. This chapter throws a light on how well the firefly algorithm is utilized to solve the EED problems. The EED problem is very difficult to be solved by direct approach and thus creates prominent damage to the power system operation and planning in the existing scenario, so a metaheuristic approach such as FA is generally preferred for optimal EED solutions.

2.2 Problem Formulation

The following objectives and constraints of the HPS with N_i thermal units and N_h hydro plants over M time subintervals are considered.

2.2.1 *Economic Objective* $\mathbf{F_1}$

The fuel cost function of each thermal unit considering the valve-point loadings is realistically expressed as the superposition of a quadratic function and a sinusoidal function. The total fuel cost can be accurately denoted in terms of real power output as a non-smooth cost function:

$$F_1 = \sum_{m=1}^{M} \sum_{i=1}^{N_i} t_m \left[a_i + b_i P_{mi} + c_i P_{mi}^2 + \left| e_i \sin \left\{ f_i \left(P_i^{\min} - P_{mi} \right) \right\} \right| \right] \tag{2.1}$$

where F_1 is the total cost of generation; P_{mi} is the generation of the ith thermal unit in the mth subinterval; a_i, b_i, and c_i are coefficients of the cost curve of the ith generator; e_i and f_i are fuel cost coefficients of the ith unit with valve-point loadings, and t_m is the generating duration.

2.2.2 *Emission Objective* $\mathbf{F_2}$

Fossil-based generating stations are the primary sources of nitrogen oxides, so the Environmental Protection Agency has strongly urged them to reduce their emissions. In this study, the amount of emitted nitrogen oxides is taken as the selected index from the perspective of environmental conservation. The emission from each generator is given as a function of its output, which is the sum of a quadratic and exponential functions. The emission objective can be mathematically modeled as [1]:

$$F_2 = \sum_{m=1}^{M} \sum_{i=1}^{N_i} t_m \left[\alpha_i + \beta_i P_{mi} + \gamma_i P_{mi}^2 + \xi_i e^{(\zeta_i P_{mi})} \right] \tag{2.2}$$

where α_i, β_i, γ_i, ξ_i, and ζ_i are coefficients of generator emission characteristics.

2.2.3 System Constraints

The power balance and water availability equality constraints of the HPS are imposed.

2.2.3.1 Power Balance Equality Constraints

$$\sum_{i=1}^{N_i} P_{mi} + \sum_{h=1}^{N_h} P_{mh} - P_{mD} - P_{Lm} = 0, \quad m = 1, \ldots, M \tag{2.3}$$

The power balance constraints (2.3) are M equalities, where P_{mh} is the generation of the hth hydro plant in the mth subinterval, and P_{mD} is the total demand in the mth subinterval. The P_{Lm} is the real power loss of the transmission lines in the mth subinterval, and is given as follows:

$$P_{Lm} = \sum_{i=1}^{N_i+N_h} \sum_{j=1}^{N_i+N_h} P_{mi} B_{ij} P_{mj} \tag{2.4}$$

2.2.3.2 Water Availability Equality Constraints

$$\sum_{m=1}^{M} t_m \left(a_{0h} + a_{1h} P_{mh} + a_{2h} P_{mh}^2 \right) - W_h = 0, \quad h = 1, \ldots, N_h \tag{2.5}$$

The water availability constraints (2.5) are N_h equalities; a_{0h}, a_{1h}, and a_{2h} are characteristic coefficients of the hth hydro unit, and W_h is the water availability of the hth hydro unit.

System limits. The inequality constraints of the HPS imposed on unit output are (2.6) and (2.7), respectively:

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{2.6}$$

$$P_h^{\min} \le P_h \le P_h^{\max} \tag{2.7}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum limits of the *i*th thermal generator, and $P_h^{\min}$ and $P_h^{\max}$ are the minimum and maximum bounds of the *h*th hydro unit.

2.3 The Proposed Algorithm

2.3.1 The ε-Constraint Technique

The ε-constraint technique [3] is used to generate pareto-optimal solutions for the multi-objective problem. To proceed, one of the objective functions constitutes the primary objective function and all other objectives act as constraints. To be more specific, this procedure is implemented by replacing one objective in the EED problem with one constraint. Reformulate the problem as follows:

$$\begin{aligned}
&\min_{P_{mi}(m=1,\ldots,M \text{ and } i=1,\ldots,N_i+N_h)} && F_j(P_{mi}), \quad j = 1 \text{ or } 2 \\
&\text{Subject to} && F_k(P_{mi}) \le \varepsilon_k; \quad k = 1 \text{ or } 2, \text{and } k \ne j \\
& && \sum_{i=1}^{N_i} P_{mi} + \sum_{h=1}^{N_h} P_{mh} - P_{mD} - P_{Lm} = 0 \\
& && \sum_{m=1}^{M} t_m\left(a_{0h} + a_{1h}P_{mh} + a_{2h}P_{mh}^2\right) - W_h = 0 \\
& && P_i^{\min} \le P_i \le P_i^{\max}, \quad i = 1, \ldots, N_i \\
& && P_h^{\min} \le P_h \le P_h^{\max}, \quad h = 1, \ldots, N_h
\end{aligned} \tag{2.8}$$

where $F_j(P_{mi})$ and $F_k(P_{mi})$ are the objective functions to be minimized over the set of admissible decision vector P_{mi}. Where ε_k is the maximum tolerable objective level. The value of ε_k is chosen for which the objective constraints in problem (2.8) are binding at the optimal solution. The level of ε_k is varied parametrically to evaluate the impact on the single objective function $F_j(P_{mi})$.

2.3.2 The FA

FA is naturally inspired from flashing light of fireflies. For a given optimization problem, the objective function of FA is affiliated to the intensity of light. This assists the swarm of fireflies to relocate to more brighter and attractive places for efficient optimal solutions. Although, the FA has various resemblances with other swarm intelligence algorithms, namely Artificial Bee Colony (ABC), Ant Colony, Cuckoo Search, and Particle Swarm optimization (PSO), but its simplicity both in conceptualwise and implementation makes it distinct from other algorithms. According to [4] the characteristic feature of the FA is the fact that it simulates a parallel independent run strategy, where in every iteration, a swarm of n fireflies has generated n solutions. Each firefly works almost independently and as a result the algorithm will converge very quickly with the fireflies aggregating closely to the optimal solution [5–7].

2.3.3 The MU

Herein, the MU [8] is introduced to handle this constrained optimization problem. Such a technique can overcome the ill-conditioned property of the objective function.

Considering the nonlinear problem with general constraints as follows:

$$\begin{aligned} &\min_x F(x) \\ \text{subject to} \quad & h_k(x) = 0, \quad k = 1, \ldots, m_e \\ & g_k(x) \le 0, \quad k = 1, \ldots, m_i \end{aligned} \tag{2.9}$$

where $h_k(x)$ and $g_k(x)$ stand for equality and inequality constraints, respectively.

The augmented Lagrange function (ALF) [6] for constrained optimization problems is defined as:

$$\begin{aligned} L_a(x, \nu, \upsilon) = f(x) &+ \sum_{k=1}^{m_e} \alpha_k \left\{ [h_k(x) + \nu_k]^2 - \nu_k^2 \right\} \\ &+ \sum_{k=1}^{m_i} \beta_k \left\{ \langle g_k(x) + \upsilon_k \rangle_+^2 - \upsilon_k^2 \right\} \end{aligned} \tag{2.10}$$

where α_k and β_k are the positive penalty parameters, and the corresponding Lagrange multipliers $\nu = (\nu_1, \ldots, \nu_{m_e})$ and $\upsilon = (\upsilon_1, \ldots, \upsilon_{m_i}) \ge 0$ are associated with equality and inequality constraints, respectively.

The contour of the ALF does not change shape between generations while constraints are linear. Therefore, the contour of the ALF is simply shifted or biased in relation to the original objective function, *f*(*x*). Consequently, small penalty parameters can be used in the MU. However, the shape of contour of L_a is changed by penalty parameters while the constraints are nonlinear, demonstrating that large penalty parameters still create computational difficulties. Adaptive penalty parameters of the MU are employed to alleviate the above difficulties. More details of the MU are found in [8].

2.4 System Simulations

An HPS was employed to demonstrate the effectiveness of the proposed approach, as determined by the quality of the solutions obtained. This test system includes two hydro plants and four thermal generators whose characteristics are the same as those in [2]. The short-term scheduling of this HPS is divided into four subintervals and involves four subinterval demands. For the purpose of comparing the previous method [2] with the same situations, the duration of each subinterval is 12 h. The transmission loss (P_{Lm}) in each subinterval was represented using *B*-coefficient method. The proposed algorithm was compared with Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [2], Strength Pareto Evolutionary Algorithm-2 (SPEA2) [2], and Multi-objective Differential Evolution (MODE) [2] in the best compromise. The computation was implemented on a personal computer (P5-3.0 GHz) in FORTRAN-90. Setting factors utilized in this case were as follows: the population size *Np* was set to 5, and iteration numbers of the outer loop and inner loop were set to (outer, inner) as (50, 5,000) for the proposed FA-MU. The implementation of this example can be described as follows:

$$L_a(x,\nu,\upsilon) = f(x) + \sum_{k=1}^{4} \alpha_k \left\{ [h_k(x) + \nu_k]^2 - \nu_k^2 \right\} + \sum_{k=1}^{3} \beta_k \left\{ \langle g_k(x) + \upsilon_k \rangle_+^2 - \upsilon_k^2 \right\} \tag{2.11}$$

$$\text{SCV} = \sum_{k=1}^{4} |h_k| + \sum_{k=1}^{2} \max\{g_k, 0.0\} \tag{2.12}$$

where

$$F_1 = \sum_{m=1}^{4} \sum_{i=1}^{4} t_m \left[a_i + b_i P_{mi} + c_i P_{mi}^2 + \left| e_i \sin\left\{ f_i \left(P_i^{\min} - P_{mi} \right) \right\} \right| \right] (\$) \tag{2.13}$$

$$F_2 = \sum_{m=1}^{4} \sum_{i=1}^{4} t_m \left[\alpha_i + \beta_i P_{mi} + \gamma_i P_{mi}^2 + \xi_i e^{(\zeta_i P_{mi})} \right] (\text{lb}) \tag{2.14}$$

And subject to

$$h_1 \sim h_4 : \sum_{i=1}^{4} P_{mi} + \sum_{h=1}^{2} P_{mh} - P_{mD} - P_{Lm} = 0 \tag{2.15}$$

$$g_1, g_2 : \sum_{m=1}^{4} t_m \left(a_{0h} + a_{1h} P_{mh} + a_{2h} P_{mh}^2 \right) - W_h \le 0 \tag{2.16}$$

$$g_3 : F_2 - E_{\text{lim}} \le 0 \tag{2.17}$$

This scheduling of the best compromise includes the prime function (2.11) with 24 variables ($P_{11}, \ldots, P_{16}, P_{21}, \ldots, P_{26}, P_{31}, \ldots, P_{36}, P_{41}, \ldots, P_{46}$), 4 equality constraints ($h_1, \ldots, h_4$), and 3 inequality constraints (g_1, g_2, g_3). The g_3 stands the violation of emission criterion for the expected ε_2. For comparison, the sum of the equality and inequality constraint violations defined as $\mathrm{SCV} = \sum_{k=1}^{4} |h_k| + \sum_{k=1}^{2} \max\{g_k, 0.0\}$ is used to evaluate the effect of the equality and inequality constraints on the final solutions. SCV doesn't take g_3 into account for the purpose of directly using results obtained from the previous algorithms.

Table 2.1 lists the compared results of the best compromise obtained by NSGA-II [2], SPEA2 [2], MODE [2], and the proposed FA-MU. The cost (F_1) obtained by the proposed approach is satisfactory, in relation to those obtained by NSGA-II [2], SPEA2 [2], and MODE [2]. The proposed FA-MU completely meets the system constraints (SCV = 0.00). It is superior to NSGA-II [2], SPEA2 [2], and MODE [2] in the quality of solutions. Results in this case, with SCV are 3.89 and 5.84, obtained by NSGA-II [2] and SPEA2 [2], respectively. There are infeasible solutions. Consequently, the proposed FA-MU is more effective and efficient than the previous methods.

Table 2.1 Compared results of the previous methods and FA-MU

Method item	NSGA-II [2]	SPEA2 [2]	MODE [2]	FA-MU
h_1	0.00	0.00	0.00	0.00
h_2	0.00	0.00	0.00	0.00
h_3	0.00	0.00	0.00	0.00
h_4	0.00	0.00	0.00	0.00
g_1	1.90	3.03	−3.18	0.00
g_2	1.99	2.81	−3.84	0.00
g_3	–	–	–	0.00
SCV	**3.89**	**5.84**	0.00	0.00
F_1 (\$)	68,332.9417[a]	68,392.3888[a]	68,388.1897	67,027.0135
F_2 (lb)	25,278.2860	26,005.7492	25,759.3182	25,278.2308
CPU_time (s)	–	–	–	9.47

[a]Infeasible solution

2.5 Conclusions

The proposed FA-MU yields optimal values, taking into account different objectives, and the pareto-optimal set represents the trade-off between the objectives. The proposed approach integrates the FA, the MU and the ε-constraint technique, showing that the proposed algorithm has the following merits—(1) ease of implementation; (2) applicability to non-smooth fuel cost and emission level functions; (3) better effectiveness than the previous method, and (4) the need for only a small population. System simulations have shown that the proposed approach has the advantages mentioned above for solving optimal EED problems of the HPS.

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