MULTI-OBJECTIVE OPTIMUM ECONOMIC-EMISSION DISPATCH CONSIDERING THE ENVIRONMENTAL ASPECTS

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ABSTRACT

In this paper, the economic-emission dispatch problem (EED) considering power losses is solved using a modified bacterial foraging algorithm (MBF). To solve this bi-objective economic-emission dispatch problem, the weighted-sum method is utilized. The well-known bacterial foraging algorithm (BFA) is one of the evolutionary optimization methods enthused by the foraging behavior of the E. coli bacteria. The primary BFA has been successfully employed to deal with small scale optimization problems. Quite the opposite, poor convergence characteristics have been observed when applied to large-scaled optimization problems with more complicated constrains. Due to the nonlinearity, high-dimensionality and complexity of the search region of the EED optimization problem, essential adaptations are suggested to improve the performance of the original BFA. A well-known test system is employed to validate the proposed MBF.

Keywords:Bacterial foraging optimization, economic-emission dispatch, Multiobjective optimization

1. INTRODUCTION

Alarge number of research papers have explored the typical economic dispatch optimization (ED). This problem is among the most important power system operation and planning tasks. In addition to the economic side of the problem, another dimension is highly deliberated due to the recent environmental considerations, the objective of the EED problem is not anymore restricted to decreasing the fuel cost alone but also the emissions of gaseous. The ever-increasing worldwide demand for electric power has resulted in a major rise in the produced electric energy and the numbers of power plants. A wide-range of conventional and renewable sources is utilized to generate electrical power. Thermal plants with fossil-based fuel (coal, oil, natural gases…etc.) are the main source of the generated electricity. Due to their nature, thermal power plants are the main source of released pollutant gaseous. Nitrogen oxides (NO_x) is among these harmful gaseous produced by the fossil fuel combustion is. Various constraints including power balance, limits of the generating units and ramp rates are taken inti consideration.To solve the EED problem, many deterministic optimization techniques have been exploited. These include gradient search, lambda iteration method, Newton-based methods, linear programming, quadratic programming, and dynamic programming [1-3]. Even though these calculus-based methods show good performance in solving the classic EED problem, they fail to achieve satisfactory success when used to solve EED large scale problems especially when higher nonlinearities and non-smooth characteristics are involved [4]. Recently, heuristic non-classical methods have been proposed to solve this problem. These include evolutionary programming [5], genetic algorithm [6, 7], and particle swarm optimization [8-11]. These non derivative-based methods demonstrate good performance in solving the EED problem regardless of the non-linear and non-smooth shape of the input-output characteristics of the thermal generating unit [4].

One of the recently introduced optimization technique is the Bacterial foraging algorithm (BFA) which is inspired by the foraging behavior of the *Ecoli*. bacteria [12]. BFA has been successfully applied to solve various optimization problems such as distributed optimization and control [12], optimal power flow [13, 14], design of optimal power system stabilizers [15] and harmonic estimation [16]. However, simulation results revealed that the BFA suffers from poor convergence properties and high timing requirements. This poor behavior gets worse in dynamic environments and high dimension search spaces associated with complex problems [17, 18].

A modified bacterial foraging algorithm (MBF) is presented in this paper, and applied to solve the EED bi-criteria problem considering the power losses. The reminder of the paper is organized as follows: Section 2 provides the problem formulation of the EED problem. In Section 3, the MBF is described. Simulation results are demonstrated in Section 4. The conclusion is drawn in Section 5.

2. ECONOMIC-EMISSION DISPATCH

Determining the optimum loading of all generation units so that both the cost and emission functions are minimized subject to specified constraints is the objective of the EED problem [3].

2.1. Objective function

The formulation of the EED for all-thermal power generation system is expressed as a multi-objective optimization problem. This formulation is conducted considering the environmental aspects due to emission of various gaseous in addition to the operating cost. Mathematically, these objective functions are expressed as follows [3]:

The first objective, F_1 is the fuel cost function of the thermal generating unit:

$$F_1 = \sum_{i=1}^{N_g} (a_i P_{gi}^2 + b_i P_{gi} + c_i) \quad \$/h \qquad (1)$$

P_{gi}: Power generation of unit i

a_i, b_i and c_i: The fuel cost coefficients for unit i.

N_g: Number of generation units

The second objective, F_2 is the amount of NO_x emission as a quadratic function of the output power of the generating unit:

$$F_2 = \sum_{i=1}^{N_g} (d_{1i} P_{gi}^2 + e_{1i} P_{gi} + f_{1i}) \quad kg/h \qquad (2)$$

where d_{1i}, e_{1i} and f_{1i} are coefficients for the NO_x gaseous emission [19]

2.2. Constraints

These objective functions represented by are subject to a number of constraints including the following:

Load balance

$$\sum_{i=1}^{N_g} P_{g_i} - P_D - P_L = 0 \qquad (3)$$

where, PL is the system total real power losses and PD is the total system load demand.

Generating unit capacity limits

$$P_{g_i}^{\min} \le P_{g_i} \le P_{g_i}^{\max} \tag{4}$$

Where, P_{gi}^{max} is the maximum power generation for unit i

Network system losses

The transmission line losses are expressed as function of the real power and the B-coefficient matrix [20].

$$P_L = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P_{g_i} B_{ij} P_{g_j} + \sum_{i=1}^{N_g} B_{i0} P_{g_i} + B_{00} \tag{5}$$

where the parameters $B_{ij}$are the loss coefficients and the expression of equation (5) is the Korn's loss formula [21].

2.3. Weighted-sum method

The weighted-sum method [22], is one of the widely applied techniques to solve multi-objective optimization problems. In order to apply this method, the multi-objective optimization problem is converted to a single one. Weights are assigned for each of the objectives according to the decision makers' preference. The values of these weighting factors reflect the relative importance of the conflicting objectives. The problem is expressed as follows [23]:

$$min \qquad \sum_{k=1}^{M} w_k F_k (P_{gi}) \tag{6}$$

Subject to: $\sum_{k=1}^{M} w_k = 1 \;\; (w_k \ge 0)$ (7)

where M is the number of objective functions and w_k is the weight assigned to the k^{th} objective.

3. THE MODIFIED BACTERIAL FORAGING ALGORITHM

3.1. Bacterial foraging algorithm (BFA)

BFA is an optimization technique motivated by the foraging behavior of the E coli. bacteria. The biological aspects of the bacterial foraging strategies and their motile behavior as well as their decision making mechanisms can be found in [12]. BFA is designed to solve non-gradient optimization problems and to handle complex and non-differentiable objective functions. Searching the hyperspace is performed through three main operations, namely; chemotaxis, reproduction and elimination dispersal activities [12]. The chemotaxis process is performed through swimming and tumbling. The bacterium spends its life alternating between these two modes of motion. In the BFA, a tumble is represented by a unit length in a random direction, $¤(j)$, which specifies the direction of movement after a tumble. The size of the step taken in the random direction is represented by the constant run-length unit, C(i). For a population of bacteria, the location of the ith bacterium at the jth chemotactic step, kth reproduction step and lth elimination/dispersal event is represented by $^{-\,i}(j,k,l) \in \Re^{p}$. At this location the cost function is denoted by $J(i,j,k,l)$, which is also known as the nutrient function. After a tumble, the location of the ith bacterium is represented by

$$^{-\,i}(j+1,k,l) = {}^{-\,i}(j,k,l) + C(i,j)¤(j) \qquad (8)$$

When at $\theta^{i}(j+1,k,l)$ the cost function $J(i,j+1,k,l)$ is lower than $J(i,j,k,l)$, another step of size C(i,j) in the same direction is taken. This operation is repeated as long as a lower cost is obtained until a maximum number of steps, Ns, is reached. The cost function of each bacterium is affected by a kind of swarming that is performed by the cell-to-cell signaling released by the bacteria groups to form swarm patterns. This swarming is expressed as follows:

$$
\begin{aligned}
J_{cc}\left(\theta, P(j,k,l)\right) &= \sum_{i=1}^{S} J_{cc}^{i}\left(\theta, \theta^{i}(j,k,l)\right) \\
&= \sum_{i=1}^{S}\left[-d_{attract}\exp\left(-\mu_{attract}\sum_{m=1}^{p}(\theta_{m}-\theta_{m}^{i})^{2}\right)\right] \\
&+\sum_{i=1}^{S}\left[h_{repellant}\exp\left(-\mu_{repellant}\sum_{m=1}^{p}(\theta_{m}-\theta_{m}^{i})^{2}\right)\right]
\end{aligned}
\qquad (9)
$$

where dattract, ωattract, hrepellant and ωrepellant are coefficients represent the characteristics of the attractant and repellant signals released by the cell and θ_{m}^{i} is the mth component of ith bacterium position θ^{i}. $P(j,k,l)$ is the position of each member of the population of the S bacteria and defined as:

$$P(j,k,l)=\left\{\theta^{i}(j,k,l)\,|\,i=1,2,\ldots,S\right\} \qquad (10)$$

where S is the size of the bacteria population. The function (9) which represents the cell-to-cell signaling effect is added to the cost function

$$J(i,j,k,l)+J_{cc}(\theta,P) \qquad (11)$$

A reproduction process is performed after taking a maximum number of chemotactic steps, Nc. The population is halved so that the least healthy half dies and each bacterium in the other healthiest one splits into two bacteria which takes the same position.

$$S_r = \frac{S}{2} \tag{12}$$

After Nre reproduction steps an elimination/dispersal event takes place for Ned number of excisions. In this operation each bacterium could be moved to explore another parts of the search space. The probability for each bacterium to experience the elimination/dispersal event is determined by a predefined fraction ped.

3.2. Modified bacterial foraging algorithm (MBF)

As mentioned, the original BFA shows poor performance characteristics in some cases because of the high dimensionality and nonlinearities and due to the constant length unit step. To guarantee good searching results and control the local and global search ability of the algorithm, the run-length unit is adjusted. This to balance the exploration and exploitation of the search. To achieve this goal a nonlinear decreasing dynamic function is augmented to perform the swim walk instead of the static step as the following [24]:

$$C(i, j+1) = \left(\frac{C(i, j) - C(N_C)}{N_C + C(N_C)}\right)\left(N_C - j\right) \tag{13}$$

4. SIMULATION RESULTS

The proposed MBF is implemented to solve an EED case study considering the system losses. In each test case 30 independent runs were conducted with different random initial solution for each run. This case study is the IEEE30-bus system with 6 generators and a total load demand of 1800 MW and the fuel cost characteristics are given in Table 1 [3, 25]. In this EED problem, two conflicting objectives are considered; the cost and NO_x emission functions.

TABLE 1: DATA FOR THE 6-GENERATOR SYSTEM

	Parameter				
Unit i	a_i \$/MW^{2}h	b_i \$/MWh	c_i \$/h	P_{gi}^{min} MW	P_{gi}^{max} MW
1	0.002035	8.43205	85.6348	150	600
2	0.003866	6.41031	303.7780	150	600
3	0.002182	7.42890	847.1484	150	600
4	0.001345	8.30154	274.2241	150	600
5	0.002182	7.42890	847.1484	150	600
6	0.005963	6.91559	202.0258	150	600

The load demand is 1800 MW and coefficients for the fuel cost and emission equations are given in Table 2 [3]:

TABLE 2: COEFFICIENTS FOR COST AND EMISSION EQUATIONS

Obj.		Coef.	Generator 1	2	3	4	5	6
Cost	F1($/h)	a	0.002035	0.003866	0.002182	0.001345	0.002162	0.005963
		b	8.43205	6.41031	7.4289	8.30154	7.4289	6.91559
		c	85.6348	303.778	847.1484	274.2241	847.1484	202.0258
NOX	F2(kg/h)	d_1	0.006323	0.006483	0.003174	0.006732	0.003174	0.006181
		e_1	-0.38128	-0.79027	-1.36061	-2.39928	-1.36061	-0.39077
		f_1	80.9019	28.8249	324.1775	610.2535	324.1775	50.3808

The non-inferior solution is determined using the weighted-sum method. The Pareto-optimal set of non-dominated solutions is obtained. Fuel cost and NO_x emission objective functions are both simultaneously optimized in order to solve the problem. The bi-objective optimization problem is converted into a single one by using the weighting factors. The non-inferior solution set is presented in Fig 1. The upper and lower limits of w_1 and w_2 (0 and 1.0) signify both ends of the Pareto-optimal front as shown in Fig 1. It is evidently obvious that any decrease in emission results in an increase in the fuel cost which understandable as the two objectives are non-commensurable and conflicting.

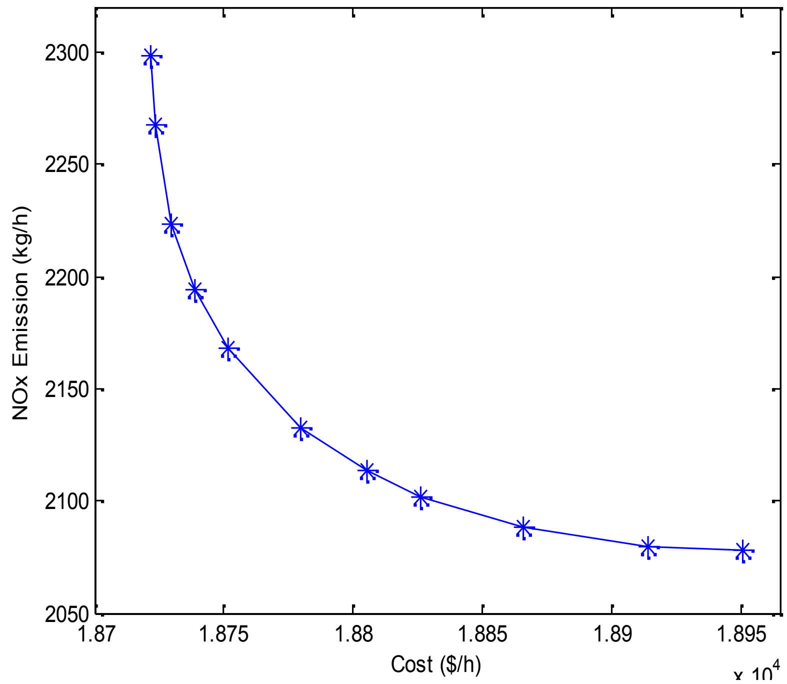

Figure 1. Pareto-optimal front and the trade-off set of optima

5. CONCLUSIONS

The bi-objective EED problem has been presented and a developed bacterial foraging algorithm is utilized to solve it. This algorithm is a modified bacterial foraging method which is characterized by an augmented dynamic nonlinear function for updating the solution trajectory and improving the algorithm convergence properties. The proposed MBF has effectively captured the shape of the Pareto-optimal front and the trade-off set of optima. The efficacy of the algorithm has been demonstrated by simulation results.

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