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Artificial bee colony algorithm with dynamic population size to combined economic and emission dispatch problem

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ABSTRACT

Incremental Artificial Bee Colony algorithm with Local Search (IABC-LS) is one of efficient variant of artificial bee colony optimization which was successfully applied to economic power dispatch problems before. However IABC-LS algorithm has some tunable parameters which are directly affecting the algorithm behavior. In this study, we have introduced a new algorithm namely Artificial Bee Colony with Dynamic Population size (ABCDP) which is using similar mechanisms defined in IABC-LS without using many parameters to be tuned. To prove the efficiency and robustness of algorithm in power dispatch, the algorithm is used for the combined economic and emission dispatch problem which is converted into single objective optimization problem. For fair comparison, the parameters of both IABC and ABCDP algorithms are determined via automatic parameter configuration tool, Iterated F-Race. IEEE 30 bus test system and 40-generator units problem are used as the problem instances. The results of the algorithms indicate that ABCDP is giving good results in both systems and very competitive with the state-of-the-art.

1. Introduction

Economic dispatch (ED) problem is one of the main subjects of power system operations. The main objective of the ED problem can be explained as meeting the power demand by operating power generation units with the minimum cost while satisfying the equality and inequality constraints of the system. Optimal solution of the ED problem provides significant economic advantages. With the increased interest in environmental pollution, the traditional ED, which ignores the pollutant emissions of the fossil fuels used by the thermal plants, no longer satisfies the needs. Therefore, the environmental economic dispatch (EED), as an alternative, has become more attractive, because it considers the pollutant emissions as well as economic advantages. The solution of the EED problem comprises some important evaluation criteria such as fuel cost, environmental impact and total active power loss. So, the EED problem is a multi-objective mathematical problem in which conflicting objectives are optimized simultaneously [1–5].

In general, the EED problem can be solved by three approaches in the literature [5,6]. In the first approach, the amount of emission is calculated as a constant within the permitted limits. However, it is quite difficult to formulate the trade-off relations between fuel cost and emission. As an example to this approach, the EED problem was solved with Davidon–Fletcher–Powell's method (DFPM) [7] with the emission amount taken as a constant in the permitted limits.

In the second approach, decreasing emission is considered in addition to the cost minimization. In this case, multi objective optimization problem in the solution of the EED problem is converted into a single objective optimization problem that considers only one objective at a time or the linear combination of two objectives. In the literature, This type of optimization problem was solved using algorithms such as genetic algorithm [8], differential evolution algorithm (DE) [9], particle swarm optimization algorithm (PSO) [10], artificial bee colony algorithm (ABC) [11], the fast successive linear programming algorithm (SLP) [12], the evolutionary programming algorithms (EP) [13], the hybrid bacterial foraging Nelder–Mead algorithm (MF–NM) [14], hybrid differential evolution with biogeography-based optimization algorithm (DE/BBO) [15], analytical solution (AS) [16], Newton–Raphson method (NRM) [17], opposition-based gravitational search algorithm (OGSA) [18] and first order gradient method (FOGM) [19].

As for the third approach, simultaneously conflicting objectives are evaluated together in the solution of the EED problem. Both the fuel cost and the emission are minimized together. In the literature, as an example to such an approach, the optimization problem was solved with methods such as multi-objective Mathematical Programming (MMP) formulation based on a fast ε-constraint

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(EC) approach [1], non-dominated sorting bacterial foraging (NSBF) and fuzzy dominance based bacterial foraging (FSBF) algorithms [2], shuffle frog leaping (SFL) and modified shuffle frog leaping (MSFL) algorithms [3], PSO [4], DE and modified differential evolution (MODE) algorithms [20–22], hybrid optimization algorithm (MO-DE/PSO) [23], adaptive Hopfield neural network approach (AHNN) [24], linear programming techniques (LP) [25], multi objective stochastic search technique (MOSST) [26], the NIMBUS algorithm [27], non-dominated sorted genetic (NSGA), niched Pareto genetic (NPGA) and strength Pareto evolutionary (SPEA) algorithms [28], hybrid evolutionary algorithm (NSGA-II/CAO) [29], the elitist non-dominated sorting genetic algorithm (NSGA-II) [30], modified non-dominated sorting genetic algorithm with dynamic crowding distance (MNSGA-II + DCD) and controlled elitism (MNSGA-II + DCD + CE) [31] and interactive fuzzy satisfying method (IFSM) [32].

In the literature, the multi objective optimization problems were solved both directly and by converting into single objective optimization problem, with algorithms such as PSO and improved particle swarm optimization (FMOPSO) algorithms [5,6], NSGA [33], NPGA [34], SPEA [35] and fuzzy based bacterial foraging algorithms (MBFA) [36].

Fossil fuels cause atmospheric waste emission composed of gases and particles such as carbon dioxide (CO_2), sulfur dioxide (SO_2), nitrogen oxide (NO_x). These waste gases endanger all living creatures and even lead to global warming. Emission of SO_2, one of the waste gases, is dependent only on the fuel consumption therefore easier to model mathematically. On the contrary, mathematical modeling of NO_x emission is far more difficult since it depends on a few factors such as boiler temperature and air fuel mixture [20].

In this study, first of all, combined economic and NO_x emission dispatch problem has been converted into single objective optimization problem by weighted sum method (WSM). The transformation of the multi-objective optimization problem to single-objective problem by using the suitable transforms is called scalarization. WSM is one of the oldest and the most common methods of scalarization. The method is mostly appropriate for convex problems. More than one objective functions are scalarized with this method by multiplying with positive weights and adding with them. The total of the positive weights must be one (1). In this way, multi-objective optimization problem has been transformed into single-objective optimization problem [9–11]. After that, both incremental artificial bee colony and artificial bee colony with dynamic population size algorithms are used for the solution of the converted problem. Iterated F-Race method is utilized to determine the parameters of the algorithms.

2. Formulation of the problem

The solution of the combined economic and NO_x emission dispatch problem is achieved by minimizing the objective function (OF) combined with the WSM under the system constraints.

$$\mathrm{OF} = \mathrm{Min}\left\{ w \sum_{n \in N_G} F_n(P_{G,n}) + (1-w)\gamma \sum_{n \in N_G} E_n(P_{G,n}) \right\} \tag{1}$$

In Eq. (1), the fuel cost rate (\$/h) is shown with $F_n(P_{G,n})$ and NO_x emission rate (ton/h) with $E_n(P_{G,n})$. Scaling factor, weight factor and the set of all the thermal generation units are denoted as γ, w $(0 \leqslant w \leqslant 1)$ and N_G respectively. $w = 1.0$ corresponds to the minimization of total fuel cost only, likewise, $w = 0.0$ corresponds to the minimization of total NO_x emission only.

Fuel cost function of each unit in the system is regarded as a quadratic function as shown in the following equation [37]:

$$F_n(P_{G,n}) = a_n + b_n P_{G,n} + c_n P_{G,n}^2 \ (\$/\mathrm{h}) \tag{2}$$

where a_n, b_n, and c_n are the cost coefficients. When the valve-point loading effects are considered in cost function, then the equation can be expressed as:

$$F_n(P_{G,n}) = a_n + b_n P_{G,n} + c_n P_{G,n}^2 + |e_n \sin(f_n(P_{G,n}^{\min} - P_{G,n}))| \ (\$/\mathrm{h}) \tag{3}$$

where e_n and f_n are fuel cost coefficients for valve-point effects.

The NO_x emission function of each thermal unit is defined in the following equation [1]:

$$E_n(P_{G,n}) = \alpha_n + \beta_n P_{G,n} + \eta_n P_{G,n}^2 + \xi_n \exp(\lambda_n P_{G,n}) \ (\mathrm{ton/h}) \tag{4}$$

where $\alpha_n, \beta_n, \eta_n, \xi_n$ and λ_n are coefficients of the nth generator emission characteristics. In the Eqs. (2)–(4), the $P_{G,n}$ is in MW. Power equality constraint in the system with transmission losses is shown in Eq. (5):

$$\sum_{n \in N_G} P_{G,n} - P_{load} - P_{loss} = 0 \tag{5}$$

where P_{load} is the total load demand and P_{loss} is total power loss in transmission lines. The generation capacity constraints of the thermal generation units are shown in Eq. (6) [1]:

$$P_{G,n}^{\min} \leqslant P_{G,n} \leqslant P_{G,n}^{\max} \quad (n \in N_G) \tag{6}$$

where $P_{G,n}^{\min}$ and $P_{G,n}^{\max}$ are the minimum and maximum range of power loading limit for nth generator unit, respectively. The transmission losses of the system are calculated using Eq. (7) with the B loss matrix [26]:

$$P_{loss} = \sum_{n \in N_G} \sum_{j \in N_G} P_{G,n} \cdot B_{nj} \cdot P_{G,j} + \sum_{n \in N_G} B_{0n} \cdot P_{G,n} + B_{00} \tag{7}$$

The total fuel cost rate $F_{total}(P_{G,n})$ and total NO_x emission rate $E_{total}(P_{G,n})$ are calculated with Eqs. (8) and (9) respectively [10].

$$F_{total}(P_{G,n}) = \sum_{n \in N_G} F_n(P_{G,n}) \ (\$/\mathrm{h}) \tag{8}$$

$$E_{total}(P_{G,n}) = \sum_{n \in N_G} E_n(P_{G,n}) \ (\mathrm{ton/h}) \tag{9}$$

3. Artificial bee colony algorithm

The artificial bee colony (ABC) algorithm, proposed by Karaboga in 2005 [38] for real-parameter optimization, which simulates the intelligent foraging behavior of a honeybee swarm, is one of the most recently introduced swarm-based optimization techniques. A simple pseudo-code of the original ABC is shown in Fig. 1. ABC algorithm basically consists of four phases: initialization, employed bees, onlooker bees and scout bees steps. In initialization step of the algorithm, population is generated and other parameters about the algorithm are initialized. After initialization, algorithm tries to solve optimization problems within the loop which is comprised of other three steps [38–42]. The main steps of the basic ABC metaheuristic are explained in detail in the following:

```
Algorithm: The Artificial Bee Colony

Initialization step
while termination condition is not met do
    Employed Bees Step
    Onlooker Bees Step
    Scout Bees Step
end while
```

Fig. 1. General steps of original artificial bee colony algorithm.