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Hybrid ant optimization system for multiobjective economic emission load dispatch problem under fuzziness

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ABSTRACT

In this paper, a new hybrid optimization system is presented. Our approach integrates the merits of both ant colony optimization and steady state genetic algorithm and it has two characteristic features. Firstly, since there is instabilities in the global market and the rapid fluctuations of prices, a fuzzy representation of the economic emission load dispatch (EELD) problem has been defined, where the input data involve many parameters whose possible values may be assigned by the expert. Secondly, by enhancing ant colony optimization through steady state genetic algorithm, a strong robustness and more effectively algorithm was created. Also, stable Pareto set of solutions has been detected, where in a practical sense only Pareto optimal solutions that are stable are of interest since there are always uncertainties associated with efficiency data. Moreover to help the decision maker DM to extract the best compromise solution from a finite set of alternatives a Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) method is adopted. It is based upon simultaneous minimization of distance from an ideal point (IP) and maximization of distance from a nadir point (NP). The results on the standard IEEE systems demonstrate the capabilities of the proposed approach to generate true and well-distributed Pareto optimal nondominated solutions of the multiobjective EELD.

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1. Introduction

Optimal Power Flow (OPF) was the first discussed by Carpentier [1]. In the past two decades, OPF problem has received much attention, because of its ability to determine the dispatch of generators so as to meet the load demand while minimizing the total fuel cost, subject to the satisfaction of all constraints on the system. OPF is a nonlinear, non-convex, large-scale, static optimization problem with both continuous and discrete control variables [2]. More objectives have recently been incorporated into the OPF problem. These include optimization of active/reactive losses, plant emissions, voltage profile and power plant stability. This has extended the definition of the OPF problem from a single objective case to a multiobjective one [3,4]. The Environmental/Economic Dispatch multiobjective problem seeks to simultaneously minimize both fuel cost and the emissions produced by power plants. Environmental concerns on the effect of SO_2 and NO_X emissions produced by the fossil-fueled power plants led to the inclusion of minimization of emissions as an objective in the OPF formulation.

In the previous literatures various mathematical programming and optimization techniques have been used to solve OPF. Previously a number of conventional approaches such as the gradient method, linear programming Algorithm, lambda iteration method, quadratic programming, nonlinear programming algorithm, Lagrange relaxation algorithm [5–10], etc. have been applied for solving the EELD problems. These traditional classical methods are based on the assumption that the incremental cost of generator monotonically increases. Also, dynamic programming [10] was proposed as a new algorithm, which does not impose any restrictions on the nature of the cost curves and hence it can solve both the convex and non-convex EELD problems. But this method suffers from the curse of dimensionality in the solution procedure.

Nonlinear features of generators in practical aspects is the main reason that generally a classical optimization technique may not be able to find a solution with a significant computational time for medium or large-scale EELD problem and on the other hand these techniques may further being restricted by their lack of robustness and efficiency in a number of practical limitations. Accordingly, these limitations are redounded to introduce the evolutionary algorithms methods [11]. Evolutionary algorithms (EAs) are stochastic search methods that mimic the metaphor of natural biological evolution and/or the social behavior of species. Because of their universality, ease of implementation, and fitness for parallel computing, EAs often take less time to find the optimal solution than classical methods [12,13]. Also, availability of high-speed computer system, more and more interests has been

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focused on the application of artificial intelligence technology for solution of EELD problems. Recently, there has been a boom in applying evolutionary algorithms to solve EELD problems. Several artificial intelligence methods, such as the genetic algorithm [12–15]; artificial neural networks [16]; simulated annealing, Tabu search [17]; evolutionary programming [18]; swarm optimization [19–22]; differential evolution [23], have been developed and applied successfully to ELD problems. Hopfield neural networks have also implemented [24] to solve EELD problems for units with piecewise quadratic fuel cost functions and prohibited zones constraint. In order to meet the ever increasing demands in the design problems, a new evolutionary algorithm called ant colony optimization algorithm have all been used successfully to mimic the corresponding natural, or physical, or social phenomena[25–27]. Ant colony optimization (ACO) is a metaheuristic inspired by the shortest path searching behavior of various ant species. Since the initial work of Dorigo et al. on the first ACO algorithm, the ant system [28], several researchers have designed ACO systems to deal with multiobjective problems.

Recently, other powerful techniques called hybridization methods have been suggested, The hybrid methods are applied to handle more complicated constraints, including fuzzy adaptive PSO algorithm with Nelder–Mead simplex search (FAPSO–NM) [29], hybrid PSO and sequential quadratic programming (PSO–SQP) [30], hybrid PSO and local serach scheme (PSO–LS) [31], hybrid EP and sequential quadratic programming (EP–SQP) [32], hybrid DE and sequential quadratic programming (DE–SQP) [33], multiobjective evolutionary algorithm based on decomposition (MOEA/D) [34], and Combining ACO with EA based on decomposition MOEA/D [35].

This paper intends to present a new optimization algorithm for solving EELD under fuzziness. The proposed approach integrates the merits of both ACO and steady state Genetic algorithm SSGA [36]. Since there is instabilities in the global market, implications of global financial crisis and the rapid fluctuations of prices, for this reasons a fuzzy representation of the multiobjective EELD has been defined, where the input data involve many parameters whose possible values may be assigned by the experts. In practice, it is natural to consider that the possible values of these parameters as fuzzy numerical data which can be represented by means of fuzzy subsets of the real line known as fuzzy numbers. The proposed approach has two characteristic features. Firstly, a fuzzy representation of the optimal power flow problem has been defined. Secondly, by enhancing ACO through SSGA, a strong robustness and more effectively optimization system was created. Moreover to help the DM to extract the best compromise solution from a finite set of alternatives a TOPSIS method is adopted. Several optimization runs of the proposed approach will be carry out on the standard IEEE systems to verify the validity of the proposed approach.

Section 2 provides a brief description on multiobjective optimization. The mathematical formulation of EELD problem is discussed in Section 3. Section 4 reviews the standard ACO metaheuristic The original optimization system is described in Section 5 along with a short description of the algorithm used in this test system. The parameter settings for the test system to evaluate the performance of the optimization system and the simulation studies are discussed in Section 6. Results and discussion are given in Section 7. Finally, the conclusions is drawn in Section 8.

2. Fuzzy multiobjective optimization

A Multi-objective Optimization Problem (MOP) can be defined as determining a vector of design variables within a feasible region to minimize a vector of objective functions that usually conflict with each other. The following fuzzy vector minimization problem (FVMP) involving fuzzy parameters in the objective functions and constraints such a problem takes the form:

$$\left.\begin{array}{l} Min \quad \{f_1(X,\tilde{a}), f_2(X,\tilde{a}), ...,f_m(X,\tilde{a})\} \\ subject \text{ to } g(X,\tilde{a}) \le 0 \end{array}\right\} \tag{1}$$

where $f_1(X,\tilde{a})$ is the ith objective function; and $g(X,\tilde{a})$ is constraint vector, X is vector of decision variables; and $\tilde{a} = (\tilde{a}_1, \tilde{a}_2, ...\tilde{a}_n)$ represented a vector of fuzzy parameters in the problem. Fuzzy parameters are assumed to be characterized as the fuzzy numbers. The real fuzzy numbers $\tilde{a}$ form a convex continuous fuzzy subset of the real line whose membership function $\mu_{\tilde{a}}(a)$ is defined by:

1) a continuous mapping from R^1 to the closed interval [0,1];
2) $\mu_{\tilde{a}}(a) = 0$ for all $a \in [-\infty, a_1]$;
3) strictly increasing on $[a_1, a_2]$;
4) $\mu_{\tilde{a}}(a) = 1$ for all $a \in [a_2, a_3]$;
5) strictly decreasing on $[a_3, a_4]$;
6) $\mu_{\tilde{a}}(a) = 0$ for all $a \in [a_4, +\infty]$;

Assume that $\tilde{a}$ in the FM-RAP are fuzzy numbers whose membership functions are $\mu_{\tilde{a}}(a)$.

Definition 1. (**α-level set).** The α-level set or α-cut of the fuzzy numbers $\tilde{a}$ is defined as the ordinary set $L_\alpha(\tilde{a})$ for which the degree of their membership functions exceeds the level $\alpha \in [0, 1]$: $L_\alpha(\tilde{a}) = \{a | \mu_{\tilde{a}}(a) \ge \alpha\}$.

For a certain degree α, the (FM-RAP) can be represented as a nonfuzzy α-VMP as follows:

$$\left.\begin{array}{l} Min \quad \{f_1(X,a), f_2(X,a), ...,f_m(X,a)\} \\ subject\ to\ g(X,a) \le 0 \\ X = (x_1, x_2, ...x_n), a = (a_1, a_2, ..., a_n) \\ L_{\alpha i} \le a_i \le U_{\alpha i} \end{array}\right\} \tag{2}$$

where constraint $L_{\alpha i} \le a_i \le U_{\alpha i}$ gives the lower and upper bound for the parameters a_i

Definition 2. (**α–Pareto optimal solution**). $x^* \in X$ is said to be an α–Pareto optimal solution to the (α-VMP), if and only if there does not exist another $x \in X$, $a \in L_\alpha(\tilde{a})$ such that $f_i(x,a) \ge f_i(x^*, a^*)$, $i = 1, 2, .., k$, with strictly inequality holding for at least one i, where the corresponding values of parameters a_i^* are called α-level optimal parameters.

In real world application problems, input data or related parameters are frequently imprecise/fuzzy owing to incomplete or unobtainable information, so the concept of Pareto stability is introduced for the Pareto optimal solutions of a vector valued problem of the allocation of resources to activities.

Definition 3. (**Stable Pareto optimality)** A Pareto- optimal solution x of the problem FVMP is said to be stable if and only if there exists a real number $\alpha \in [0, 1]$ such that x is still Pareto-optimal if $a$is replaced by any a' satisfying the following requirement:

$$a' \in L_\alpha(\tilde{a}) = \{a | \mu_{\tilde{a}}(a) \ge \alpha\} \tag{3}$$

Such a solution x is said to be a stable Pareto-optimal solution. In practical sense only Pareto optimal solutions that are stable are of interest since there are always uncertainties associated with the efficiency data (input data).

3. Multiobjective formulation of EELD problem

The economic emission load dispatch involves the simultaneous optimization of fuel cost and emission objectives which are

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