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# A survey on multi-objective evolutionary algorithms for the solution of the environmental/economic dispatch problems

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ABSTRACT

Development of efficient multi-objective evolutionary algorithms (MOEAs) has provided effective tools to solve environmental/economic dispatch (EED) problems. EED is a highly constrained complex bi-objective optimization problem. Since 1990s, numerous publications have reported the applications of MOEAs to solve the EED problems. This paper surveys the state-of-the-art of research related to this direction. It covers topics of typical MOEAs, classical EED problems, Dynamic EED problems, EED problems incorporating wind power, EED problems incorporating electric vehicles and EED problems within micro-grids. In addition, some potential directions for future research are also presented.

## 1. Introduction

In recent decades, the highly constrained nonlinear multi-objective optimization problem known as environmental/economic dispatch (EED) problem has attracted research efforts due to the increasing concerns about environmental pollution. EED is a bi-objective problem with two conflicting objectives which are the minimization of generation cost and pollution emission. Various approaches have been reported in literature to handle the EED problem.

Initially, conventional optimization methods such as linear programming techniques were mainly used as the optimizing tool for solving the EED problem [1,2]. However, these methods are not effective when the dispatch problem becomes complex. Hence, researchers turned to artificial intelligent techniques especially evolutionary algorithms (EAs) and swarm algorithms (SAs). These meta-heuristics use mechanisms inspired by Darwinian Theory of biological evolution and social interactions, respectively. The studies have shown that EAs and SAs can effectively overcome most of the drawbacks of classical method. EAs and SAs have been successfully adopted to solve various kinds of power dispatch problems [3–11].

Since EAs and SAs use a population of solutions to conduct the search process, multiple non-dominated solutions can be found in one single run. Moreover, EAs and SAs require few domain information of the given problem. These features are attractive for solving complex multi-objective EED optimization problems. Numerous multi-objective evolutionary algorithms (MOEAs) have been suggested to solve the EED problem [12–15]. The aim of this paper is to provide a broad view of using MOEAs in EED applications and encourage researchers in power application domains to benefit from further use of MOEAs. The taxonomy adopted in this paper is based on the topics reviewed and it is divided into 5 parts. The first one studies the classical EED problems using MOEAs while the remaining sections reviews other types of the EED applications.

The remainder of this paper is organized as follows. Section 2 provides a brief introduction of multi-objective optimization and the state-of-the-art MOEAs. Sections 3–7 present MOEAs for the classical EED problems, Dynamic EED problems, EED problems with wind power, EED problems with electric vehicles and EED problems within a micro-grid, respectively. The paper is concluded in Section 8.

## 2. Multi-objective optimization

In this part, the basic concepts of multi-objective optimization and some typical MOEAs are introduced.

### 2.1. Formulation of multi-objective optimization problems

The multi-objective optimization problems (MOPs) can be mathe-

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matically formulated as follows assuming as minimization problems:

$$\begin{cases} min\ \boldsymbol{y} = \boldsymbol{F}(\boldsymbol{x}) = [f_1(x), f_2(x), ..., f_m(x)]^T \\ s.\ t. \qquad g_j(x) \le 0, j = 1, 2, ..., p \\ \qquad\quad h_k(x) = 0, k = 1, 2, ..., q \end{cases} \tag{1}$$

where $\boldsymbol{x} = (x_1, x_2, ..., x_n) \in X \subset \boldsymbol{R}^n$ is the vector of decision variables, which constitute the decision space $X$, and $\boldsymbol{R}^n$ is an $n$ dimensional Euclidean space; $\boldsymbol{y} = (y_1, y_2, ..., y_m) \in \boldsymbol{Y} \subset \boldsymbol{R}^m$ is the vector of objectives, which constitute the objective space $\boldsymbol{Y}$;$g_j(\boldsymbol{x}) \le 0 (j = 1, 2, ..., p)$ and $h_k(\boldsymbol{x}) = 0 (k = 1, 2, ..., q)$ are the constraint functions of the problem.

To solve multi-objective optimization problems, the following concepts are essential.

**Feasible solution set**: For $\boldsymbol{x} \in X$ , if $\boldsymbol{x}$ satisfies all constraints, $\boldsymbol{x}$ is a feasible solution and the set of all feasible solutions is the feasible solution set, denoted as $X_f$ , where $X_f \subseteq X$ .

**Domination:** Given two feasible solutions $\boldsymbol{x}_1$ and $\boldsymbol{x}_2$, we say that $\boldsymbol{x}_1$ dominates $\boldsymbol{x}_2$(denoted as $\boldsymbol{x}_1 \prec \boldsymbol{x}_2$), if $\forall\ i \in \{1, 2, ..., m\}, f_i(\boldsymbol{x}_1) \le f_i(\boldsymbol{x}_2)$, $\exists\ i \in \{1, 2, ..., m\},\ f_i(\boldsymbol{x}_1) < f_i(\boldsymbol{x}_2)$.

**Pareto-optimal set:** For a feasible solution $\boldsymbol{x} \subseteq X$, if there does not exist another feasible solution $x' \subseteq X$ satisfying $x' \prec \boldsymbol{x}$, we say that $\boldsymbol{x}$ is non-dominated with respect to $X$, and this feasible solution $\boldsymbol{x}$ is defined as a Pareto-optimal solution as $\boldsymbol{x}^*$. The set of all Pareto-optimal solutions is defined as the Pareto-optimal set denoted as $P^*$, i. e.,$P^* = \{\boldsymbol{x}^* | \neg\ \exists\ \boldsymbol{x} \in X: \boldsymbol{x} \prec \boldsymbol{x}^*\}$.

**Pareto-optimal front:** The Pareto-optimal front is defined as $P_F$, where $P_F = \{\boldsymbol{F}(\boldsymbol{x}^*) = [f_1(\boldsymbol{x}^*), f_2(\boldsymbol{x}^*), ..., f_m(\boldsymbol{x}^*)]^T | \boldsymbol{x}^* \in P^*\}$.

Based on the above concepts, obtaining the Pareto-optimal set is the key task of multi-objective optimization algorithms.

### *2.2. Typical MOEAs for solving EED problem*

EAs and SAs are stochastic optimization techniques inspired by the natural evolutionary and swarming processes. Due to their own properties, they are more suitable for solving MOPs than other conventional mathematical techniques. Since early 1990s, researchers proposed numerous Multi-objective Evolutionary Algorithms (MOEAs) and used them to solve complex MOPs. In this section, we aim to present a short review of some typical MOEAs especially those used for solving the EED problems. These MOEAs are presented in the chronological order.

(1) Vector Evaluated Genetic Algorithm (VEGA) [16]: VEGA is commonly known as the first MOEA. It modifies the original genetic algorithm to make it capable of handling multi-objective optimization problems. In VEGA, the population is divided into several subpopulations and the number of subpopulations is equal to the number of objectives. Each subpopulation is responsible for searching one objective. While the concept of this algorithm is straightforward, the solutions obtained by this technique are usually not uniformly distributed along the Pareto front especially in the tradeoff regions.

(2) Non-dominated Sorting Genetic Algorithm (NSGA) [14,17]: NSGA was introduced by Srinivas and Deb in 1994. This method uses ranking selection and niching techniques to find the non-dominated solutions and maintain the diversity of the population. Two main steps are involved in this method known as fitness assignment and fitness sharing. Fitness assignment helps fast convergence while fitness sharing increase the diversity.

(3) Multi-Objective Stochastic Search Technique (MOSST) [13]: The MOSST heuristic has been designed as a combination of real coded genetic algorithm (GA) and simulated annealing (SA) techniques. It incorporates a genetic crossover operator BLX-α and a problem specific mutation operator with a local search heuristic to provide a better search capability [13]. It can offer the advantages of both GA and SA.

(4) Non-dominated Sorting Genetic Algorithm II (NSGA-II) [18]: NSGA-II is the most popular multi-objective evolutionary algorithm. The dominance concept is used in NSGA-II to sort/rank the solutions. Moreover, it uses crowding distance to estimate the density of solutions near each solution. NSGA-II uses both the non-domination rank and crowding distance to select individuals to survive to the next generation.

(5) Niched Pareto Genetic Algorithm (NPGA) [19]: NPGA uses Pareto domination tournaments selection scheme to find the good solutions and remove the bad ones. Different from the method used in [17], only two candidates are randomly picked for tournament each time. To compare the two candidates, a randomly selected comparison set is used. Then, the dominance of both individuals with respect to the comparison set is checked. Sharing procedure will be used if both individuals are dominated by the comparison set.

(6) Multi-objective Particle Swarm Optimization (MOPSO) [20]: MOPSO is a variation of the PSO to solve MOPs [21]. Determining global best (*gbest*) is the key issue of MOPSO. MOPSO uses the non-dominated solutions as the basis of selecting the *gbest*. The algorithm maintains two archives to save the global best individuals found so far and the local bests, respectively. The selection of a global best is based on roulette wheel selection of a hypercube score [22].

(7) Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) [23]: MOEA/D was introduced by Zhang et al. in 2007. It provides a new framework to solve MOPs. MOEA/D handles an MOP by decomposing it into numerous single objective sub-problems and optimizes the sub-problems using evolutionary approach collaboratively and concurrently.

(8) Multi-objective Differential Evolution (MODE) [24]: MODE is like the basic DE algorithm expect the selection process. Generally, MODE adopts the non-dominated sorting and ranking selection methods developed by Deb et al. [18]. The non-dominated sorting is performed on the combined population of new generated offspring and parents and the selection is based on the non-dominated rank and crowding distance. Other techniques like summation based sorting and diversified selection were also proposed and used in the literature [25].

## 3. Classical EED problems

### *3.1. Problem formulation*

The prime target of traditionally electric power systems is to schedule the outputs of the generators to meet the load requirement with a minimum fuel cost regardless of emissions produced [1]. With the increasing requirements for the environmental protection, alternative operational strategies are needed to reduce the pollution of the electric power plants. Environmental/Economic Dispatch (EED) problems treat the pollution emissions and the fuel cost as two conflicting objectives which are optimized simultaneously subjected to the practical constraints. Generally, the problem can be formulated as follows:

Fuel cost objective: The cost curves of the generators can be represented by quadratic functions and the total fuel cost $/h can be expressed as:

$$\min \quad F(P_G) = \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \tag{2}$$

where $a_i$, $b_i$, $c_i$ are the cost coefficients for the $i^{th}$ thermal power generator. $F(P_G)$ is the total fuel cost of the system while $N_G$ identifies the number of thermal units. If the rippling effects produced by the steam admission valve openings are considered, a sine component needs to be added to Eq. (2) and expression becomes [12,26]: