A Review of Multi-objective Particle Swarm Optimization Algorithms in Power System Economic Dispatch

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Abstract — **Particle swarm optimization (PSO) has received increasing attention in solving multi-objective economic dispatch (ED) problems in power systems because of parallel computation, faster convergence, and easier implementation. This paper presents a detailed overview of multi-objective particle swarm optimization (MOPSO) and provides a comprehensive survey on its applications in power system economic dispatch including economic environmental dispatch (EED), multi area EED (MAEED), and multi-objective economic environmental hydrothermal scheduling (MEEHS) problems. It highlights MOPSO advantages over other optimization methods and MOPSO improvements in various applications. Furthermore, MOPSO design suggestion in this area is also discussed.**

Keywords — Multi-objective optimization; Power systems; Particle swarm optimization; Economic dispatch

I. INTRODUCTION

Economic dispatch (ED) in power system can provide decision support information for improving power system operation [1]. Generally, the objective of traditional ED is to optimize generation output so as to meet load demand at minimum operating cost while satisfying operational and security constraints of power systems. However, with the increasing awareness of environment protection, some new objectives related to minimization of CO_2, SO_2, and NO_x emission are added into the traditional ED and thus economic environmental dispatch (EED) problems are formed. Mathematically, the new EED problem is a constrained multiobjective optimization problem (MOP) with conflicting optimization objectives and multiple equality and inequality constraints:

$$\begin{aligned} &\text{Min } \vec{f}(\vec{x}) = (f_1(\vec{x}), f_2(\vec{x}), \cdots, f_m(\vec{x})) \\ &\text{Subject to } g_i(\vec{x}) = 0,\ i=1,...,p \qquad (1) \\ &h_j(\vec{x}) \le 0,\ j=1,...,q \end{aligned}$$

where $\vec{x} = (x_1, x_2, \cdots, x_n)$ is a n dimensional vector having n decision variables, $\vec{f}(\vec{x})$ is a m dimensional objective function vector having m sub-objectives to be optimized simultaneously, $g_i(\vec{x})$ and $h_j(\vec{x})$ are equality and inequality constraints in power systems respectively. The solution of MOP is not a global optimum, but a set of so called Pareto optimal solutions.

Conventional optimization methods such as linear programming [2] and dynamic programming [3] can not find Pareto optimal solutions in a run due to its gradient-based searching mechanism. This leads to the development of multiobjective evolutionary algorithms (MOEAs) which can overcome these shortcomings. MOEAs, including multiobjective particle swarm optimization (MOPSO) [4], nondominated sorted genetic algorithm (NSGA) [5], [6], niched Pareto genetic algorithm (NPGA) [7], and strength Pareto evolutionary algorithm (SPEA) [8], are more suitable to solve MOP in power system economic dispatch. Therefore, a review of MOPSO applications in power system economic dispatch is presented in the paper. This paper, as a useful reference, is very helpful for MOPSO designer and those who are trying to solve multiobjective economic dispatch problems.

II. STANDARD AND IMPROVED MOPSO

A. *Standard MOPSO*

Particle swarm optimization (PSO) was invented by Eberhart and Kennedy in 1995 [9], [10]. PSO, as a powerful heuristic optimizer, can search global optima in problem space by imitating bird swarm flying behavior under the guidance of individual flying experience *pbest* and swarm flying experience *gbest*. Its velocity and position update equations are given below:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (pbest_i^t - x_i^t) + c_2 r_2 (gbest^t - x_i^t) \quad (2)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

where ω is inertia weight, c_1 and c_2 are learning factors, r_1 and r_2 are random numbers between 0 and 1, v is particle velocity, x is particle position, i is the ith particle in a swarm, t is the tth iteration number in optimization process. PSO can be directly used to solve single objective optimization problem. It has been reported that single objective ED problem with the minimization of generation cost has been successfully solved by PSO [11]-[13].

However, PSO can not directly solve multiple objective ED problems, e.g., EED, multiarea EED (MAEED), and multiobjective economic environmental hydrothermal scheduling (MEEHS), because

- the solution of multiple objective ED problem is not a global optimum, but Pareto optimal solutions.
- PSO can only find global optimum since particles in a swarm share the same swarm flying experience *gbest*.
- PSO can not find Pareto optimal solutions in a run.

In order to solve multiple objective ED problem, PSO has to be modified and standard MOPSO for searching Pareto optimal solutions of EED should at least include the following features [14]-[26]:

- Each particle has its own swarm flying experience $gbest_i^t$.

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (pbest_i^t - x_i^t) + c_2 r_2 (gbest_i^t - x_i^t) \quad (3)$$

- $gbest_i^t$ is chosen from external archive A_t which stores non-dominated or Pareto optimal solutions.
- New external archive A_{t+1} is obtained form current external archive A_t and population P_t.

B. Improved MOPSO

In order to solve multiple objective ED problem efficiently, requirements for MOPSO performance can be classified into two levels:

- MOPSO can find Pareto optimal solutions, which can be guaranteed by standard MOPSO.
- MOPSO can accompolish better diversity and distribution of Pareto optimal solutions with faster convergence, which should be implemented by MOPSO improvements.

MOPSO with different improvements proposed in [16]-[26] are summarized in Table I. These improvements may influence MOPSO parameters including inertia weight ω and learning factors c_1, c_2, alter the selection way of $gbest_i^t$ from external archive A_t, or partly update population P_t by increasing population diversity. It is clear that MOPSO improvements generally require additional computation consumption for obtaining better diversity and distribution of Pareto optimal solutions. In the design of MOPSO oriented to multiple objective ED problem, the tradeoff between convergence speed and diversity and distribution of Pareto optimal solutions should be considered according to application scenarios in power systems. Detailed comments on these MOPSO improvements are also given in Table I.

TABLE I. MOPSO IMPROVEMENT FOR MOP

MOPSO Improvement	Comments	Reference
Inertia weight or learning factors are adjustable.	balance global exploration and local exploitation abilities.	
Dynamic neighborhood	easy to implement but only suitable for two-objective optimization problems.	[16],[17]
Dominated tree	inappropriate member from dominated tree may be chosen as *gbest*.	[18]
Sigma method	faster convergence and premature convergence.	[19]
Grid-based selection	better distribution of Pareto optimal solutions.	[4],[20]
Non-dominated sorting PSO	helpful to search Pareto optimal solution.	[21]
ε-dominance concept	better convergence and diversity compared with Pareto dominance concept.	[22]
Sub-swarm PSO	suitable for parallel computation.	[23],[24]
Turbulence operator	avoid to be trapped into local optima.	[18],[19],[26]
Mutation operator	avoid to be trapped into local optima.	[4],[20],[25]
Crowding distance assignment	maintain diversity of non-dominated solutions in the archive.	[4],[21]
Clustering techniques	control archive size without destroying the characteristics of archive member.	[24]

It is also clear from Table I. that different MOPSO improvement types can be adopted simultaneously in the design of MOPSO algorithm oriented to multiple objective ED problems. For example, two MOPSO improvement types are used in [4]: 1) grid-based selection is adopted to produce well-distributed Pareto fronts; 2) mutation operator is used to avoid convergence into a false Pareto front, and, moreover, the effect of mutation operator on particles in a swarm decreases as the number of iterations increases. The combination of these two improvements makes MOPSO algorithm proposed in [4] having two advantages of better distribution of Pareto optimal solutions and avoiding premature convergence.

C. MOPSO Advantages Applied in Multi-objective Economic Dispatch

Based on the above analysis of MOPSO principles, MOPSO has many advantages in the solution of power system multiobjective economic dispatch problems over traditional optimization methods, e.g., linear programming and dynamic programming, and other evolutional algorithms, e.g., NSGA, NPGA, and SPEA:

- MOPSO is still effective for nonlinear, non-differentiable, and non-convex objective functions, whereas traditional optimization methods are very difficult to deal with.
- MOPSO is still effective for large-scale power system with high dimension decision variables and numerous operational and security constraints, whereas traditional optimization methods may not be applicable because of the curse of dimensionality.

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- MOPSO can obtain Pareto optimal solutions in a run, whereas traditional optimization methods can not.
- MOPSO has faster convergence speed than other evolutional algorithms.
- MOPSO has well-balanced mechanism to enhance the global exploration and local exploitation ability by adjusting inertia weight ω , or embedding operators into it for the tradeoff between extensive exploration and intensive exploitation in search space.

Therefore, MOPSO is very suitable to solve power system economic dispatch problems with conflicting objectives. This paper, as a further development of [11]-[13], aims to present a detailed overview of MOPSO and give a comprehensive survey on MOPSO applications in power system economic dispatch so as to provide valuable MOPSO design guide to solve practical multiobjective ED problems emerging in power systems.

III. APPLICATIONS OF MOPSO IN POWER SYSTEM ECONOMIC DISPATCH

Unlike traditional ED only focusing on minimizing the total generation cost, EED is a complex MOP with conflicting objectives of minimizing total generation cost and atmospheric pollutant emission simultaneously. Abido has done systematic and valuable research on EED problem by using NSGA [27], SPEA [28], NPGA [29], and MOPSO [14]. In [14], Abido extended the single objective PSO into MOPSO by redefinition of global best and local best individuals with the utilization of nondominated local set, nondominated global set, and external set. This innovation of flying guidance selection together with a hierarchical clustering technique for sizing Pareto optimal set guarantees the superiority of the proposed MOPSO in terms of the diversity and quality of the obtained Pareto optimal solutions. That is why MOPSO performs better than SPEA in the multiobjective EED.

Zhang *et al.* [15] and Gong *et al.* [30] also proved that MOPSO, if properly designed according to the inherent nature of EED problem, is capable of finding Pareto optimal solutions and is superior over NSGA, NSGA-II, and SPEA. In their works, two modification versions of MOPSO, BB-MOPSO [15] and MO-DE/PSO [30], are designed. BB-MOPSO has three distinctive features: a particle updating strategy without parameter tuning, a Gaussian mutation operator with action range varying over time, and diversity based *gbest* updating approach. MO-DE/PSO enhances the exploration ability and the exploitation ability by adopting a PSO with time variant acceleration coefficients to explore the entire search space and utilizing a local version of differential evolution (DE) to exploit the sub-space with sparse solutions. These two MOPSO variants demonstrated that MOPSO can be improved based on the following directions: 1) embedding operators into MOPSO to enhance the ability of global exploration or local exploitation; 2) integrating MOPSO with other MOEAs to make good use of the advantages of MOPSO and other MOEAs.

In terms of the first direction, Cai *et al*. [26] introduced Tent equation based chaotic operator into MOPSO and obtained higher quality EED solutions. The chaotic operator enhances MOPSO local search ability, but increases additional computation consumption. Similarly, Chen and Wang [31] incorporated a thumb rule based mutation operator into MOPSO to solve reserve-constrained multiarea EED (MAEED) problem. Members in the archive may be preferentially mutated and then replace the poorest particles in the swarm. Unlike chaotic operator for local exploitation, the mutation operator is to enhance global exploration ability and to maintain population diversity. With respect to the second direction, Mori and Okawa [32] proposed hybrid MOPSO for EED by combining PSO with SPEA2 and Zhang *et al*. [33] developed a culture algorithm (CA) based MOPSO, in which CA accelerates evolution speed by acquiring the elite knowledge from the evolving population simulated by PSO, and obtained the optimal generation schedule of multi-objective economic environmental hydrothermal scheduling (MEEHS) problem considering the influence of hydro plants. These successful applications of hybrid MOPSO variants demonstrate that they have more powerful optimization ability and are suitable to solving more complex EED problems.

Fuzzy set theory has been utilized for sizing archive and selecting *gbest* to improve MOPSO performance for EED problem. Fuzzy clustering technique can adjust archive size by using membership function of objective functions, and thus maintain reasonable archive size to decrease unnecessary computation consumption. Agrawal *et al*. [34] and Niknam *et al.* [35] successfully adopted fuzzy clustering technique based sizable archive to improve the effectiveness of MOPSO. In [34], in addition to fuzzy clustering technique, other improvements are also added into the MOPSO algorithms: 1) self-adaptive mutation operator; 2) fitness sharing. Self-adaptive mutation operator is applied to avoid getting stuck in local optima and enhance global exploration capability in search space. Fitness sharing, a niching technique, is employed to avoid the particles drifting towards densely populated regions, guide the particles towards lesser explored regions and thereby obtain a uniformly distributed Pareto front. MOPSO with these three improvements in [34] are tested on the standard IEEE 30 bus system and a uniformly distributed Pareto front of EED problem is generated successfully. It is worthy to mention that phase angle vector θ-PSO proposed by Niknam *et al.* [35] has faster convergence mainly because phase angle mapping makes search space more compact. Wang and Singh [36], [37] developed a fuzzified global guide selection method, in which a fuzzification mechanism together with tournament selection is used for selection of *gbest* within an area rather than a point, and successfully employed it to solve deterministic and stochastic EED problems. Also, they tried enhanced MOPSO [38] and local search based MOPSO [39] to solve MAEED problem and obtained the scheme of optimal power dispatch in multiple areas for MAEED. Wang's design experience demonstrates that MOPSO design is subjective and ultimate standard of evaluating MOPSO design is whether it can solve practical MOP in economic dispatch efficiently.

Victoire and Suganthan [40] proposed a comprehensive learning MOPSO for EED by allowing each particle to learn from the *pbest* of itself or other particle, but they added new user-defined parameters such as learning probability and elitism probability in MOPSO. Man-Im *et al*. [41] proved in IEEE 30-bus test system that MOPSO with non-dominated sorting and crowding distance can provide better Pareto fronts of multiobjective ED considering wind generation uncertainty than NSGA-II. Unfortunately, MOPSO performance verification on larger power system is not given in [41]. Bilil *et al*. [42] solved EED problem with optimizing three competing objectives that represent the fuel cost, the quantity of NOx emissions and the real power losses by accelerated MOPSO, in which matrix computation for improving best positions set instead of an external archive for saving best solutions is introduced. The improved MOPSO speeded up the convergence but may slip into the local near-optimal solutions more easily. Based on the above analysis, MOPSO for solving EED problem is different from each other but it has to comply with the general procedure of MOPSO. Because MAEED and MEEHS are more difficult to be solved than EED, hybrid MOPSO integrated with other MOEAs is suggested to be used.

IV. DESIGN SUGGESTION OF MOPSO

MOPSO design oriented to economic dispatch is a skillful and creative task. For some complex multi-objective ED, e.g. MAEED and MEEHS, hybrid MOPSO with CA, DE, or SPEA2 is preferable because the combination of two algorithms helps to search feasible region more efficiently. Hybrid MOPSO has two distinctive advantages:

- MOPSO advantages including faster convergence and less computation;
- Embedded evolutionary algorithm advantages, e.g., better local exploitation ability of DE.

Certainly, hybrid MOPSO requires additional computation consumption for embedding evolutionary algorithm into MOPSO. Hence, hybrid MOPSO is generally suitable in the context that computation speed is not required but computation result quality is strongly demanded.

Mutation and turbulence operators added in MOPSO can keep population diversity and avoid premature convergence. Crowding distance and grid-based selection can improve distribution feature of Pareto optimal solutions. These techniques, which improve the quality of solutions despite of adding extra computation consumption, are very useful for multiobjective ED where diverse and well-distributed Pareto optimal solutions are required preferentially.

V. CONCLUSIONS

This paper presents a comprehensive survey of MOPSO applications in power system economic dispatch. Because these MOP are generally with high-dimension state variables, nonlinear or non-differentiable optimization objectives, continuous or discrete decision variables, and numerous constraints, MOPSO has its superiority over other optimization algorithms in power system economic dispatch.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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