Applications of Multi-objective Particle Swarm Optimization Algorithms in Smart Grid: a Comprehensive Survey

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Abstract

Multi-objective optimization problems (MOP) emerging in smart grid, such as optimal operation of distributed generation (DG) and microgrid, are very complex because of conflicting objectives, high dimension variables, and numerous operational or security constraints, and difficult to be solved. Multi-objective particle swarm optimization (MOPSO) has powerful potential for obtaining Pareto optimal solutions of these MOPs in a run because it has advantages of parallel computation, faster convergence, and easier implementation. This paper summarizes general procedure of MOPSO at first and then well categorizes MOPSO improvements according to parameter adjusting method, archive update scheme, flying guidance selection, diversity preservation approach, and hybridization with other algorithms. Moreover, it also provides a comprehensive survey on MOPSO applications in smart grid, and gives valuable MOPSO design suggestions to solve MOP in smart grid. This paper can serve a very useful purpose by providing a good reference source of MOPSO design to those interested in Multi-objective optimization issues in smart grid.

Keywords: Multi-objective optimization, particle swarm optimization, smart grid, distributed generation

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1. Introduction

Smart grid is a new development trend for electricity industry. It will greatly influence the way of generation, transmission, distribution, and delivery in power systems, and make electricity consumption more efficiently, reliably, and securely. Unlike contemporary power systems, which only deliver electricity in a one-way flow from generators to electricity consumers, the smart grid permits the two-way flow of both electricity and information between generation and consumption sides. Therefore, the smart grid, also called "electricity with a brain," can make power system become smarter. From a technology perspective, in order to implement the smart grid, some new but more complex Multi-objective optimization problems (MOP) in electric power systems, such as optimal operation of renewable energy generators, distributed generation (DG), and microgrid, need to be studied. These problems generally include high-dimension state variables, a large number of operational or security constraint conditions, and multiple conflict objectives to be optimized simultaneously, which determine the great difficulty of solving them by traditional optimization methods such as linear programming [1] and dynamic programming [2] based on gradient-based mechanism. Fortunately, multiobjective particle swarm optimization (MOPSO), which overcomes disadvantages of traditional optimization methods, is very suit to solve MOP emerging in smart grid and obtain their solutions which are also called Pareto optimal solutions. In this paper, a review of MOPSO and its various applications in smart grid are given, and then MOPSO application benchmark in this area is provided.

The original contributions of this paper are below:
1) References only deal with a review of particle swarm optimization (PSO) in power systems. They can only provide direct guidance for designing PSO to solve single objective optimization problems (SOP) in power systems and can not guide MOPSO design to solve...
MOP in power systems. This paper, as a further development of [3-5], is a good and useful reference for those interested in learning about the development of MOPSO and its applications in smart grid.

2) This paper not only well summarizes general procedure of MOPSO, but also well categorizes MOPSO variants into the following types: parameter adjustable MOPSO, guide selection of MOPSO, operator embedded MOPSO, and archive adjustable MOPSO. These general procedure and variants of MOPSO is a good reference for the design of MOPSO oriented to MOP emerging in smart grid.

3) This paper deals with applications of MOPSO in smart grid in detail, including Multi-objective optimal operation problems of DG and microgrid, and gives suggestive comments on MOPSO. These applications and comments of MOPSO are very helpful for those who try to solve Multi-objective optimal operation problems in smart grid.

2. Principles of MOPSO

MOPSO is based on particle swarm optimization (PSO) which was invented as a new heuristic optimizer by Eberhart and Kennedy in 1995 [6-7]. PSO has following features including three advantages and one disadvantage:

- It can find global optimum by imitating bird swarm flying behavior under the guidance of personal flying experience (pbest) and population flying experience (gbest).
- It has better convergence performance than other evolutionary algorithms like genetic algorithm.
- It is effective for nonlinear and non-differentiable objective functions which traditional optimization method is very difficult to deal with.
- It can not find Pareto optimal solutions because it shares the same gbest during optimization process.

In order to find Pareto front efficiently, the mechanism of guide selection and diversity preservation needs to be redesigned in MOPSO. In MOPSO, each particle in a population $P_t$ in the $t$th iteration has its own population flying experience $gbest$, and the $gbest$ is chosen according to a certain rule from external archive $A_t$ which stores non-dominated or Pareto optimal solutions. New external archive $A_{t+1}$ needs to be updated at each iteration based on current external archive $A_t$ and current population $P_t$. Though different variants of MOPSO algorithm have been proposed, the general procedure of MOPSO can be briefly summarized below:

Step 1: $t=0$
Step 2: 1) Initialize population $P_t$:
   For $i=1$ to population scale
   \{Initialize the $i$th particle position $x_i^t$ and velocity $v_i^t = 0$ \} End
   2) Initialize external archive $A_0=\{\}$;
Step 3: Evaluate $P_t$ according to Multi-objective function $f(x_i^t)$
Step 4: $A_{t+1} = UpdateArchive(P_t, A_t)$
Step 5: $P_{t+1} = UpdatePopulation(P_t, A_{t+1})$
   1) $pbest_i^t = FindPersonelBest(pbest_i^{t-1}, x_i^t)$
   2) $gbest_i^t = FindGlobalBest(A_{t+1}, x_i^t)$
   3) For $i=1$ to population scale \{\[
   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) \\
   x_i^{t+1} = x_i^t + v_i^{t+1} \} \} End
   4) $P_{t+1} = DiversityPreservation(P_{t+1})$
Step 6: $t=t+1$ and goto step 3 if a termination criterion is not met.

where $\omega$ is inertia weight, $c_1$ and $c_2$ are learning factors, $r_1$ and $r_2$ are random numbers between 0 and 1. The introduction of $A_t$ is the biggest difference between MOPSO and PSO. Compared with traditional optimization methods and other evoloutional computation algorithms, MOPSO has some distinctive advantages such as the following:

- It has only two fundamental updating rules and has fewer parameters to be adjusted.
- It is easy to implement and program with basic mathematical and logic operations.
• It requires less computation time.
• It can conveniently balance the global exploration and local exploitation ability.

3. MOPSO Improvement for Better Performance

In order to solve MOP in real world efficiently, faster convergence, and better diversity and distribution among Pareto optimal solutions are goals that MOPSO tries to obtain, which drives MOPSO improvement. A number of MOPSO variants with different improvements have been proposed [8]. It is known from the above procedure that MOPSO improvement can be made in the following four aspects: parameter adjusting method for velocity update formulation, archive update scheme for $A_t$, flying guidance selection for $gbest$ or $pbest$, and diversity preservation approach for $P_t$. Based on the principle, four types of MOPSO improvement are summarized below.

3.1. Parameter Adjustable MOPSO

It is the simplest MOPSO improvement in which parameters of velocity update formulation, inertia weight and learning factors, are adjustable. Because inertia weight balances abilities of global exploration and local exploitation and learning factors determine the influence of personal flying experience ($pbest$) and population flying experience ($gbest$) on particle flight behavior, appropriately adjusting inertia weight and learning factors can improve MOPSO performance. Linearly decreasing inertia weight is a popular parameter adjusting method, by which MOPSO can explore wider problem space in early iterations and intensively search local area in later iterations. It is noted that this type of MOPSO improvement is also fit for PSO improvement in the context of solving single objective optimization problems.

3.2. Guide Selection of MOPSO

Guide particle selection is the core of MOPSO and thereby forms many MOPSO variants. Eberhart introduced dynamic neighborhood strategy to produce guide particle, where the first objective is used for identifying neighborhood and the second for selecting guide particle [9], but the strategy is only suitable for two-objective optimization problems. Similarly, dominated tree, a new data structure which stores elite particles, is also proposed to generate $gbest$ [10]. Mostaghim and Teich developed a sigma method based MOPSO in which an index to guide particle flight direction, sigma value, is defined and $gbest$ is chosen based on closer sigma value [11]. Sigma method based MOPSO can accelerate convergence since particles can fly in a controllable direction, but it is susceptible to be trapped into local optima due to its faster convergence. In order to obtain better Pareto optimal solutions, some more complex approaches of guide selection have been proposed. Grid-based selection [12-13], in which objective function space is divided into many grids where $gbest$ is chosen, can obtain well-distributed Pareto optimal solutions. By sorting elite particles based on non-dominated rule [14] and $\varepsilon$-dominance concept [15], $gbest$ selection may be more reasonable compared with Pareto-dominance concept. Sub-swarm PSO, in which swarms evolve separately based on $gbest$ produced independently, is very suitable for parallel computation.

3.3. Operator Embedded MOPSO

Turbulence operator and mutation operator embedded in MOPSO can keep population diversity and thus prevent particles from trapping into local optima. It is clear that the implementation way of embedded operator in MOPSO is selectable according to specific requirements of MOP to be solved. For example, in, mutation operators are different but all of MOPSO with these mutation operators have successfully obtained Pareto optimal solutions of MOP.

3.4. Archive Adjustable MOPSO

Crowding distance assignment and clustering techniques are used to improve elite solutions in the archive $A_t$. The former can maintain archive member in an evenly distributed manner when the archive is full, and the latter can adjust archive size within limits but do not destroy the characteristics of archive member.
Comprehensively and selectively utilizing the above improvements can produce better MOPSO which can obtain well-distributed Pareto-optimal solutions with less computation complexity. It is noted that the four improvement types can be adopted simultaneously in the design of MOPSO if necessary.

4. Applications of MOPSO in Smart Grid

Distributed generation (DG) is a small-scale generation unit situated close to energy consumers. Wind turbines, photovoltaic (PV), fuel cells, and batteries belong to DG. Microgrid is an aggregation of DGs and loads along with the storage options operating as a single system providing both power and heat. The proper design of DG and microgrid can improve distribution system performance in terms of voltage support, loss minimization, emission reduction, and reliability. Maciela et al. modeled the location and size design of DG as MOP with two conflicting objectives of minimizing real power loss and short circuit level while satisfying voltage and capacity constraints, and solved it by integrating MOPSO with evolutionary strategies (ES). The improved MOPSO showed fine convergence features to the true Pareto front because ES gives intense exploration of the visited regions of the search space. Also, Phonrattanasak and Jain et al. tried MOPSO to find optimal placement and sizing of DG with the objectives of 1) minimizing economic cost and emission; 2) minimizing DG size, emission, and power loss, and maximizing voltage profile improvement. Jain’s method was successfully applied in Indian distribution system. Cui adopted another MOPSO with mutation operation and crowding distance to design DG capacity comprehensively considering system operating cost and environmental benefit. Molazei and Ahsaee modeled DG placement problem as three objective optimization problem of maximizing loss reduction, reducing capital and operational DG costs, and improving voltage profile. MOPSO with Sigma method in three-dimension space as well as turbulence factor successfully and efficiently obtained the size and number of DGs because the advantage of Sigma method, faster convergence, is fully utilized, while the disadvantage of Sigma method, premature convergence, is overcome by turbulence factor. Similarly, Xu and Singh employed MOPSO with turbulence factor to solve energy storage design problem with two conflicting objectives of distribution system reliability and energy purchasing and storage cost. Mutation operation and turbulence factor enhance the solution diversity. Veeramachaneni et al. utilized non-dominated sorting MOPSO to solve the Multi-objective wind farm design of maximizing the energy output under the consideration of wake effects and minimizing the cost of the turbines and land area used for the wind farm. In terms of PV grid-connected system, Kornelakis adopted MOPSO to obtain the optimal number of system devices and the optimal PV module installation details by maximizing the system’s total net profit in its lifetime period and the pollutant gas emissions avoided due to the use of the system. It is noticed that though standard MOPSO without any improvement is used in, expected design objective still achieves.

Efficient operation of DG and microgrid is a big engineering challenge, which produces another hot field for MOPSO applications. In, Wang and Singh adopted MOPSO with niching and fitness sharing mechanism to analyze the influence of wind power on dispatch scheme with the tradeoff between system risk and operational cost. Niknam et al. employed a fuzzy self-adaptive MOPSO to solve optimal distribution network operation considering fuel cell power plants. The objective functions are to decrease: 1) the total electrical energy losses, the total electrical energy cost, the total pollutant emission; 2) deviation of bus voltages. Niknam’s MOPSO has faster convergence and better searching ability since some improvements including adjustable inertia weight and learning factors, chaotic operator, and fuzzy clustering technique are adopted. Bazmohammadi et al. used differential evolution (DE) based MOPSO to optimize the operation of microgrid with DGs and storage devices, and achieved a market price based schedule to charge and discharge these storage devices. The hybridization of DE into MOPSO enhances local exploitation ability of the algorithm at the cost of additional computation consumption.

Some researchers studied more complex optimization operation problem of hybrid generating system composed of wind turbine, PV, fuel cells, batteries, etc. Due to the unpredictable nature of wind and solar energy sources and the volatile feature of load demand, the design and operation of hybrid system is more complex. Wang and Singh designed a grid-connected hybrid generating system comprising wind turbine generators, photovoltaic panels, and storage batteries in terms of cost and reliability by constrained MOPSO, in which particles
that violate constraints are discarded and do not affect archive updating. The rejecting strategy is simple to implement but may consume longer computation time in population initialization. Baghaee et al. designed a hybrid wind/PV/hydrogen/fuel cell generation system to supply power demand with regard to minimizing annualized cost of the system, expected loss of load, and expected loss of energy by MOPSO. Sharaf and Gammal studied a hybrid wind/diesel/fuel cell generation system with battery backup, and used MOPSO to track the maximum power efficiency and optimal energy capture from the wind, diesel, and the fuel cell. These applications demonstrate that MOPSO has powerful optimization ability for Multi-objective hybrid generating system operation problem.

5. Results and Analysis

In order to obtain well-distributed Pareto optimal solutions with better convergence, MOPSO design oriented to smart grid is a skillful and creative task. For some complex MOP in smart grid where more computation time consumption is allowable, hybrid MOPSO with ES and DE is preferable because the combination of two algorithms helps to search feasible region more efficiently. For two-objective MOP in smart grid, MOPSO with dynamic neighborhood, in which each particle selects best particle from its own neighborhood in objective space as its $g_{best}$, provides an alternative to archive based MOPSO since it has the advantages of faster convergence and simpler design.

Comprehensively utilizing MOPSO improvements simultaneously in MOPSO design depends on specific requirements of MOP in smart grid. When there is no special requirement on the distribution of Pareto optimal solutions, crowding distance assignment and clustering techniques are not adopted so as to decrease unnecessary computation consumption and obtain applicable MOP solutions as soon as possible. Similarly, when the diversity of Pareto optimal solutions is strongly required, mutation operator needs to be adopted so that MOPSO mutation operator has enhanced global exploration capability and can avoid to be trapped into local optima.

6. Conclusions

Based on the above analysis, the following conclusions can be drawn:

1) MOPSO can find Pareto front in a run and it has better computational efficiency such as faster convergence, less memory space, fewer adjustable parameters, and easier implementation. This powerful parallel computation capability determines that MOPSO is very suitable to solve MOP in smart grid. The wide application of MOPSO in this area has strongly verified this.

2) MOPSO improvements are classified according to parameter adjusting method, archive update scheme, flying guidance selection, diversity preservation approach, and hybridization with other algorithms. MOPSO improvement types proposed in this paper is very meaningful since they can provide valuable MOPSO design guidance for those trying to solve MOP emerging in smart grid.

3) In MOPSO design, selecting and utilizing MOPSO improvements is based on requirements of smart grid applications on convergence speed, diversity, and distribution among Pareto optimal solutions.

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