Balanced Global and Local Properties Multi-objective Particle Swarm Optimization (GL-MOPSO): A microgrid scheduling optimization algorithm

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Abstract. Many multi-objective optimization problems exist in electric power systems. Traditional multi-objective particle swarm optimization (MOPSO) adopts the crowding distance method to find the global best position; consequently, the algorithm presents satisfactory local property but poor global property. In this paper, a fuzzy similarity matrix method, which can enhance global search capability, is introduced into MOPSO to replace the crowding distance method. However, this method sacrifices the local property of the algorithm. To harmonize the global and local search capabilities, an improved MOPSO called Balanced Global and Local Properties MOPSO (GL-MOPSO) is proposed in this paper. In each generation of the process, the selection between the crowding distance method and the fuzzy similarity matrix method is guided by monitoring the convergence and diversity of the swarm. Furthermore, the strategy for updating the local best position is improved.

1. Introduction

The promotion of clean energy in recent years has increased the concern on the development of microgrids [1]. Microgrids can allow for the incorporation of new energy into the grid. Owing to their merits of improving the economy and the reliability of power systems and protecting the environment, microgrids have become a cutting-edge research topic in electrical engineering [2, 3]. Therefore, adopting proper methods is important and necessary for managing energy dispatch optimally [4].

Microgrid optimal scheduling is a multi-objective optimization process. Similar to most engineering problems, the process contains an internal problem, that is, the objectives of microgrids (e.g., economic benefit and environmental protection) are generally conflicting with each other. The method for obtaining the Pareto-optimal solution set for multi-objective optimization problems has always been the focus of discussion in academic research and engineering [5, 6].

Correctly constructing non-dominated solutions is crucial for deriving the Pareto-optimal solution set; these solutions must exhibit good diversity and distribution and must be as close as possible to the true Pareto-optimal fronts [7, 8]. Thus, satisfactory local and global properties are required for an intelligent optimization algorithm [9].

Among intelligent optimization algorithms, particle swarm optimization (PSO) [10] has been widely used because of its simple operation flow and rapid convergence rate [11]. Although PSO has...
matured in its application to single objective optimization, balancing the local and global properties of the algorithm in multi-objective optimization situations remains a serious challenge among researchers [12].

The first multi-objective PSO (MOPSO) algorithm, which extends PSO to handle multi-objective problems using a non-dominated and hypercube arching technique, was proposed by Coello et al [13]. Thereafter, many other MOPSO approaches have been proposed. Raquel [14] introduced the crowding distance method of NSGA-II [15] into MOPSO to improve the distribution of optimization results. After that, various improved MOPSO methods based on the crowding distance method have been proposed. Ching-Shih Tsou [16] incorporated a local search procedure and a flight mechanism, both based on crowding distance, into MOPSO; the author thus proposed MOPSO-CDLS, which can generate a well-distributed and non-dominated set. Santana [17] proposed an improved MOPSO, which incorporates the crowding distance mechanism and roulette wheel to select the social leader and delete the solutions of the external archive; this algorithm can derive better Pareto-optimal solution sets. Wei-xing Li [18] proposed an improved strategy for external archive maintenance by using the crowding distance method; this strategy requires low particle number and small archive size, thereby decreasing the computational cost. Jing Zhang [19] proposed an MOPSO algorithm based on global crowding distance to provide every non-dominated solution in the archive with a high probability to be selected as the global best position and improve the global search capability of the algorithm.

Although the crowding degree between particles can be reflected satisfactorily with the use of the crowding distance method, the diversity of its corresponding optimization results is insufficient because of the drawback of this method [20,21]. Thus, MOPSO based on the crowding distance method results in poor global search capability.

When the local search capability of the algorithm is strong, the optimization results are close to the true Pareto-optimal fronts; by contrast, when the global search capability is strong, the diversity of the optimization results is better [22]. Recent studies have shown that, when the amount of information exchanges between particles is high, the global search capability is strong but the local property of the algorithm is weak; on the contrary, when the amount of information exchanges between particles is less, the local search capability is strong but the global property of the algorithm is weak [23-25]. The amount of information exchanges between particles is mainly dependent on the strategy for updating the global best position and the method for maintaining the external file [26].

Traditional MOPSO uses the crowding distance method to update the global best position of each generation [27]. During this process, particles communicate only with their adjacent particles. Accordingly, the algorithm presents good local search capability but poor global search capability.

On the basis of the given analysis, an improved algorithm called Balanced Global and Local Properties (GL-MOPSO) is proposed in this paper. It can balance local and global properties to derive a desirable Pareto-optimal solution set.

2. GL-MOPSO

2.1. Traditional MOPSO and Its Characteristics

PSO is a swarm intelligence technique inspired by bird flocks. In this algorithm, each particle has a position defined as \( \mathbf{x} = [x_1, x_2, \ldots, x_D] \) and a velocity defined as \( \mathbf{v} = [v_1, v_2, \ldots, v_D] \) in the variable space. In generating \( t + 1 \), the velocity and position of each particle are updated as follows:

\[
\begin{align*}
  v_{i,t+1} &= w \cdot v_{i,t} + c_1 \cdot r_1 \cdot (x_{\text{gbest}} - x_{i,t}) + c_2 \cdot r_2 \cdot (x_{\text{gbest}} - x_{i,t}) \\
  x_{i,t+1} &= x_{i,t} + v_{i,t+1}
\end{align*}
\]

where \( i = 1, 2, \ldots, D \) is the dimension of the particle; \( w \) is the inertia weight; \( c_1 \) is the “self-learning” factor representing the attraction that a particle has toward its own success; \( c_2 \) is the “social learning” factor representing the attraction that a particle has toward the success of others; \( r_1 \) and \( r_2 \) are random numbers between 0 and 1.
are the random values in the range \([0,1]\); \(x_{pbest}\) and \(x_{gbest}\) are the local and global best positions in generation \(t\), respectively.

In the traditional MOPSO, the crowding distance method is used to measure the population density. The most sparse location in each generation will be selected as the global best position, whereas the most dense position in the external file will be deleted when the external file is full. In this process, the crowding degree of each particle is obtained by comparing its distance with its adjacent particles; thus, the amount of information exchanges between particles is less. Therefore, the optimization results for the traditional MOPSO are approximate to the true Pareto-optimal fronts but with poor diversity. A flowchart of the traditional MOPSO is presented in Figure 1.

![Flowchart of the traditional MOPSO](image)

**Figure 1: Flowchart of the traditional MOPSO**

2.2. Improvements on the Global Property of the Traditional MOPSO

In this study, the diversity of the initial population is increased to enhance the search capability in the early iteration by improving the strategy for the population initialization. The fuzzy nearness degree is adopted to measure the similarity degree among initial particles. In the traditional strategy for population initialization, the particles are produced randomly and are thus similar with one another. This process is unfavorable for the extensive search of the algorithm in the early iteration. The maximum limit for the fuzzy nearness degree of the initial particles is restricted to improve the diversity of initial population. The process of the improved strategy is as follows.
First, a particle satisfying the constraints is produced randomly and stored in the file of the initial particle swarm (IPS-file). Subsequently, the rest of the particles are produced randomly.

Each generated particle must be compared immediately with the particles in the IPS-file. If the fuzzy nearness degrees between a particle and all the other particles in the IPS-file are lower than the predetermined limit, $\lambda$, then this particle can be stored in the IPS-file; otherwise, it will be re-initialized.

Before determining the fuzzy nearness degree, the membership degree of each objective value of each particle must be calculated. The membership degree is expressed as follows:

$$f_{i,k} = \frac{y_{i,k} - y_{i,k}}{y_{i,k} - y_{i,k}}$$

where $f_{i,k} \in (0,1)$ is the membership degree of objective $k$ in particle $i$. When $f_{i,k}$ is high, the calculated value of objective $k$ is close to its actual optimal value. Furthermore, $y_{i,k}$ is the calculated value of objective $k$ in particle $i$; $y_{i,k,min}$ and $y_{i,k,max}$ are the possible maximum and minimum values of objective $k$, respectively.

The fuzzy nearness degree between particle A and B can be calculated as follows:

$$\sigma(A, B) = \frac{2(A, B)}{(A, A) + (B, B)},$$

where

$$(A, B) = \sum_{i=1}^{m} f_{i,k}f_{B,i},$$

where $m$ is the number of objectives, and $\sigma(A, B)$ is the fuzzy nearness degree between particles A and B. High $\sigma(A, B)$ means the two particles are similar.

The improved population initialization strategy enhances the diversity of the initial population; consequently, the search scope of the algorithm at the initial stage is expanded. The flowchart of the improved strategy is shown in Figure 2.

![Flowchart of the improved population initialization strategy](image-url)
To improve global search capability further, the fuzzy similarity matrix method is introduced into the algorithm for assisting in updating $x_{gbest}$ in each generation. Therefore, an improved MOPSO based on fuzzy similarity matrix (FMOPSO) is proposed in this paper. The fuzzy similarity matrix method can calculate the similarity degree between each particle and all the other particles. Therefore, the amount of information exchanges between the particles is increased, and the global property of the algorithm is enhanced.

On basis of the membership degree defined by (14), the fuzzy similarity matrix can be calculated by the absolute value inverse method as follows:

$$r_{ij} = \left\{ \begin{array}{ll}
1 & i = j \\
c & i \neq j \\
\sum_{k=1}^{N} |f_{i,k} - f_{j,k}| & 
\end{array} \right.$$  \hspace{1cm} (5)

where $r_{ij}$ is the fuzzy similarity matrix element that represents the similarity degree between particle $i$ and particle $j$; $c$ is an appropriate parameter to ensure that $r_{ij}$ can satisfy $0 \leq r_{ij} \leq 1$.

The fuzzy similarity vector can be constructed by calculating the average value of all the elements in each row of the fuzzy similarity matrix as follows:

$$R_i = \frac{1}{N} \sum_{j=1}^{N} r_{ij},$$  \hspace{1cm} (6)

where $N$ is the total number of particles, and $R_i$ is the fuzzy similarity vector element that represents the average similarity degree between particle $i$ and all the other particles. Small $R_i$ means the difference between particle $i$ and the other particles is significant.

In the iterative process, the particle with the smallest $R_i$ can be selected as the global best particle in the current generation to ensure the good diversity of optimization solutions. If the external file has no remaining capacity, then the particle with the largest $R_i$ must be deleted.

Both algorithms present their own advantages and disadvantages. In MOPSO, the amount of information exchanges between particles is less; thus, MOPSO exhibits good local search capability but poor global property. Consequently, the optimization results are close to the true Pareto-optimal fronts, but the diversity of these results is unsatisfactory. In FMOPSO, the particles exchange high amount of information. Thus, FMOPSO presents good global property but poor local property. In other words, the optimization solutions can maintain good diversity, but they are far from the true Pareto-optimal fronts.

3. Conclusions

This study investigates multi-objective scheduling optimization methods for microgrids and provides the following contributions:

(1) The traditional MOPSO has been extended by improving the population initialization strategy, which enhances the search capability in the early generation. The amount of information exchanges between particles is used as basis to study the global and local properties of the algorithm. FMOPSO is proposed for improved global search capability. In this strategy, the fuzzy similarity matrix method is introduced into the traditional MOPSO.

(2) The membership degrees of the global and local properties of the swarm are introduced to measure the features of certain populations in the operation process.

(3) Given that MOPSO presents good local search capability but poor global property and FMOPSO exhibits good global search capability but poor local property, the advantages of both algorithms are combined to establish an improved algorithm called GL-MOPSO to balance global and local properties.

(4) GL-MOPSO can be used to solve not only multi-objective optimization problems related to microgrids but also other multi-objective engineering problems.
However, the capability of GL-MOPSO to solve multi-modal problems must be improved in future studies.

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