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Improved multi-objective particle swarm optimization with preference strategy for optimal DG integration into the distribution system

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ABSTRACT

Considering the different requirements for decision and state variables in engineering optimizations, an improved multi-objective particle swarm optimization with preference strategy (IMPSO-PS) is presented and applied to the optimal integration of distributed generation (DG) into the distribution system. Preference factors are introduced to quantify the degree of preference for certain attributes in the constraint-space. In addition to the application of a popular non-dominated sorting technique for identifying Pareto solutions, the performance of IMPSO-PS is strengthened via the inclusion of a dynamic selection of the global bests, a novel circular non-dominated selection of particles from one iteration to the next and a special mutation operation. The proposed algorithm has been successfully applied to benchmark functions and to the multi-objective optimal integration of DG into an IEEE 33-bus system. This real-world application aims to satisfy some special preferences and determine the optimal locations and capacities of DG units to minimize the total active power loss of the system and decrease cost caused by power generation and pollutant emissions. The results show that the proposed approach can provide a wider range of Pareto solutions of high quality, while satisfying special preference demands.

1. Introduction

Multi-objective optimization problems (MOPs) arise often and the involved objectives are normally non-commensurable and often in conflict with each other. As a fast-growing field of research and application, multi-objective optimization (MOO) has been extensively studied and widely applied to MOPs to find a set of well-distributed Pareto solutions. In modern society, the diversification and flexibility of choices can bring about convenience and satisfy the requirements for special situations. Incorporating preference information into either the MOOs for generating a set of preferred solutions or final decision making with a set of diverse solutions has important benefits, such as easing computational effort and providing meaningful solutions in the desired regions of interest. Previous preference-based MOOs [1–4] consider preferences from the point of view of objectives. However, preferences on decision and state variables cannot be replicated by objective-functions.

In current energy planning, in particular, the optimal integration of distributed generation (DG) into the distribution systems represents a challenging MOP. Some effective MOO solver techniques can be employed to deal with this non-linear MOP which contains both continuous and discrete variables. In addition, however, consumers in a distribution system have differing requirements. Different properties of loads determine the difference in power demands. For example, consumers with electrical equipments that are sensitive to power quality have voltage preferences while some consumers, such as hospitals and communications providers, require the power supply to be reliable. The capability to incorporate such preferences for state and decision variables in special situations often encounters practical problems.

Based on a consideration of different requirements for decision and state variables, this study proposes an improved multi-objective particle swarm optimization (MPSO) scheme which includes a preference strategy (IMPSO-PS). The preference strategy is used to express the users' preferences and a preference factor is introduced to quantify the degree of preference for certain attributes in the constraints. How to maintain diversity in the swarm in order to avoid premature convergence to a single solution is one of the main issues to be addressed when designing a MPSO algorithm. Within IMPSO-PS, the popular non-dominated sorting technique used in NSGA-II [5] has been incorporated in order to indentify the Pareto optimal set. The diversity of the swarm is maintained via the introduction of the dynamic selection of the global bests and a special mutation operation in the case of premature convergence, resulting from the loss of diversity in the swarm. The diversity of the Pareto solutions is enhanced by a novel circular non-dominated selection of particles

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from one iteration to the next. The effectiveness and feasibility of IMPSO-PS algorithm has been successfully tested on a set of benchmark functions and subsequently applied to the multi-objective optimal integration of DG into a distribution system IEEE 33-bus system.

2. IMPSO-PS algorithm

PSO is an evolutionary computation technique. In the real number space, each potential solution can be represented as a particle that moves in the problem hyperspace, and each particle i is associated with its velocity $v_i=[v_{i1},v_{i2},\ldots,v_{iD}]^T$ and position $x_i=[x_{i1},x_{i2},\ldots,x_{iD}]^T$, where D stands for the dimension of the solution space. The best position ever found so far by particle i is recorded as $p_i=[p_{i1},p_{i2},\ldots,p_{iD}]^T$ and the best position found by any particle is recorded as $p_g=[p_{g1},p_{g2},\ldots,p_{gD}]^T$. During the evolutionary process, the velocity and position update formulae of particle i on the dimension $d_{|d=1,2,\ldots,D}$ are updated according to (Eqs. (1) and 2), respectively:

$$v_{id}(t+1)=wv_{id}(t)+c_1r_1[p_{id}-x_{id}(t)]+c_2r_2[p_{gd}-x_{id}(t)] \tag{1}$$

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \tag{2}$$

where t is the current iteration, w is the inertia weight, and c_1 and c_2 are acceleration coefficients, and r_1 and r_2 are random numbers with uniform distribution between 0 and 1.

2.1. Techniques for diversity

MPSO is the process of finding well-spread solutions of the Pareto front as diverse as possible and as close to the real Pareto front as possible. First of all, techniques must be used to strengthen the convergence property, enhance the global search ability and prevent the premature convergence of the PSO. Next, the suitable generation of diverse solutions must be managed. The inertia weight w controls the convergence behavior of the PSO algorithm and provides a balance between global and local exploration. Instead of using a linearly decreasing inertia weight, an adaptive one, which was proved to improve the performance of the PSO in some benchmark functions [6], is used in this study:

$$w(t)=w_0+r_3(1-w_0) \tag{3}$$

where r_3 is a random number uniformly distributed in [0,1]. Eq. (3) ensures that w changes dynamically between w_0 and 1.

As shown in (Eqs. (1) and 2), when solving a single-objective optimization problem, the leader, p_g, that each particle uses to update its position, is easily identified because each particle has only one fitness value. However, in MOPs there is, in general, no unique solution; rather there are a family of solutions. Under these circumstances, the choice of the leader is a key point and a quality measure is very important [7] in order to indicate how good a leader is. In previous studies [8,9], a dynamic aggregation method was used to guide the flight of particles. Here, with consideration of diversity, we select a different leader for each particle and the quality measure uses the dynamic weighted aggregating function expressed as

$$fitness=1\Big/\sum_{i=1}^{M}w_if_i,\quad w_i=\lambda_i\Big/\sum_{i=1}^{M}\lambda_i,\quad \lambda_i=U(0,1) \tag{4}$$

where M is the number of objectives, and f_i is the ith objective-function. The function $U(0,1)$ generates a uniformly distributed random number within the interval [0,1]. (Note that while minimization problems are assumed, maximization problems are easily converted to this form.).

In this way, at each iteration and for each particle in the swarm, the fitness of each individual in the current Pareto solution set is dynamically computed and the individual with the largest fitness value is selected as the particle's leader. The technique of dynamic selection of leaders means that all Pareto solutions have the same probability of being selected as leaders; this avoids the drawback of diversity loss.

In this study, the particles for the next iteration are selected from the current non-dominated solutions *NDlist*, when the length of *NDlist* is larger than the population size N. In the previous work [8,9], those particles were chosen randomly and chosen sequentially according to crowding distances. According to the NSGA-II sorting technique, the individual with the larger crowding distance will have the greater probability of being chosen. This is not good for diversity because, after eliminating the individual with the smaller crowding distance, the adjacent individuals may become too sparse. Thus, for diversity enhancement, we propose the circular non-dominated selection (CNS) of particles for the next iteration, in the case of $N_{NDlist}>N$, N_{NDlist} is the total number of solutions in *NDlist*. Firstly, compute the crowding distance of each non-dominated solution in *NDlist* and eliminate the solution with the least crowding distance. Then, recompute the crowding distances of the remaining solutions and eliminate the solution with the least crowding distance. This operation is cycled until N non-dominated solutions remain. The current non-dominated solutions are identified from a newly generated swarm, R (see subsection of IMPSO-PS algorithm procedure). Suppose all the particles in R to be non-dominated. With regard to random and sequential methods, after calculating the crowding distance of each particle, the only operations are to select N individuals randomly and sequentially, respectively. While for the proposed method, the computational complexity of the first elimination is $\boldsymbol{O}(M(2N)\log(2N))$, the second is $\boldsymbol{O}(M(2N-1)\log(2N-1)),\ldots$, the Nth, namely the last step, is $\boldsymbol{O}(M(N)\log(N))$. The computational complexity of the proposed method is $\boldsymbol{O}(\sum_{i=N}^{2N}Mi\log(i))$. Therefore, diversity improvement leads to increased computational complexity.

Despite the techniques mentioned above, premature convergence may still occur due to diversity loss of the swarm. When each particle's velocity is rather small (less than a threshold value V_{limit}), we randomly select some particles according to some predefined mutation rate and then perform mutation on the selected particles according to Eq. (5). This special mutation operator can make the particles jump out the local optimum and thus maintain the diversity of the population:

$$x_{id}=x_{id}+\mathrm{sign}[2(r_4-0.5))]\beta Vmax_d \tag{5}$$

where sign is the sign function, r_4 is a random number uniformly distributed in $[0,1]$, $\beta\in[0,1]$, is mutation degree, and $Vmax_d$ is the maximum velocity of the dth dimension.

2.2. Preference strategy

As stated above, even though the diversification of demands has been reflected via the multi-objective formulation, a user's preference cannot be represented by objectives but can be fully represented via constraints. With consideration of the special requirements for decision and/or state variables, this study proposes a preference strategy and introduces a preference factor to quantify the preference for a particular attribute. The strategy can be mathematically expressed as follows:

$$\begin{cases} X_{UP}=X_U-N_P(n_a)K(n_a)M_P(n_a) \\ X_{LP}=X_L+N_P(n_a)K(n_a)M_P(n_a) \end{cases} \tag{6}$$