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Solving non-convex economic dispatch problem with valve point effects using modified group search optimizer method

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ABSTRACT

This paper presents a novel solution based on the group search optimizer (GSO) methodology in order to determine the feasible optimal solution of the economic dispatch (ED) problem considering valve loading effects. The basic disadvantage of the original GSO algorithm is the fact that it gives a near-optimal solution rather than an optimal one in a limited runtime period. In this paper, a new modified group search optimizer (MGSO) is presented for improving the scrounger and ranger operators of GSO. The proposed MGSO is applied on different test systems and compared with most of the recent methodologies. The results show the effectiveness of the proposed method and prove that MGSO can be applicable for solving the power system economic load dispatch problem, especially in large scale power systems.

1. Introduction

The economic dispatch optimization problem is one of the fundamental issues in power systems in order to obtain stable, reliable and secure benefits. The objective is to dispatch the power demand among the committed generators in the most economical manner while all physical and operational constraints are satisfied. The cost of power generation, particularly in fossil fuel plants, is high and economic dispatch helps in saving a significant amount of revenue [1]. Generally, there are two types of ED problem, i.e. static and dynamic. Solving the static ED problem is subject to the power balance constraints and generator operating limits. The dynamic ED problem is an extension of the static ED problem which takes the ramp rate limits and prohibited operating zone of the generating units into consideration [2].

To solve the static ED problem, a wide variety of optimization techniques have been applied. Over the past years, a number of approaches have been developed for solving this problem using mathematical programming, i.e. lambda iteration method [3], gradient method [4], linear programming [5], Lagrangian relaxation algorithm [6], quadratic programming [7] and dynamic programming [2]. However, these methods may not be able to provide an optimal solution in large power systems because they usually get stuck at a local optimum. In these classical methods, the cost function of each generator is approximately represented by a simple quadratic function and the effects of valve-points are ignored. Linear programming methods are fast and reliable; however, they have the disadvantage of being associated with the piecewise linear cost approximation. Non-linear programming methods have the known problems of convergence and algorithmic complexity. Newton-based algorithms have difficulty in handling a large number of inequality constraints [8].

Many modern heuristics stochastic search algorithms such as genetic algorithms (GA) [9–11,30], Tabu Search (TS) [12], evolutionary programming (EP) [13–15], simulated annealing (SA) [16], particle swam optimization (PSO) [17,18], differential evolution algorithm (DE) [19–22], harmony search [23] and Bacterial Foraging (BF) [24] have been implemented preciously for solving the ED problem with no restriction on its non-smooth and non-convex characteristics. However, none of the mentioned methods have guaranteed obtaining a global optimal solution in finite computational time which could be attributed to their drawbacks. SA algorithm has difficulty in tuning the related control parameters of the annealing schedule and may be too slow when applied for solving the ED problem. GA suffers from the premature convergence and, at the same time, the encoding and decoding schemes essential in the GA approach take longer time for convergence. In PSO and DE, the premature convergence may trap the algorithm into a local optimum, which may reduce their optimization ability when applied for solving the ED problem.

Recently, a new, easy-to-implement, reasonably fast and robust evolutionary algorithm has been introduced known as group search optimizer (GSO) which is inspired by group-living, a phenomenon typical of the animal kingdom [25]. Original GSO often converges

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to local optima and also its convergence speed is almost low. In order to avoid this deficiency, in this paper, a modified GSO algorithm is proposed for solving the ED problem. Here, the modified group search optimizer algorithm (MGSO) is proposed for solving the non-convex economic dispatch problem. The structure of this algorithm is based on GSO but it has new scrounger and ranger operators. The proposed MGSO methodology is tested by four test systems with non-convex solution spaces. The comparison shows the effectiveness of the proposed MGSO method in terms of solution quality and consistency. In most test systems, MGSO achieves better results compared with the existing results.

The remainder of the paper is organized as follows: Section 2 provides a brief overview of the basics of GSO; Section 3 explains the proposed MGSO algorithm and compares it with the base GSO. Section 4 presents the ED problem formulation and application of MGSO in order to solve the considered problem; Section 5 shows the case studies using the proposed method in order to solve the non-convex ED problem and gives the corresponding comparison with other methods and Section 6 gives the conclusions.

2. Basics of group search optimizer algorithm

This section presents a brief overview of GSO. Then, the modification procedure of the proposed MGSO algorithm will be presented in the following section.

GSO is a novel optimization algorithm which is based on animal searching behavior and group-living theory inspired by animals. The framework is mainly based on the producer–scrounger (PS) model, which assumes that the group members search for either “finding” (producer) or for “joining” (scrounger) opportunities. In other words, the animal scanning mechanisms are employed metaphorically for designing an optimum searching strategies in order to solve continuous optimization problems [25].

The population of this algorithm is called a group and each individual in the population is called a member. In an n dimensional search space, the ith member at the kth iteration has a current position, $X_i^k \in R^n$, and a head angle, $\varphi_i^k = (\varphi_{i1}^k, \ldots, \varphi_{i(n-1)}^k) \in R^{n-1}$. The search direction of the ith member, which is a unit vector, $D_i^k = (d_{i1}^k, \ldots, d_{in}^k) \in R^n$, can be calculated from φ_i^k via a polar to Cartesian coordinate transformation [25] as follows:

$$d_{i1}^k = \prod_{q=1}^{n-1} \cos(\varphi_{iq}^k)$$
$$d_{ij}^k = \sin(\varphi_{i(j-1)}^k) \cdot \prod_{q=j}^{n-1} \cos(\varphi_{iq}^k) \quad (j = 2, \ldots, n-1) \tag{1}$$
$$d_{in}^k = \sin(\varphi_{i(n-1)}^k)$$

In GSO, a group consists of three types of members: producers, scroungers and dispersed members named as rangers. The behavior of producers and scroungers are based on the PS model [26] and rangers perform random walk motions. The algorithm of GSO contains a simple cycle of stages, which is presented in Fig. 1.

In each iteration, a group member, which is located in the most promising area and confers the best fitness value, is chosen as the producer. Then it stops and scans the environment in order to seek the optima. Scanning is an important component of search orientation [27].

During each searching bout, a number of group members (80% of members) are selected randomly as scroungers. The scroungers keep on searching for opportunities in order to join the resources found by the producer [25].

The rest of the group members are dispersed from their current positions. In the GSO algorithm, if the ith group member is dispersed, it performs ranging. These members are called rangers. In nature, ranging animals perform searching strategies, which include random walks and systematic search strategies for locating resources efficiently. Random walks, which are thought to be the most efficient searching method for randomly distributed resources, are employed by rangers. More details on GSO can be found in [25].

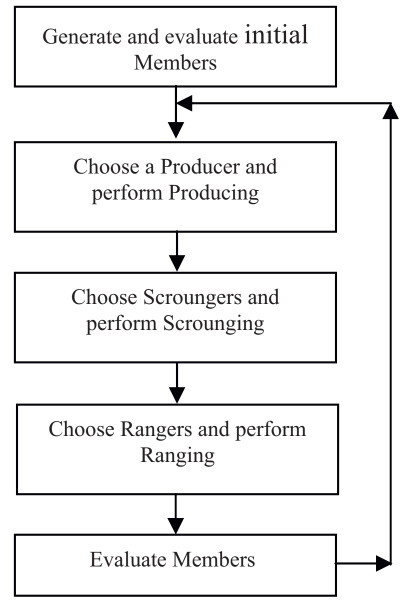

Fig. 1. The GSO cycle of stages.

3. The proposed modified group search optimizer solution

GSO is conceptually simple and easy-to-implement; also, it has competitive performance compared with other evolutionary algorithms in terms of accuracy and insensitivity to the parameters. But, there are two disadvantages: (1) it gives a near-optimal solution rather than an optimal one and (2) its convergence speed is almost low. The objective of the proposed modified GSO methodology is to overcome these two weaknesses during its application to give a solution for the ED problem.

In this section, a modified group search optimizer algorithm (MGSO) with different scroungers and rangers is proposed for solving the ED problem. The main goal of incorporating different scroungers and rangers in this algorithm is to enhance the global search ability of the algorithm and increase the convergence speed. The description of the scrounger and ranger operators is as follows.

3.1. Scrounger operator

The scrounger operation searches for opportunities of joining the resources found by the producer which is usually regarded as the main search operation in the algorithm. The scrounger operator of the proposed GSO is based on the passive congregation [28] inspired by particle swarm optimizer with passive congregation (PSOPC). Passive congregation (PC) is an important biological force preserving group integrity, by which the information can be transferred among the individuals; this helps them to avoid misjudging information and becoming trapped by poor local minima. The position of the ith scrounger at $(k+1)$th iteration is modified by:

$$X_i^{k+1} = X_i^k + \omega_1 r_1 (X_p^k - X_i^k) + \omega_2 r_2 (X_r^k - X_i^k) \tag{2}$$