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Research Article

A Modified Social Spider Optimization for Economic Dispatch with Valve-Point Effects

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Economic dispatch (ED) aims to allocate the generation of units to minimize the total production cost. This dispatch is generally formulated with nonsmooth and nonconvex cost function due to valve-point effects and various constraints, where the conventional methods are inapplicable. An improved social spider optimization algorithm, namely, ISSO, is proposed in this paper to solve the ED problem with valve-point effects. That is, dynamic updating mechanism of the subpopulations, Gaussian mating radius, and multimating strategy are introduced into the ISSO. These mechanisms facilitate a compromise between the global exploration and local exploitation of the search process. Numerical experiments are conducted on benchmark functions and different scale generation units commonly considered in the literature to validate the feasibility of the proposed ISSO. Computational results are analyzed in terms of solution quality by the statistical method, which shows the superiority of the ISSO algorithm in comparison with the state-of-the-art algorithms.

1. Introduction

Economic dispatch (ED) is one of the important issues in the power system. The objective of ED is to save the power generation cost while satisfying all kinds of operational constraints [1–4]. However, ED has nonsmooth, nonlinear, nonconvex, and nondifferentiable characteristics when valve-point effects of generation units are considered. Classical mathematical optimal approaches, such as Lagrangian relaxation [5], linear programming [6], branch and bound [7], and quadratic programming [8], are infeasible in solving ED problems due to the aforementioned characteristics. With the development of intelligent optimization theory and computer technology, metaheuristics based on natural evolution, as a novel simulated evolutionary computation technology, have shown their outstanding performance in solving complex optimization problems due to the absence of special requirements for the objective function. This condition guarantees the search for an effective solution within a time limit by a large probability. In recent decades, metaheuristic algorithms, which have got fast development [9–12], are utilized to solve ED problems with valve-point effects, such as genetic algorithm (GA) [13, 14], particle swarm optimization (PSO) [15–19], grey wolf optimization (GWO) [20], simulated annealing (SA) [21], bat algorithm (BA) [22], biogeography-based optimization (BBO) [23], differential evolution (DE) [24], whale optimization algorithm (WOA) [25], teaching-learning-based optimization (TLBO) [26], and cuckoo search algorithm (CSA) [27, 28].

Although the progress of the above methods has been made for the applicability to ED problems, the complexity of the ED problem reveals the necessity for the development of efficient algorithms to precisely locate the optimal solution. Within this context, the contribution of this paper is to develop a novel method for solving the ED problem, aiming to provide a workable solution for ED problems. Considering the intelligent behavior of a gregarious colony of spiders, a novel metaheuristic optimization approach called social spider optimization (SSO) is proposed by Cuevas et al. [29], which is simple, easy to realize, and adaptable to a wide range of optimization fields [30–33]. However, SSO has the following drawbacks during the evolution process: one is that interactive learning within female subpopulation or male subpopulation makes subpopulation similar; another one is that the fixed mating radius reduces convergence speed; and the last one is that single mating operator decreases the possibility of introducing good genes into offspring. All these drawbacks may lower the diversity of the population and eventually lead to premature convergence. Hence, a variant of SSO, namely, ISSO, including dynamic updating mechanism of the subpopulations, Gaussian mating radius, and multimating strategy, is proposed to solve ED problems with valve-point effects and enhance the performance of the conventional SSO. Furthermore, updating mechanism of the subpopulations and Gaussian mating is different from other references, which is illustrated in detail in Section 4.

The remainder of this paper is organized as follows. Section 2 presents the formulation of the ED problem with valve-point effects. Section 3 describes the conventional SSO, followed by Section 4 where the proposed ISSO for solving the ED problem is proposed in detail. Section 5 evaluates comprehensively the performance of the proposed method on benchmark problems with the comparative study. Finally, the paper ends with conclusions and further research works.

2. Problem Statement

2.1. Objective Function. The ED is a complicated optimal decision problem in power systems that allocates the generation of units to minimize the total fuel cost under a given load demand. Additionally, the ED problem in this work must satisfy operation constraints, which can be generally defined by a polynomial function as follows:

$$\min F = \sum_{i=1}^{n} F_i(P_i), \tag{1}$$

where F, P_i, and n are the total fuel cost for all generation units, the power output of the ith generation unit, and the number of generation units, respectively. $F_i(P_i)$ is the fuel cost of the ith generation unit and usually expressed as a quadratic function:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i. \tag{2}$$

The valve-point effect is a problem that generally cannot be ignored for thermal power generation units. Thus, the ED problem becomes nonsmooth and nonconvex. The valve-point effect, which is generally equivalent to a sinusoidal term, must be involved in modeling the ED problem to solve the practical ED problem accurately. Therefore, the fuel cost function considering the valve-point effects of the generating units is given by

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i \times \sin\left(f_i \times \left(P_i^{\min} - P_i \right) \right) \right|, \tag{3}$$

where a_i, b_i, c_i, e_i, and f_i are the generation cost coefficients of the ith generation unit and $P_i^{\min}$ is the minimum power output.

2.2. Constraints. The main constraints related to the ED problem are as follows:

(i) Power balance constraints

$$\sum_{i=1}^{n} P_i = P_D + P_L, \tag{4}$$

where P_D and P_L are the total power demand and the total transmission loss, respectively. While power network is concentrated, thus P_L is ignored.

(ii) Power output limits

$$P_i^{\min} \le P_i \le P_i^{\max}, \tag{5}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and the maximum power outputs of the ith generation unit, respectively.

3. Conventional SSO

A new swarm intelligence algorithm called SSO was proposed by Cuevas et al. [29] considering the predation behavior of the spiders. Herein, the position of spiders corresponds to the solution of optimization problem. Meanwhile, the spider web, which is associated with the search space of optimization problems, is employed to facilitate interaction among spiders through the vibrations of spiders. Furthermore, the mating behavior of the female and male spiders, which is considered to be coevolution, serves to obtain the optimal or quasioptimal of the objective function. The basic principles of conventional SSO can be summarized as follows.

3.1. Initialization of the Population. The most prominent characteristic that differentiates the spiders from all other species is highly female-biased. The number of females N_f accounts for 65%–90% of the entire population N, which is defined as follows:

$$N_f = \operatorname{floor}\left[(0.9 - \text{rand1} \times 0.25) \times N\right], \tag{6}$$

where rand1 $\in [0, 1]$ is a random number. In the spider population comprising female and male spiders, the number of males N_m can be calculated as follows:

$$N_m = N - N_f. \tag{7}$$

The population of N spiders is randomly initialized, for any spider $i \in \{1, 2, \ldots, N\}$, and its position is presented by a vector as the parameter values to be optimized, which represents one solution of the optimization problem.

Herein, female and male spiders can be initialized according to the following equation:

$$\begin{cases} F_{ij} = p_{j\min} + \text{rand2} \times \left(p_{j\max} - p_{j\min}\right), \\ M_{kj} = p_{j\min} + \text{rand3} \times \left(p_{j\max} - p_{j\min}\right), \end{cases} \tag{8}$$

where rand2 and rand3, which are uniformly distributed between 0 and 1, are random numbers. F_{ij} and M_{kj} are the jth dimension of the position of the ith female spider and the jth dimension of the kth male spider, respectively. $p_{j\min}$ and $p_{j\max}$ correspond to the minimum and maximum values of the jth dimension of the spider.

3.2. Female Cooperative Operator. The positions of female spiders are updated in accordance with the vibration on the communal web generated by the superior spiders. Such vibration denotes an attraction or repulsion over other spiders, which is determined by probability factor PF. That is, for a random number $r_m \in [0, 1]$, if r_m is smaller than PF, then an attraction operation is performed; otherwise, a repulsion operation is executed. Considering the minimization problem in this paper, the mathematical models of such cooperative operator are defined as follows:

$$F_i^{t+1} = \begin{cases} F_i^t + \alpha Vib_{ci}\left(S_c - F_i^t\right) + \beta Vib_{bi}\left(S_b - F_i^t\right) + \delta\left(\text{rand4} - 0.5\right), & r_m \le \text{PF}, \\ F_i^t - \alpha Vib_{ci}\left(S_c - F_i^t\right) - \beta Vib_{bi}\left(S_b - F_i^t\right) + \delta\left(\text{rand5} - 0.5\right), & r_m > \text{PF}, \end{cases} \tag{9}$$

$$Vib_{ij} = w_j * e^{-d_{ij}^2}, \tag{10}$$

$$w_i = \frac{J\left(S_i\right) - \text{worst}_S}{\text{best}_S - \text{worst}_S}, \tag{11}$$

$$\begin{aligned} \text{best}_S &= \min_{k\in\{1,2,\ldots,N\}}\left\{J\left(S_k\right)\right\}, \\ \text{worst}_S &= \max_{k\in\{1,2,\ldots,N\}}\left\{J\left(S_k\right)\right\}, \end{aligned} \tag{12}$$

where F_i^t indicates the position of the ith female spider in tth iteration. α, β, and δ are random numbers between 0 and 1. The weight w_i represents the solution quality of the ith spider. d_{ij} is the Euclidian distance between the spiders i and j. S_c and S_b denote the closest members, which have a high weight to the female spider i and the best spider in the population S, respectively. Vib_{ij} is the vibration perceived by the ith spider generated by the jth spider. In the end, $J(S_i)$ is the fitness value of the ith spider position with respect to the objective function.

3.3. Male Cooperative Operator. From a biological viewpoint, male spiders M comprise dominant and nondominant individuals. Herein, dominant individuals are those that have better weight than the median male spider. All the male spiders are sorted in descending order of weights in advance to obtain the median male spider $N_f + m$, and the individual located in the middle is considered the median male member. By contrast, other male spiders are nondominant individuals. The dominant individuals can attract the closest female spider. However, nondominant individuals gather around the median male member. Thus, the position of the male spider i can be updated using the following equation:

$$M_i^{t+1} = \begin{cases} M_i^t + \alpha Vib_{fi}\left(S_f - M_i^t\right) + \delta\left(\text{rand6} - 0.5\right), & \omega_{N_f+i} \ge \omega_{N_f+m}, \\ M_i^t + \alpha\left(\dfrac{\sum_{h=1}^{N_m} M_h^t \omega_{N_f+h}}{\sum_{h=1}^{N_m} \omega_{N_f+h}} - M_i^t\right), & \text{else}, \end{cases} \tag{13}$$

where S_f and $\sum_{h=1}^{N_m} M_h^t \omega_{N_f+h} / \sum_{h=1}^{N_m} \omega_{N_f+h}$ represent the female spider closest to male spider i and the mean weight of all the male spiders, respectively.

3.4. Mating Operator. Any dominant male spider M_G can possibly mate with the female spiders. Under such circumstances, when the female spiders within a mating radius

r, which is calculated by equation (14), form the set of mating members T_G (that is, T_G must not be empty), then the mating operation can be performed between dominant males and T_G. Furthermore, the roulette method is adopted to generate offspring. This method guarantees that the bigger the weight of the spider $i \in T_G$ is, the more chance it will have to reproduce. Therefore, the probability PS_i by which each spider $i \in T_G$ is selected to mate is described by equation (15):

$$r = \sum_{j=1}^{n} \frac{\left(p_{j\max} - p_{j\min}\right)}{2n}, \tag{14}$$

$$PS_i = \frac{\omega_i}{\sum_{k \in T_G \cup M_G} \omega_k}, \quad i \in T_G \cup M_G, \tag{15}$$

where n is the dimension size of the problem. After mating, the acceptance of new spider S_{new} depends on its weight. If the weight ω_{new} of the new spider S_{new} is larger than the weight ω_o of the worst spider S_o of the entire spider population, then the worst spider will be replaced with the new one; otherwise, the new spider S_{new} is discarded. Once the replacement has occurred, the new spider S_{new} will have the same gender as the replaced one to maintain the population. The flowchart of the SSO algorithm is described in Figure 1.

4. Proposed ISSO

4.1. Subpopulation Dynamically Updating Strategy. According to the principle of SSO, cooperative operators, which are all used within the female and male spiders, contribute to learning from each other within subpopulations. Hence, the difference among individuals gradually decreases with evolution. This reduction lowers the convergence rate and even results in prematurely getting stuck in the local optimal. Updating subpopulations is essential to overcome such shortcomings and mitigate their negative influence. Subpopulation strategy, which equates to multipopulation to some extent, has been applied in many swarm intelligence evolutionary algorithms before. However, the updating strategy of subpopulations, which is based on the subpopulation similarity, has been rarely considered during the evolution process in [34–36]. Nevertheless, improved subpopulation diversity for the entire population can guarantee that the search spaces from each subpopulation have relatively small overlaps. Thus, subpopulation separately evolves in each region, which is comparatively independent of the others. As previously mentioned, it can further help SSO to search toward the global optimal solution, and the global searching capability is considerably strengthened. To this end, a subpopulation dynamically updating strategy, which is utilized to improve the optimization capability of the subpopulation, is proposed in this paper. In this strategy, an index ϕ, which can reflect the diversity of the population, is defined as equation (17) and employed to determine how each subpopulation fulfills the update requirement. This index mainly realizes information exchange between subpopulations through an evolution operator called migration operator. Specifically, the migration operator indicates that a better spider from the best subpopulation diversity, which is furthest from the best spider from the worst subpopulation diversity, migrates and replaces the worst spider. Considering the emigrating operation, the subpopulation is where a new spider is randomly generated to maintain the size of the subpopulation constant. For clarity, the subpopulation dynamically updating strategy during the evolution process is illustrated in Figure 2.

Definition 1. Suppose the ith spider S_i is the best solution of the subpopulation thus far. The Euclidian distance d_{ij} between S_i and S_j is adopted and mathematically modeled as shown below to measure the distance from S_i to other spider S_j:

$$d_{ij} = \sqrt{\sum_{k=1}^{n} \left(s_{ik} - s_{jk}\right)^2}, \quad i \in \{1, 2, \ldots, n\} \backslash \{j\}, \tag{16}$$

where s_{ik} and s_{jk} are the kth decision variables in the solutions S_i and S_j, respectively, and n is the number of solution dimensions.

Definition 2. Designing an index of population diversity measuring the quality of the structure of subpopulation is necessary to address the challenging issue of effectively updating the operation of subpopulations. This index φ, which includes total distance D_s and total fitness F_{total}, can be formulated as follows:

$$\varphi = \varepsilon_1 \times D_s + \varepsilon_2 \times F_{\text{total}}, \tag{17}$$

$$D_s = \sum_{i \in \{1,2,\ldots,N_s\} \backslash \{j\}} d_{ij}, \tag{18}$$

$$F_{\text{total}} = \sum_{i=1}^{N_s} J\left(S_i\right), \tag{19}$$

where ε_1 and ε_2 are the weight coefficients of D_s and F_{total}, respectively, which represent the importance of D_s and F_{total} to the population diversity index ϕ. A large D_s indicates a wide solution space. That is, D_s provides a remarkable contribution to the population diversity compared with F_{total}. Based on the above consideration, ε_1 and ε_2 are set to 2 and 1, respectively. Moreover, the detailed description of the subpopulation dynamically updating strategy is presented in Algorithm 1.

4.2. Gaussian Mating Radius. To the best of our knowledge, the spiders get close to one another with evolution generations. However, the evolution process of SSO shows that the mating radius always remains unchanged, leading to more female spiders within the mating radius. Thus, the quantity of the worse female spiders, which are mated with the dominant male spiders, gradually increases. This condition means that the fixed mating radius will result in the poor quality of mating. That is to say, SSO will spend some time searching for the optimal

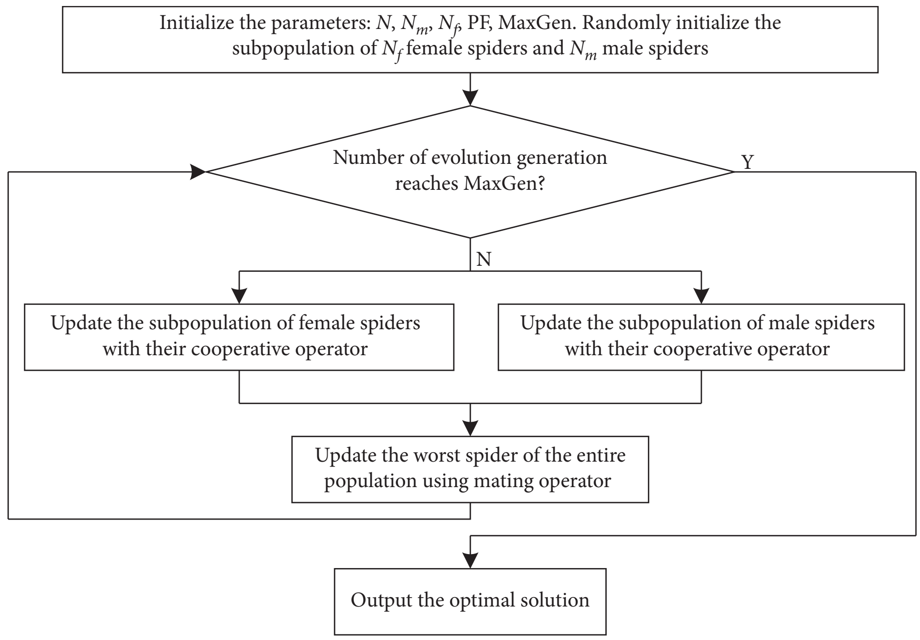

Figure 1: Flowchart of the original SSO algorithm.

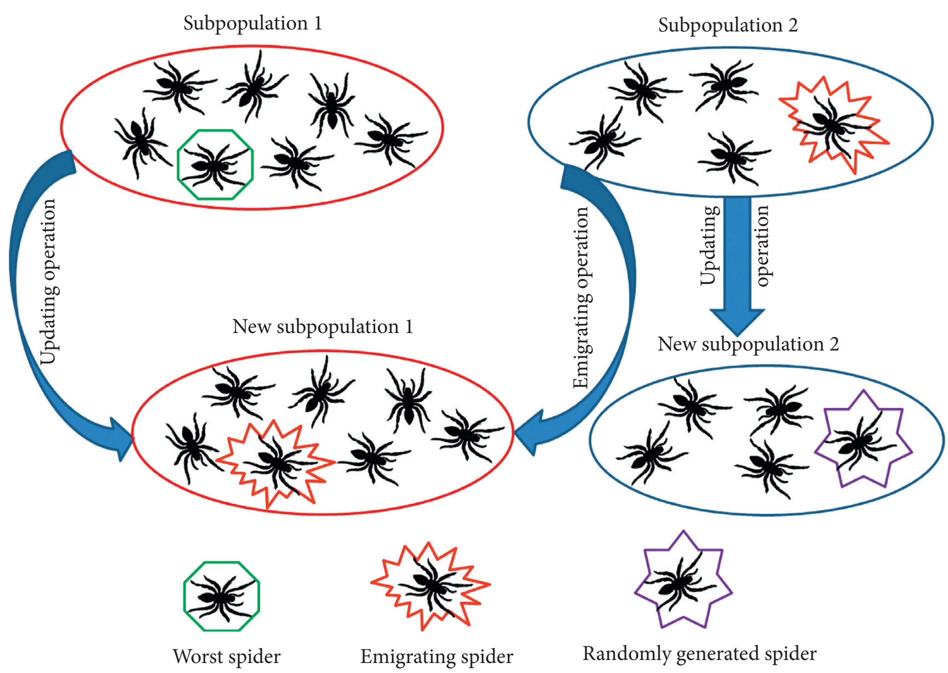

Figure 2: Subpopulation dynamically updating operation.

solution meaninglessly, making SSO less efficient and competitive. Introducing the adaptive mating radius is necessary to overcome such defects; that is, a large mating radius of the previous generation facilitates global optimization, while a small mating radius of the later generation improves the local optimal capability. In view of this, the oscillation decay strategy that combines negative exponential and Gaussian functions is proposed to guide the change in the mating radius. This strategy is comprehensively described as follows. The large mating radius, which corresponds to the large solution space, can rapidly guide the ISSO to approach the optimal or suboptimal solution in the previous period of search. Instead, ISSO will exploit the optimum by mating with high-quality female spiders in the later evolution stage. Furthermore, the overall mating radius decreases despite such oscillation. Owing to such characteristics, ISSO can provide a good balance between the exploration and the exploitation capabilities. Therefore, equation (14) can be modified by the following expression:

(1) **for** each subpopulation SP_i belonging to male subpopulation or female subpopulation
(2) **for** each individual S_i in SP_i
(3) Calculate $J(S_i)$ for each $S_i \in SP_i$ according to the opposite of equation (1).
(4) Calculate d_{ij} for each S_i $(S_i, S_j \in SP_i)$ according to the opposite of equation (1), where S_j is the best individual.
(5) **end for** S_i
(6) Calculate ϕ_i for SP_i according to equation (17).
(7) **end for** SP_i
(8) Determine the updated subpopulation denoted as SP_u based on the small ϕ_i. Another one denoted as SP_d. Then, all the spiders in SP_d in descending order of the fitness and the top 20% of spiders are selected to form a set of candidate migrator Ω.
(9) **for** each individual S_i in Ω
(10) Calculate d_{ij} for each $S_i (S_j \in SP_u)$ according to the opposite of equation (1), where S_j is the best individual.
(11) **end for** S_i
(12) Select the spider $S_i \in \Omega$ with the largest d_{ij}, which is used to replace the spider with the worst fitness in SP_u. Meanwhile, S_i is replaced by new spider randomly generated in SP_d.

Algorithm 1: Pseudocode of the subpopulation dynamically updating strategy.

$$r = \left[\sum_{j=1}^{n} \frac{\left(p_{j\max} - p_{j\min}\right)}{2n}\right] \cdot e^{-(t/\mathrm{MaxGen})} \cdot N(\mu, \sigma), \tag{20}$$

where $N(\mu, \sigma)$ is a random number of Gaussian distribution in [0, 1], and the mean and standard deviation are 0.5 and 0.16, respectively. t is the tth generation of the evolution process, and MaxGen is the maximal number of generations.

4.3. Multimating Operator. The mating operator of SSO is an effective tool for ensuring high-quality offspring. Nevertheless, the genes from the dominant male spiders, which have not been fully inherited by the children, inevitably affect the solution quality of the next generation. Hence, modifications of original mating technology will be necessary to pass good genes from generation to generation. This technology can guide evolution toward promising areas. Based on the aforementioned analysis, the multimating strategy, which takes full advantage of the neighborhoods of parents, is presented to accelerate the solving process. Suppose two spiders $S_m = [s_{1m}, s_{2m}, \ldots, s_{nm}]$ and $S_f = [s_{1f}, s_{2f}, \ldots, s_{nf}]$ are two mating partners in the tth generation. The improved multimating operator described above can be depicted as follows:

(a) Weighted mating operator

$$s_{im}^{\mathrm{new}} = \mathrm{rand7} \cdot s_{im} + [1 - \mathrm{rand7}] \cdot s_{if}. \tag{21}$$

(b) Average mating operator

$$s_{im}^{\mathrm{new}} = \frac{s_{im} + s_{if}}{2}. \tag{22}$$

(c) Extreme mating operator

$$s_{im}^{\mathrm{new}} = \lfloor \mathrm{rand8} \rfloor \cdot s_{im} + (1 - \lfloor \mathrm{rand8} \rfloor) \cdot s_{if}. \tag{23}$$

(d) Bound mating operator

$$s_{im}^{\mathrm{new}} = \lfloor \mathrm{rand9} \rfloor \cdot p_{i\min} + (1 - \lfloor \mathrm{rand9} \rfloor) \cdot p_{i\max}. \tag{24}$$

In equations (21)–(24), rand7, rand8, and rand9 are all random numbers in the range [0, 1]. The symbol $\lfloor \cdot \rfloor$ is an operator through which fractions are rounded down. $p_{i\,\min}$ and $p_{i\,\max}$ are the upper and lower bounds of the ith dimension of the spider, respectively. Notably, the proposed multimating operators provide remarkable efforts to compromise with the local and the global explorations by utilizing the neighborhood of the two mating spiders and the bound of the solution space. Thus, the chance of producing good solutions is significantly increased. The proposed mating approach can help overcome the limitations introduced by the origin mating operator. Considering the efficiency of the ISSO, one of the four proposed mating operators is randomly selected during mating operation. After the new offspring individual is produced, the new child is compared with the worst individual of the entire population. If this offspring is better in terms of fitness, then this offspring will replace the worst individual; otherwise, this offspring is discarded.

The pseudocode is summarized in Algorithm 2 to understand the principle of the proposed ISSO.

5. Simulation Results

In this section, the performance of the ISSO is tested by comparison with other variants of SSO, such as SSO [29], NISSO [37], MSSO [38], and OBSSO [39]. Comparisons with some state-of-the-art algorithms, which are the variants of PSO (CLPSO) [40] and DE (JADE) [41], are also conducted. The above experiments are performed by conducting a set of well-known benchmark functions [42], where functions f_1–f_4 and f_5–f_8 are unimodal and multimodal functions, respectively, as listed in Table 1. The unimodal function is easily solved due to only one optimum. By contrast, the number of local minimum increases with the dimension of problems in multimodal function, thus

Initialize the parameters: N, N_f, N_m, and PF.
Initialize a subpopulation S of N_f female spiders and N_m male spiders with random positions.
Define the maximal number of iterations MaxGen and set $t = 1$.
while ($t < \text{MaxGen}$)
for $i = 1 : N$
Evaluate the weight of each spider in the population S using equation (11).
end for i
Record the best individual.
for $j = 1 : N_f$
Compute Vib_{ci} and Vib_{bi} by equation (10) and generate a random $r_m \in [0, 1]$
if ($r_m \leq \text{PF}$)
$F_j^{t+1} = F_j^t + \alpha Vib_{cj} (S_c - F_j^t) + \beta Vib_{bj} (S_b - F_j^t) + \delta(\text{rand4} - 0.5)$
else
$F_j^{t+1} = F_j^t - \alpha Vib_{cj} (S_c - F_j^t) - \beta Vib_{bj} (S_b - F_j^t) + \delta(\text{rand5} - 0.5)$
end if
end for j
Calculate the weight ω_{N_f+m} of the median male spider from M.
for $k = 1 : N_m$
if ($\omega_{N_f+i} \geq \omega_{N_f+m}$)
Determine the closest female S_{fi} and compute Vib_{fi} by equation (10).
$M_k^{t+1} = M_k^t + \alpha Vib_{fk} (S_f - M_k^t) + \delta(\text{rand6} - 0.5)$
else
$M_k^{t+1} = M_k^t + \alpha((\sum_{h=1}^{N_m} M_h^t \omega_{N_f+h} / \sum_{h=1}^{N_m} \omega_{N_f+h}) - M_k^t)$
end if
end for k
Calculate the weights of the spiders, and the self-adaptive mating radius r by equation (20).
for $l = 1 : N_m$
if (M_l is the dominant male spider)
if (T_G is not empty)
for $m = 1 : n$
Select each dimension s_{mf} of the female spider based on the roulette method.
end for m
All the dimensions selected, such as s_{1f}, s_{2f}, ..., and s_{nf}, form the female spider S_f.
Randomly select one of the multimating operators among weighted, average, extreme, and bound mating operator.
Generate the new spider S_{new} by mating M_l with S_f based on the mating operator selected.
if ($\omega_{\text{new}} > \omega_o$)
$S_o = S_{\text{new}}$
end if
end if
end if
end for l
Perform the subpopulation dynamically update strategy using Algorithm 1.
$t = t + 1$
end while
Output the best solution

Algorithm 2: Pseudocode of the proposed ISSO.

making it difficult to obtain optimal solutions. Therefore, considering the above analysis, the selected benchmark functions can effectively evaluate the performance of the algorithm in terms of escaping from the local optimum and convergence speed. Eventually, the ISSO is applied to the ED problem with valve-point effects.

All experiments in this study are conducted in a PC with Windows 10 system, 3.7 GHz Intel Core, 4 GB RAM, and MATLAB R2014b. For the parameters of each algorithm, the parameter N follows the recommendation in [29] and is set to 50, and the parameters of other algorithms are the same as those of the corresponding references, such as SSO in [29], NISSO in [37], MSSO in [38], OBSSO in [39], CLPSO in [40], and JADE [41]. For fairness, each algorithm, which evaluates the function with D dimension, terminates after reaching the maximum number of function evaluations (MaxFES). Herein, the benchmark functions with 50 dimensions are employed to examine the performance of the algorithms, of which MaxFES are set to 500,000. Simultaneously, each algorithm has 30 independent runs for each trial.

5.1. Sensitivity Analysis of the Probability factor PF. For the proposed ISSO, the female spider decides whether or not to approach the superior spider based on the probability factor PF

Table 1: Details about benchmark functions.

Name	Function	Search range	Min
Sphere	$f_1(x) = \sum_{i=1}^{D} x_i^2$	[−100, 100]	0
SumSquare	$f_2(x) = \sum_{i=1}^{D} ix_i^2$	[−10, 10]	0
Schwefel 2.21	$f_3(x) = \max\{\lvert x_i\rvert, 1 \le x_i \le D\}$	[−100, 100]	0
Schwefel 2.22	$f_4(x) = \sum_{i=1}^{D} \lvert x_i\rvert + \prod_{i=1}^{D} \lvert x_i\rvert$	[−10, 10]	0
Rosenbrock	$f_5(x) = \sum_{i=1}^{D-1}\left\{100\cdot(x_{i+1}-x_i^2)^2 + (1-x_i)^2\right\}$	[−5, 10]	0
Rastrigin	$f_6(x) = \sum_{i=1}^{D} (x_i^2 - 10\cos(2\pi x_i) + 10)$	[−5.12, 5.12]	0
Ackley	$f_7(x) = -20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right) + 20 + e$	[−32, 32]	0
Levy	$f_8(x) = \sum_{i=1}^{D-1}(x_i-1)^2[1+\sin^2(3\pi x_{i+1})] + \sin^2(3\pi x_1) + \lvert x_n - 1\rvert[1+\sin^2(3\pi x_n)]$	[−10, 10]	0

during the female cooperative stage. Thus, PF is an important parameter influencing the performance of the ISSO, and tuning the probability factor PF is crucial. Without loss of generality, three kinds of different test functions are selected to investigate the impact of the parameter PF. These test functions include Sphere, Schwefel2.22, and Ackley, with 50 dimensions as listed in Table 1. The mean values of the 30 runs of the ISSO are presented in Table 2. As seen in Table 2, the variance of the PF has a powerful effect on the performance of the ISSO, and two out of three functions can obtain the best mean results with the PF 0.6. Thus, the PF should be set to 0.6, where the performance of the ISSO is satisfactory.

Table 2: Comparisons of the results varying PF.

PF	Sphere	Schwefel2.22	Ackley
0.1	$6.20E-58$	$3.16E-26$	$8.28E-09$
0.2	$8.47E-59$	$4.82E-28$	$4.25E-09$
0.3	$3.05E-59$	$9.24E-29$	$8.47E-11$
0.4	$5.68E-60$	$6.11E-29$	$7.09E-11$
0.5	$8.49E-62$	$5.92E-30$	$6.22E-13$
0.6	$\mathbf{7.05E-62}$	$5.75E-31$	$\mathbf{3.30E-14}$
0.7	$3.44E-61$	$\mathbf{4.84E-31}$	$1.40E-13$
0.8	$1.89E-59$	$2.15E-30$	$7.34E-13$
0.9	$5.60E-57$	$4.38E-28$	$2.58E-11$
1	$8.42E-57$	$6.87E-28$	$5.81E-10$

5.2. Performance Evaluation. Table 3 shows the comparison results in terms of the minimum "Min," the mean "Mean," the standard deviation "Std" of the best-so-far solution, and the average computing time "At," where the best results are highlighted in boldface.

Table 3 shows that the proposed ISSO is better than any other SSO variants according to the statistical results. Meanwhile, CLPSO and JADE are also better behaved than SSO variants, such as SSO, NISSO, MSSO, and OBSSO. More importantly, the optimization performance of ISSO is superior to that of CLPSO and JADE for all benchmark functions, except the functions SumSquare, Rosenbrock, and Levy. Specifically, the small mean and standard deviation to different kinds of functions indicate the high solution precision and stability of ISSO. Furthermore, compared with other methods, ISSO significantly reduces the time of computing. Such improvements are related to these strategies, such as subpopulation dynamically updating strategy, Gaussian mating radius, and multimating operator, which are introduced into ISSO. These results fully demonstrate that the proposed ISSO is promising and competitive.

5.3. Application to ED Problem with Valve-Point Effects. Three cases from the reference [1], which are 3-unit, 13-unit, and 40-unit system ED problems with valve-point effects, are considered to verify the validity and feasibility of the proposed method ISSO for solving these problems. The detailed data on the three cases are provided in [1]. The results obtained by ISSO are compared with the aforementioned algorithms, including SSO [29], NISSO [37], MSSO [38], OBSSO [39], CLPSO [40], and JADE [41]. The maximum evolution generations of each case remain the same as [1] to realize a fair comparison. Thus, 3-unit, 13-unit, and 40-unit systems are, respectively, set to 50, 800, and 1000, and other parameters are the same as those in Section 5.2. The comparison results are summarized as the minimum cost "Min," the mean cost "Mean," the maximum cost "Max," and the average computing time "At" in Tables 4–6, respectively. The best dispatch schemes corresponding to 3-unit, 13-unit, and 40-unit systems, which are achieved by utilizing ISSO, are, respectively, listed in Tables 7–9. The mean values of 30 trials and the convergence performance curves are, respectively, illustrated in Figures 3 and 4 to

Table 3: Comparisons of the results among the algorithms with $D = 50$.

Function		SSO [29]	NISSO [37]	MSSO [38]	OBSSO [39]	CLPSO [40]	JADE [41]	ISSO
Sphere	Min	$2.39E-06$	$5.70E-20$	$7.44E-35$	$4.57E-28$	$1.38E-53$	$8.22E-45$	$\mathbf{2.84E-63}$
	Mean	$6.88E-06$	$1.63E-19$	$1.40E-34$	$5.09E-26$	$1.70E-52$	$5.60E-44$	$\mathbf{7.05E-62}$
	Std	$7.06E-07$	$9.44E-20$	$8.21E-35$	$7.49E-28$	$4.41E-53$	$3.15E-45$	$\mathbf{1.11E-62}$
	At (s)	7.47	5.86	7.05	5.34	4.14	4.94	**3.68**
SumSquare	Min	$1.88E-16$	$4.66E-32$	$5.49E-43$	$8.73E-35$	$\mathbf{1.79E-59}$	$5.14E-52$	$4.61E-59$
	Mean	$4.30E-14$	$7.68E-30$	$4.87E-42$	$8.44E-34$	$8.60E-57$	$1.80E-51$	$\mathbf{3.87E-58}$
	Std	$5.79E-15$	$3.13E-30$	$9.40E-43$	$4.97E-34$	$9.63E-58$	$3.19E-52$	$\mathbf{7.53E-59}$
	At (s)	7.41	5.79	7.14	5.61	4.05	5.01	**3.74**
Schwefel 2.21	Min	$9.29E-01$	$5.11E-01$	$8.44E-02$	$5.94E-01$	$8.63E-03$	$2.05E-02$	$\mathbf{4.72E-03}$
	Mean	$3.52E+01$	$2.20E+00$	$2.01E-01$	$1.33E+00$	$2.24E-02$	$3.81E-02$	$\mathbf{7.38E-03}$
	Std	$3.03E+00$	$4.93E-01$	$4.62E-02$	$5.33E-01$	$9.82E-03$	$4.57E-03$	$\mathbf{9.46E-04}$
	At (s)	7.69	5.83.	6.93	5.44	4.10	4.86	**3.79**
Schwefel 2.22	Min	$7.27E-06$	$5.60E-09$	$4.33E-15$	$2.61E-12$	$3.04E-29$	$7.83E-24$	$\mathbf{1.58E-31}$
	Mean	$5.69E-04$	$8.05E-07$	$4.20E-14$	$7.44E-12$	$3.47E-27$	$9.53E-23$	$\mathbf{4.84E-31}$
	Std	$2.56E-04$	$8.77E-08$	$6.73E-15$	$9.25E-13$	$6.89E-28$	$6.80E-23$	$\mathbf{9.15E-32}$
	At (s)	7.51	5.90	7.02	5.29	4.22	4.57	**3.70**
Rosenbrock	Min	$7.29E+01$	$3.60E+01$	$4.34E-01$	$2.05E+00$	$\mathbf{1.05E-01}$	$5.60E-01$	$1.17E-01$
	Mean	$1.14E+02$	$6.51E+01$	$1.39E+00$	$2.48E+01$	$1.88E-01$	$6.47E-01$	$\mathbf{1.20E-01}$
	Std	$1.58E+01$	$7.20E+01$	$1.11E+01$	$8.95E+00$	$1.03E+00$	$6.97E-01$	$\mathbf{2.93E-01}$
	At (s)	7.60	5.94	7.15	5.48	4.27	4.95	**3.91**
Rastrigin	Min	$7.23E-02$	$4.80E-05$	$3.09E-09$	$3.25E-08$	$6.64E-14$	$5.57E-11$	$\mathbf{2.31E-14}$
	Mean	$4.36E-01$	$6.49E-04$	$3.22E-08$	$8.20E-08$	$1.08E-13$	$4.51E-10$	$\mathbf{3.16E-14}$
	Std	$7.66E-02$	$9.17E-05$	$1.37E-08$	$9.79\ E-09$	$5.43E-14$	$9.03E-11$	$\mathbf{1.27E-14}$
	At (s)	7.55	5.98	7.17	5.69	4.59	5.20	**3.84**
Ackley	Min	$4.26E-09$	$7.15E-10$	$\mathbf{2.09E-14}$	$8.32E-10$	$2.53E-14$	$3.28E-14$	$2.86E-14$
	Mean	$2.30E-06$	$3.29E-08$	$7.83E-14$	$1.55E-09$	$6.14E-14$	$4.70E-14$	$\mathbf{3.30E-14}$
	Std	$4.61E-07$	$2.40E-08$	$9.76E-15$	$8.40E-10$	$1.25E-13$	$8.34E-15$	$\mathbf{6.87E-15}$
	At (s)	7.63	6.03	7.09	5.58	4.19	4.97	**3.77**
Levy	Min	$8.85E-10$	$3.19E-16$	$8.74E-23$	$4.89E-23$	$\mathbf{1.25E-31}$	$7.82E-27$	$3.58E-31$
	Mean	$3.41E-08$	$6.84E-14$	$1.48E-22$	$8.47E-21$	$5.63E-31$	$3.61E-26$	$\mathbf{4.25E-31}$
	Std	$1.37E-08$	$9.07E-15$	$4.61E-23$	$8.99E-22$	$3.01E-31$	$8.64E-27$	$\mathbf{2.53E-31}$
	At (s)	7.56	6.15	7.01	5.45	4.16	5.03	**3.62**

Table 4: Comparisons of the results of 3-unit system with P_D 850 MW.

Algorithm	Min	Mean	Max	At (s)
SSO [29]	**8234.07**	8240.89	8244.15	0.97
NISSO [37]	**8234.07**	8238.44	8242.04	0.91
MSSO [38]	**8234.07**	8236.08	8240.57	0.72
OBSSO [39]	**8234.07**	8235.96	8241.70	0.78
CLPSO [40]	**8234.07**	**8234.07**	**8234.07**	0.29
JADE [41]	**8234.07**	**8234.07**	**8234.07**	0.37
CEP [1]	**8234.07**	8235.97	8241.83	20.46
FEP [1]	**8234.07**	8234.24	8241.78	4.54
MFEP [1]	8234.08	8234.71	8241.80	8.00
IFEP [1]	**8234.07**	8234.16	8234.54	6.77
ISSO	**8234.07**	**8234.07**	**8234.07**	**0.12**

provide an intuitive comparison of the 40-unit system ED problems.

Tables 4–6 show that the solutions obtained by the ISSO are almost better than those by any other methods in terms of minimum cost, mean cost, maximum cost, and average computing time regardless of the ED problem (i.e., 3-unit, 13-unit, and 40-unit). As for small-scale ED problem, almost all the compared algorithms can obtain the optimal solutions; nevertheless, only ISSO and/or CLPSO can achieve them as the scale of the units increases, which demonstrates a remarkable advantage of ISSO. Moreover, Figure 3 shows that the mean value is closer to each other among 30 trials compared with other algorithms. This finding adequately demonstrates that ISSO not only has high precision but also has strong stability. Figure 4 intuitively indicates that the convergence curve of ISSO is the steepest, which indicates that ISSO has an overwhelming advantage on convergence speed. Therefore, the improvement in standard SSO is

Table 5: Comparisons of the results of 13-unit system with P_D 1800 MW.

Algorithm	Min	Mean	Max	At (s)
SSO [29]	18164.53	18288.43	18451.66	3.16
NISSO [37]	18143.14	18232.08	18289.58	2.33
MSSO [38]	18119.80	18186.50	18212.35	2.69
OBSSO [39]	18136.42	18219.63	18294.75	2.01
CLPSO [40]	**17988.92**	18095.04	18147.20	1.83
JADE [41]	18073.61	18101.29	18193.68	1.96
CEP [1]	18048.21	18190.32	18404.04	294.96
FEP [1]	18018.00	18200.79	18453.82	168.11
MFEP [1]	18028.09	18192.00	18416.89	317.12
IFEP [1]	17994.07	18127.06	18267.42	157.43
ISSO	**17988.92**	**18064.37**	**18101.81**	**1.31**

Table 6: Comparisons of the results of 40-unit system with P_D 10500 MW.

Algorithm	Min	Mean	Max	At (s)
SSO [29]	123577.12	124812.78	126201.69	5.26
NISSO [37]	122896.60	124664.79	125884.04	4.07
MSSO [38]	122873.11	124100.01	124867.20	4.36
OBSSO [39]	123049.59	124471.71	124928.04	3.52
CLPSO [40]	122737.83	122800.96	122851.22	3.11
JADE [41]	122755.05	123356.12	124127.51	3.30
CEP [1]	123488.29	124793.48	126902.89	1956.93
FEP [1]	122679.71	124119.37	127245.59	1037.90
MFEP [1]	122647.57	123489.74	124356.47	2196.10
IFEP [1]	122624.35	123382.00	125740.63	1167.35
ISSO	**122519.24**	**122575.24**	**122731.07**	**2.64**

Table 7: Best dispatch obtained by ISSO for 3-unit system with P_D 850 MW.

Unit	1	2	3
Output (MW)	300.27	149.73	400.00
Total cost ($)		8234.07	

Table 8: Best dispatch obtained by ISSO for 13-unit system with P_D 1800 MW.

Unit	1	2	3	4	5	6	7	8	9	10	11	12	13
Output (MW)	628.32	224.40	297.55	60.00	60.00	60.00	60.00	60.00	159.73	40.00	40.00	55.00	55.00
Total cost ($)							17988.92						

Table 9: Best dispatch obtained by ISSO for 40-unit system with P_D 10500 MW.

Unit	1	2	3	4	5	6	7	8	9	10
Output (MW)	113.81	110.94	119.93	179.71	96.91	140.00	300.00	300.00	284.64	130.00
Unit	11	12	13	14	15	16	17	18	19	20
Output (MW)	94.00	94.00	125.00	214.77	304.39	483.77	498.09	489.49	511.50	511.22
Unit	21	22	23	24	25	26	27	28	29	30
Output (MW)	523.27	546.12	549.56	549.47	549.97	549.76	10.21	10.00	10.03	88.18
Unit	31	32	33	34	35	36	37	38	39	40
Output (MW)	190.00	190.00	190.00	200.00	200.00	200.00	110.00	110.00	109.98	511.29
Total cost ($)						122519.24				

effective, as presented in the following three aspects. First, subpopulation dynamically updating strategy is good for improving the diversity and quality of the subpopulation, and prematuration is prevented. Second, Gaussian mating radius ensures that the mating radius approaches a certain value with oscillation, which improves the efficiency of mating in a very clear way. Third, multimating operators, which refer to a large number of neighboring information of

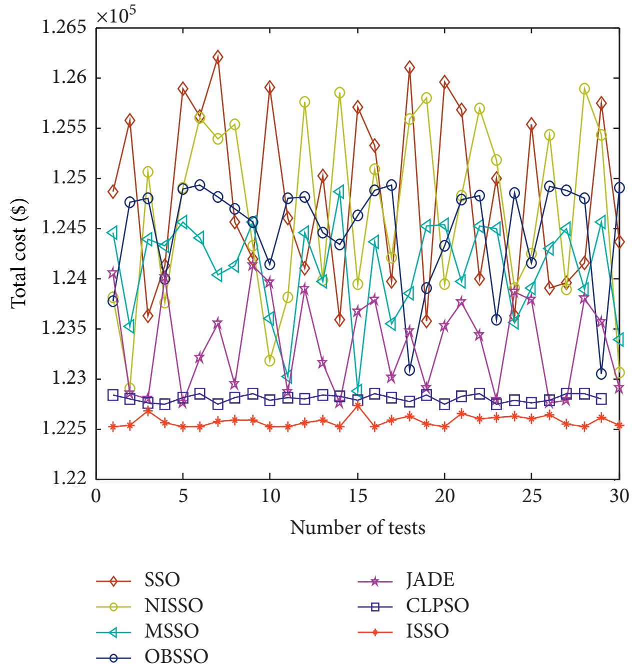

Figure 3: Mean of 30 tests of the 40-unit system.

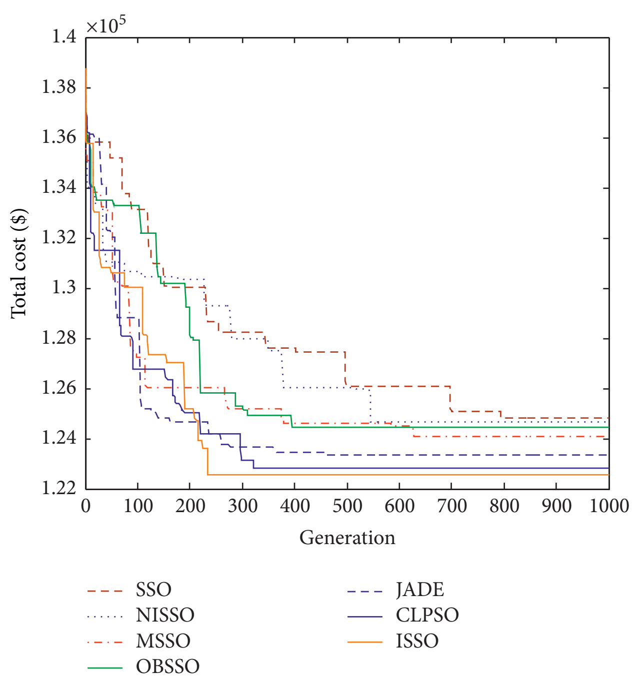

Figure 4: Convergence performance of the 40-unit system.

spiders, further increase the search depth and beneficial to ameliorate the accuracy of the solution to some extent. In summary, the abovementioned improvements on ISSO better balance exploration and exploitation.

6. Conclusion

A modified version of the conventional SSO, called ISSO, is presented in this paper to solve the ED problem with valve-point effects efficiently. Specifically, ISSO improves the subpopulation, mating radius, and mating operator of the SSO, remarkably enhances searching efficiency, and effectively avoids premature convergence. The comparison results of benchmark functions with some popular approaches demonstrate that high-quality solutions can be obtained by using the ISSO. Finally, three different scale ED problems with valve-point effects, which include 3-unit, 13-unit, and 40-unit, are solved with ISSO. The computational results show that ISSO has satisfactory solution precision and robustness, especially in large-scale problems. Moreover, the improvements in SSO are valid and reasonable. These improvements are also suitable for ED problems with valve-point effects, which are characterized as nonsmooth, nonlinear, nonconvex, and nondifferentiable.

Considering the flexibility of the ED problem, future work will be addressed on dynamic ED problems, which are close to ED problems in real life. More importantly, ISSO can be effectively applied to ED problems in practical engineering.

Data Availability

The data used to support the findings of this study are supplied by the Henan Institute of Science and Technology under license and so cannot be made freely available. Requests for access to these data should be made to Wenqiang Yang at yangwqjsj@163.com.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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