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Research Article

A Novel Method for Economic Dispatch with Across Neighborhood Search: A Case Study in a Provincial Power Grid, China

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Economic dispatch (ED) is of cardinal significance for the power system operation. It is mathematically a typical complex nonlinear multivariable strongly coupled optimization problem with equality and inequality constraints, especially considering the valve-point effects. In order to effectively solve the problem, a simple yet very young and efficient population-based algorithm named across neighborhood search (ANS) is implemented in this paper. In ANS, a group of individuals collaboratively navigate through the search space for obtaining the optimal solution by simultaneously searching the neighborhoods of multiple superior solutions. Four benchmark test cases with diverse complexities and characteristics are firstly employed to comprehensively verify the feasibility and effectiveness of ANS. The experimental and comparison results fully demonstrate the superiority of ANS in terms of the final solution quality, convergence speed, robustness, and statistics. In addition, the sensitivities of ANS to variations of population size and across-search degree are studied. Furthermore, ANS is applied to a practical provincial power grid of China. All the comparison results consistently indicate that ANS is highly competitive and can be used as a promising alternative for ED problems.

1. Introduction

Economic dispatch (ED), playing an important role in the power system operation and planning, has received significant attention in recent years. The purpose of ED is to schedule the committed generating unit outputs so as to simultaneously minimize the operating cost and meet the load demand of a power system while satisfying all the equality and inequality constraints [1]. Traditionally, an approximate quadratic function is utilized to make the mathematical formulation of ED problem convex to reduce the computational difficulty. However, in practice, on one hand, the multi-valve steam turbines make the input–output curves of generators inherently present highly nonlinear characteristic. On the other hand, faults in the machines themselves or the associated auxiliaries prohibit generators from operating in some zones [2]. Therefore, the solution space of ED problem with the presence of valve-point effects and prohibited operating zones is highly nonlinear and discontinuous, making the optimization hard to be tractable. In this context, conventional solution methods including linear

programming, Lagrange relaxation, nonlinear programming, quadratic programming, dynamic programming, and interior point method are likely to encounter dire difficulties and challenges mainly due to their heavy imposition of various restrictions such as continuity, convexity, and differentiability on the objective functions, and high sensitivity to the initial values of involved optimized variables.

As a promising alternative to the conventional solution methods, metaheuristic methods for ED problems have attracted considerable attention recently. They have no strict requirements on the form of optimization problems and can avoid the influences of the initial condition sensitivity and gradient information. Up to now, the successfully implemented metaheuristic methods include simulated annealing [3], genetic algorithm [4, 5], particle swarm optimization [6–8], differential evolution [9, 10], artificial bee colony [11, 12], harmony search [13–17], biogeography-based optimization [18–22], teaching-learning-based optimization [23–25], firefly algorithm [26], crisscross optimization algorithm [27, 28], bat algorithm [29], grey wolf optimizer [30, 31], cuckoo search [32–34], ant lion optimizer [35], exchange market algorithm [36], symbiotic organisms search [37, 38], backtracking search algorithm [39, 40], interior search algorithm [41], whale optimization algorithm [42], mine blast algorithm [43], and hybrid methods [44–56].

The abovementioned metaheuristic methods have verified their efficacy in solving the ED problems. Regardless of the achieved promising results, the no free lunch theorem [57] indicates that there is no specific method which can be adopted as a gold standard for all kinds of optimization problems. Namely, there is no single universal superior method that, theoretically, always performs best in solving the ED problems. Therefore, there are still some possibilities to attempt new ones to provide more alternatives, which inspires the authors to apply a recently developed metaheuristic method named across neighborhood search (ANS) [58] to obtain high quality solutions for the ED problems.

As a simple yet versatile metaheuristic method, ANS is motivated by two common straightforward assumptions existing in different population-based algorithms: that searching around a superior solution has a higher probability to find another better solution and that high-quality solutions possess good solution components. In this context, ANS, following the law of parsimony, attempts to simultaneously search across the neighborhoods of multiple superior solutions to get as many potential good solution components as possible. The merits of ANS are its simple structure, ease of implementation, and strong robustness. In this paper, ANS is employed for the ED problems. The main contributions of this work are as follows.

(1) Four benchmark test cases with diverse complexities and characteristics are firstly used to verify the feasibility and effectiveness of ANS comprehensively. The superior performance of ANS is experimentally verified by comparing with four popular population-based algorithms and some recently proposed ED solution methods.

(2) The sensitivities of ANS to variations of population size and across-search degree are empirically investigated.

(3) ANS is finally applied to a practical provincial power grid of China. Its performance is further verified. In addition, the experimental results reflect the necessity and importance of the power construction policy of "replacing small power plants with large ones" in China.

The remainder of this paper is organized as follows. Section 2 briefly introduces the mathematical formulation of ED problems. In Section 3, ANS is described. Next, in Section 4, the flowchart of ANS in solving the ED problems is illustrated. In Section 5, four benchmark test cases are employed to verify ANS. ANS is then applied to a practical provincial power grid of China in Section 6. Finally, Section 7 is devoted to conclusions and future work.

2. Problem Formulation

2.1. Objective Function. The mathematical model of ED can be formulated as follows [59]:

$$\begin{aligned} \min \quad & C(P) = \sum_{i=1}^{N_g} F_i(P_i), \quad P = \left[P_1, P_2, \ldots, P_{N_g}\right] \in R^{N_g} \\ & s.t. \quad h_j(P) = 0, \quad j = 1, 2, \ldots, m \\ & g_j(P) \le 0, \quad j = 1, 2, \ldots, q \end{aligned} \tag{1}$$

where $C(P)$ is the total generation cost (in \$/h), N_g is the number of operating generators, P_i is the active power output of the i-th generator (in MW), $i = 1, 2, \ldots, N_g$, $F_i(P_i)$ is the generation cost function of the i-th generator (in \$/h), $i = 1, 2, \ldots, N_g$, m and q are the number of equality constraints and inequality constraints, respectively, $h_j(P)$ is the j-th equality constraint, $j = 1, 2, \ldots, m$, and $g_j(P)$ is the j-th inequality constraint, $j = 1, 2, \ldots, q$.

The objective function of traditional ED problem is approximately formulated as follows [1, 2, 4]:

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

where a_i, b_i, and c_i are cost coefficients of the i-th generator.

In practice, modelling valve-point effects is necessary and can be formulated as follows [60]:

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

where e_i and f_i are valve-point effects coefficients of the i-th generator and $P_{i,\min}$ is the minimum active power generation limit of the i-th generator (in MW).

2.2. Equality and Inequality Constraints

2.2.1. Active Power Balance Constraint. The total active generated power must be equal to the sum of the total system demand (P_D) and the total transmission network loss (P_L):

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

where P_L is commonly calculated using the following B-coefficient method [9]:

$$P_L = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P_i B_{ij} P_j + \sum_{i=1}^{N_g} B_{0i} P_i + B_{00} \tag{5}$$

where B_{ij}, B_{0i}, and B_{00} are loss coefficients.

2.2.2. Generation Capacity Constraints. The active power output of each generator should be within its minimum and maximum limits:

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{6}$$

where $P_{i,\max}$ is the maximum active power generation limit of the i-th generator (in MW).

2.2.3. Ramp Rate Limits Constraints. The adjustment of active power output of each generator should be in an acceptable range:

$$\begin{aligned} P_i - P_i^{\mathrm{pr}} &\le UR_i \\ P_i^{\mathrm{pr}} - P_i &\le DR_i \end{aligned} \tag{7}$$

where P_i^{pr} is the previous active power output of the i-th generator and UR_i and DR_i are the up-ramp and down-ramp limits of the i-th generator, respectively.

2.2.4. Prohibited Operating Zones Constraints. Generators should avoid operating in prohibited zones [2]:

$$P_i \in \begin{cases} P_{i,\min} \le P_i \le P_{i,1}^L \\ P_{i,k-1}^U \le P_i \le P_{i,k}^L, \quad k = 2, 3, \ldots, pz_i \\ P_{i,pz_i}^U \le P_i \le P_{i,\max} \end{cases} \tag{8}$$

where pz_i is the number of prohibited operating zones of the i-th generator and $P_{i,k}^L$ and $P_{i,k}^U$ are the lower bound and upper bound of the k-th prohibited zone of the i-th generator, respectively.

3. Across Neighborhood Search

ANS is a very young population-based algorithm proposed by Wu [58] in 2016. ANS, following the law of parsimony and showing good performance compared with other methods [61], attempts to simultaneously search across the neighborhoods of multiple superior solutions to achieve as many potential good solution components as possible. At the same time, it needs to dynamically maintain and update the superior solutions to guarantee the advancement and convergence of the population. The main difference between ANS and other population-based algorithms is that other algorithms mainly utilize some operations such as crossover and mutation to generate new solutions, whereas ANS directly searches across the neighborhoods of multiple superior solutions to produce new solutions.

Like other population-based algorithms, ANS starts with a population of ps individuals $\boldsymbol{X} = [X_1, X_2, \ldots, X_{ps}]$ representing the potential solutions. Each individual $X_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,D}]$ ($i = 1, 2, \ldots, ps$) consists of D variables and it is initialized as

$$x_{i,d} = l_d + \mathrm{rand}\,(0,1) \times (u_d - l_d) \tag{9}$$

where $d = 1, 2, \ldots, D$, rand(0,1) is a uniformly distributed random real number in (0,1), and l_d and u_d are the lower bound and upper bound of the d-th dimension, respectively.

In ANS, a group of individuals collaboratively navigate through the search space for obtaining the optimal solution. Each individual searches across the neighborhoods of multiple superior solutions. These superior solutions, being archived in a collection $\boldsymbol{S} = (S_1, S_2, \ldots, S_c)$ where c is the cardinality and is generally set to be the population size ps, are directly derived from the individuals' best positions found so far. The searching strategy is as follows:

$$x_{i,d} = \begin{cases} s_{i,d} + G\left(0, \sigma^2\right) \times \left|s_{i,d} - x_{i,d}\right| & \text{if } d \notin O \\ s_{r,d} + G\left(0, \sigma^2\right) \times \left|s_{r,d} - x_{i,d}\right| & \text{else} \end{cases} \tag{10}$$

where O is a pool used to record the randomly selected n (n is called across-search degree, $1 \le n \le D$) dimensions for individual i, r ($\neq i$) is a randomly superior solution selected from the superior solution collection $\boldsymbol{S}$, and $G(0, \sigma^2)$ is a Gaussian random value with mean zero and standard deviation σ which is usually set to be 0.5.

It can be seen from (10) that each individual, on one hand, searches across the neighborhood of the individual's best position achieved so far. On the other hand, it also simultaneously searches across the neighborhoods of other individuals' best positions found so far. After updating individual X_i, $i = 1, 2, \ldots, ps$, its own superior solution S_i will be replaced by X_i if X_i has a better fitness value.

The main procedure of ANS is given in Algorithm 1. It can be seen that the individuals are guided by multiple superior solutions and the structure, following the law of parsimony, is very simple, making the implementation easy.

4. Implementing ANS for Solving ED Problem

The flowchart of implementing ANS for solving ED problem is depicted in Figure 1. The main steps are as follows.

Step 1. Initialize a random population using (9).

Step 2. Handle the quality and inequality constraints using the following strategy [18, 59]:

```
Generate a random initial population X
Evaluate the fitness for each individual
Set X to be the superior solutions S = (S_1, S_2, ..., S_c)
Initialize the iteration counter t = 1
While the stopping condition is not satisfied do
  for i = 1 to ps do
    Generate a pool O to record the randomly selected n
    (1 ≤ n ≤ D) dimensions for individual i
    for d = 1 to D do
      if d ∉ O then
        x_{i,d} = s_{i,d} + G(0, σ^2) × |s_{i,d} − x_{i,d}|
      else
        Select a random superior solution r (r ≠ i) from S
        x_{i,d} = s_{r,d} + G(0, σ^2) × |s_{r,d} − x_{i,d}|
      end if
      Evaluate the fitness for individual X_i
      if X_i is better than S_i then
        Replace S_i with X_i
      end if
    end for
  end for
  t = t + 1
End while
```

Algorithm 1: The main procedure of ANS.

(1) Truncate $x_{i,d}^t$ according to

$$x_{i,d}^t = \begin{cases} P_{d,\min}, & \text{if } x_{i,d}^t < P_{d,\min} \\ P_{d,\max}, & \text{if } x_{i,d}^t > P_{d,\max} \end{cases} \tag{11}$$

where $i = 1, 2, \ldots, ps$, $d = 1, 2, \ldots, N_g$, and $t = 1, 2, \ldots, t_{\max}$; $t_{\max}$ is the maximum number of allowed iterations.

(2) For the prohibited operating zones constraints, if $x_{i,d}^t$ locates in the k-th prohibited operating zone, i.e., $P_{d,k}^L < x_{i,d}^t < P_{d,k}^U$, $k = 2, 3, \ldots, pz_d$, it is truncated to the closest boundary of the k-th prohibited operating zone as follows:

$$x_{i,d}^t = \begin{cases} P_{d,k}^L, & \text{if } P_{d,k}^L < x_{i,d}^t < \dfrac{P_{d,k}^L + P_{d,k}^U}{2} \\ P_{d,k}^U, & \text{if } \dfrac{P_{d,k}^L + P_{d,k}^U}{2} \le x_{i,d}^t < P_{d,k}^U \end{cases} \tag{12}$$

(3) Calculate the corresponding transmission network loss $P_L(i)$.

(4) Calculate the amount of the active power balance violation $P_V(i)$:

$$P_V(i) = \sum_{d=1}^{N_g} x_{i,d}^t - \left(P_D + P_L(i)\right) \tag{13}$$

(5) If $|P_V(i)| = 0$, go to Step (7). Otherwise, randomly select a generator r ($r \neq d$) that has not been selected before and then use (14) to eliminate the power violation:

$$x_{i,r}^t = \begin{cases} x_{i,r}^t - \min\left\{P_V(i), x_{i,r}^t - P_{r,\min}\right\}, & \text{if } P_V(i) > 0 \\ x_{i,r}^t + \min\left\{\left|P_V(i)\right|, P_{r,\max} - x_{i,r}^t\right\}, & \text{if } P_V(i) < 0 \end{cases} \tag{14}$$

(6) Go back to Step (2) to handle the r-th generator.

(7) Handle the next individual.

Step 3. Evaluate the fitness for each individual.

Step 4. Replace the superior solution S_i with X_i^t if X_i^t has a better fitness value.

Step 5. Update the position of each individual.

Step 6. Go to Step 2 to handle constraints if the stopping condition is not satisfied. Otherwise, stop the ANS and output the obtained results. In this study, the maximum number of fitness evaluations (Max_FEs) is used as the stopping condition.

5. Experimental Results on Benchmark Test Cases

In this section, we employ four benchmark test cases with different characteristics to verify the proposed ED method. These cases are described as follows.

Case I. A 13-generator system considering valve-point effects [62].

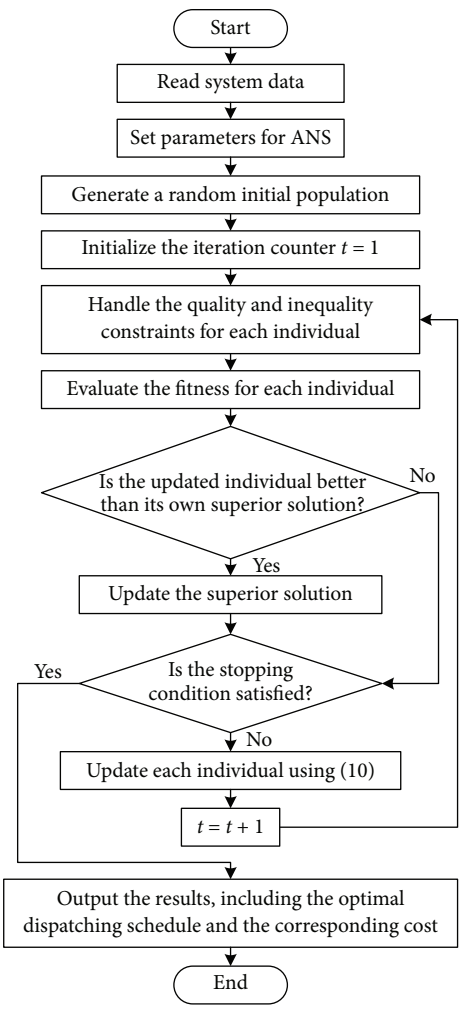

Figure 1: Flowchart of implementing ANS for solving ED problem.

Case II. A 15-generator system considering ramp rate limits, prohibited operating zones, and transmission network losses [63].

Case III. A 38-generator system without considering valve-point effects [15].

Case IV. A 40-generator system considering valve-point effects [62].

In order to validate the feasibility and effectiveness of the proposed ED method, four popular population-based algorithms, i.e., biogeography-based optimization (BBO) [64], competitive swarm optimizer (CSO) [65], differential evolution (DE) [66], and particle swarm optimization (PSO) [67], are employed for comparison. Their involved parameters are listed in Table 1. For the following experiments, ps and Max_FEs are, respectively, set to be 10 and $1 \times 10^3 \times N_g$ for the test cases without considering the valve-point effects, whereas they are 40 and $1 \times 10^4 \times N_g$ for the test cases with the valve-point effects unless a change is mentioned. 50 independent runs are conducted to eliminate contingency. All experiments are executed in MATLAB 2017b.

Table 1: Parameter settings of different algorithms.

Algorithm	Parameters settings
BBO	$I = E = 1.0$, $m_{\max} = 0.05$
DE	$F = 0.5$, $CR = 0.9$
CSO	$\varphi = 0.1$
PSO	$w = 0.9 \longrightarrow 0.5$, $c_1 = c_2 = 2.0$
ANS	$n = 1$, $\sigma = 0.5$

5.1. Experimental Results and Comparison

5.1.1. Solution Quality. The experimental results of Cases I to IV are summarized in Tables 2–5, respectively. The results include the minimum (Min), maximum (Max), mean costs, and standard deviation (Std Dev). These tables also list some recently proposed ED solution methods' reported results for comparison.

Case II is a canonical traditional ED problem with a smooth and continuous solution space. Although the solution space of Case III is discontinued by the prohibited operating zones, its objective function is also quadratic. Therefore, both cases are typical multiconstraint unimodal optimization problems which have high requirement on the solution methods' local searching ability. It can be observed from Tables 3 and 4 that ANS outperforms BBO, CSO, DE, and PSO on both cases in terms of minimum, maximum, and mean costs. In addition, ANS is also better than other reported solution methods. The comparisons demonstrate that ANS is able to search local range meticulously and thereby possesses good exploitation ability.

Cases I and IV, whose solution spaces are highly nonconvex due to the valve-point effects, are multiconstraint multimodal optimization problems. The number of local minima increases at an exponential rate with the problem scale. They demand a lot on the solution methods' global searching ability. The experimental results tabulated in Tables 2 and 5 consistently indicate that ANS is significantly better than BBO, CSO, DE, and PSO in both cases in terms of minimum, maximum, and mean costs. Furthermore, the larger the system scale, the more significant the superiority. Additionally, ANS also can achieve better or highly competitive results compared with other reported solution methods. The comparisons fully conclude that ANS is with the capability of breaking away from the local minima and locating the global or near-global range. Namely, ANS has good exploration ability.

The obtained optimal dispatching schedules for these four cases are presented in Tables 6–9, respectively.

In conclusion, the abovementioned comparison results sufficiently demonstrate that ANS is able to achieve a strong equilibrium between the local exploitation and global exploration.

5.1.2. Convergence Property. The convergence curves of the mean costs for the four cases are plotted in Figures 2–5, respectively. It can be seen that although CSO and DE are slightly faster than ANS at the very beginning, both methods are quickly trapped into local search later and thus suffer from prematurity. The convergence speed of BBO

Table 2: Comparison of simulation results ($/h) for 13-generator system (Case III).

Method	Min.	Max.	Mean	Std Dev
FCASO-SQP [1]	17964.08	NA	18001.96	NA
TSARGA [4]	17963.94	18089.61	17974.31	3.18
DE [10]	17963.83	17975.36	17965.48	NA
ABC [11]	17963.86	17995.11	17987.22	NA
IHSWM [14]	17963.83	18041.3456	17976.4750	25.6079
aBBOmDE [20]	17963.8521	17975.0552	17967.3560	NA
TLBO [24]	18115	NA	NA	NA
CTLBO [25]	17972.81	18159.34	18013.38	43.2
FA [26]	17963.83	18168.80	18029.16	148.542
CBA [29]	17963.8339	17995.2256	17965.4889	6.8473
GWO [30]	18051.11	NA	NA	NA
GA–PS–QSP [44]	17964	NA	18199	NA
HMAPSO [48]	17969.31	17969.31	17969.31	NA
CE-SQP [54]	17963.85	NA	17965.97	NA
ANS-SDP [68]	17964	17985	17973	NA
BFO [69]	17974.48	17997.12	18018.75	NA
RTO [70]	17969.8024	18204.6303	18056.9358	NA
CMSFLA [71]	18294.9953	18297.3126	18295.7308	NA
OIWO [72]	17963.83	NA	NA	NA
IA_EDA [73]	17961.4331	18052.3155	17980.1898	21.6666
NSS [74]	17976.9512	17976.9512	17976.9512	NA
MSOS [75]	17963.8292	17963.8292	17963.8292	6.80E-12
QOSLTLBO [76]	18421.1718	NA	NA	NA
BBO	17973.1883	18090.6042	17993.9942	27.0827
CSO	17972.8619	18136.4236	18073.9003	56.1710
DE	17972.8105	18075.5913	17993.5153	38.8380
PSO	17981.3621	18312.9831	18127.7452	85.8468
ANS	17963.9031	17973.4437	17969.1487	3.0015

NA means not available in the corresponding literature.

and PSO, especially the latter, is slow. ANS can consistently improve the solution quality and converge towards the global optima throughout the whole evolutionary process in all cases especially in Cases I and IV, which, from another perspective, indicates that ANS possesses better exploration and exploitation abilities of jumping out of local search and finding a more promising searching direction.

5.1.3. Robustness. Since population-based algorithms use random numbers to initialize the population and employ randomization procedures to promote the search process, randomness is inevitable. In this context, it may be inappropriate to comprehensively assess their performance just through one single run. Thus, a number of independent runs with different initial populations can be used to measure their stability and consistency, i.e., robustness. The standard deviation results provided in Tables 2–5 clearly illustrate that the recorded values of ANS are significantly smaller than those of BBO, CSO, DE, and PSO. Moreover, they are also very competitive with those of other recently proposed ED problem solution methods. The comparisons indicate that ANS has strong robustness and it can achieve a relatively stable optimal result in each trial. In addition, through careful observation, we can see that the standard deviation values of Cases I and IV are bigger than those of Cases II and III.

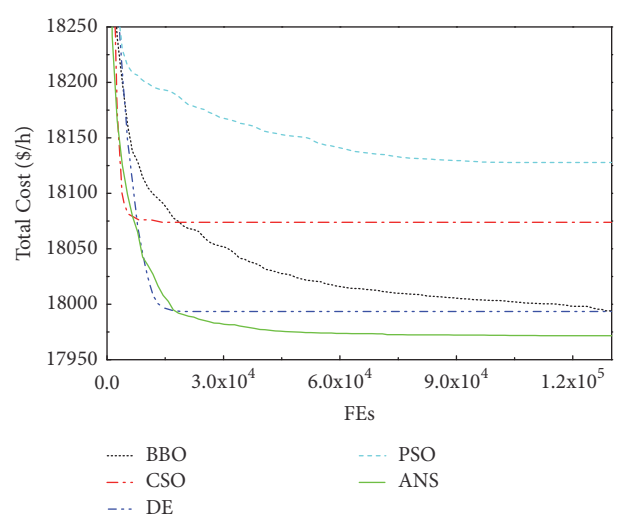

Figure 2: Convergence curves for the 13-generator system (Case I).

Table 3: Comparison of simulation results ($/h) for 15-generator system (Case II).

Method	Min.	Max.	Mean	Std Dev
MPSO [8]	32738.4177	NA	NA	NA
PVHS [13]	32780.00	NA	32892.463	35.331
IHSWM [14]	32693.1304	32721.3988	32699.5168	4.6937
FA [26]	32704.5	33175.0	32856.1	147.1702
ICS [32]	32706.7358	32752.5183	32715.4669	NA
EMA [36]	32704.4503	32704.4506	32704.4504	NA
BSA [39]	32704.4504	32704.5816	32704.4721	0.0280
GAAPI [46]	32732.95	32756.01	32735.06	NA
DSPSO-TSA [47]	32715.06	32730.39	32724.63	8.40
HHS [50]	32692.8571	NA	32740.1885	24.6697
ABF-NM [51]	32784.5024	NA	32976.81	85.7743
ANS-SDP [68]	32693	32693	32693	NA
RTO [70]	32701.81	32715.18	32704.53	5.07
AIS [77]	32854	32892	32873.25	10.8079
MVMO [78]	32704.47	32709.32	32706.65	NA
SCKF-PSO [79]	32725.8431	NA	NA	NA
SFS [80]	32702	NA	NA	NA
BBO	32692.3988	32693.7153	32692.6927	0.2592
CSO	32692.3972	32875.3601	32718.8607	38.0358
DE	32692.3966	32755.3193	32699.1724	12.9351
PSO	32692.3991	32781.9374	32701.0786	13.8044
ANS	32692.3962	32692.4016	32692.3973	0.0009

Table 4: Comparison of simulation results ($/h) for 38-generator system (Case III).

Method	Min.	Max.	Mean	Std Dev
New-PSO [6]	9516448.312	NA	NA	NA
PSO_TVAC [6]	9500448.307	NA	NA	NA
HS [15]	9419960	9427466	9421056	NA
HHS [15]	9417325	9417466	9417336	NA
BBO(Model 6) [22]	9417557.25	9419854.237	9418394.069	NA
GWO [30]	9419270.188	9421100	9419978.978	NA
BBO [81]	9417633.6376	NA	NA	NA
DE/BBO [81]	9417235.7864	NA	NA	NA
BBO	9417446.0804	9418959.2333	9418143.6500	390.1769
CSO	9417307.5544	9417745.6891	9417494.7251	103.1130
DE	9417235.7977	9417235.8465	9417235.8184	0.0136
PSO	9426679.1431	9461023.8147	9441014.5256	9278.1375
ANS	9417235.7864	9417235.7864	9417235.7864	8.4314E-09

This is because the valve-point effects make the ED problems exhibit highly multimodal characteristic and the solution methods are more likely trapped into different local minima in different trials. Therefore, the valve-point effects are more challenging for solution methods.

5.1.4. Statistical Analysis. A nonparametric statistical test called Wilcoxon's rank sum test for independent samples is employed to compare the significance differences between ANS and its competitors. The results based on the Wilcoxon's rank sum test at a 0.05 confidence level are summarized in Table 10. The mark "†" symbolizes that ANS is statistically better than its competitor. It can be seen that ANS performs significantly better than BBO, CSO, DE, and PSO in all cases, meaning that ANS is capable of obtaining overall higher quality of the final solutions than the other four popular population-based algorithms.

5.2. Influence of Population Size. Choosing an appropriate population size is always critical for population-based algorithms in solving different problems. In this subsection, an experiment is conducted to investigate the sensitivity of ANS to variations in population size. The population size *ps* is set as 10 to 100 with interval 10. The results are shown in Figure 6.

Table 5: Comparison of simulation results ($/h) for 40-generator system (Case IV).

Method	Min.	Max.	Mean	Std Dev
FCASO-SQP [1]	121456.98	NA	122026.21	NA
TSARGA [4]	121463.07	124296.54	122928.31	NA
DE [10]	121416.29	121431.47	121422.72	NA
ABC [11]	121441.03	122023.77	121995.82	NA
IABC-LS [12]	121488.7636	121582.2525	121526.0333	NA
PVHS [13]	121415.4560	NA	121567.0292	94.1498
IHSWM [14]	121416.2652	121855.5521	121553.4208	90.1271
THS [16]	121425.15	NA	121528.65	NA
NTHS [17]	121412.7374	NA	121549.95	NA
BBO [19]	121426.953	121688.6634	121508.0325	NA
aBBOmDE [20]	121414.8734	121568.3254	121487.8532	NA
BBO(Model 5) [22]	121418.70	121954.4	121635.4	NA
TLBO [24]	12996	NA	NA	NA
CTLBO [25]	121553.83	122116.18	121790.23	150
FA [26]	121415.05	121416.57	121424.56	1.784
CBA [29]	121412.5468	121436.15	121418.9826	1.611
EMA [36]	121412.5355	121426.1548	121417.1328	NA
BSA [40]	121415.6139	121524.9577	121474.8823	NA
GA–PS–SQP [44]	121458	NA	122039	NA
HMAPSO [48]	121586.90	121586.90	121586.90	NA
FAPSO-NM [49]	121418.3	121419.8	121418.803	NA
HHS [50]	121415.5922	NA	121615.8544	114.5632
ABF-NM [51]	121423.6379	NA	121814.9465	124.8756
CE-SQP [54]	121412.88	NA	121423.65	NA
ANS-DSP [68]	12141E+05	12187E+05	12185E+05	NA
OIWO [72]	121412.54	NA	NA	NA
IA-EDA [73]	121436.9729	121648.4401	122492.7018	182.5274
NSS [74]	122186.9048	122186.9048	122186.9048	NA
MSOS [75]	121412.5355	121412.5355	121412.5355	2.47E-11
NGPSO [82]	121513.4808	122697.7672	122065.1193	267
C-GRASP-SaDE [83]	121414.621	122245.696	121736.025	166.896
BBO	121669.9298	122446.1176	121865.0181	150.4038
CSO	121440.8040	122092.4350	121637.1868	141.5265
DE	121420.9029	121618.6298	121509.0360	42.6215
PSO	122636.1149	125429.5349	123836.7368	603.6246
ANS	121412.6226	121472.9213	121427.7107	13.6539

The following can be seen: (i) For the unimodal ED problems, i.e., Cases II and III, the smaller the population size, the better the performance ANS yields. (ii) For the multimodal ED problems, i.e., Cases I and IV, the bigger or smaller the population size, the worse the performance ANS obtains, and ANS can achieve the best results in $ps = 40$. The reason might be that, for the unimodal ED problems, it is relatively easy for ANS to find the correct searching direction and there is no need for exploring the entire solution space. Therefore, a small population can swarm towards the global optimum easily. While for the multimodal ED problems, on one hand, a small population tends to converge very fast before fully exploring the entire solution space, thus resulting in prematurity. On the other hand, although a large population can increase the population diversity significantly, the distribution of individuals is sparse and the probability of finding the correct searching direction is sharply reduced. In addition, a large population size will consume a large number of fitness evaluations in each iteration, which is not proper for computationally expensive problems. In general, for the traditional ED problems without considering the valve-point effects, a small population size is recommended, whereas for the nonconvex ED problems, it is safe to set a moderate population size.

5.3. Influence of the Across-Search Degree. The across-search degree n in ANS is utilized to control the amount of information deriving from other superior solutions. In this subsection, an experiment is conducted to investigate the influence of n on the performance of ANS. The experimental

Table 6: Best output power for 13-generator system (Case III).

Generator	BBO	CSO	DE	PSO	ANS
P_1	628.1947	628.3185	628.3185	538.5587	628.3187
P_2	223.4227	223.8651	297.5488	299.5838	223.2845
P_3	298.6788	298.0833	224.3995	224.8434	149.0866
P_4	60.0000	60.0000	60.0000	109.8666	60.0000
P_5	109.8650	60.0000	109.8666	60.0000	109.8661
P_6	60.0000	60.0000	60.0000	60.0000	109.8615
P_7	60.0000	60.0000	109.8666	109.8666	109.8603
P_8	60.0000	109.8665	60.0000	60.0004	109.8603
P_9	109.8388	109.8665	60.0000	109.8666	109.8620
P_{10}	40.0000	40.0000	40.0000	40.0063	40.0000
P_{11}	40.0000	40.0000	40.0000	40.0062	40.0000
P_{12}	55.0000	55.0000	55.0000	92.4002	55.0000
P_{13}	55.0000	55.0000	55.0000	55.0012	55.0000
TP[a] (MW)	1800.0000	1800.0000	1800.0000	1800.0000	1800.0000
TC[b] ($/h)	17973.1883	17972.8619	17972.8105	17981.3621	17963.9031

[a]TP denotes the total power output.
[b]TC denotes the total generation cost.

Table 7: Best output power for 15-generator system (Case II).

Generator	BBO	CSO	DE	PSO	ANS
P_1	455.0000	455.0000	455.0000	455.0000	455.0000
P_2	380.0000	380.0000	380.0000	380.0000	380.0000
P_3	130.0000	130.0000	130.0000	130.0000	130.0000
P_4	130.0000	130.0000	130.0000	130.0000	130.0000
P_5	170.0000	170.0000	170.0000	170.0000	170.0000
P_6	460.0000	460.0000	460.0000	460.0000	460.0000
P_7	430.0000	430.0000	430.0000	430.0000	430.0000
P_8	69.9471	68.8487	69.7626	70.4928	69.4768
P_9	59.6421	60.7332	59.8226	59.0961	60.1079
P_{10}	159.9943	160.0000	160.0000	159.9999	160.0000
P_{11}	80.0000	80.0000	80.0000	80.0000	80.0000
P_{12}	80.0000	80.0000	80.0000	80.0000	80.0000
P_{13}	25.0000	25.0000	25.0000	25.0000	25.0000
P_{14}	15.0020	15.0000	15.0006	15.0005	15.0000
P_{15}	15.0011	15.0000	15.0001	15.0000	15.0000
TL[a] (MW)	29.5866	29.5819	29.5859	29.5893	29.5847
TP (MW)	2659.5866	2659.5819	2659.5859	2659.5893	2659.5847
TC ($/h)	32692.3988	32692.3972	32692.3966	32692.3991	32692.3962

[a]TL denotes the total transmission network loss.

results in different across-search degrees are presented in Figure 7.

It can be observed that the best values of n for all cases are all 1. Besides, for the unimodal ED problems, the bigger the value n is, almost the worse the performance of ANS gets. For the multimodal ED problems, a temperate value of n will considerably deteriorate ANS though a bigger value is also not good for ANS. The reason might be that, for both unimodal and multimodal ED problems, bigger values of n will damage individuals' solution components vastly in each iteration, which is not conducive to the consistency of convergence. In addition, for the multimodal ED problems, although a more bigger value of n can fully recombine each individual to maintain the population diversity, it will make individuals trap into different local optima frequently and thus slow down the convergence considerably. Generally, the recommendation value of n for different ED problems is 1.

6. Application to a Practical Provincial Power Grid of China

In the previous section, the feasibility and effectiveness of ANS in solving ED problems are comprehensively validated on four benchmark test cases. In this section, ANS is applied

Table 8: Best output power for 38-generator system (Case III).

Generator	BBO	CSO	DE	PSO	ANS
P_1	417.4699	431.4435	426.6061	423.2786	426.6061
P_2	428.6549	432.7667	426.6061	447.2694	426.6061
P_3	430.7266	432.4754	429.6632	377.7218	429.6631
P_4	429.5193	426.7217	429.6632	391.1059	429.6632
P_5	438.8225	425.0443	429.6632	371.5138	429.6632
P_6	436.7947	426.7682	429.6632	417.4801	429.6631
P_7	424.1592	429.8489	429.6632	468.3885	429.6632
P_8	427.7913	433.0439	429.6632	376.9151	429.6631
P_9	114.0000	114.0000	114.0000	137.9410	114.0000
P_{10}	114.1613	114.0001	114.0000	155.5833	114.0000
P_{11}	114.7729	120.6554	119.7680	142.6568	119.7681
P_{12}	127.0026	128.0361	127.0728	187.8007	127.0729
P_{13}	110.0000	110.0000	110.0000	110.0000	110.0000
P_{14}	90.0025	90.0000	90.0000	90.0000	90.0000
P_{15}	82.0000	82.0000	82.0000	82.0000	82.0000
P_{16}	120.0000	120.0000	120.0000	120.0000	120.0000
P_{17}	160.1416	158.7822	159.5980	161.4797	159.5980
P_{18}	65.0008	65.0000	65.0000	65.0000	65.0000
P_{19}	65.0000	65.0000	65.0000	65.0000	65.0000
P_{20}	272.0000	272.0000	272.0000	271.9999	272.0000
P_{21}	272.0000	272.0000	272.0000	272.0000	272.0000
P_{22}	259.3185	260.0000	260.0000	260.0000	260.0000
P_{23}	130.9561	129.4275	130.6486	138.0732	130.6486
P_{24}	10.0000	10.0000	10.0000	10.0002	10.0000
P_{25}	116.3424	108.7907	113.3050	110.9243	113.3050
P_{26}	90.6858	87.3194	88.0669	88.8202	88.0669
P_{27}	35.0000	36.1978	37.5051	39.1707	37.5051
P_{28}	20.0000	20.0000	20.0000	20.0000	20.0000
P_{29}	20.0000	20.0000	20.0000	20.0000	20.0000
P_{30}	20.0005	20.0000	20.0000	20.0000	20.0000
P_{31}	20.0000	20.0000	20.0000	20.0000	20.0000
P_{32}	20.0000	20.0000	20.0000	20.0000	20.0000
P_{33}	25.0000	25.0000	25.0000	25.0000	25.0000
P_{34}	18.0000	18.0000	18.0000	18.0000	18.0000
P_{35}	8.0000	8.0000	8.0000	8.0000	8.0000
P_{36}	25.0000	25.0000	25.0000	25.0000	25.0000
P_{37}	21.6764	21.5606	21.7821	21.3068	21.7821
P_{38}	20.0000	21.1175	21.0622	20.5701	21.0622
TP (MW)	6000.0000	6000.0000	6000.0000	6000.0000	6000.0000
TC ($/h)	9417446.0804	9417307.5544	9417235.7977	9426679.1431	9417235.7864

to a practical power grid of China. This system is more large-scale and has 46 operating generators which contain four different rated capacities, i.e., 150MW (#1~#2), 200MW (#3~#8), 300MW (#9~#38), and 600MW (#39~#46). The load demand is 10048MW. It is worth pointing out that the ED objective of this system is minimization of the total coal consumption rather than the total generation cost. The main reasons are twofold. On one hand, the price of coal fluctuates frequently. On the other hand, utilizing the coal consumption instead of coal cost to measure the generation efficiency of generators is more intuitive and reasonable. The objective function is a canonical traditional ED problem with a smooth and continuous solution space. The experimental results are tabulated in Table 11. It can be seen that ANS is better than the other involved methods in terms of the minimum, maximum, and mean values of the total coal consumption. The statistical results based on Wilcoxon's rank sum test also further confirm the conclusion. With respect to the standard deviation, the value of ANS is significantly smaller than those of compared methods, indicating that

Table 9: Best output power for 40-generator system (Case IV).

Generator	BBO	CSO	DE	PSO	ANS
P_1	112.2570	111.5065	110.8699	111.7714	110.8020
P_2	114.0000	112.0271	110.8626	75.1768	110.8004
P_3	101.5985	97.3999	97.3999	97.4000	97.4001
P_4	179.8608	179.7331	179.7331	129.8666	179.7330
P_5	97.0000	89.0477	97.0000	93.8081	87.8004
P_6	140.0000	140.0000	140.0000	140.0000	140.0000
P_7	260.2515	300.0000	259.5997	260.1252	259.5998
P_8	284.8846	284.6023	284.5997	285.0625	284.6000
P_9	285.6941	284.5997	284.5999	287.7589	284.5997
P_{10}	131.2062	130.0000	130.0000	204.7998	130.0000
P_{11}	168.4760	168.7998	168.7998	168.7998	94.0000
P_{12}	168.7683	94.0000	94.0000	243.5997	94.0000
P_{13}	215.2662	214.7598	214.7598	304.5196	214.7598
P_{14}	393.1850	394.2794	394.2794	394.2794	394.2794
P_{15}	306.7599	394.2794	394.2794	394.2794	394.2796
P_{16}	305.2877	304.5196	304.5196	304.5196	394.2793
P_{17}	488.9168	489.2794	489.2794	489.2794	489.2795
P_{18}	489.2538	489.2794	489.2794	489.2794	489.2793
P_{19}	511.3833	511.2794	511.2794	511.2794	511.2794
P_{20}	512.0211	511.2794	511.2794	511.2794	511.2795
P_{21}	523.1479	523.2794	523.2794	433.7901	523.2793
P_{22}	524.9892	523.2794	523.2794	523.4705	523.2794
P_{23}	523.5749	523.2794	523.2794	523.2794	523.2793
P_{24}	524.6906	523.2794	523.2794	523.2794	523.2798
P_{25}	523.6776	523.2794	523.2794	523.2939	523.2794
P_{26}	526.3109	523.2794	523.2794	523.2794	523.2794
P_{27}	10.0000	10.0000	10.0000	10.0000	10.0000
P_{28}	10.0000	10.0000	10.0000	10.0000	10.0000
P_{29}	10.0000	10.0000	10.0000	10.0000	10.0000
P_{30}	93.4661	88.0999	87.8236	88.2486	87.8000
P_{31}	190.0000	190.0000	190.0000	190.0000	190.0000
P_{32}	190.0000	190.0000	190.0000	161.4680	189.9998
P_{33}	190.0000	190.0000	190.0000	161.6225	190.0000
P_{34}	199.8577	165.1100	164.8006	165.0999	164.7997
P_{35}	168.7132	165.1627	200.0000	168.0133	199.9752
P_{36}	184.9895	200.0000	200.0000	165.3862	194.4181
P_{37}	110.0000	110.0000	110.0000	91.6051	110.0000
P_{38}	109.1741	110.0000	110.0000	110.0000	110.0000
P_{39}	110.0000	110.0000	110.0000	110.0000	110.0000
P_{40}	511.3378	511.2794	511.2794	511.2794	511.2794
TP (MW)	10500.0000	10500.0000	10500.0000	10500.0000	10500.0000
TC ($/h)	121669.9298	121440.8040	121420.9029	122636.1149	121412.6226

Table 10: Statistical analysis results based on Wilcoxon's rank sum test.

ANS vs.	BBO	CSO	DE	PSO
Case III	†	†	†	†
Case II	†	†	†	†
Case III	†	†	†	†
Case IV	†	†	†	†

Table 11: Comparison of simulation results (t/h).

Method	Min.	Max.	Mean	Std Dev	Statistical result
BBO	3357.2587	3358.3753	3357.6023	0.2373	†
CSO	3356.9538	3363.8324	3357.5218	1.6223	†
DE	3356.9533	3357.2138	3357.0257	0.1061	†
PSO	3357.1167	3366.9071	3359.2455	2.4471	†
ANS	3356.9528	3356.9533	3356.9529	9.9122E-05	†

Table 12: Operation performance of various capacity generators.

Performance indicator	Generator capacity			
	150MW	200MW	300MW	600MW
Mean load rate (%)	70.00	58.73	65.61	67.28
Mean coal consumption (g/kWh)	373.95	391.77	337.64	321.73

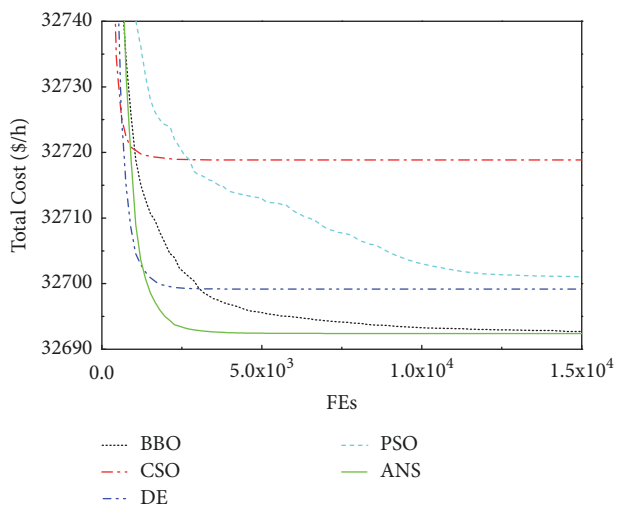

Figure 3: Convergence curves for the 15-generator system (Case II).

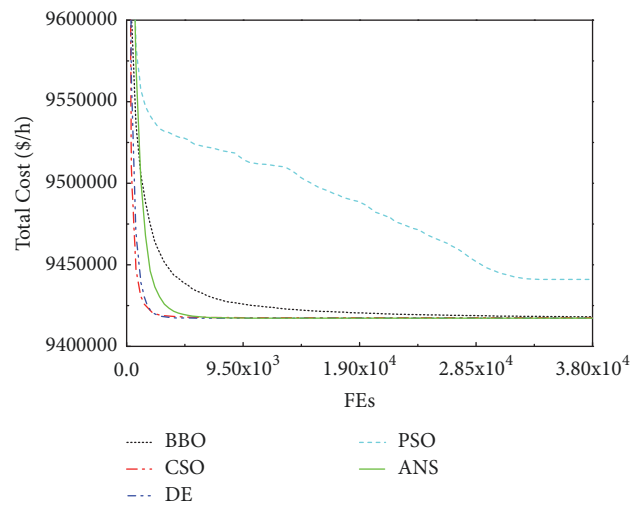

Figure 4: Convergence curves for the 38-generator system (Case III).

ANS is the most robust method among the five methods. In addition, the convergence curves in Figure 8 show that CSO converges the fastest in the early phase, followed by DE, ANS, PSO, and BBO. However, both CSO and DE stagnate quickly and are surpassed by ANS after about 7500 FEs. BBO and PSO are very slow during the whole evolutionary process. ANS is able to converge to the optimal solution.

In order to learn the operation performance of each generator, the detailed load rate and coal consumption values are presented in Figure 9. It is worth noting that the 150MW generators (#1~#2) are combined heat and power (CHP) generators whose peak regulation depth must not exceed 30%; namely, the adjusting range is from 70% to 100% of the rated capacity. For the other generators, their peak regulation depths are all 50%. It can be seen from Figure 9 that the operation performance indicators of different generators vary from one to another. The mean values of load rate and coal consumption of various capacity generators are summarized in Table 12. It is obvious that, except the 150MW generator, the larger the rated capacity of the generator, the higher the load rate, and the lower the coal consumption. For the 150MW generator, the load rate equals the allowed minimum

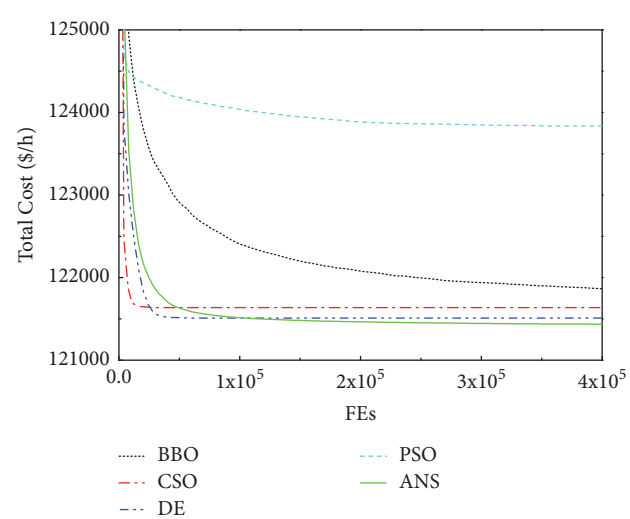

Figure 5: Convergence curves for the 40-generator system (Case IV).

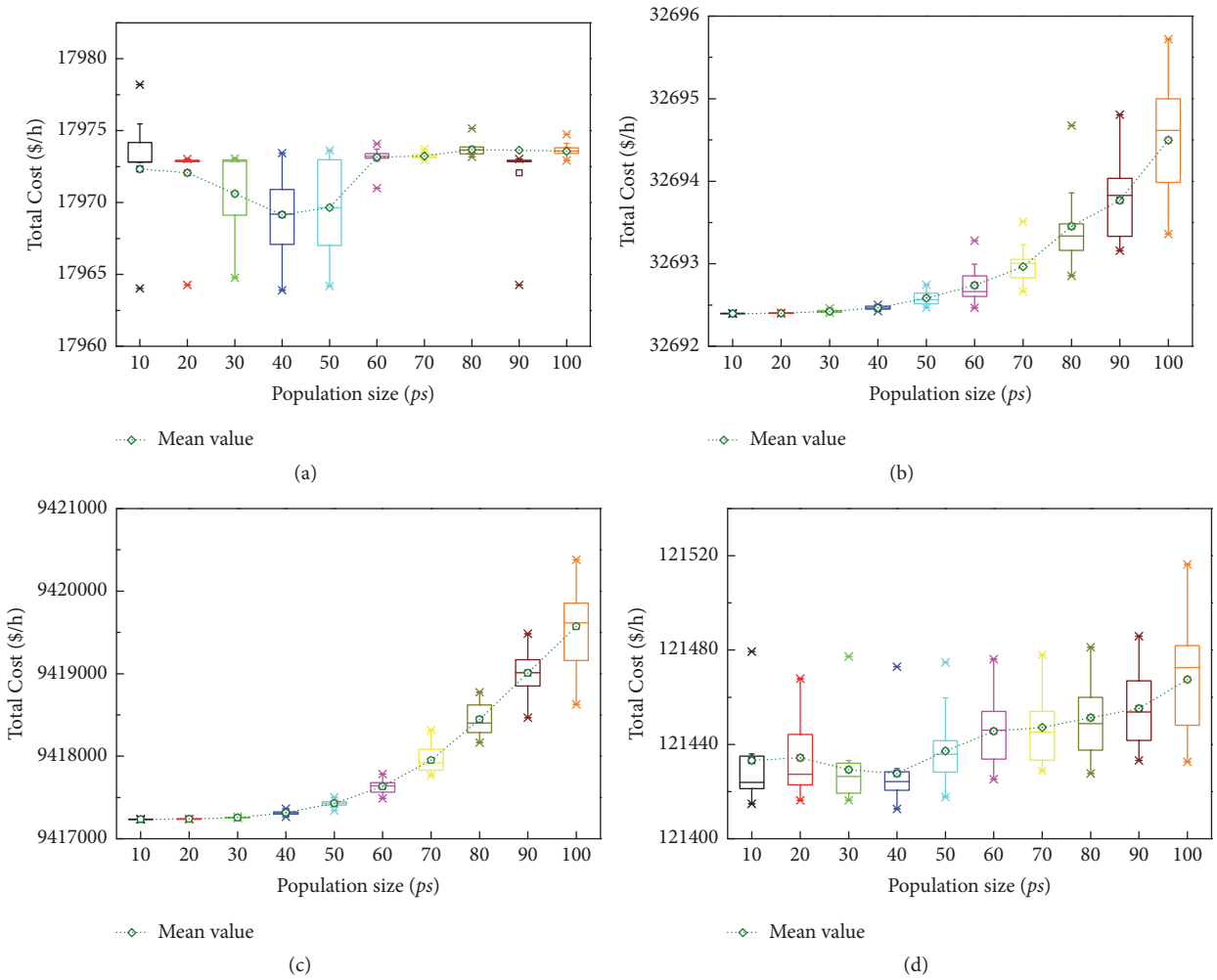

Figure 6: Influence of population size. (a) Case I. (b) Case II. (c) Case III. (d) Case IV.

limit, meaning that its operation performance is poor. In addition, although its load rate is greater than those of the 300MW and 600MW generators, its coal consumption is significantly higher, which indicates that its energy conservation is inefficient. The abovementioned results fully reflect the necessity and importance of the power construction policy of "replacing small power plants with large ones" in China.

7. Conclusions and Future Work

In this paper, a simple yet very young and efficient population-based algorithm named across neighborhood search (ANS) is applied to ED problems. Four benchmark test cases with diverse complexities and characteristics are firstly employed to comprehensively verify the feasibility and effectiveness of ANS. The experimental results demonstrate that ANS is able to effectively coordinate the local exploitation and global exploration. It significantly outperforms four popular population-based algorithms (BBO, DE, CSO, and PSO) in terms of the final solution quality, convergence speed, robustness, and statistics. ANS is also capable of achieving better or competitive results compared with some recently proposed ED solution methods. In addition, the sensitivities of ANS to variations of population size and across-search degree are investigated. The experimental results indicate that a small population size is recommended for the traditional ED problems, whereas a moderate population size is relatively safe for the nonconvex ED problems with valve-point effects. For both convex and nonconvex ED problems, the across-search degree with value 1 is appropriate. In addition to the benchmark test cases, ANS is further applied to a practical provincial power grid of China. The experimental results strongly verify ANS once again and fully reflect the necessity and importance of the power construction policy of "replacing small power plants with large ones" in China. In conclusion, ANS can be used as an efficient and reliable alternative for the ED problems.

ANS is a young and promising population-based algorithm. In future work, we will employ some advanced learning strategies such as orthogonal learning and oppositional learning to further enhance its performance and then apply it to solve other power system optimization problems such as combined economic and emission dispatch and optimal power flow.

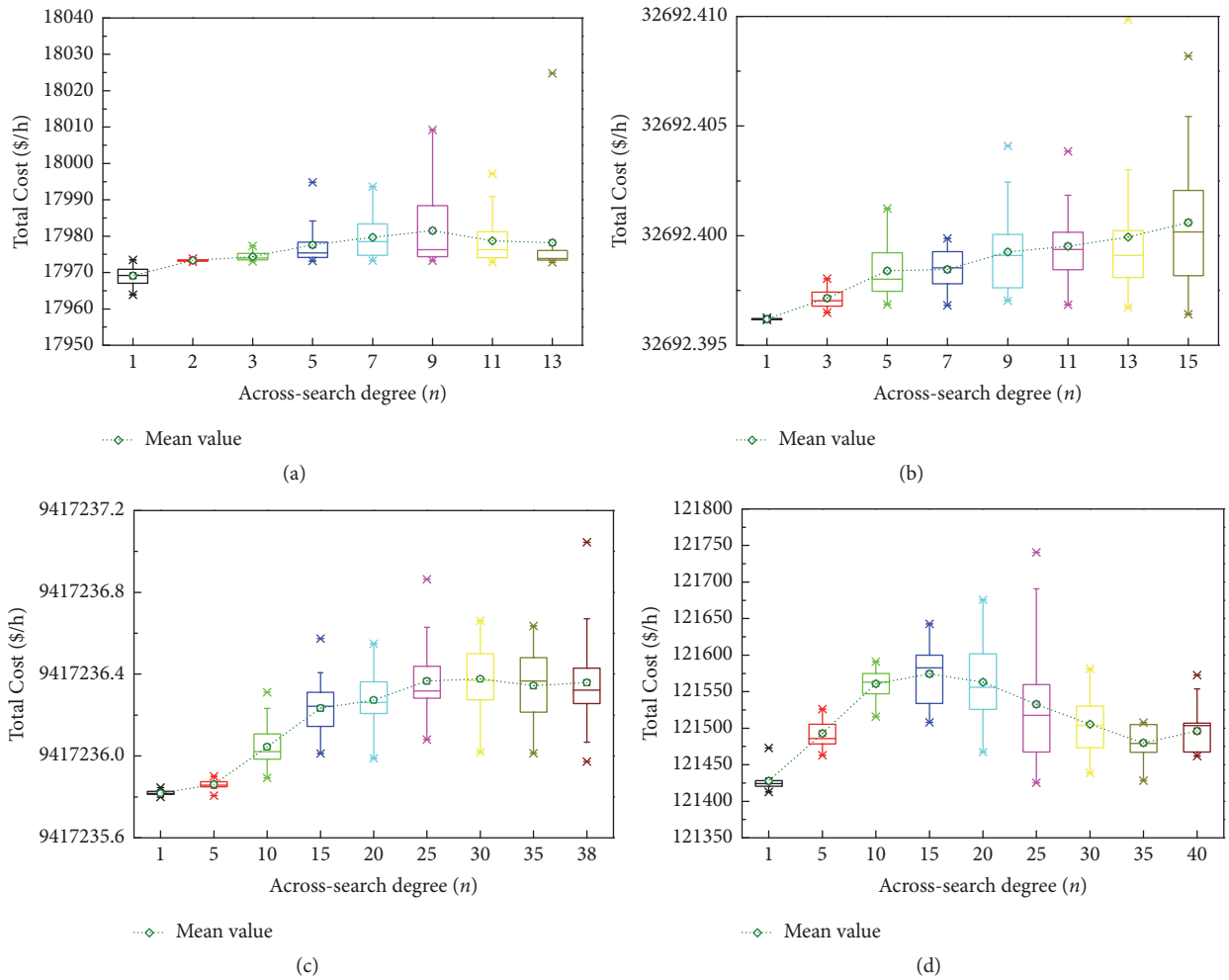

Figure 7: Influence of across-search degree. (a) Case I. (b) Case II. (c) Case III. (d) Case IV.

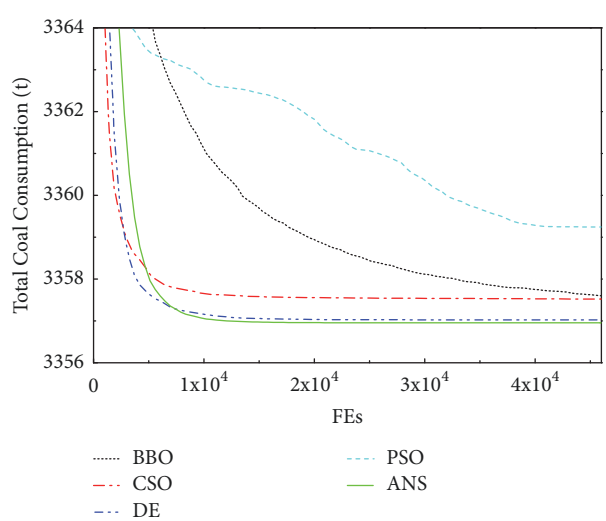

Figure 8: Convergence curves for the practical provincial power grid of China.

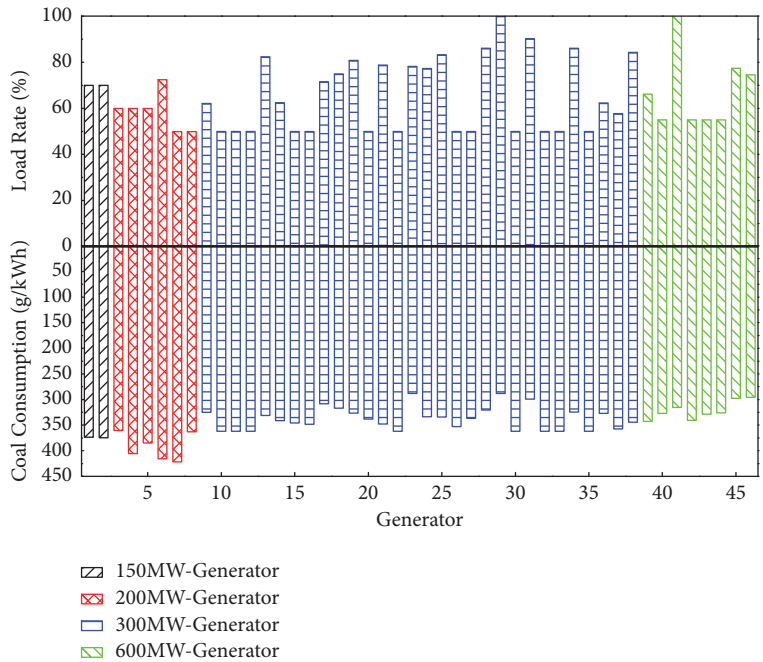

Figure 9: Operation performance of all generators.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] J. Cai, Q. Li, L. Li, H. Peng, and Y. Yang, "A hybrid FCASO-SQP method for solving the economic dispatch problems with valve-point effects," *Energy*, vol. 38, no. 1, pp. 346–353, 2012.

[2] J.-B. Park, Y.-W. Jeong, J.-R. Shin, and K. Y. Lee, "An improved particle swarm optimization for nonconvex economic dispatch problems," *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 156–166, 2010.

[3] I. Ziane, F. Benhamida, and A. Graa, "Simulated annealing algorithm for combined economic and emission power dispatch using max/max price penalty factor," *Neural Computing and Applications*, vol. 28, no. 1, pp. 197–205, 2017.

[4] P. Subbaraj, R. Rengaraj, and S. Salivahanan, "Enhancement of Self-adaptive real-coded genetic algorithm using Taguchi method for Economic dispatch problem," *Applied Soft Computing*, vol. 11, no. 1, pp. 83–92, 2011.

[5] H. Yang, J. Yi, J. Zhao, and Z. Dong, "Extreme learning machine based genetic algorithm and its application in power system economic dispatch," *Neurocomputing*, vol. 102, pp. 154–162, 2013.

[6] K. T. Chaturvedi, M. Pandit, and L. Srivastava, "Particle swarm optimization with time varying acceleration coefficients for non-convex economic power dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 31, no. 6, pp. 249–257, 2009.

[7] Y.-Z. Hsieh and M.-C. Su, "A Q-learning-based swarm optimization algorithm for economic dispatch problem," *Neural Computing and Applications*, vol. 27, no. 8, pp. 2333–2350, 2016.

[8] M. Neyestani, M. M. Farsangi, and H. Nezamabadi-Pour, "A modified particle swarm optimization for economic dispatch with non-smooth cost functions," *Engineering Applications of Artificial Intelligence*, vol. 23, no. 7, pp. 1121–1126, 2010.

[9] M. Basu, "Improved differential evolution for economic dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 63, pp. 855–861, 2014.

[10] N. Noman and H. Iba, "Differential evolution for economic load dispatch problems," *Electric Power Systems Research*, vol. 78, no. 8, pp. 1322–1331, 2008.

[11] S. Hemamalini and S. P. Simon, "Artificial bee colony algorithm for economic load dispatch problem with non-smooth cost functions," *Electric Power Components and Systems*, vol. 38, no. 7, pp. 786–803, 2010.

[12] S. Özyön and D. Aydin, "Incremental artificial bee colony with local search to economic dispatch problem with ramp rate limits and prohibited operating zones," *Energy Conversion and Management*, vol. 65, pp. 397–407, 2013.

[13] Z. Cui, Z. Shi, J. Abonyi et al., "Economic load dispatch using population-variance harmony search algorithm," *Transactions of the Institute of Measurement and Control*, vol. 34, no. 6, pp. 746–754, 2012.

[14] V. P. Ravikumar, B. K. Panigrahi, A. Mohapatra, and M. K. Mallick, "Economic load dispatch solution by improved harmony search with wavelet mutation," *International Journal of Computational Sciences and Engineering*, vol. 6, no. 1-2, pp. 122–131, 2011.

[15] M. Fesanghary and M. M. Ardehali, "A novel meta-heuristic optimization methodology for solving various types of economic dispatch problem," *Energy*, vol. 34, no. 6, pp. 757–766, 2009.

[16] M. A. Al-Betar, M. A. Awadallah, A. T. Khader, and A. L. Bolaji, "Tournament-based harmony search algorithm for non-convex economic load dispatch problem," *Applied Soft Computing*, vol. 47, pp. 449–459, 2016.

[17] M. A. Al-Betar, M. A. Awadallah, A. T. Khader, A. L. Bolaji, and A. Almomani, "Economic load dispatch problems with valve-point loading using natural updated harmony search," *Neural Computing and Applications*, vol. 29, no. 10, pp. 767–781, 2018.

[18] G. Xiong, D. Shi, and X. Duan, "Multi-strategy ensemble biogeography-based optimization for economic dispatch problems," *Applied Energy*, vol. 111, pp. 801–811, 2013.

[19] A. Bhattacharya and P. K. Chattopadhyay, "Biogeography-based optimization for different economic load dispatch problems," *IEEE Transactions on Power Systems*, vol. 25, no. 2, pp. 1064–1077, 2010.

[20] M. R. Lohokare, B. K. Panigrahi, S. S. Pattnaik, S. Devi, and A. Mohapatra, "Neighborhood search-driven accelerated biogeography-based optimization for optimal load dispatch," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 42, no. 5, pp. 641–652, 2012.

[21] G. Xiong, Y. Li, J. Chen, D. Shi, and X. Duan, "Polyphyletic migration operator and orthogonal learning aided biogeography-based optimization for dynamic economic dispatch with valve-point effects," *Energy Conversion and Management*, vol. 80, pp. 457–468, 2014.

[22] S. Kanoongo and P. Jain, "Biogeography based optimization for different economic load dispatch problem with different migration models," in *Proceedings of the IEEE Students' Conference on Electrical, Electronics and Computer Science: Innovation for Humanity (SCEECS '12)*, pp. 1–4, March 2012.

[23] M. Basu, "Teaching-learning-based optimization algorithm for multi-area economic dispatch," *Energy*, vol. 68, pp. 21–28, 2014.

[24] T. T. Nguyen and D. N. Vo, "The application of one rank cuckoo search algorithm for solving economic load dispatch problems," *Applied Soft Computing*, vol. 37, pp. 763–773, 2015.

[25] X. He, Y. Rao, and J. Huang, "A novel algorithm for economic load dispatch of power systems," *Neurocomputing*, vol. 171, pp. 1454–1461, 2016.

[26] X.-S. Yang, S. S. S. Hosseini, and A. H. Gandomi, "Firefly algorithm for solving non-convex economic dispatch problems with valve loading effect," *Applied Soft Computing*, vol. 12, no. 3, pp. 1180–1186, 2012.

[27] A. Meng, J. Li, and H. Yin, "An efficient crisscross optimization solution to large-scale non-convex economic load dispatch with multiple fuel types and valve-point effects," *Energy*, vol. 113, pp. 1147–1161, 2016.

[28] A. Meng, H. Hu, H. Yin, X. Peng, and Z. Guo, "Crisscross optimization algorithm for large-scale dynamic economic dispatch problem with valve-point effects," *Energy*, vol. 93, pp. 2175–2190, 2015.

[29] B. R. Adarsh, T. Raghunathan, T. Jayabarathi, and X.-S. Yang, "Economic dispatch using chaotic bat algorithm," *Energy*, vol. 96, pp. 666–675, 2016.

[30] V. K. Kamboj, S. K. Bath, and J. S. Dhillon, "Solution of non-convex economic load dispatch problem using Grey Wolf Optimizer," *Neural Computing and Applications*, vol. 27, no. 5, pp. 1301–1316, 2016.

[31] T. Jayabarathi, T. Raghunathan, B. R. Adarsh, and P. N. Suganthan, "Economic dispatch using hybrid grey wolf optimizer," *Energy*, vol. 111, pp. 630–641, 2016.

[32] E. Afzalan and M. Joorabian, "An improved cuckoo search algorithm for power economic load dispatch," *International Transactions on Electrical Energy Systems*, vol. 25, no. 6, pp. 958–975, 2015.

[33] M. A. Mellal and E. J. Williams, "Cuckoo optimization algorithm with penalty function for combined heat and power economic dispatch problem," *Energy*, vol. 93, pp. 1711–1718, 2015.

[34] T. T. Nguyen, T. T. Nguyen, and D. N. Vo, "An effective cuckoo search algorithm for large-scale combined heat and power economic dispatch problem," *Neural Computing and Applications*, pp. 1–20, 2017.

[35] V. K. Kamboj, A. Bhadoria, and S. K. Bath, "Solution of non-convex economic load dispatch problem for small-scale power systems using ant lion optimizer," *Neural Computing and Applications*, vol. 28, no. 8, pp. 2181–2192, 2017.

[36] N. Ghorbani and E. Babaei, "Exchange market algorithm for economic load dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 75, pp. 19–27, 2016.

[37] M. Kenan Dosoglu, U. Guvenc, S. Duman, Y. Sonmez, and H. Tolga Kahraman, "Symbiotic organisms search optimization algorithm for economic/emission dispatch problem in power systems," *Neural Computing and Applications*, vol. 29, no. 3, pp. 721–737, 2018.

[38] S. Duman, "Symbiotic organisms search algorithm for optimal power flow problem based on valve-point effect and prohibited zones," *Neural Computing and Applications*, vol. 28, no. 11, pp. 3571–3585, 2017.

[39] M. Modiri-Delshad, S. H. Aghay Kaboli, E. Taslimi-Renani, and N. A. Rahim, "Backtracking search algorithm for solving economic dispatch problems with valve-point effects and multiple fuel options," *Energy*, vol. 116, pp. 637–649, 2016.

[40] M. Modiri-Delshad and N. A. Rahim, "Solving non-convex economic dispatch problem via backtracking search algorithm," *Energy*, vol. 77, pp. 372–381, 2014.

[41] I. N. Trivedi, P. Jangir, M. Bhoye, and N. Jangir, "An economic load dispatch and multiple environmental dispatch problem solution with microgrids using interior search algorithm," *Neural Computing and Applications*, pp. 1–17, 2016.

[42] M. Nazari-Heris, M. Mehdinejad, B. Mohammadi-Ivatloo, and G. Babamalek-Gharehpetian, "Combined heat and power economic dispatch problem solution by implementation of whale optimization method," *Neural Computing and Applications*, pp. 1–16, 2017.

[43] E. S. Ali and S. M. Abd Elazim, "Mine blast algorithm for environmental economic load dispatch with valve loading effect," *Neural Computing and Applications*, pp. 1–10, 2016.

[44] J. S. Alsumait, J. K. Sykulski, and A. K. Al-Othman, "A hybrid GA-PS-SQP method to solve power system valve-point economic dispatch problems," *Applied Energy*, vol. 87, no. 5, pp. 1773–1781, 2010.

[45] Z.-U. Chouhdry, K. M. Hasan, and M. A. Z. Raja, "Design of reduced search space strategy based on integration of Nelder–Mead method and pattern search algorithm with application to economic load dispatch problem," *Neural Computing and Applications*, pp. 1–13, 2017.

[46] I. Ciornei and E. Kyriakides, "A GA-API solution for the economic dispatch of generation in power system operation," *IEEE Transactions on Power Systems*, vol. 27, no. 1, pp. 233–242, 2012.

[47] S. Khamsawang and S. Jiriwibhakorn, "DSPSO-TSA for economic dispatch problem with nonsmooth and noncontinuous cost functions," *Energy Conversion and Management*, vol. 51, no. 2, pp. 365–375, 2010.

[48] R. Kumar, D. Sharma, and A. Sadu, "A hybrid multi-agent based particle swarm optimization algorithm for economic power dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 33, no. 1, pp. 115–123, 2011.

[49] T. Niknam, "A new fuzzy adaptive hybrid particle swarm optimization algorithm for non-linear, non-smooth and non-convex economic dispatch problem," *Applied Energy*, vol. 87, no. 1, pp. 327–339, 2010.

[50] V. R. Pandi, B. K. Panigrahi, R. C. Bansal, S. Das, and A. Mohapatra, "Economic load dispatch using hybrid swarm intelligence based harmony search algorithm," *Electric Power Components and Systems*, vol. 39, no. 8, pp. 751–767, 2011.

[51] B. K. Panigrahi and V. Ravikumar Pandi, "Bacterial foraging optimisation: Nelder-Mead hybrid algorithm for economic load dispatch," *IET Generation, Transmission & Distribution*, vol. 2, no. 4, pp. 556–565, 2008.

[52] M. A. Z. Raja, U. Ahmed, A. Zameer, A. K. Kiani, and N. I. Chaudhary, "Bio-inspired heuristics hybrid with sequential quadratic programming and interior-point methods for reliable treatment of economic load dispatch problem," *Neural Computing and Applications*, pp. 1–29, 2017.

[53] A. Rajagopalan, V. Sengoden, and R. Govindasamy, "Solving economic load dispatch problems using chaotic self-adaptive differential harmony search algorithm," *International Transactions on Electrical Energy Systems*, vol. 25, no. 5, pp. 845–858, 2015.

[54] M. S. P. Subathra, S. E. Selvan, T. A. A. Victoire, A. H. Christinal, and U. Amato, "A hybrid with cross-entropy method and sequential quadratic programming to solve economic load dispatch problem," *IEEE Systems Journal*, vol. 9, no. 3, pp. 1031–1044, 2015.

[55] H. Yang, Y. Zhang, S. Wang et al., "Stochastic optimal dispatch of power system considering the correlation of multiple wind farm outputs," *Electric Power Components and Systems*, vol. 44, no. 6, pp. 616–627, 2016.

[56] G. Xiong and D. Shi, "Hybrid biogeography-based optimization with brain storm optimization for non-convex dynamic economic dispatch with valve-point effects," *Energy*, vol. 157, pp. 424–435, 2018.

[57] D. H. Wolpert and W. G. Macready, "No free lunch theorems for optimization," *IEEE Transactions on Evolutionary Computation*, vol. 1, no. 1, pp. 67–82, 1997.

[58] G. Wu, "Across neighborhood search for numerical optimization," *Information Sciences*, vol. 329, pp. 597–618, 2016.

[59] G. Xiong and D. Shi, "Orthogonal learning competitive swarm optimizer for economic dispatch problems," *Applied Soft Computing*, vol. 66, pp. 134–148, 2018.

[60] E. S. Fraga, L. Yang, and L. G. Papageorgiou, "On the modelling of valve point loadings for power electricity dispatch," *Applied Energy*, vol. 91, no. 1, pp. 301–303, 2012.

[61] A. P. Piotrowski, "Across neighborhood search algorithm: a comprehensive analysis," *Information Sciences*, vol. 435, pp. 334–381, 2018.

[62] N. Sinha, R. Chakrabarti, and P. K. Chattopadhyay, "Evolutionary programming techniques for economic load dispatch," *IEEE Transactions on Evolutionary Computation*, vol. 7, no. 1, pp. 83–94, 2003.

[63] Z. Gaing, "Particle swarm optimization to solving the economic dispatch considering the generator constraints," *IEEE Transactions on Power Systems*, vol. 18, no. 3, pp. 1187–1195, 2003.

[64] D. Simon, "Biogeography-based optimization," *IEEE Transactions on Evolutionary Computation*, vol. 12, no. 6, pp. 702–713, 2008.

[65] R. Cheng and Y. Jin, "A competitive swarm optimizer for large scale optimization," *IEEE Transactions on Cybernetics*, vol. 45, no. 2, pp. 191–204, 2015.

[66] R. Storn and K. Price, "Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces," *Journal of Global Optimization*, vol. 11, no. 4, pp. 341–359, 1997.

[67] Y. H. Shi and R. C. Eberhart, "A modified particle swarm optimizer," in *Proceedings of the IEEE International Conference on Evolutionary Computation (ICEC '98)*, pp. 69–73, Anchorage, AL, USA, May 1998.

[68] G. Wu, L. Zhang, M. He, Y. Yu, H. Chen, and R. Wang, "An across neighborhood search algorithm with a solution difference perturbation mechanism for solving economic dispatch problems," in *Proceedings of the Tenth International Conference on Advanced Computational Intelligence (ICACI '18)*, pp. 122–127, March 2018.

[69] R. Vijay, "Intelligent bacterial foraging optimization technique to economic load dispatch problem," *International Journal of Soft Computing and Engineering*, vol. 2, no. 2, pp. 2231–2307, 2012.

[70] Y. Labbi, D. B. Attous, H. A. Gabbar, B. Mahdad, and A. Zidan, "A new rooted tree optimization algorithm for economic dispatch with valve-point effect," *International Journal of Electrical Power & Energy Systems*, vol. 79, pp. 298–311, 2016.

[71] T. Niknam, B. B. Firouzi, and H. D. Mojarrad, "A new evolutionary algorithm for non-linear economic dispatch," *Expert Systems with Applications*, vol. 38, no. 10, pp. 13301–13309, 2011.

[72] A. K. Barisal and R. C. Prusty, "Large scale economic dispatch of power systems using oppositional invasive weed optimization," *Applied Soft Computing*, vol. 29, pp. 122–137, 2015.

[73] V. S. Aragón, S. C. Esquivel, and C. C. Coello, "An immune algorithm with power redistribution for solving economic dispatch problems," *Information Sciences*, vol. 295, pp. 609–632, 2015.

[74] M.-T. Tsai, H.-J. Gow, and W.-M. Lin, "A novel stochastic search method for the solution of economic dispatch problems with non-convex fuel cost functions," *International Journal of Electrical Power & Energy Systems*, vol. 33, no. 4, pp. 1070–1076, 2011.

[75] D. C. Secui, "A modified Symbiotic Organisms Search algorithm for large scale economic dispatch problem with valve-point effects," *Energy*, vol. 113, pp. 366–384, 2016.

[76] T. Prakash, V. P. Singh, S. P. Singh, and S. R. Mohanty, "Economic load dispatch problem: quasi-oppositional self-learning TLBO algorithm," *Energy Studies Review*, vol. 9, no. 2, pp. 415–438, 2018.

[77] B. K. Panigrahi, S. R. Yadav, S. Agrawal, and M. K. Tiwari, "A clonal algorithm to solve economic load dispatch," *Electric Power Systems Research*, vol. 77, no. 10, pp. 1381–1389, 2007.

[78] T. H. Khoa, P. M. Vasant, M. S. B. Singh, and V. N. Dieu, "Swarm based mean-variance mapping optimization for convex and non-convex economic dispatch problems," *Memetic Computing*, vol. 9, no. 2, pp. 91–108, 2017.

[79] Y. Wu, G. Liu, X. Guo, Y. Shi, and L. Xie, "A self-adaptive chaos and Kalman filter-based particle swarm optimization for economic dispatch problem," *Soft Computing*, vol. 21, no. 12, pp. 3353–3365, 2017.

[80] M. I. Alomoush and Z. B. Oweis, "Environmental-economic dispatch using stochastic fractal search algorithm," *International Transactions on Electrical Energy Systems*, vol. 28, 2018.

[81] A. Bhattacharya and P. K. Chattopadhyay, "Hybrid differential evolution with biogeography-based optimization for solution of economic load dispatch," *IEEE Transactions on Power Systems*, vol. 25, no. 4, pp. 1955–1964, 2010.

[82] D. Zou, S. Li, Z. Li, and X. Kong, "A new global particle swarm optimization for the economic emission dispatch with or without transmission losses," *Energy Conversion and Management*, vol. 139, pp. 45–70, 2017.

[83] J. X. V. Neto, G. Reynoso-Meza, T. H. Ruppel, V. C. Mariani, and L. D. S. Coelho, "Solving non-smooth economic dispatch by a new combination of continuous GRASP algorithm and differential evolution," *International Journal of Electrical Power & Energy Systems*, vol. 84, pp. 13–24, 2017.