개선된 PSO 기법을 적용한 전력계통의 경제급전

論 文
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An Improved Particle Swarm Optimization Adopting Chaotic Sequences for Nonconvex Economic Dispatch Problems

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Abstract - This paper presents a new and efficient approach for solving the economic dispatch (ED) problems with nonconvex cost functions using particle swarm optimization (PSO). Although the PSO is easy to implement and has been empirically shown to perform well on many optimization problems, it may easily get trapped in a local optimum when solving problems with multiple local optima and heavily constrained. This paper proposes an improved PSO, which combines the conventional PSO with chaotic sequences (CPSO). The chaotic sequences combined with the linearly decreasing inertia weights in PSO are devised to improve the global searching capability and escaping from local minimum. To verify the feasibility of the proposed method, numerical studies have been performed for two different nonconvex ED test systems and its results are compared with those of previous works. The proposed CPSO algorithm outperforms other state-of-the-art algorithms in solving ED problems, which consider valve-point and multi-fuels with valve-point effects.

Key Words : Nonconvex economic dispatch problem, Improved particle swarm optimization, Crossover operation

1. INTRODUCTION

Most of power system optimization problems including economic dispatch (ED) have complex and nonlinear characteristics with heavy equality and inequality constraints [1]. The primary objective of the ED problem is to determine the optimal combination of power outputs of all generating units so as to meet the required demand at minimum cost while satisfying the equality and inequality constraints. Conventionally, the cost function for each unit in ED problem has been approximately represented by a single quadratic function and is solved using mathematical programming techniques [2]. Generally, these mathematical methods require marginal cost information to find the global optimal solution. Unfortunately, the input-output characteristics of generating units are highly nonlinear because of prohibited operating zones, valve-point loadings, and multi-fuel effects, etc. Thus, the practical ED problem is represented as a nonconvex optimization problem with equality and inequality constraints, which directly cannot be solved by the traditional mathematical methods. Dynamic programming method [3] can solve such types of problems, but it suffers from the curse of dimensionality. Over the past few decades, in order to solve these problems, many salient methods have been developed such as hierarchical numerical method [4], genetic algorithm [5]-[7], evolutionary programming [8]-[10], Tabu search [11], neural network approaches [12], [13], differential evolution [14], and particle swarm optimization [15]-[17].

Particle swarm optimization (PSO) is one of the modern heuristic algorithms, which can be efficiently used to solve nonlinear and non-continuous optimization problems. The original PSO suggested by Kennedy and Eberhart in 1995 is based on the analogy of swarm of bird and school of fish. In PSO, each particle makes his decision using his own experience together with his neighbor's experiences. The particles are drawn stochastically toward the new position based on the present velocity of each particle, their own previous best performance, and the best previous performance of their neighbors [18], [19].

Chaos, apparently disordered behavior that is nonetheless deterministic, is a universal phenomenon that occurs in many areas of science [20]. Coelho and Mariani [14] combined the chaotic sequences with the mutation factor in differential evolution. Caponetto *et al.*[21] applied various chaotic sequences in evolutionary algorithms

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(EAs) in lieu of the random numbers and Shengsong *et al.* [22] adopted a chaotic hybrid algorithm to solve the optimal power flow problems. The application of the chaotic sequences showed the promising results in each engineering application.

In this paper, the application of PSO with chaotic sequences (CPSO) is proposed for solving the ED problems with various nonconvex cost functions. The PSO with chaotic sequences as dynamic inertia weights can be successfully used as is the global optimizer by enhancing the global exploration capacity. The suggested chaotic dynamic inertial weights combine the linearly decreasing inertial weights [23], [24] and logistic map chaotic sequences [21] to employ the benefits of both approaches. The employment of the chaotic sequences in PSO is a useful strategy to improve the global searching capability by preventing the premature convergence to local minima.

This paper is organized as follows. After this introduction, Section 2 describes the mathematical formulations of ED problems. Section 3 describes the application of chaotic sequences in PSO while Section 4 details the implementation of the proposed CPSO for solving ED problems. In order to verify the performance of the proposed CPSO, two ED problems with nonconvex cost functions are tested and its results are compared with those of previous works in Section 5. Finally, the conclusion drawn from the study is described in Section 6.

2. FORMULATIONS OF ED PROBLEMS

2.1 Basic Economic Dispatch Formulation

The objective of the ED problem is to minimize the total fuel cost of power plants subjected to the operating constraints of a power system. Generally, it can be formulated with an objective function and two constraints [2]:

$$F_T = \sum_{i=1}^{n} F_i(P_i) \tag{1}$$

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

where,

- F_T total generation cost,
- F_i cost function of generator i,
- a_i, b_i, c_i cost coefficients of generator i,
- P_i power output of generator i,
- n number of generators.

2.1.1 Active Power Balance Equation

For power balance, an equality constraint should be satisfied. The total generated power should be the same as the total load demand plus the total line loss. However, the transmission loss is not considered in this paper for simplicity.

2.1.2 Minimum and Maximum Power Limits

Generation output of each generator should be laid between minimum and maximum limits. The corresponding inequality constraints for each generator are

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{3}$$

where $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum output of generator i, respectively.

2.2 ED Problem Considering Valve-Point Effects

The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions. Since the valve point results in the ripples, a cost function contains higher order nonlinearity. Therefore, the cost function (2) should be replaced by the following to consider the valve-point effects:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + |e_i \sin(f_i (P_{i,\min} - P_i))| \tag{4}$$

where e_i and f_i are the cost coefficients of generator i reflecting valve-point effects.

2.3 ED Problem Considering Multi-Fuels with Valve-Point Effects

Since the dispatching units can be supplied with multi-fuel sources in practice, each unit should be represented with several piecewise quadratic functions reflecting the effects of fuel type changes. In general, a piecewise quadratic function is used to represent the input-output curve of a generator with multiple fuels [4] and described as

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1} P_i + c_{i2} P_i^2 & \text{fuel 1} \quad P_{i,\min} \le P_i \le P_{i1} \\ a_{i2} + b_{i2} P_i + c_{i2} P_i^2 & \text{fuel 2} \quad P_{i1} \le P_i \le P_{i2} \\ \vdots & \qquad\qquad \vdots \\ a_{ik} + b_{ik} P_i + c_{ik} P_i^2 & \text{fuel } k \quad P_{ik-1} \le P_i \le P_{i,\max} \end{cases} \tag{5}$$

where a_{ik}, b_{ik}, c_{ik} are the cost coefficients of generator i for fuel type k. In general, fuels are supplied by fuel suppliers under a multitude of contracts between the suppliers and the utility. Determining the selection of fuels for each unit is dictated by the contracts, and can be solved by economic fuel dispatch [25]. This paper assumes that such selection is given a-priori. Therefore, to obtain an accurate and practical ED solution, the fuel cost function should be considered with both multi-fuels and valve-point effects simultaneously [7]. Thus, the fuel cost function (4) should be combined with (5), and can be represented as follows:

$$F_i(P_i) = \begin{cases} F_{i1}(P_i) & \text{fuel 1} \quad P_{i,\min} \le P_i \le P_{i1} \\ F_{i2}(P_i) & \text{fuel 2} \quad P_{i1} \le P_i \le P_{i2} \\ \vdots & \qquad\qquad \vdots \\ F_{ik}(P_i) & \text{fuel } k \quad P_{ik-1} \le P_i \le P_{i,\max} \end{cases} \tag{6}$$

where

$$F_{ik}(P_i) = a_{ik} + b_{ik} P_i + c_{ik} P_i^2 + |e_{ik} \sin(f_{ik} (P_{ik,\min} - P_i))| \tag{7}$$

and e_{ik} and f_{ik} are the cost coefficients of generator i

reflecting valve-point effects for fuel type k, and $P_{ik,\min}$ is the minimum output of generator i using fuel type k.

3. PARTICLE SWARM OPTIMIZATION WITH CHAOTIC SEQUENCES

3.1 Overview of Particle Swarm Optimization

Kennedy and Eberhart developed a PSO algorithm based on the behavior of individuals (i.e., particles or agents) of a swarm [18]. Its roots are in zoologist's modeling of the movement of individuals within a group. It has been noticed that members of the group seem to share information among them, a fact that leads to increased efficiency of the group [19]. The PSO algorithm searches in parallel using a group of particles. Each particle corresponds to a candidate solution to the problem. Particles in a swarm approach to the optimum through its present velocity, its previous experience, and the experience of its neighbors. In a n-dimensional search space, the position and velocity of particle i are represented as the vectors $X_i = (x_{i1}, \cdots, x_{in})$ and $V_i = (v_{i1}, \cdots, v_{in})$ in the PSO algorithm. Let $Pbest_i = (x_{i1}^{Pbest}, \cdots, x_{in}^{Pbest})$ and $Gbest = (x_1^{Gbest}, \cdots, x_n^{Gbest})$ be the best position of particle i and its neighbors' best position so far, respectively. The modified velocity and position of each particle can be calculated using the current velocity and the distance from $Pbest_i$ to $Gbest$ as follows:

$$V_i^{k+1} = w\,V_i^k + c_1\,rn_1\left(Pbest_i^k - X_i^k\right) + c_2\,rn_2\left(Gbest^k - X_i^k\right) \quad (8)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (9)$$

where,

V_i^k	velocity of particle i at iteration k,
w	inertia weight factor,
c_1, c_2	acceleration coefficients,
rn_1, rn_2	random numbers between 0 and 1,
X_i^k	position of particle i at iteration k,
$Pbest_i^k$	best position of particle i until iteration k,
$Gbest^k$	best position of the group until iteration k.

In velocity updating process, the values of parameters such as w, c_1, and c_2 should be determined in advance. The constants c_1 and c_2 represent the weighting of the stochastic acceleration terms that pull each particle toward the $Pbest_i$ and $Gbest$ positions. Suitable selection of inertia weight provides a balance between global exploration and local exploitation, and results in less iteration on average to find an optimal solution. In general, the inertia weight w has a linearly decreasing dynamic parameter framework (i.e., Inertial Weights Approach [IWA] [1], [23], [24]) descending from $w_{\max}$ to $w_{\min}$ to enhance the convergence characteristics as follows.

$$w^k = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times k \quad (10)$$

Here, $iter_{\max}$ corresponds to the maximum iteration number and k is the current iteration number.

3.2 Application of Chaotic Sequences in PSO

One of the simplest dynamic systems evidencing chaotic behavior is the iterator called the logistic map [21], whose equation is described as follows:

$$f_k = \mu \times f_{k-1} \times (1 - f_{k-1}) \quad (11)$$

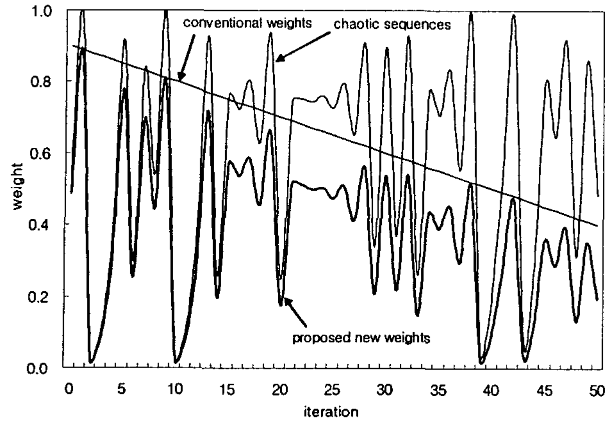
where μ is a control parameter and has a real value between [0,4]. Despite the apparent simplicity of the equation, the solution exhibits a rich variety of behaviors. The behavior of the system represented by (11) is greatly changed with the variation of μ. The value of μ determines whether f is stabilized at a constant size, oscillates between a limited sequence of sizes, or behaves chaotically in an unpredictable pattern. And also the behavior of the system is sensitive to the initial value of f [14], [21], [22]. Equation (11) is deterministic, displaying chaotic dynamics when μ=4.0 and $f_0 \not\in \{0, 0.25, 0.50, 0.75, 1\}$.

The performance of PSO greatly depends on its parameters such as inertia weight factor and two acceleration coefficients. It is clear that the first part of (8) represents the influence of previous velocity, which provides the necessary momentum for particles to fly around in a search space. The inertia weight factor is a modulus that manipulates the impact of previous velocity on the current one. Consequently, the balance between exploration and exploitation is treated by the value of inertia weight. Thus, the proper control of inertia weight is very important to find the optimum solution efficiently. It is regarded that a larger inertia weight facilitates a global search while a smaller inertia weight facilitates a local search. Shi and Eberhart [23], [24] made a significant improvement in the performance of the PSO with a linearly varying inertia weights over the iterations, which linearly decrease from 0.9 at the beginning of the run to 0.4 at the end.

In this paper, in order to improve the global searching capability and escape from local minima, the new weight approach, Chaotic Inertial Weights Approach (CIWA), is defined as follows:

$$w_{new}^k = w^k \times f_k \quad (12)$$

Whereas the weight in the conventional IWA decreases monotonously from $w_{\max}$ to $w_{\min}$, the proposed new weight decreases and oscillates simultaneously as shown in Fig. 1.



* $iter_{\max}$=50, $w_{\max}$=0.9, $w_{\min}$=0.4, μ=4.0, f_0=0.54

Fig. 1 Comparison of inertia weights for IWA and CIWA.

4. IMPLEMENTATION OF PROPOSED CPSO ALGORITHM FOR ED PROBLEMS

Since the decision variables in ED problems are real power outputs of generating units, the structure of a particle is composed of a set of elements corresponding to the generator outputs. Therefore, particle i's position at iteration k can be represented as the vector $X_i^k = (P_{i1}^k, \cdots, P_{in}^k)$ where n is the number of generators in the ED problem. The velocity of particle i (i.e., $V_i^k = (v_{i1}^k, \cdots, v_{in}^k)$) corresponds to the generation update quantity covering all generators.

4.1 Solution Procedure of CPSO

The process of the proposed CPSO algorithm can be summarized as follows:

Step 1) Initialize the position and velocity of a group at random while satisfying constraints.

Step 2) Update the velocity of particles.

Step 3) Modify the position of particles while satisfying constraints.

Step 4) Update *Pbest* and *Gbest*.

Step 5) Go to Step 2 until satisfying stopping criteria.

In the subsequent sections, the detailed implementation strategies of the proposed method are described.

4.1.1 Creating Initial Position and Velocity of Particles

In the initialization process, a set of particles is created at random as follows:

$$P_{ij}^{(0)} = P_{j,\min} + r_{ij} \times (P_{j,\max} - P_{j,\min}) \quad (13)$$

where r_{ij} is a random number between [0,1] for element j in particle i. Although the value of each element created by (13) satisfies the inequality constraint, the problem of equality constraint still remains to be resolved. To do this, the position initialization process should be used with the treatment technique for equality and inequality constraints.

After creating the initial position of each particle, the velocity of each particle is also created at random. The following strategy is used in creating the initial velocity:

$$(P_{j,\min} - \epsilon) - P_{ij}^0 \le v_{ij}^0 \le (P_{j,\max} + \epsilon) - P_{ij}^0 \quad (14)$$

where ϵ is a small positive real number. The velocity element j in particle i is generated at random within the boundary. The initial *Pbest* of particle i is set as the initial position of the particle and the initial *Gbest* is determined as the position of the particle with minimum cost of (1).

4.1.2 Velocity Update

To modify the position of each particle, it is necessary to calculate the velocity of each particle in the next stage which is obtained from (8). In this process, the new weight approach CIWA (12) is employed to improve the global searching capability.

4.1.3 Position Modification

The position of each particle is modified by (9). Since the resulting position of a particle is not always guaranteed to satisfy the equality and inequality constraints due to over/under velocity, the position modification procedure should be conducted with the treatment method of equality and inequality constraints.

4.1.4 Update of Pbest and Gbest

The *Pbest* of each particle at iteration k+1 is updated as follows:

$$Pbest_i^{k+1} = \begin{cases} X_i^{k+1} & \text{if } TC_i^{k+1} < TC_i^k \\ Pbest_i^k & \text{otherwise} \end{cases} \quad (15)$$

where TC_i is the value of the object function at the position of particle i. Also, *Gbest* at iteration k+1 is set as the best evaluated position among $Pbest_i^{k+1}$.

4.1.5 Stopping Criteria

The proposed CPSO is terminated if the iteration reaches a predefined maximum iteration.

4.2 Treatment of equality and inequality constraints

It is very important to create a group of particles satisfying the equality and inequality constraints. That is, summation of all elements of particle i (i.e., $\sum_{j=1}^{n} P_{ij}$) should be equal to the total system demand (i.e., P_D) and each element j in particle i (i.e., P_{ij}) should be within its upper and lower limits. Therefore, it is necessary to develop a strategy for satisfying the equality and inequality constraints. In [15], the heuristic-based technique was developed to handle the equality and inequality constraints where the strategy is also applied in this paper.

5. CASE STUDIES

To verify the feasibility of the proposed method, two different power systems were tested: (i) 40-unit system with valve-point effects and (ii) 10-unit system considering multiple fuels with valve-point effects. For each case, 100 independent trials are conducted to observe the variation during the evolutionary processes and compare the quality of solution and convergence characteristics. The results obtained from the CPSO are compared with those of previous works in order to show the superiority of the proposed method.

To successfully implement the CPSO, some parameters must be assigned in advance. The population size NP and maximum iteration count $iter_{\max}$ are set to 50 and 10,000, respectively. Since the performance of PSO depends on its parameters such as inertia weight w and two acceleration coefficients (i.e., c_1 and c_2), it is very important to determine the suitable values of parameters. The inertia weight is varied from 0.9 (i.e., $w_{\max}$) to 0.4 (i.e., $w_{\min}$), as these values are accepted as typical for solving wide varieties of problems. Two acceleration coefficients are determined through the experiments for each ED problem so as to find the optimal combination. In chaotic sequences, the control parameter μ is set to 4.0 and initial value of f is a random number between [0,1] except for 0, 0.25, 0.5, 0.75, and 1, respectively.

5.1 Example 1: Valve-point Effects

This system consists of 40 generating units and the input data for 40-generator system are given in [10]. The total demand is set to 10,500MW.

In order to find the optimal combination of acceleration coefficients (i.e., c_1 and c_2), nine cases are considered as given in Table I. The acceleration coefficients are determined through the experiments for this system using the conventional PSO. The optimal values for c_1 and c_2 are selected as 2.0 and 1.0, respectively, based on the results given in Table 1.

In Table 2, the results achieved by CPSO are compared with those from evolutionary programming (EP) [10], modified particle swarm optimization (MPSO) [15], PSO-SQP [16], and DEC-SQP [14], NPSO [17], and NPSO-LRS [17]. Although the acquired best solution is not guaranteed to be the global solution, the CPSO has shown the superiority to the existing methods as shown in Table 2.

Table 1 Influence of acceleration coefficients on PSO performance

Cases	c_1	c_2	Minimum Cost ($)	Average Cost ($)
1	2.0	2.0	121,772.9177	122,150.2930
2	2.0	1.5	121,751.9378	122,080.4060
3	2.0	1.0	121,751.3390	121,977.6028
4	1.5	2.0	121,754.0167	122,167.8336
5	1.5	1.5	121,751.3390	122,134.5597
6	1.5	1.0	121,752.1647	122,081.7638
7	1.0	2.0	121,753.9811	122,344.6859
8	1.0	1.5	121,761.0886	122,309.8234
9	1.0	1.0	121,751.9378	122,247.2560

Table 2 Comparison of results of each method for Example 1

Methods	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)	Standard Deviation
EP [10]	122,624.35	123,382.00	125,740.63	N/A
MPSO [15]	122,252.265	N/A	N/A	N/A
PSO-SQP [16]	122,094.67	122,245.25	N/A	N/A
DEC-SQP [14]	121,741.9793	122,295.1278	122,839.2941	386.1809
NPSO [17]	121,704.7391	122,221.3697	122,995.0976	N/A
NPSO-LRS [17]	121,664.4308	122,209.3185	122,9815913	N/A
CPSO	121,427.7588	121,810.6629	122,989.2257	275.2155

The convergence characteristics of the conventional PSO and the proposed CPSO are illustrated in Fig. 2.

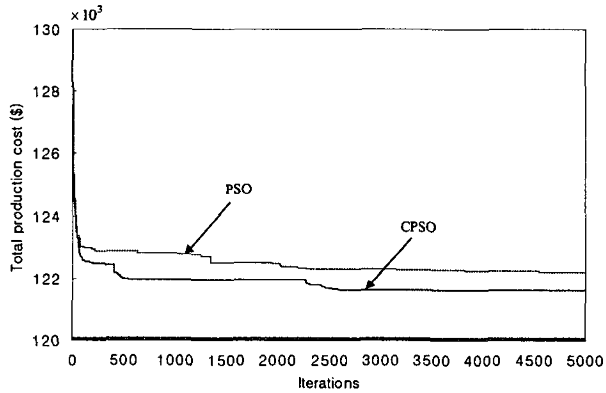


Fig. 2 Convergence characteristics of PSO and CPSO for Example 1.

The generation outputs and corresponding costs of the best solution of the proposed CPSO algorithm are compared with those of DEC-SQP [14] and NPSO-LRS [17] in Table 4. We have also observed that the solutions obtained by CPSO always satisfy the equality and inequality constraints.

Table 4 Generation output of each generator and the corresponding cost in 40-unit system

Unit	DEC-SQP [14]	NPSO-LRS [17]	CPSO
1	111.7576	113.9761	113.5595
2	111.5584	113.9986	110.8387
3	97.3999	97.4241	97.4016
4	179.7331	179.7327	179.7354
5	91.6560	89.6511	94.2282
6	140.0000	105.4044	140.0000
7	300.0000	259.7502	259.5998
8	300.0000	288.4534	284.6062
9	284.5997	284.6460	284.5996
10	130.0000	204.8120	130.0000
11	168.7998	168.8311	168.8010
12	94.0000	94.0000	94.0000
13	214.7598	214.7663	214.7586
14	394.2794	394.2852	394.2782
15	304.5196	304.5187	394.2794
16	304.5196	394.2811	304.5173
17	489.2794	489.2807	489.2802
18	489.2794	489.2832	489.2792
19	511.2794	511.2845	511.2795
20	511.2794	511.3049	511.2787
21	523.2794	523.2916	523.2796
22	523.2853	523.2853	523.2794
23	523.2847	523.2797	523.2789
24	523.2794	523.2994	523.2781
25	523.2794	523.2865	523.2794
26	523.2794	523.2936	523.2799
27	10.0000	10.0000	10.0000
28	10.0000	10.0001	10.0000
29	10.0000	10.0000	10.0000
30	90.3329	89.0139	87.8777
31	190.0000	190.0000	190.0000
32	190.0000	190.0000	190.0000
33	190.0000	190.0000	190.0000
34	200.0000	199.9998	200.0000
35	200.0000	165.1397	200.0000
36	200.0000	172.0275	164.8463
37	110.0000	110.0000	110.0000
38	110.0000	110.0000	110.0000
39	110.0000	93.0962	109.9999
40	511.2794	511.2996	511.2797
TP	10,500.0000	10,500.0000	10,500.0000
TC	121,741.9793	121,664.4308	121,427.7588

* TP: total power [MW], TC: total generation cost [$].

5.2 Example 2: Multi-Fuels with Valve-Point Effect

This test system consists of 10 generating units considering multi-fuels with valve-point effects. The input data and related constraints of the test system are given in [7]. The total demand is set to 2,700MW.

To select the optimal acceleration coefficients for this example, the same parameter determination strategy is adopted as in Example 1. Through experiments, c_1 and c_2 are set to 1.0 and 2.0, respectively.

In Table 5, the results of the CPSO are compared with those of conventional genetic algorithm with multiplier updating (CGA_MU) [7], improved genetic algorithm with multiplier updating (IGA_MU) [7], NPSO [17], and NPSO-LRS [17]. Table 5 clearly shows that the proposed CPSO algorithm outperforms other previous works.

Table 5 Convergence results for Example 2

Methods	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)	Standard Deviation
CGA_MU [7]	624.7193	627.6087	633.8652	N/A
IGA_MU [7]	624.5178	625.8692	630.8705	N/A
NPSO [17]	624.1624	625.2180	627.4237	N/A
NPSO-LRS [17]	624.1273	624.9985	626.9981	N/A
CPSO	623.8493	623.9001	623.9822	0.0284

In Table 6, the generation outputs, fuel types, and total generation costs of the best solution obtained from the proposed CPSO are compared with those of IGA_MU [7] and NPSO-LRS [17].

Table 6 Comparison of results of each method for Example 2

Unit	IGA_MU [7]		NPSO-LRS [17]		CPSO	
	F	GEN	F	GEN	F	GEN
1	2	219.1261	2	223.3352	2	218.5548
2	1	211.1645	1	212.1957	1	211.7118
3	1	280.6572	1	276.2167	1	282.6748
4	3	238.4770	3	239.4187	3	239.2363
5	1	276.4179	1	274.6470	1	276.4919
6	3	240.4672	3	239.7974	3	240.0425
7	1	287.7399	1	285.5388	1	290.1008
8	3	240.7614	3	240.6323	3	240.3113
9	3	429.3370	3	429.2637	3	428.1556
10	1	275.8518	1	278.9541	1	272.7203
TP	2,700.0000		2,700.0000		2,700.0000	
TC	624.5178		624.1273		623.8493	

6. CONCLUSION

This paper presents a new approach for solving the nonconvex ED problems considering valve-point and multi-fuels with valve-point effects using an improved PSO. The proposed CPSO method combines the conventional PSO with chaotic sequences. The chaotic sequences combined with the linearly decreasing inertia weights in PSO are devised to improve the global searching capability by preventing the premature convergence to local minima. In order to verify the superiority of the proposed CPSO, two ED problems with nonconvex cost functions are tested and its results are compared with those of previous works. The simulation results clearly show that the proposed CPSO can be used as an optimizer providing satisfactory solutions while satisfying system equality and inequality constraints for the nonconvex ED problems.

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REFERENCES

[1] K. Y. Lee and M. A. El-Sharkawi (Editors), Modern Heuristic Optimization Techniques with Applications to Power Systems, IEEE Power Engineering Society (02TP160), 2002.

[2] A. J. Wood, and B. F. Wollenberg, Power Generation, Operation, and Control. New York: John Wiley & Sons, Inc., 1984.

[3] Z. X. Liang and J. D. Glover, "A zoom feature for a dynamic programming solution to economic dispatch including transmission losses," IEEE Trans. on Power Systems, Vol. 7. No. 2, pp. 544-550, May 1992.

[4] C. E. Lin and G. L. Viviani, "Hierarchical economic dispatch for piece-wise quadratic cost functions," IEEE Trans. Power App. Syst., Vol. PAS-103, No.6, pp. 1170-1175, June 1984.

[5] D. C. Walters and G. B. Sheble, "Genetic algorithm solution of economic dispatch with the valve point loading," IEEE Trans. on Power Systems, Vol. 8, No. 3, pp. 1325-1332, Aug. 1993.

[6] S. O. Orero and M. R. Irving, "Economic dispatch of generators with prohibited operating zones: a genetic algorithm approach," IEE Proc.-Gener. Transm. Distrib., Vol. 143, No. 6, pp. 529-534, Nov. 1996.

[7] C. L. Chiang, "Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels," IEEE Trans. on Power Systems, Vol. 20, No. 4, pp. 1690-1699, Nov. 2005.

[8] H. T. Yang, P. C. Yang, and C. L. Huang, "Evolutionary programming based economic dispatch for units with non-smooth fuel cost functions," IEEE Trans. on Power Systems, Vol. 11, No. 1, pp. 112-118, Feb. 1996.

[9] Y. M. Park, J. R. Won and J. B. Park, "A new approach to economic load dispatch based on improved evolutionary programming," Engineering Intelligent Systems for Electrical Engineering and Communications, Vol. 6, No. 2, pp. 103-110, June 1998.

[10] N. Sinha, R. Chakrabarti, and P. K. Chattopadhyay, "Evolutionary programming techniques for economic load dispatch," IEEE Trans. on Evolutionary Computations, Vol. 7, No. 1, pp. 83-94, Feb. 2003.

[11] W. M. Lin, F. S. Cheng, and M. T. Tsay, "An improved Tabu search for economic dispatch with multiple minima," IEEE Trans. on Power Systems, Vol. 17, No. 1, pp. 108-112, Feb. 2002.

[12] J. H. Park, Y. S. Kim, I. K. Eom, and K. Y. Lee, "Economic load dispatch for piecewise quadratic cost function using Hopfield neural network," IEEE Trans. on Power Systems, Vol. 8, No. 3, pp. 1030-1038, August 1993.

[13] K. Y. Lee, A. Sode-Yome, and J. H. Park, "Adaptive Hopfield neural network for economic load dispatch," IEEE Trans. on Power Systems, Vol. 13, No. 2, pp. 519-526, May 1998.

[14] L. S. Coelho and V. C. Mariani, "Combining of chaotic differential evolution and quadratic programming for economic dispatch optimization with valve-point effect," IEEE Trans. On Power Systems, Vol. 21, No. 2, May 2006.

[15] J. B. Park, K. S. Lee, J. R. Shin, and K. Y. Lee, "A particle swarm optimization for economic dispatch with nonsmooth cost functions," IEEE Trans. on Power Systems, Vol. 20, No. 1, pp. 34-42, Feb. 2005.

[16] T. A. A. Victoire and A. E. Jeyakumar, "Hybrid PSO-SQP for economic dispatch with valve-point effect," Electric Power Systems Research, Vol. 71, pp. 51-59, Sep. 2004.

[17] A. I. Selvakumar and K. Thanushkodi, "A new particle swarm optimization solution to nonconvex economic dispatch problems," IEEE Trans. on Power Systems, Vol. 22, No. 1, pp. 42-51, Feb. 2007.

[18] J. Kennedy and R. C. Eberhart, "Particle swarm optimization," Proceedings of IEEE International Conference on Neural Networks (ICNN'95), Vol. IV, pp. 1942-1948, Perth, Australia, 1995.

[19] J. Kennedy and R. C. Eberhart, Swarm Intelligence. San Francisco, CA: Morgan Kaufmann, 2001.

[20] G. Wang and S. He, "A quantitative study on detection and estimation of weak signals by using chaotic duffing oscillators," IEEE Trans. on Circuits and Systems-I: Fundamental Theory and Applications, Vol. 50, No. 7, pp. 945-953, Jul. 2003.

[21] R. Caponetto, L. Fortuna, S. Fazzino, and M. G. Xibilia, "Chaotic sequences to improve the performance of evolutionary algorithms," IEEE Trans. on Evolutionary Computation, Vol. 7, No. 3, pp. 289-304, Jun. 2003.

[22] L. Shengsong, W. Min, and H. Zhijian, "Hybrid algorithm of chaos optimization and SLP for optimal power flow problems with multimodal characteristic," IEE Proc.-Gener. Transm. Distrib., Vol. 150, No. 5, pp. 543-547, Sep. 2003.

[23] Y. Shi and R. C. Eberhart, "Empirical study of particle swarm optimization," Proceedings of the 1999 Congress on Evolutionary Computation, pp. 1945-1950, 1999.

[24] Y. Shi and R. C. Eberhart, "Parameter selection in particle swarm optimization,"Proceedings of the 7th International Conference of Evolutionary Programming, pp. 591-600, 1999.

[25] Trefny, F. J. and K. Y. Lee, "Economic Fuel Dispatch," IEEE Trans. on Power Apparatus and Systems, Vol. PAS-100, pp. 3468-3477, July/ August 1981.

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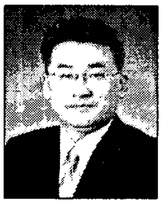

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