An Improved Particle Swarm Optimization for Economic Dispatch with Valve-Point Effect

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***Abstract*—This paper presents a novel and efficient method for solving the economic dispatch (ED) problems with valve-point effect, by integrating the particle swarm optimization (PSO) with the chaotic sequences. In the ED problems, the inclusion of valve-point loading effects makes the modeling of the fuel cost functions of generating units more practical. However, this increases the nonlinearity as well as number of local optima in the solution space. Also the solution procedure can easily trap in the local optima in the vicinity of optimal value. The proposed improved particle swarm optimization (IPSO) combines the PSO algorithm with chaotic sequences technique. PSO is one of the most powerful methods for solving global optimization problems. The application of chaotic sequences in PSO is an efficient strategy to improve the global searching capability and escape from local minima. To demonstrate the effectiveness of the proposed method, the numerical studies have been performed for two different sample systems. The results clearly show that the proposed IPSO outperforms other state-of-the-art algorithms in solving ED problems with the valve-point effect.**

***Index Terms*—Constrained optimization, economic dispatch, valve-point effect, particle swarm optimization, chaotic sequences**

I. Introduction

Most of power system optimization problems including economic dispatch (ED) have complex and nonlinear characteristics with heavy equality and inequality constraints [1].

Economic dispatch is one of the most important problems to be solved in the operation and planning of a power system. 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 load demand at minimum operating cost while satisfying system equality and inequality constraints. In the traditional ED problem, the cost function for each generator has been approximately represented by a single quadratic function and is solved using mathematical programming based on the optimization techniques such as lambda-iteration method, gradient-based method, etc. [2]. These mathematical methods require incremental or marginal fuel cost curves which should be monotonically increasing to find global optimal solution.

The fuel cost functions of generating units can be modeled in a more practical fashion by including the valve-point effects. The valve-point effects result in the ripples in the fuel cost function, thereby the number of local optima is increased. Thus, the practical ED problem is represented as a nonsmooth optimization problem with equality and inequality constraints, which cannot be solved by the traditional mathematical methods. Dynamic programming method [3] can solve such types of problems, but it suffers from so-called the curse of dimensionality. Over the past few years, in order to solve this problem, many salient methods have been developed such as genetic algorithm [4], evolutionary programming [5], [6], tabu search [7], neural network approaches [8], and particle swarm optimization [9], [10].

Particle swarm optimization (PSO) is suggested by Eberhart and Kennedy based on the analogy of swarm of birds and school of fish [11]. PSO mimics the behavior of individuals in a swarm to maximize the survival of the species. In PSO, each individual makes his decision using his own experience together with other individuals' experiences. The algorithm, which is based on a metaphor of social interaction, searches a space by adjusting the trajectories of moving points in a multidimensional space. The individual particles are drawn stochastically toward the position of present velocity of each individual, their own previous best performance, and the best previous performance of their neighbors [1], [12]. The main advantages of the PSO algorithm are summarized as: simple concept, easy implementation, robustness to control parameters, and computational efficiency when compared with mathematical algorithms and other heuristic optimization techniques [9]. PSO can be easily applied to nonlinear and non-continuous optimization problems.

Chaos, apparently disordered behaviors that is nonetheless deterministic, is a universal phenomenon that occurs in many systems in all areas of science [13]. Recently, chaotic sequences have been adopted instead of random ones and have shown very promising results in many engineering applications [13-15].

In this paper, we propose a novel approach for solving the ED problem with valve-point effect using an improved PSO (IPSO). The application of chaotic sequences in PSO is a useful strategy to improve the global searching capability and prevent the premature convergence to local minima. The proposed IPSO method is tested for two different systems and the results are compared with those of other methods in order to demonstrate its performance.

The rest of the paper is organized as follows. Section II describes the formulation of an ED problem. Section III explains the PSO algorithm for solving the ED problems. Simulation results are presented and compared with those of other algorithms in section IV. Lastly, section V outlines the conclusions.

II. Formulation of Economic Dispatch

A. Basic Economic Dispatch Formulation

The objective of the economic dispatch problem is to minimize the total fuel cost of thermal power plants subjected to the operating constraints of a power system. In general, it can be formulated mathematically with an objective function and two constraints [2] as follows:

$$F_T = \sum_{i=1}^{N} F_i(P_i) \quad (1)$$

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \quad (2)$$

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 of generator *i*,
- N number of generators.

!) Active power balance equation

For power balance, an equality constraint should be satisfied. The total generated power should be the same as total load demand plus the total line loss

$$\sum_{i=1}^{N} P_i = P_D + P_{Loss} \quad (3)$$

where P_D is the total system demand and P_{Loss} is the total line loss. However, the transmission loss is not considered in this paper for simplicity (i.e., $P_{Loss} = 0$).

2) Minimum and maximum power limits

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

$$P_{i,\min} \le P_i \le P_{i,\max} \quad (4)$$

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

B. 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 as shown in Fig. 1, a cost function contains higher order nonlinearity [9]. Therefore, the equation (2) should be replaced as the equation (5) to consider the valve-point effects. Here, the sinusoidal functions are thus added to the quadratic cost functions as follows.

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \times \sin(f_i \times (P_{i,\min} - P_i)) \right| \quad (5)$$

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

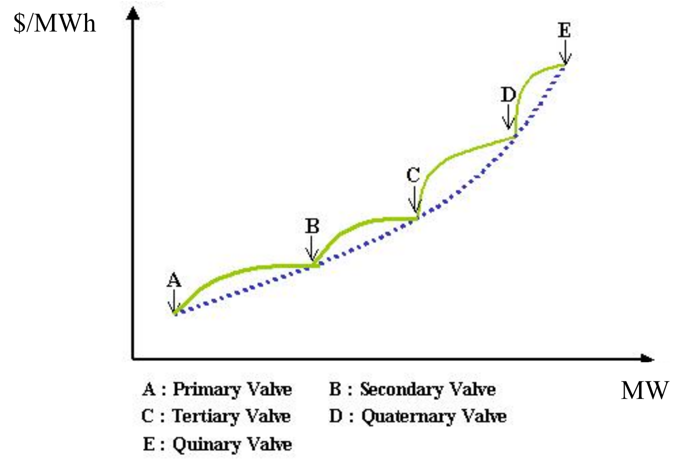


Fig. 1 Incremental fuel cost versus power output for a 5 valve steam turbine unit.

III. Optimization Methodologies for ED Problems

A. Overview of the PSO

Kennedy and Eberhart developed a PSO algorithm based on the behavior of individuals (i.e., particles or agents) of a swarm [11]. Its roots are in zoologist's modeling of the movement of individuals (i.e., fish, birds, and insects) 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. The PSO algorithm searches in parallel using a group of individuals similar to other AI-based heuristic optimization techniques [12]. Each individual corresponds to a candidate solution to the problem. Individuals in a swarm approach to the optimum through its present velocity, previous experience, and the experience of its neighbours.

In a physical *n*-dimensional search space, the position and velocity of individual *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 individual *i* and its neighbors' best position so far, respectively. Using the information, the updated velocity of individual *i* is modified under the following equation in the PSO algorithm:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 \times (Pbest_i^k - X_i^k) + c_2 r_2 \times (Gbest^k - X_i^k) \quad (6)$$

where,

V_i^k	velocity of individual i at iteration k,
ω	inertia weight parameter,
c_1, c_2	acceleration coefficients,
r_1, r_2	random numbers between 0 and 1,
X_i^k	position of individual i at iteration k,
$Pbest_i^k$	best position of individual i until iteration k,
$Gbest^k$	best position of the group until iteration k.

In this velocity updating process, the values of parameters such as ω, c_1, and c_2 should be determined in advance. In general, the weight ω is set according to the following equation [1], [9]:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{Iter_{\max}} \times Iter \tag{7}$$

where,

$\omega_{\max}, \omega_{\min}$	initial and final weights,
$Iter_{\max}$	maximum iteration number,
$Iter$	current iteration number.

Each individual moves from the current position to the next one by the modified velocity in (6) using the following equation:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{8}$$

Fig. 2 shows the concept of the searching mechanism of PSO using the modified velocity and position of individual i based on (6) and (8) if the values of ω, c_1, c_2, $rand_1, rand_2$ are 1.

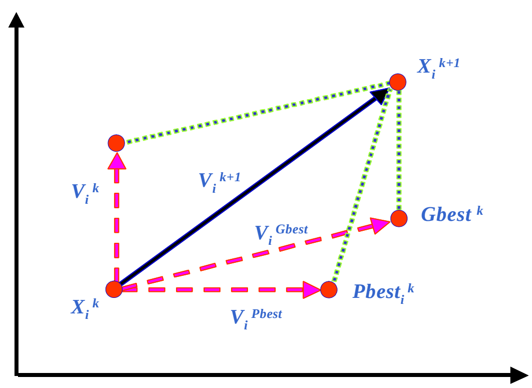


Fig. 2. Concept of modification of a searching point by PSO.

B. Chaotic Sequences for Weight Parameter

One of the simplest dynamic systems exhibiting a chaotic behavior is an iterator called the logistic map [14], whose equation is described as follows:

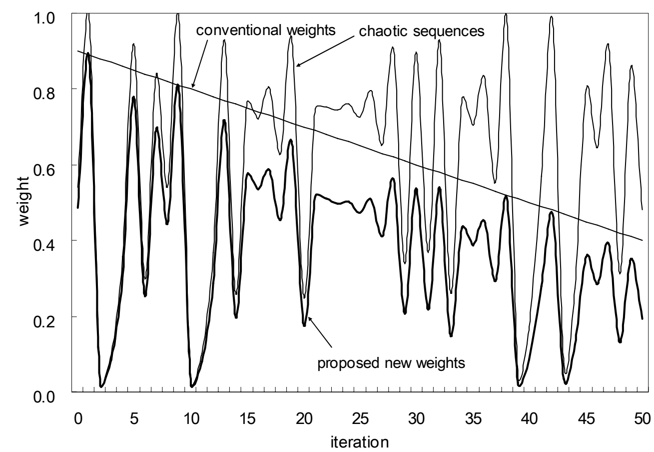
$$f_k = \mu \cdot f_{k-1} \cdot (1 - f_{k-1}) \tag{9}$$

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 (9) is greatly changed with the variation of μ. The value of μ determines whether f stabilizes 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 initial value of f [14, 15]. Equation (9) is deterministic, displaying chaotic dynamics when $\mu = 4.0$ and $f_0 \notin \{0, 0.25, 0.50, 0.75, 1.0\}$.

One of the major drawbacks of the PSO is its premature convergence, especially while handling problems with more local optima and heavily constrained. In this paper, the new weight is defined as multiplying (7) by (9) in order to improve the global searching capability as follows:

$$\omega_{new} = \omega \cdot f \tag{10}$$

Whereas the conventional weight decreases monotonously from $\omega_{\max}$ to $\omega_{\min}$, the proposed new weight decreases and oscillates simultaneously for total iteration as shown in Fig. 3.



$Iter_{\max} = 50$, $\omega_{\max} = 0.9$, $\omega_{\min} = 0.4$, $\mu = 4.0$, $f_0 = 0.54$

Fig. 3. Comparison of inertia weights by each approach

C. Implementation of IPSO Algorithm for ED Problems

In this section, we will describe how the proposed IPSO algorithm is implemented for solving the ED problems. We not only improved the existing PSO algorithm but also added new strategy in order to find the global solution better than other state-of-the-art algorithms by applying the chaotic sequences for weight parameter. In the subsequent sections, the detailed implementation strategies of the proposed method are described.

1) Creating Initial Position and Velocity of Individuals

In the initialization process, a set of individuals (i.e., a group) is created at random. In this paper, the structure of an individual for ED problem is composed of a set of elements (i.e., generation outputs). Therefore, individual i's position at iteration 0 can be represented as the vector $X_i^0 = (P_{i1}, \cdots, P_{in})$

where N is the number of generators in the ED problem. The velocity of individual i (i.e., $V_i^0 = (v_{i1}, \cdots v_{in})$) corresponds to the generation update quantity covering all generators.

It is very important to create a group of individuals satisfying the equality constraint (3) and inequality constraints (4). That is, summation of all elements of individual i (i.e., $\sum_{j=1}^{N} P_{ij}$) should be equal to the total system demand (i.e., P_D) and the created element j of individual i at random (i.e., P_{ij}) should be located within its boundary. Unfortunately, the created position of an individual is not always guaranteed to satisfy the inequality constraints. If any element of an individual violates its inequality constraint then the position of the individual is fixed to its maximum/minimum operating point as follows:

$$P_{ij}^k = \begin{cases} P_{ij}^k & \text{if } P_{ij,\min} \le P_{ij}^k \le P_{ij,\max} \\ P_{ij,\min} & \text{if } P_{ij}^k < P_{ij,\min} \\ P_{ij,\max} & \text{if } P_{ij}^k > P_{ij,\max} \end{cases} \tag{11}$$

Although the aforementioned method always produces the position of each individual satisfying the inequality constraints (4), the problem of equality constraint still remains to be resolved. Therefore, it is necessary to develop a new strategy such that the summation of all elements in an individual is equal to the total system demand. To do this, the following procedure is suggested for any individual in a group:

Step 1) Set $j = 1$.
Step 2) Select an element (i.e., generator) of individual i at random and store in an index array $A(n)$.
Step 3) Create the value of the element (i.e., generation output) at random satisfying its inequality constraint.
Step 4) If $j = n$-1 then go to Step 5, otherwise $j = j$+1 and go to Step 2.
Step 5) The value of the last element of individual i is determined by subtracting $\sum_{j=1}^{N-1} P_{ij}$ from P_D. If the value is within its boundary then go to Step 8, otherwise adjust the value using (11).
Step 6) Set $l = 1$.
Step 7) Readjust the value of element l in the index array $A(n)$ to the value satisfying equality condition (i.e., $P_D - \sum_{\substack{j=1 \\ j\neq l}}^{n} P_{ij}$). If the value is within its boundary then go to Step 8; otherwise, change the value of element-l using (11). Set $l = l$+1, and go to Step 7. If $l = n$+1, go to Step 6.
Step 8) Stop the initialization process.

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

$$\left(P_{ij,\min} - \varepsilon\right) - P_{ij}^0 \le v_{ij} \le \left(P_{ij,\max} + \varepsilon\right) - P_{ij}^0 \tag{12}$$

where ε is a small positive real number. The velocity element j of individual i is generated at random within the boundary. The initial $Pbest_i$ of individual i is set as the initial position of individual i and the initial $Gbest$ is determined as the position of the individual with minimum payoff of (1).

2) Velocity Update

To modify the position of each individual, it is necessary to calculate the velocity of each individual in the next stage which is obtained from (6). In this process, the new weight approach (10) is employed to improve the global searching capability.

3) Position Modification Considering Constraints

The position of each individual is modified by (8). Since the resulting position of an individual is not always guaranteed to satisfy the inequality constraints due to over/under velocity, the modified position of an individual is adjusted by (11). At the same time it is necessary to satisfy the equality constraint (3). To resolve the equality constraint problem without intervening the dynamic process inherent in the PSO algorithm, we propose the following heuristic procedures:

Step 1) Set $j = 1$.
Step 2) Select an element (i.e., generator) of individual i at random and store in an index array $A(n)$.
Step 3) Modify the value of element j using (8) and (11).
Step 4) If $j = n$-1 then go to Step 5, otherwise $j = j$+1 and go to Step 2.
Step 5) The value of the last element of individual i is determined by subtracting $\sum_{j=1}^{n-1} P_{ij}$ from P_D. If the value is not within its boundary then adjust the value using (11) and go to Step 6, otherwise go to Step 8.
Step 6) Set $l = 1$.
Step 7) Readjust the value of element l in the index array $A(n)$ to the value satisfying equality condition (i.e., $P_D - \sum_{\substack{j=1 \\ j\neq l}}^{n} P_{ij}$). If the value is within its boundary then go to Step 8; otherwise, change the value of element-l using (9). Set $l = l$+1, and go to Step 7. If $l = n$+1, go to Step 6.
Step 8) Stop the modification procedure.

4) Update of Pbest and Gbest

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

$$Pbest_i^{k+1} = \begin{cases} X_i^{k+1} & \text{if } TC_i^{k+1} < TC_i^k \\ Pbest_i^k & \text{otherwise} \end{cases} \tag{13}$$

where TC_i is the object function evaluated at the position of individual i.

Also, *Gbest* at iteration k+1 is set as the best evaluated position among $Pbest_i^{k+1}$ s.

5) Stopping criteria

The proposed IPSO is terminated if the iteration approaches to the predefined maximum iteration.

IV. Case Studies

To verify the feasibility of the proposed IPSO method, two different power systems were tested. The results obtained from the IPSO are compared with those of other methods: the genetic algorithm (GA) [4], the evolutionary programming (EP) [5], [6], the modified PSO (MPSO) [9], and the hybrid PSO-SQP [10].

Some parameters must be assigned before IPSO is used to solve ED problems as follows:

- Number of particles = 50;
- Maximum iteration number = 10000;
- Inertia weight parameters $\omega_{\max} = 0.9$, $\omega_{\min} = 0.4$;
- Acceleration coefficients $c_1 = 2.0$, $c_2 = 1.0$;
- Control parameter of chaotic sequences μ = 4.0;
- Initial value of f is a random number between [0, 1] except for 0, 0.25, 0.5, 0.75, and 1.

A. Case I

This system comprises of 3 generating units and the input data of 3-generator system are given in Table I. Here, the total demand for the system is set to 850MW.

TABLE I
DATA FOR TEST CASE I (3-UNIT SYSTEM)

Unit	a_i	b_i	c_i	e_i	f_i	$P_{i,min}$	$P_{i,max}$
1	561	7.92	0.001562	300	0.0315	100	600
2	310	7.85	0.001940	200	0.0420	100	400
3	78	7.97	0.004820	150	0.0630	50	200

The obtained results for the 3-generator system using the IPSO are given in Table II and the results are compared with those from GA [4], EP [5], and MPSO [9]. It shows that the IPSO has succeeded in finding a global optimal solution presented in [7].

TABLE II
COMPARISON OF SIMULATION RESULTS OF EACH METHOD CONSIDERING VALVE-POINT EFFECT (3-UNIT SYSTEM)

Unit	GA [4]	EP [5]	MPSO [9]	IPSO
1	300.00	300.26	300.27	300.27
2	400.00	400.00	400.00	400.00
3	150.00	149.74	149.73	149.73
TP	850.00	850.00	850.00	850.00
TC	8237.60	8234.07	8234.07	8234.07

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

B. Case II

The proposed IPSO has also been applied to the 40-generator system. The input data for 40 generating units are given in [6]. The total demand is set to 10,500MW.

Table III shows the minimum, mean, maximum cost, and the standard deviation achieved by the IPSO algorithm in 100 independent runs.

TABLE III
CONVERGENCE RESULTS OF TEST CASE II (40-UNIT SYSTEM)

	Best Cost	Mean Cost	Worst Cost	Standard Deviation
IPSO	121,432.177	121,801.909	122,700.948	287.452

Although the acquired best solution is not guaranteed to be the global solution, the IPSO has shown the superiority to the existing methods as described in Table IV. Table IV shows the simulation results for the 40-generator system using the IPSO and compares with those from EP [6], MPSO [9], and PSO-SQP [10].

The generation outputs and the corresponding costs of the best solution are described in Table V, and the results are satisfying the equality and inequality constraints.

TABLE IV
COMPARISON OF SIMULATION RESULTS OF EACH METHOD CONSIDERING VALVE-POINT EFFECT (40-UNIT SYSTEM)

EP [6]	MPSO [9]	PSO-SQP [10]	IPSO
122,624.350	122,252.265	122,094.670	121,432.177

It is clear from Table II and IV that the proposed IPSO has provided better solutions compared with other heuristic approaches. We have also observed that the solutions obtained by IPSO always satisfy the equality and inequality constraints.

V. Conclusion

This paper presents a new approach for solving the nonsmooth ED problems with valve-point effect based on the improved PSO (IPSO) algorithm. The suggested IPSO includes chaotic sequences for weight parameter, equality and inequality constraints treatment methods, and creation of initial position. The IPSO has provided the global solution in the 3-unit test system and the better solution than the previous studies for 40-unit test system. The application of chaotic sequences in PSO is a powerful strategy to improve the global searching capability and escape from local minima. Also, the equality and inequality constraints treatment methods have always provided the solutions satisfying the constraints without disturbing the optimum process of the PSO.

Although the proposed IPSO algorithm had been successfully applied to ED with valve-point loading effect, the practical ED problems should consider multiple fuels as well as prohibited operating zones. This remains a challenge for future work.

VI. Acknowledgment

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TABLE V

GENERATION OUTPUT OF EACH GENERATOR AND THE CORRESPONDING COST IN 40-UNIT SYSTEM

Unit	$P_{i,min}$	$P_{i,max}$	Generation	Cost
1	36	114	110.8731	926.3173
2	36	114	111.2066	931.8736
3	60	120	97.4000	1190.5509
4	80	190	179.7332	2143.5514
5	47	97	87.9256	708.5861
6	68	140	140.0000	1596.4643
7	110	300	259.6023	2603.9339
8	135	300	284.5999	2779.8419
9	135	300	284.6004	2798.2431
10	130	300	130.0000	2502.0650
11	94	375	168.7999	2959.4598
12	94	375	94.0000	1908.1668
13	125	500	214.7598	3792.0707
14	125	500	304.5196	5149.6990
15	125	500	394.2794	6436.5863
16	125	500	394.2794	6436.5866
17	220	500	489.2794	5296.7118
18	220	500	489.2795	5288.7669
19	242	550	511.2795	5540.9325
20	242	550	511.2794	5540.9098
21	254	550	523.2794	5071.2907
22	254	550	523.2796	5071.2934
23	254	550	523.2795	5057.2252
24	254	550	523.2794	5057.2233
25	254	550	523.2794	5275.0886
26	254	550	523.2794	5275.0886
27	10	150	10.0000	1140.5240
28	10	150	10.0000	1140.5240
29	10	150	10.0000	1140.5240
30	47	97	89.0624	727.4465
31	60	190	190.0000	1643.9913
32	60	190	190.0000	1643.9913
33	60	190	190.0000	1643.9913
34	90	200	200.0000	2101.0169
35	90	200	172.2847	1666.4847
36	90	200	200.0000	2043.7270
37	25	110	110.0000	1220.1661
38	25	110	110.0000	1220.1661
39	25	110	110.0000	1220.1661
40	242	550	511.2794	5540.9299
Total Generation & Cost			10500.0000	121432.1767

VII. 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] 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.

[5] 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.

[6] 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.

[7] 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.

[8] 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.

[9] 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.

[10] T. A. A. Victoire and A. E. Jeyakumar, "Hybrid PSO-SQP for economic dispatch with valve-point effect," *Electric Power Systems Research*, Vol. 71, No. 1, pp. 51-59, 2004.

[11] 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.

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

[13] 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.

[14] 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.

[15] 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.

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