An Improved Particle Swarm Optimization for Nonconvex Economic Dispatch Problems

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***Abstract*—This paper presents an efficient approach for solving economic dispatch (ED) problems with nonconvex cost functions using an improved particle swarm optimization (IPSO). Although the particle swarm optimization (PSO) approaches have several advantages suitable to heavily constrained nonconvex optimization problems, they still can have the drawbacks such as local optimal trapping due to premature convergence (i.e., exploration problem), insufficient capability to find nearby extreme points (i.e., exploitation problem), and lack of efficient mechanism to treat the constraints (i.e., constraint handling problem). This paper proposes an improved PSO framework employing chaotic sequences combined with the conventional linearly decreasing inertia weights and adopting a crossover operation scheme to increase both exploration and exploitation capability of the PSO. In addition, an effective constraint handling framework is employed for considering equality and inequality constraints. The proposed IPSO is applied to three different nonconvex ED problems with valve-point effects, prohibited operating zones with ramp rate limits as well as transmission network losses, and multi-fuels with valve-point effects. Additionally, it is applied to the large-scale power system of Korea. Also, the results are compared with those of the state-of-the-art methods.**

***Index Terms*—Chaotic inertia weights, constraint treatment technique, crossover operation, economic dispatch problem, improved particle swarm optimization, nonconvex optimization.**

I. Introduction

MANY power system optimization problems including economic dispatch (ED) have nonconvex characteristics with heavy equality and inequality constraints [1]. The objective of ED is to determine an optimal combination of power output to meet the demand at minimum cost while satisfying the constraints. For simplicity, the cost function for each unit in the ED problems has been approximately represented by a single quadratic function and is solved using mathematical programming techniques [2]. Generally, these mathematical methods require the derivative information of the cost function. Unfortunately, the input-output characteristics of generating units are nonconvex due to prohibited operating zones, valve-point loadings, multi-fuel effects, etc. Thus, the practical ED problem should be represented as a nonconvex optimization problem with constraints, which cannot be directly solved by mathematical methods. Dynamic programming [3] can treat such types of problems, but it suffers from the curse of dimensionality. Over the past decade, many salient methods have been developed to solve these problems, such as the hierarchical numerical method [4], genetic algorithm (GA) [5]–[7], evolutionary programming [8]–[10], Tabu search [11], neural network approaches [12], [13], differential evolution [14], particle swarm optimization (PSO) [15]–[18], and hybrid artificial intelligence (AI) method [19].

PSO is one of the modern heuristic algorithms suitable to solve large-scale nonconvex optimization problems. It is a population-based search algorithm and searches in parallel using a group of particles. The PSO suggested by Kennedy and Eberhart in 1995 is based on the analogy of swarm of bird and school of fish [20]. In PSO, each particle makes its decision using its own experience together with its neighbor's experiences [20], [21]. The main advantages of the PSO algorithm are: simple concept, easy implementation, relative robustness to control parameters, and computational efficiency [1]. Although the PSO-based approaches have several advantages, it may get trapped in a local minimum when handling heavily constrained problems due to the limited local/global searching capabilities [22], [23].

This paper proposes a PSO-based approach for the nonconvex ED problems with heavy constraints. In order to overcome the existing drawbacks of PSO to some extents, this paper proposes an improved PSO (IPSO) framework combining the *chaotic sequences* and the *crossover operation*. The chaotic sequences combined with the linearly decreasing inertia weights are suggested as new dynamic inertia weights in PSO. In addition, the crossover operation inspired by GA can increase the diversity of the population in the PSO mechanism. The employment of chaotic sequences and the crossover operation in PSO can improve the global searching capability by preventing premature convergence through increased diversity of the population. In addition, an effective constraint handling technique is proposed to improve the solution quality without scarifying the computational efficiency. The suggested IPSO is applied to three different nonconvex ED problems and the large-scale Korean power system. The solutions are compared with those of the conventional PSO as well as other state-of-the-art AI methods.

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II. Formulation of Economic Dispatch Problem

A. Objective Function

The objective of an ED problem is to minimize the total fuel cost subjected to the constraints of a power system. The simplified cost function of each generating unit can be represented as described in (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.

1) ED Problem Considering Valve-Point Effects: The generating units with multi-valve steam turbines exhibit a greater variation in the fuel cost function. 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:

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

where e_i and f_i are the cost coefficients of generator i reflecting valve-point effects [10].

2) ED Problem Considering Multi-Fuels With Valve-Point Effects: Since the dispatching units can be supplied with multi-fuel sources, each unit can be represented with several piecewise quadratic functions reflecting the effects of different fuel types. In general, a piecewise quadratic function is used to represent the input-output curve of a generator with multiple fuels [4] and described as

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1} P_i + c_{i1} P_i^2, & \text{fuel } 1, \quad P_{i\min} \le P_i \le P_{i1} \\ a_{i2} + b_{i2} P_i + c_{i2} P_i^2, & \text{fuel } 2, \quad P_{i1} \le P_i \le P_{i2} \\ \vdots & \qquad\qquad \vdots \\ a_{ik} + b_{ik} P_i + c_{ik} P_i^2, & \text{fuel } k, \quad P_{ik-1} \le P_i \le P_{i\max} \end{cases} \tag{4}$$

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 [24]. 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 (3) should be combined with (4), and can be represented as follows:

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

where

$$F_{ik}(P_i) = a_{ik} + b_{ik} P_i + c_{ik} P_i^2 + |e_{ik} \times \sin(f_{ik} \times (P_{ik,\min} - P_i))| \tag{6}$$

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.

B. Equality and Inequality Constraints

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

$$\sum_{i=1}^{n} P_i = P_{load} + P_{loss} \tag{7}$$

where P_{load} is the total system load. The total transmission network loss, P_{loss}, is a function of the unit power outputs that can be represented using B coefficients [2] as follows:

$$P_{loss} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00}. \tag{8}$$

2) Minimum and Maximum Power Limits: Power output of each generator should be within its minimum and maximum limits. Corresponding inequality constraint for each generator is

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{9}$$

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

3) Ramp Rate Limits: The actual operating range of all the online units is restricted by their corresponding ramp rate limits. The ramp-up and ramp-down constraints can be written as follows:

$$P_i - P_i^0 \le UR_i \quad \text{and} \quad P_i^0 - P_i \le DR_i \tag{10}$$

where P_i^0 is the previous power output of the ith generating unit. UR_i and DR_i are the up-ramp and down-ramp limits of generator i, respectively.

To consider the ramp rate limits and power output limits constraints at the same time, (10) and (9) can be rewritten as an inequality constraint as follows:

$$\max\left\{P_{i,\min}, P_i^0 - DR_i\right\} \leq P_i \leq \min\left\{P_{i,\max}, P_i^0 + UR_i\right\}. \tag{11}$$

4) ED Problem Considering Prohibited Operating Zones: In some cases, the entire operating range of a generating unit is not always available due to physical operation limitations. Units may have prohibited operating zones due to faults in machines themselves or associated auxiliaries. Such faults may lead to instability in certain ranges of generator power output [6]. Therefore, for units with prohibited operating zones, there are additional constraints on the unit operating range as follows:

$$P_i \in \begin{cases} P_{i,\min} \leq P_i \leq P_{i,1}^l \\ P_{i,k-1}^u \leq P_i \leq P_{i,k}^l \\ P_{i,pz_i}^u \leq P_i \leq P_{i,\max} \end{cases}, \quad k = 2, 3, \ldots, pz_i$$
$$i = 1, 2, \ldots, n_{PZ} \tag{12}$$

where $P_{i,k}^l$ and $P_{i,k}^u$ are, respectively, the lower and upper bounds of prohibited operating zone of unit i. Here, pz_i is the number of prohibited zones of unit i and n_{PZ} is the number of units which have prohibited operating zones.

III. 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 [20]. 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 [21]. The PSO algorithm searches in parallel using a group of particles. Each particle corresponds to a candidate solution to the problem. A particle moves toward the optimum based on its present velocity, its previous experience, and the experience of its neighbors. In an n-dimensional search space, the position and velocity of particle i are represented as vectors $X_i = (x_{i1}, \ldots, x_{in})$ and $V_i = (v_{i1}, \ldots v_{in})$, where the dimension represents the number of components. Let $Pbest_i = \left(x_{i1}^P, \ldots, x_{in}^P\right)$ and $Gbest = \left(x_1^G, \ldots, x_n^G\right)$ 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 as follows:

$$\begin{aligned} V_i^{k+1} = &\omega \cdot V_i^k + c_1 \cdot rn_1 \cdot (Pbest_i^k - X_i^k) \\ &+ c_2 \cdot rn_2 \cdot (Gbest^k - X_i^k) \end{aligned} \tag{13}$$
$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{14}$$

where

V_i^k	velocity of particle i at iteration k;
ω	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.

In the velocity updating process, the values of parameters such as ω, 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 can provide a balance between global exploration and local exploitation, and results in a lower number of iterations to find the optimal solution. In general, to enhance the convergence characteristics, the inertia weight factor ω is designed to decrease linearly (i.e., Inertia Weight Approach (IWA) [1], [22], [23]), descending from $\omega_{\max}$ to $\omega_{\min}$ as follows:

$$\omega^k = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \times k \tag{15}$$

where $iter_{\max}$ corresponds to the maximum iteration number. Using the new position X_i^{k+1}, the $Pbest_i$ and $Gbest$ are updated at iteration $k+1$ using the greedy selection.

IV. Improved PSO With Chaotic Sequences, Crossover Operation, and Constraint Treatment Strategy

A. Application of Chaotic Sequences in PSO

Chaos, apparently disordered behavior that is nonetheless deterministic, is a universal phenomenon that occurs in many areas of science [25]. Coelho and Mariani [14] combined the chaotic sequences with the mutation factor in differential evolution to improve the solution quality. Caponetto *et al.* [26] applied various chaotic sequences in evolutionary algorithms (EAs) in lieu of the random numbers. Shengsong *et al.* [27] adopted a chaotic hybrid algorithm to solve the optimal power flow problems. The application of the chaotic sequences has shown promising results in some engineering applications.

One of the dynamic systems evidencing chaotic behavior is the iterator called the logistic map [26], whose equation is described as follows:

$$\gamma_k = \mu \cdot \gamma_{k-1} \cdot (1 - \gamma_{k-1}) \tag{16}$$

where μ is a control parameter and has a real value between [4], and γ_k is the chaotic parameter at iteration k. Despite the apparent simplicity of the equation, the solution exhibits a rich variety of behaviors. The behavior of the system represented by (16) is greatly changed with the variation of μ. The value of μ determines whether γ is stabilized at a constant size, oscillates between a limited sequence of sizes, or behaves chaotically in an unpredictable pattern. The system (16) is deterministic, and displays chaotic behaviors when $\mu = 4.0$ and $\gamma_0 \notin \{0, 0.25, 0.50, 0.75, 1.0\}$.

The performance of a PSO can depend on its parameters such as the inertia weight factors and two acceleration coefficients. The first term in (13) represents the influence of previous velocity, which provides the necessary momentum for particles to fly around in a search space. The balance between exploration and exploitation can be treated by the value of inertia weight.

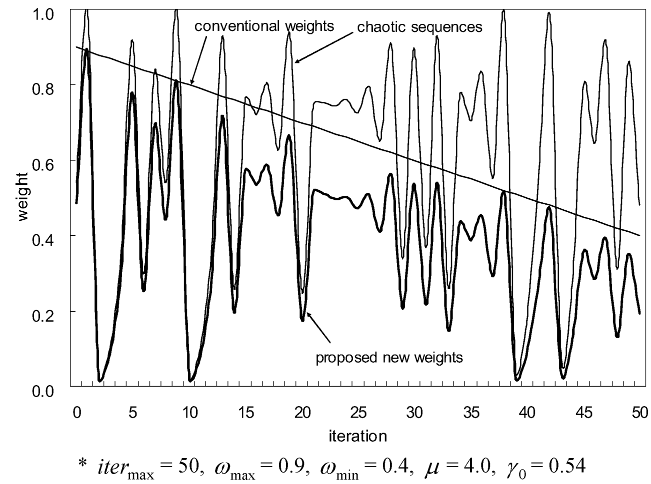

Fig. 1. Comparison of inertia weights for IWA and CIWA.

Therefore, a proper control of inertia weight is very important to find the optimum solution efficiently. Shi and Eberhart [22], [23] made a significant improvement in the performance of the PSO with a linearly varying inertia weights over the iterations [i.e., IWA in the form of (15)], which is widely used in PSO applications [16], [17].

In this paper, in order to improve the global searching capability and to increase the probability of escaping from a local minimum, a new weight-changing approach, Chaotic Inertial Weight Approach (CIWA), is suggested as defined as follows:

$$c\omega^k = \omega^k \cdot \gamma_k \tag{17}$$

where $c\omega^k$ is a chaotic weight at iteration k, ω^k is the weight factor from the IWA, and γ_k is the chaotic parameter.

Whereas the weight in the conventional IWA decreases monotonously from $\omega_{\max}$ to $\omega_{\min}$, the proposed chaotic weight decreases and oscillates simultaneously as shown in Fig. 1. Since the suggested CIWA can encompass the whole weight domain under the decreasing line in a chaotic manner, the searching capability of the proposed algorithm can be increased as illustrated in numerical studies.

B. Crossover Operation

In order to increase the diversity of a population, the crossover operation is newly introduced to the PSO mechanism, thereby can effectively explore and exploit promising regions in a search space. The position of particle i, $X_i = (x_{i1}, \ldots, x_{in})$, obtained in (14) is mixed with $Pbest_i$ to generate a trial vector $\hat{X}_i = (\hat{x}_{i1}, \ldots, \hat{x}_{in})$ as follows:

$$\hat{x}_{ij}^{k+1} = \begin{cases} x_{ij}^{k+1}, & \text{if } r_{ij} \le CR \\ x_{ij}^{P,k}, & \text{otherwise} \end{cases} \tag{18}$$

for $j = 1, 2, \ldots, n$, where r_{ij} is a uniformly distributed random number between [1], and *CR* is the crossover rate in the range of [1]. When the value of *CR* becomes one, there is no crossover like in the conventional PSO. If the value of *CR* is zero, the position will always have the crossover operation similar to the GA mechanism. A proper crossover rate *CR* can be determined by empirical studies to improve the diversity of a population. Fig. 2 gives an example of the crossover mechanism for an individual i.

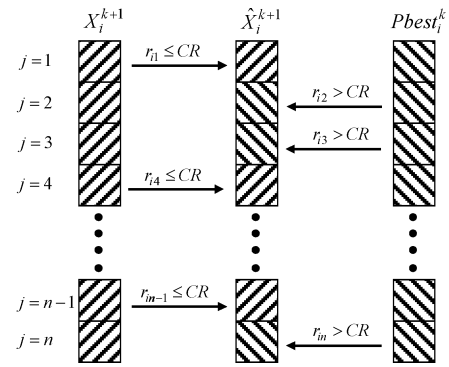

Fig. 2. Illustration of the crossover operation.

The trial vector $\hat{X}_i^{k+1}$ is used to update the $Pbest_i$ and $Gbest$ at iteration $k+1$ using the greedy selection. The $Pbest_i^{k+1}$ is set to $\hat{X}_i^{k+1}$ if the fitness value of $\hat{X}_i^{k+1}$ is better than that of $Pbest_i^k$. The developed crossover operation is applied for the improvement of $Pbest_i$ while the PSO evolution process of each particle is conserved by (14).

C. Treatment of Equality and Inequality Constraints

It is very important to create a group of particles satisfying the equality and inequality constraints. The summation of all elements within a particle should be equal to the total system demand and each element j in particle i should be within its operating boundaries. Therefore, it is necessary to develop a strategy for satisfying the constraints. This paper proposes an efficient heuristic constraint-handling technique as follows.

Step 1) Set $\alpha = 1$ and adjust the value of all elements in the ith individual to satisfy the inequality constraints as follows:

$$P_{ij}^{k(\alpha)} = \begin{cases} P_{ij}^k, & \text{if } P_{j,\min} \le P_{ij}^k \le P_{j,\max} \\ P_{j,\min}, & \text{if } P_{ij}^k < P_{j,\min} \\ P_{j,\max}, & \text{if } P_{ij}^k > P_{j,\max}. \end{cases} \tag{19}$$

Note that the minimum and maximum power outputs of generating units should be adjusted to consider the ramp rate limits of (11).

Step 2) Calculate the transmission network loss (i.e., P_{loss}) using B coefficients formula (8).

Step 3) Calculate the residual P_{RD} by subtracting the total system demand (i.e., $P_{load} + P_{loss}$) from $\sum_{j=1}^{n} P_{ij}^{k(\alpha)}$. If $|P_{RD}| < \varepsilon$, then go to Step 7; otherwise, go to Step 4. Here, ε is the demand tolerance.

Step 4) Select an element g in individual i at random, which was not selected so far, and store the value of the element g temporarily to P_g^{Tmp}.

Step 5) Modify the value of the element g for equality constraint treatment as follows:

$$P_{ig}^{k(\alpha)} = \begin{cases} P_{ig}^{k(\alpha)} - \min\{P_{RD}, (P_{ig}^{k(\alpha)} - P_{g,\min}) \times rn_g\}, & \text{if } P_{RD} > 0 \\ P_{ig}^{k(\alpha)} - \max\{P_{RD}, (P_{ig}^{k(\alpha)} - P_{g,\max}) \times rn_g\}, & \text{if } P_{RD} < 0. \end{cases} \tag{20}$$

Here rn_g implies a uniformly distributed random number in [1]. This generation update rule for the equality constraint treatment is devised to reflect the operation boundary of each generator and distribute the residual to several generators at random.

Step 6) Recalculate $P_{RD} = P_{RD} - \left(P_g^{Tmp} - P_{ig}^{k(\alpha)}\right)$. If $|P_{RD}| < \varepsilon$, then go to Step 7; otherwise, go to Step 4.

Step 7) If $\max_{\forall j}\left\{\left|P_{ij}^{k(\alpha)} - P_{ij}^{k(\alpha-1)}\right|\right\} < \delta$, then go to Step 8; otherwise, $\alpha = \alpha + 1$ and go to Step 2. Here, δ is the solution convergence tolerance.

Step 8) Stop the constraint-handling procedure.

V. Implementation of Improved PSO Algorithm for Economic Dispatch Problems

Since the decision variables in ED problems are real power outputs, 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 $X_i^k = \left(P_{i1}^k, \ldots, P_{in}^k\right)$ where n is the number of generators. The velocity of particle i corresponds to the generation updates for all generators. The process of the proposed IPSO algorithm can be summarized as in the following steps.

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

Step 2) Update the velocity of particles.

Step 3) Modify the position of particles to satisfy the constraints, if necessary.

Step 4) Generate the trial vector through crossover operation process.

Step 5) Update $Pbest$ and $Gbest$.

Step 6) Go to Step 2 until the stopping criteria is satisfied.

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

A. Creating Initial Position and Velocity

In the initialization process, a set of particles is created at random as follows [16]:

$$P_{ij}^0 = P_{j,\min} + r_{ij} \times (P_{j,\max} - P_{j,\min}) \tag{21}$$

where r_{ij} is a uniformly distributed random number between [0,1]. Here, the minimum and maximum power outputs should be adjusted using (11) when the ramp rate limits are considered. Although each element satisfies the inequality constraint, the problem of equality constraint still remains to be resolved. To do this, the aforementioned equality constraint treatment strategy is applied. After creating the initial position of each particle, the velocity of each particle is also created at random.

B. Movement of the Particles

To modify the position of each particle, it is necessary to calculate the velocity of each particle in the next stage by (13). In this process, the new weight approach CIWA of (17) is employed to improve the global searching capability. After that, the position of each particle is updated by (14). Since the resulting position of a particle is not always guaranteed to satisfy the constraints, the constraint treatment procedure is performed.

C. Crossover Operation

The trial vector of particle i at iteration $k+1$ (i.e., $\hat{X}_i^{k+1}$) is generated by mixing the current position of particle i (i.e., X_i^{k+1}) with $Pbest_i^k$ based on a predetermined crossover rate. After that, the constraint treatment procedure is executed for each trial vector to satisfy the constraints.

D. Update of $Pbest$ and $Gbest$

The $Pbest$ of each particle at iteration $k+1$ is updated. If $Gbest$ yields a smaller cost than $Pbest$, then $\hat{X}_i^{k+1}$ is set to $Pbest_i^k$. Otherwise, the $Pbest_i^k$ is retained:

$$Pbest_i^{k+1} = \begin{cases} \hat{X}_i^{k+1}, & \text{if } f(\hat{X}_i^{k+1}) < f(Pbest_i^k) \\ Pbest_i^k, & \text{otherwise.} \end{cases} \tag{22}$$

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

E. Stopping Criteria

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

VI. Numerical Tests

The proposed IPSO approach is applied to four different power systems: 1) 40-unit system with valve-point effects; 2) 15-unit system with prohibited operating zones, ramp rate limits, and transmission network losses; 3) ten-unit system considering multiple fuels with valve-point effects; and (iv) 140-unit Korean power system with valve-point effects, prohibited operating zones, and ramp rate limits. For each case, 100 independent trials are conducted to compare the solution quality and convergence characteristics. For each ED problem, four strategies are applied and compared:

- CTPSO: The conventional PSO with the proposed constraint treatment strategy;
- CSPSO: PSO with chaotic sequences;
- COPSO: PSO with crossover operation;
- CCPSO: PSO with both chaotic sequences and crossover operation.

Here, the constraint treatment strategy is applied in common to all strategies: CTPSO, CSPSO, COPSO, and CCPSO. The proposed IPSOs have been executed on a Pentium IV 2.0-GHz computer. In implementing the proposed algorithm, some PSO parameters must be determined in advance. The population size *NP* and maximum iteration number $iter_{\max}$ are set as 30 and 10 000, respectively. Since the performance of PSO-based approach depends on the parameters such as inertia weight factor and the two acceleration coefficients, it is important to determine suitable values of these parameters. As for the linearly decreasing dynamic inertia weight, the starting value (i.e., $\omega_{\max}$)

TABLE I
DETERMINATION OF ACCELERATION COEFFICIENTS FOR TEST SYSTEM 1

Case	c_1	c_2	Minimum Cost ($)	Average Cost ($)
1	2.0	2.0	121,762.9576	122,141.5129
2	2.0	1.5	121,740.1196	122,070.9243
3	**2.0**	**1.0**	**121,694.6056**	**121,944.3959**
4	1.5	2.0	121,749.6415	122,126.5257
5	1.5	1.5	121,751.9378	122,086.6732
6	1.5	1.0	121,739.2087	121,950.2990
7	1.0	2.0	121,753.9811	122,274.9373
8	1.0	1.5	121,751.3391	122,308.8591
9	1.0	1.0	121,756.1262	122,343.2483

TABLE II
DETERMINATION OF CROSSOVER RATE FOR COPSO IN TEST SYSTEM 1

Case	*CR*	Minimum Cost ($)	Average Cost ($)
1	0.1	121,426.1795	121,522.4361
2	0.2	121,453.9981	121,527.6191
3	0.3	121,452.7133	121,517.2012
4	0.4	121,440.9613	121,510.3494
5	0.5	121,414.9825	121,503.1294
6	**0.6**	**121,411.8975**	**121,499.9769**
7	0.7	121,452.6741	121,547.8669
8	0.8	121,452.6741	121,625.8105
9	0.9	121,452.6741	121,635.9935

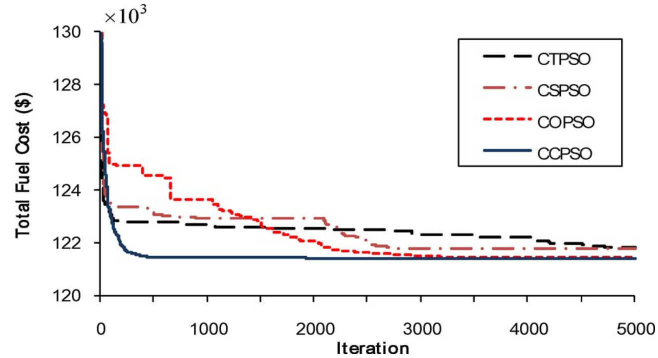

Fig. 3. Convergence characteristics of the IPSOs for Test System 1.

TABLE III
CONVERGENCE RESULTS FOR TEST SYSTEM 1

Methods	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)	Standard Deviation	Avg. Time (sec)
PSO [16]	121751.3390	122020.7539	122607.9145	210.3657	19.0
CTPSO	121694.6056	121944.3959	122244.8439	196.9282	19.0
CSPSO	121435.9581	121945.0564	123305.2476	413.8832	19.0
COPSO	121411.8975	121499.9769	121751.3390	78.7696	19.2
CCPSO	121403.5362	121445.3269	121525.4934	32.4898	19.3

is set as 0.9 and the ending value (i.e., $\omega_{\min}$) as 0.4 because these values are widely accepted in solving various optimization problems [23], [28], [29]. Two acceleration coefficients of each ED problem are determined through the experiments without employing the suggested framework such as the chaotic sequences and crossover operation. In chaotic sequences, the control parameter μ is set to 4.0 and initial value of is determined by a random number between [1] except the values 0, 0.25, 0.5, 0.75, and 1. In the crossover operation, the crossover rate *CR* is selected through experiments for each ED problem while c_1 and c_2 are being fixed.

A. *Test System 1: System With Valve-Point Effects*

The test system consists of 40 generating units and the input data are described in [10]. The total demand is set to 10 500 MW.

In order to find the optimal combination of acceleration coefficients (i.e., γ and c_1), nine cases are considered as described in Table I. Here, each acceleration parameter is varied between 2.0 and 1.0 with the step size of 0.5, whose range is widely used in other PSO applications [15]–[18], [23], [28], [29]. The acceleration coefficients are determined through the experiments for the system using the CTPSO, and 100 independent trails are conducted for each case. The optimal values for c_1 and c_2 are selected as 2.0 and 1.0, respectively.

To select the optimal crossover rate, *CR* is also varied from 0.9 to 0.1 with the step size of 0.1. For each case, 100 independent tests are also executed for the COPSO. The results are summarized in Table II, and the value for *CR* is determined as 0.6.

Table III summarizes the minimum, average, maximum cost, standard deviation, and average execution time achieved by the PSO [16], CTPSO, CSPSO, COPSO, and CCPSO. Here PSO [16] implies a conventional PSO with the constraint handling technique in [16]. The effect of the constraint treatment strategy can be observed by comparing PSO [16] and the CTPSO of this paper. The simulation results show that the proposed CCPSO provides much better solutions than PSO [16], CTPSO, CSPSO, or COPSO. The convergence characteristics of the best solution of each IPSO approach are illustrated in Fig. 3. It can be observed that both CSPSO and COPSO are improving the solution quality continuously while the CTPSO experiences a premature convergence. In addition, the convergence performance of CCPSO is dramatically improved due to the synergistic effects of crossover operation and chaotic weight sequences.

In Table IV, the results of the proposed CTPSO, CSPSO, COPSO, and CCPSO are compared with those of evolutionary programming (EP) [10], MPSO [16], PSO-SQP [17], DEC-SQP [14], NPSO [18], and NPSO-LRS [18]. Although the best solution of CCPSO is not guaranteed to be the global solution, the proposed CCPSO has shown the superiority to the existing methods. Regarding the minimum and average cost, the proposed CSPSO, COPSO, and CCPSO have found better solutions than the best solution previously found by NPSO-LRS, $121 664.4308 [18]. The generation output of each unit and the corresponding total cost of CTPSO, CSPSO, COPSO, and CCPSO are provided in Table V and compared with that of NPSO-LRS [18]. One can observe that the generation outputs of units 6, 10, 11, 15, 34, 35, and 36 by CCPSO are quite different from those of NPSO-LRS [18]. This implies that the global searching capability has been improved significantly by the proposed IPSO mechanism. Also, the solutions by the CTPSO, CSPSO, COPSO, and CCPSO always satisfy the equality and inequality constraints.

TABLE IV
COMPARISON OF RESULTS OF EACH METHOD FOR TEST SYSTEM 1

Methods	Minimum Cost ($)	Average Cost ($)
EP [10]	122,624.3500	123,382.0000
MPSO [16]	122,252.2650	N/A
PSO-SQP [17]	122,094.6700	122,245.2500
DEC-SQP [14]	121,741.9793	122,295.1278
NPSO [18]	121,704.7391	122,221.3697
NPSO-LRS [18]	**121,664.4308**	122,209.3185
CTPSO	121,694.6056	121,944.3959
CSPSO	**121,435.9581**	121,945.0564
COPSO	**121,411.8975**	121,499.9769
CCPSO	**121,403.5362**	121,445.3269

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

Unit	NPSO-LRS [18]	CTPSO	CSPSO	COPSO	CCPSO
1	113.9761	114.0000	113.8490	110.8089	110.7998
2	113.9986	114.0000	111.2670	110.8305	110.7999
3	97.4241	120.0000	97.4007	97.3999	97.3999
4	179.7327	179.7335	179.7331	179.7331	179.7331
5	89.6511	97.0000	88.2536	97.0000	87.7999
6	105.4044	140.0000	140.0000	140.0000	**140.0000**
7	259.7502	259.7341	259.6895	259.5997	259.5997
8	288.4534	286.9352	284.5997	284.5997	284.5997
9	284.6460	298.6396	284.6068	284.5997	284.5997
10	204.8120	130.0000	130.0000	130.0000	**130.0000**
11	168.8311	94.0000	168.7998	168.7998	**94.0000**
12	94.0000	168.8001	94.0000	94.0000	94.0000
13	214.7663	125.0000	214.7598	214.7598	214.7598
14	394.2852	304.5199	394.2794	394.2794	394.2794
15	304.5187	304.5195	304.5196	394.2794	**394.2794**
16	394.2811	484.0390	394.2794	304.5196	394.2794
17	489.2807	489.2800	489.2794	489.2794	489.2794
18	489.2832	489.2795	489.2794	489.2794	489.2794
19	511.2845	511.2793	511.2794	511.2794	511.2794
20	511.3049	511.2800	511.2794	511.2794	511.2794
21	523.2916	523.2805	523.2794	523.2794	523.2794
22	523.2853	523.2795	523.2794	523.2794	523.2794
23	523.2797	523.2797	523.2794	523.2794	523.2794
24	523.2994	523.2792	523.2794	523.2794	523.2794
25	523.2865	523.2813	523.2794	523.2794	523.2794
26	523.2936	523.2805	523.6283	523.2794	523.2794
27	10.0000	10.0000	10.0000	10.0000	10.0000
28	10.0001	10.0001	10.0000	10.0000	10.0000
29	10.0000	10.0000	10.0000	10.0000	10.0000
30	89.0139	97.0000	87.9351	87.9177	87.8000
31	190.0000	190.0000	190.0000	190.0000	190.0000
32	190.0000	190.0000	190.0000	190.0000	190.0000
33	190.0000	190.0000	190.0000	190.0000	190.0000
34	199.9998	200.0000	200.0000	164.7999	**164.7998**
35	165.1397	200.0000	200.0000	200.0000	**194.3976**
36	172.0275	200.0000	169.8773	200.0000	**200.0000**
37	110.0000	110.0000	110.0000	110.0000	110.0000
38	110.0000	110.0000	109.7281	110.0000	110.0000
39	93.0962	110.0000	110.0000	110.0000	110.0000
40	511.2996	511.2795	511.2794	511.2794	511.2794
TP	10500.0000	10500.0000	10500.0000	10500.0000	10500.0000
TC	121664.4308	121694.6056	121435.9581	121411.8975	121403.5362

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

TABLE VI
DETERMINATION OF ACCELERATION COEFFICIENTS FOR TEST SYSTEM 2

Case	c_1	c_2	Minimum Cost ($)	Average Cost ($)
1	**2.0**	**2.0**	**32,704.45139**	**32,704.45140**
2	2.0	1.5	32,704.45139	32,704.45141
3	2.0	1.0	32,704.45139	32,704.45141
4	1.5	2.0	32,704.45139	32,704.45141
5	1.5	1.5	32,704.45139	32,704.45143
6	1.5	1.0	32,704.45139	32,704.45142
7	1.0	2.0	32,704.45139	32,704.45142
8	1.0	1.5	32,704.45139	32,704.45141
9	1.0	1.0	32,704.45139	32,704.45143

TABLE VII
DETERMINATION OF CROSSOVER RATE FOR COPSO IN TEST SYSTEM 2

Case	*CR*	Minimum Cost ($)	Average Cost ($)
1	0.1	32,704.45139	32,704.45146
2	0.2	32,704.45139	32,704.45141
3	0.3	32,704.45139	32,704.45144
4	0.4	32,704.45139	32,704.45140
5	0.5	32,704.45139	32,704.45140
6	**0.6**	**32,704.45139**	**32,704.45139**
7	0.7	32,704.45139	32,704.45141
8	0.8	32,704.45139	32,704.45144
9	0.9	32,704.45139	32,704.45142

TABLE VIII
CONVERGENCE RESULTS FOR TEST SYSTEM 2

Methods	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)	Standard Deviation	Average Execution Time (sec)
CTPSO	32,704.4514	32,704.4514	32,704.4514	0.0000	22.5
CSPSO	32,704.4514	32,704.4514	32,704.4514	0.0004	16.1
COPSO	32,704.4514	32,704.4514	32,704.4514	0.0000	85.1
CCPSO	32,704.4514	32,704.4514	32,704.4514	0.0000	16.2

B. Test System 2: System With Prohibited Operating Zones, Ramp Rate Limits, and Transmission Network Losses

Experiments are performed on the 15-unit power system, which considers the prohibited operating zones, ramp rate limits, and transmission network losses. Units 2, 5, 6, and 12 have up to three prohibited operating zones. The system supplies a total load of 2630 MW. The input data and B coefficients for transmission network losses are provided in [15]. To determine the acceleration coefficients and crossover rate for this test system, the same parameter determination process is applied as for Test System 1. The values for c_1, c_2, and *CR* are determined as 2.0, 2.0, and 0.6, respectively, as shown in Tables VI and VII.

The minimum cost, average cost, maximum cost, standard deviation, and average execution time of CTPSO, CSPSO, COPSO, and CCPSO are described in Table VIII. The proposed CTPSO, COPSO, and CCPSO methods always provide the same solution in all trials. In Table IX, the best results from the proposed CTPSO, CSPSO, COPSO, and CCPSO are compared with those of GA [15] and PSO [15]. The results show that the CTPSO, CSPSO, COPSO, and CCPSO provide better solutions than other methods while satisfying the system constraints

TABLE IX
COMPARISON OF RESULTS OF EACH METHOD FOR TEST SYSTEM 2

Unit	GA [15]	PSO [15]	CTPSO	CSPSO	COPSO	CCPSO
1	415.3108	439.1162	455.0000	455.0000	455.0000	455.0000
2	359.7206	407.9727	380.0000	380.0000	380.0000	380.0000
3	104.4250	119.6324	130.0000	130.0000	130.0000	130.0000
4	74.9853	129.9925	130.0000	130.0000	130.0000	130.0000
5	380.2844	151.0681	170.0000	170.0000	170.0000	170.0000
6	426.7902	459.9978	460.0000	460.0000	460.0000	460.0000
7	341.3164	425.5601	430.0000	430.0000	430.0000	430.0000
8	124.7867	98.5699	71.7430	71.7408	71.7427	71.7526
9	133.1445	113.4936	58.9186	58.9207	58.9189	58.9090
10	89.2567	101.1142	160.0000	160.0000	160.0000	160.0000
11	60.0572	33.9116	80.0000	80.0000	80.0000	80.0000
12	49.9998	79.9583	80.0000	80.0000	80.0000	80.0000
13	38.7713	25.0042	25.0000	25.0000	25.0000	25.0000
14	41.9425	41.4140	15.0000	15.0000	15.0000	15.0000
15	22.6445	35.6140	15.0000	15.0000	15.0000	15.0000
TP	2668.4	2662.4	2660.6615	2660.6615	2660.6615	2660.6616
P_{loss}	38.2782	32.4306	30.6615	30.6615	30.6615	30.6616
TC	33,113	32,858	32,704	32,704	32,704	32,704

TABLE X
DETERMINATION OF ACCELERATION COEFFICIENTS FOR TEST SYSTEM 3

Case	c_1	c_2	Minimum Cost ($)	Average Cost ($)
1	2.0	2.0	624.0462	624.2136
2	2.0	1.5	623.8987	624.0004
3	2.0	1.0	623.8721	623.9671
4	1.5	2.0	623.8908	624.0035
5	1.5	1.5	623.8954	623.9576
6	1.5	1.0	623.8712	623.9584
7	**1.0**	**2.0**	**623.8588**	**623.9313**
8	1.0	1.5	623.8682	623.9375
9	1.0	1.0	623.8633	623.9338

TABLE XI
DETERMINATION OF CROSSOVER RATE FOR COPSO IN TEST SYSTEM 3

Case	*CR*	Minimum Cost ($)	Average Cost ($)
1	0.1	623.8268	623.8278
2	**0.2**	**623.8266**	**623.8274**
3	0.3	623.8266	623.8275
4	0.4	623.8266	623.8280
5	0.5	623.8266	623.8289
6	0.6	623.8266	623.8302
7	0.7	623.8266	623.8313
8	0.8	623.8266	623.8326
9	0.9	623.8271	623.8354

exactly. In addition, the proposed four IPSO methods provide the same solution with the cost of $32 704.4514, which is the minimum cost found so far.

C. Test System 3: Multi-Fuels With Valve-Point Effect

The test system consists of ten 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 system demand is set to 2700 MW. The values for c_1, c_2, and *CR* are set to be 1.0, 2.0, and 0.2, respectively, as shown in Tables X and XI.

TABLE XII
CONVERGENCE RESULTS FOR TEST SYSTEM 3

Methods	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)	Standard Deviation	Average Execution Time (sec)
PSO [16]	623.8829	623.9657	624.0907	0.0405	3.2
CTPSO	623.8588	623.9313	624.0368	0.0332	3.3
CSPSO	623.8420	623.8988	623.9852	0.0296	3.3
COPSO	623.8266	623.8274	623.8315	0.0006	3.2
CCPSO	623.8266	623.8273	623.8291	0.0005	3.2

TABLE XIII
COMPARISON OF RESULTS OF EACH METHOD FOR TEST SYSTEM 3

Methods	Minimum Cost ($)	Average Cost ($)
CGA_MU [7]	624.7193	627.6087
IGA_MU [7]	624.5178	625.8692
NPSO [18]	624.1624	625.2180
NPSO-LRS [18]	624.1273	624.9985
CTPSO	623.8588	623.9313
CSPSO	623.8420	623.8988
COPSO	623.8266	623.8274
CCPSO	623.8266	623.8273

TABLE XIV
COMPARISON OF RESULTS OF EACH METHOD FOR TEST SYSTEM 3

Unit	NPSO-LRS[18]		CTPSO		CSPSO		COPSO		CCPSO	
	F	GEN	F	GEN	F	GEN	F	GEN	F	GEN
1	2	223.3352	2	218.6807	2	219.6210	2	218.5940	2	218.5940
2	1	212.1957	1	211.4642	1	210.9690	1	211.7117	1	211.7117
3	1	276.2167	1	280.6545	1	279.6489	1	280.6571	1	280.6571
4	3	239.4187	3	240.4457	3	239.5051	3	239.6394	3	239.6394
5	1	274.6470	1	276.4034	1	279.8834	1	279.9345	1	279.9346
6	3	239.7974	3	240.1769	3	239.6394	3	239.6394	3	239.5051
7	1	285.5388	1	287.8657	1	289.9623	1	287.7275	1	287.7275
8	3	240.6323	3	240.5800	3	239.9082	3	239.6394	3	239.6394
9	3	429.2637	3	428.5886	3	425.0471	3	426.5883	3	426.7226
10	1	278.9541	1	275.1403	1	275.8157	1	275.8686	1	275.8686
TP	2700.0000		2700.0000		2700.0000		2700.0000		2700.0000	
TC	624.1273		623.8588		623.8420		623.8266		623.8266	

Table XII shows the convergence results of the PSO [16], CTPSO, CSPSO, COPSO and CCPSO methods. The simulation results reveal that CCPSO can yield better solution than CTPSO, CSPSO, and COPSO. Also, the efficiency of the constraint treatment strategy has been demonstrated as in other test systems. As shown in Table XIII, the best result from each of the proposed IPSOs is compared with those of the conventional genetic algorithm with multiplier updating (CGA_MU) [7], improved genetic algorithm with multiplier updating (IGA_MU) [7], NPSO [18], and NPSO-LRS [18]. Table XIII reveals that the proposed methods outperform other existing methods.

Also in Table XIV, the generation outputs, fuel types, and corresponding costs of the best solution obtained from the proposed IPSO approaches are compared with those of NPSO-LRS [18]. The CTPSO, CSPSO, COPSO, CCPSO have provided better solutions than the existing approaches.

TABLE XV
CONVERGENCE RESULTS FOR KOREAN POWER SYSTEM WITH CONVEX COST FUNCTIONS

Methods	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)	Required Iterations	Avg. Time (sec)
CTPSO	1,655,685	1,655,685	1,655,685	2,882	50.1
CSPSO	1,655,685	1,655,685	1,655,685	579	9.6
COPSO	1,655,685	1,655,685	1,655,685	3,156	76.9
CCPSO	1,655,685	1,655,685	1,655,685	1,590	42.9

TABLE XVI
DETERMINATION OF ACCELERATION COEFFICIENTS FOR KOREAN SYSTEM

Case	c_1	c_2	Minimum Cost ($)	Average Cost ($)
1	2.0	2.0	1,657,962.74	1,657,966.89
2	2.0	1.5	1,657,962.73	1,657,965.40
3	2.0	1.0	1,657,962.73	1,657,966.21
4	**1.5**	**2.0**	**1,657,962.73**	**1,657,964.06**
5	1.5	1.5	1,657,962.73	1,657,967.12
6	1.5	1.0	1,657,962.73	1,657,981.71
7	1.0	2.0	1,657,962.73	1,657,971.03
8	1.0	1.5	1,657,962.73	1,657,987.32
9	1.0	1.0	1,657,962.81	1,658,033.95

TABLE XVII
DETERMINATION OF CROSSOVER RATE FOR COPSO IN KOREAN SYSTEM

Case	*CR*	Minimum Cost ($)	Average Cost ($)	Standard Deviation
1	0.1	1,657,962.73	1,657,962.73	0.0005
2	**0.2**	**1,657,962.73**	**1,657,962.73**	**0.0002**
3	0.3	1,657,962.73	1,657,962.73	0.0036
4	0.4	1,657,962.73	1,657,962.77	0.0302
5	0.5	1,657,962.77	1,657,963.00	0.3307
6	0.6	1,657,962.79	1,657,963.30	0.4475
7	0.7	1,657,962.88	1,657,965.32	5.9635
8	0.8	1,657,963.02	1,657,969.52	11.6698
9	0.9	1,657,962.80	1,657,969.01	12.5054

TABLE XVIII
CONVERGENCE RESULTS FOR KOREAN POWER SYSTEM WITH NONCONVEX COST FUNCTIONS

Methods	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)	Standard Deviation	Avg. Time (sec)
CTPSO	1657962.73	1657964.06	1658002.79	7.3150	100
CSPSO	1657962.73	1657962.74	1657962.85	0.0235	99
COPSO	1657962.73	1657962.73	1657962.73	0.0002	150
CCPSO	1657962.73	1657962.73	1657962.73	0.0000	150

TABLE XIX
GENERATING UNIT DATA OF KOREAN POWER SYSTEM

Gen	a	b	c	P_{min}	P_{max}	UR	DR	P^0
COAL#01	1220.645	61.242	0.032888	71	119	30	120	98.4
COAL#02	1315.118	41.095	0.008280	120	189	30	120	134.0
COAL#03	874.288	46.310	0.003849	125	190	60	60	141.5
COAL#04	874.288	46.310	0.003849	125	190	60	60	183.3
COAL#05	1976.469	54.242	0.042468	90	190	150	150	125.0
COAL#06	1338.087	61.215	0.014992	90	190	150	150	91.3
COAL#07	1818.299	11.791	0.007039	280	490	180	300	401.1
COAL#08	1133.978	15.055	0.003079	280	490	180	300	329.5
COAL#09	1320.636	13.226	0.005063	260	496	300	510	386.1
COAL#10	1320.636	13.226	0.005063	260	496	300	510	427.3
COAL#11	1320.636	13.226	0.005063	260	496	300	510	412.2
COAL#12	1106.539	14.498	0.003552	260	496	300	510	370.1
COAL#13	1176.504	14.651	0.003901	260	506	600	600	301.8
COAL#14	1176.504	14.651	0.003901	260	509	600	600	368.0
COAL#15	1176.504	14.651	0.003901	260	506	600	600	301.9
COAL#16	1176.504	14.651	0.003901	260	505	600	600	476.4
COAL#17	1017.406	15.669	0.002393	260	506	600	600	283.1
COAL#18	1017.406	15.669	0.002393	260	506	600	600	414.1
COAL#19	1229.131	14.656	0.003684	260	505	600	600	328.0
COAL#20	1229.131	14.656	0.003684	260	505	600	600	389.4
COAL#21	1229.131	14.656	0.003684	260	505	600	600	354.7
COAL#22	1229.131	14.656	0.003684	260	505	600	600	262.0
COAL#23	1267.894	14.378	0.004004	260	505	600	600	461.5
COAL#24	1229.131	14.656	0.003684	260	505	600	600	371.6
COAL#25	975.926	16.261	0.001619	280	537	300	300	462.6
COAL#26	1532.093	13.362	0.005093	280	537	300	300	379.2
COAL#27	641.989	17.203	0.000993	280	549	360	360	530.8
COAL#28	641.989	17.203	0.000993	280	549	360	360	391.9
COAL#29	911.533	15.274	0.002473	260	501	180	180	480.1
COAL#30	910.533	15.212	0.002547	260	501	180	180	319.0
COAL#31	1074.810	15.033	0.003542	260	506	600	600	329.5
COAL#32	1074.810	15.033	0.003542	260	506	600	600	333.8
COAL#33	1074.810	15.033	0.003542	260	506	600	600	390.0
COAL#34	1074.810	15.033	0.003542	260	506	600	600	432.0
COAL#35	1278.460	13.992	0.003132	260	500	660	660	402.0
COAL#36	861.742	15.679	0.001323	260	500	900	900	428.0
COAL#37	408.834	16.542	0.002950	120	241	180	180	178.4
COAL#38	408.834	16.542	0.002950	120	241	180	180	194.1
COAL#39	1288.815	16.518	0.000991	423	774	600	600	474.0
COAL#40	1436.251	15.815	0.001581	423	769	600	600	609.8
LNG#1	669.988	75.464	0.902360	3	19	210	210	17.8
LNG#2	134.544	129.544	0.110295	3	28	366	366	6.9
LNG_CC#01	3427.912	56.613	0.024493	160	250	702	702	224.3
LNG_CC#02	3751.772	54.451	0.029156	160	250	702	702	210.0
LNG_CC#03	3918.780	54.736	0.024667	160	250	702	702	212.0
LNG_CC#04	3379.580	58.034	0.016517	160	250	702	702	200.8
LNG_CC#05	3345.296	55.981	0.026584	160	250	702	702	220.0
LNG_CC#06	3138.754	61.520	0.007540	160	250	702	702	232.9
LNG_CC#07	3453.050	58.635	0.016430	160	250	702	702	168.0
LNG_CC#08	5119.300	44.647	0.045934	160	250	702	702	208.4
LNG_CC#09	1898.415	71.584	0.000044	165	504	1350	1350	443.9
LNG_CC#10	1898.415	71.584	0.000044	165	504	1350	1350	426.0
LNG_CC#11	1898.415	71.584	0.000044	165	504	1350	1350	434.1
LNG_CC#12	1898.415	71.584	0.000044	165	504	1350	1350	402.5
LNG_CC#13	2473.390	85.120	0.002528	180	471	1350	1350	357.4
LNG_CC#14	2781.705	87.682	0.000131	180	561	720	720	423.0
LNG_CC#15	5515.508	69.532	0.010372	103	341	720	720	220.0
LNG_CC#16	3478.300	78.339	0.007627	198	617	2700	2700	369.4
LNG_CC#17	6240.909	58.172	0.012464	100	312	1500	1500	273.5
LNG_CC#18	9960.110	46.636	0.039441	153	471	1656	1656	336.0
LNG_CC#19	3671.997	76.947	0.007278	163	500	2160	2160	432.0
LNG_CC#20	1837.383	80.761	0.000044	95	302	900	900	220.0
LNG_CC#21	3108.395	70.136	0.000044	160	511	1200	1200	410.6
LNG_CC#22	3108.395	70.136	0.000044	160	511	1200	1200	422.7
LNG_CC#23	7095.484	49.840	0.018827	196	490	1014	1014	351.0
LNG_CC#24	3392.732	65.404	0.010852	196	490	1014	1014	296.0
LNG_CC#25	7095.484	49.840	0.018827	196	490	1014	1014	411.1
LNG_CC#26	7095.484	49.840	0.018827	196	490	1014	1014	263.2
LNG_CC#27	4288.320	66.465	0.034560	130	432	1350	1350	370.3
LNG_CC#28	13813.001	22.941	0.081540	130	432	1350	1350	418.7
LNG_CC#29	4435.493	64.314	0.023534	137	455	1350	1350	409.6
LNG_CC#30	9750.750	45.017	0.035475	137	455	1350	1350	412.0
LNG_CC#31	1042.366	70.644	0.000915	195	541	780	780	423.2
LNG_CC#32	1159.895	70.959	0.000044	175	536	1650	1650	428.0
LNG_CC#33	1159.895	70.959	0.000044	175	540	1650	1650	436.0
LNG_CC#34	1303.990	70.302	0.001307	175	538	1650	1650	428.0
LNG_CC#35	1156.193	70.662	0.000392	175	540	1650	1650	425.0
LNG_CC#36	2118.968	71.101	0.000087	330	574	1620	1620	497.2
LNG_CC#37	779.519	37.854	0.000521	160	531	1482	1482	510.0
LNG_CC#38	829.888	37.768	0.000498	160	531	1482	1482	470.0
LNG_CC#39	2333.690	67.983	0.001046	200	542	1668	1668	464.1
LNG_CC#40	2028.954	77.838	0.132050	56	132	120	120	118.1
LNG_CC#41	4412.017	63.671	0.096968	115	245	180	180	141.3
LNG_CC#42	2982.219	79.458	0.054868	115	245	120	180	132.0
LNG_CC#43	2982.219	79.458	0.054868	115	245	120	180	135.0
LNG_CC#44	3174.939	93.966	0.014382	207	307	120	180	252.0
LNG_CC#45	3218.359	94.723	0.013161	207	307	120	180	221.0
LNG_CC#46	3723.822	66.919	0.016033	175	345	318	318	245.9
LNG_CC#47	3551.405	68.185	0.013653	175	345	318	318	247.9
LNG_CC#48	4322.615	60.821	0.028148	175	345	318	318	183.6
LNG_CC#49	3493.739	68.551	0.013470	175	345	318	318	288.0
NUCLEAR#01	226.799	2.842	0.000064	360	580	18	18	557.4
NUCLEAR#02	382.932	2.946	0.000252	415	645	18	18	529.5
NUCLEAR#03	156.987	3.096	0.000022	795	984	36	36	800.8
NUCLEAR#04	154.484	3.040	0.000022	795	978	36	36	801.5
NUCLEAR#05	332.834	1.709	0.000203	578	682	138	204	582.7
NUCLEAR#06	326.599	1.668	0.000198	615	720	144	216	680.7
NUCLEAR#07	345.306	1.789	0.000215	612	718	144	216	670.7
NUCLEAR#08	350.372	1.815	0.000218	612	720	144	216	651.7
NUCLEAR#09	370.377	2.726	0.000193	758	964	48	48	921.0
NUCLEAR#10	367.067	2.732	0.000197	755	958	48	48	916.8
NUCLEAR#11	124.875	2.651	0.000324	750	1007	36	54	911.9
NUCLEAR#12	130.785	2.798	0.000344	750	1006	36	54	898.0
NUCLEAR#13	878.746	1.595	0.000690	713	1013	30	30	905.0
NUCLEAR#14	827.959	1.503	0.000650	718	1020	30	30	846.5
NUCLEAR#15	432.007	2.425	0.000233	791	954	30	30	850.9
NUCLEAR#16	445.606	2.499	0.000239	786	952	30	30	843.7
NUCLEAR#17	467.223	2.674	0.000261	795	1006	36	36	841.4
NUCLEAR#18	475.940	2.692	0.000259	795	1013	36	36	835.7
NUCLEAR#19	899.462	1.633	0.000707	795	1021	36	36	828.8
NUCLEAR#20	1000.367	1.816	0.000786	795	1015	36	36	846.0
OIL#01	1269.132	89.830	0.014355	94	203	120	120	179.0
OIL#02	1269.132	89.830	0.014355	94	203	120	120	120.8
OIL#03	1269.132	89.830	0.014355	94	203	120	120	121.0
OIL#04	4965.124	64.125	0.030266	244	379	480	480	317.4
OIL#05	4965.124	64.125	0.030266	244	379	480	480	318.4
OIL#06	4965.124	64.125	0.030266	244	379	480	480	335.8
OIL#07	2243.185	76.129	0.024027	95	190	240	240	151.0
OIL#08	2290.381	81.805	0.001580	95	189	240	240	129.5
OIL#09	1681.533	81.140	0.022095	116	194	120	120	130.0
OIL#10	6743.302	46.665	0.076810	175	321	180	180	218.9
OIL#11	394.398	78.412	0.953443	2	19	90	90	5.4
OIL#12	1243.165	112.088	0.000044	4	59	90	90	45.0
OIL#13	1454.740	90.871	0.072468	15	83	300	300	20.0
OIL#14	1011.051	97.116	0.000448	9	53	162	162	16.3
OIL#15	909.269	83.244	0.599112	12	37	114	114	20.0
OIL#16	689.378	95.665	0.244706	10	34	120	120	22.1
OIL#17	1443.792	91.202	0.000042	112	373	1080	1080	125.0
OIL#18	535.553	104.501	0.085145	4	20	60	60	10.0
OIL#19	617.734	83.015	0.524718	5	38	66	66	13.0
OIL#20	90.966	127.795	0.176515	5	19	12	6	7.5
OIL#21	974.447	77.929	0.063414	50	98	300	300	53.2
OIL#22	263.810	92.779	2.740485	5	10	6	6	6.4
OIL#23	1335.594	80.950	0.112438	42	74	60	60	69.1
OIL#24	1033.871	89.073	0.041529	42	74	60	60	49.9
OIL#25	1391.325	161.288	0.000911	41	105	528	528	91.0
OIL#26	4477.110	161.829	0.005245	17	51	300	300	41.0
OIL#27	57.794	84.972	0.234787	7	19	18	30	13.7
OIL#28	57.794	84.972	0.234787	7	19	18	30	7.4
OIL#29	1258.437	16.087	1.111878	26	40	72	120	28.6

D. Large-Scale Power System of Korea

To investigate the possibility of the proposed IPSOs to the large-scale power systems, experiments are conducted on the Korean power system. The system consists of 140 thermal generating units with ramp rate limits where the hydro and pump storage plants are not considered. The input data are given in Table XIX of the Appendix. The total demand is set to 49 342 MW. Since the cost function of each generating unit is considered as the second-order polynomial, the global optimum solution can be obtained using the mathematical programming techniques. Nonlinear programming (NLP), which was implemented in GAMS, found the global optimum, $1 655 685, in 0.1 (s). Table XV summarizes the performance of each IPSO approach. Although the proposed IPSOs have always reached to the global solution for the 100 independent trials and the

TABLE XX
UNIT DATA WITH VALVE-POINT LOADING

Generator	*a*	*b*	*c*	*e*	*f*
COAL#05	1976.469	54.242	0.042468	700	0.080
COAL#10	1320.636	13.226	0.005063	600	0.055
COAL#15	1176.504	14.651	0.003901	800	0.060
COAL#22	1229.131	14.656	0.003684	600	0.050
COAL#33	1074.810	15.033	0.003542	600	0.043
COAL#40	1436.251	15.815	0.001581	600	0.043
LNG_CC#10	1898.415	71.584	0.000044	1100	0.043
LNG_CC#28	13813.001	22.941	0.081540	1200	0.030
LNG_CC#30	9750.750	45.017	0.035475	1000	0.050
LNG_CC#42	2982.219	79.458	0.054868	1000	0.050
OIL#08	2290.381	81.805	0.001580	600	0.070
OIL#10	6743.302	46.665	0.076810	1200	0.043

TABLE XXI
PROHIBIT ZONES OF UNITS

Generator	Zone 1	Zone 2	Zone 3
COAL#08	[250, 280]	[305, 335]	[420, 450]
COAL#32	[220, 250]	[320, 350]	[390, 420]
LNG_CC#32	[230, 255]	[365, 395]	[430, 455]
OIL#25	[50, 75]	[85, 95]	-

CSPSO has rapidly converged into the optimum in 9.6 (s), the computational efficiency is relatively low in comparison with NLP for the convex ED problem. However, the applicability of the IPSOs to large-scale power systems is investigated throughout the experiments.

In addition, in order to show the applicability of the IPSOs to the large-scale power system with nonconvex cost function, it is assumed that 12 generators have the cost function with valve-point effects and four generators are considered the prohibited operating zones. Therefore, the mathematical methods such as NLP cannot provide the solution. The data are given in Tables XX and XXI of the Appendix . Through experiments described in Tables XVI and XVII, c_1, c_2, and *CR* are set to be 1.5, 2.0, and 0.2, respectively. The convergence results of each IPSO approach are summarized in Table XVIII.

VII. CONCLUSIONS

This paper proposes an IPSO approach for solving nonconvex ED problems. The proposed IPSO employs the chaotic sequences as well as the crossover operation to enhance the performance of the conventional PSO. The chaotic sequences combined with the linearly decreasing inertia weights are devised to improve the global searching capability and escape from a local minimum. In addition, the crossover operation is introduced to increase the diversity of the population. These strategies not only improve the global searching ability but also prevent the solution from trapping in a local optimum point. In addition, a more efficient constraint treatment strategy is proposed. The proposed IPSO algorithms have been successfully applied to three nonconvex ED problems considering valve-points, prohibited operating zones with ramp rate limits as well as transmission network losses, and multi-fuels with valve-point effects. The proposed CSPSO, COPSO, and CCPSO have found better solutions for the three test systems than other solutions found so far. Additionally, the IPSOs are applied to the large-scale Korean power system. First, each IPSO approach is tested on the power system with convex cost function considering the ramp rate limits. The results show that the IPSO can always find the global solution, and they are somewhat independent to control parameters values while the computation time is longer than the mathematical optimization method. Also the proposed IPSOs are tested on the Korean power system with nonconvex cost function considering valve-points and prohibited operating zones as well as ramp rate limits. The results clearly show that the proposed IPSO framework can be used as an efficient optimizer providing satisfactory solutions for general nonconvex ED problems; however, future researches should be followed to reduce the computation time for large-scale convex ED problems.

APPENDIX

The characteristics data of generating units for Korean power system are given in Tables XIX–XXI.

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