

## Research Article

# Combined Economic and Emission Dispatch Problem of Wind-Thermal Power System Using Gravitational Particle Swarm Optimization Algorithm

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In this paper, a novel hybrid optimization approach, namely, gravitational particle swarm optimization algorithm (GPSOA), is introduced based on particle swarm optimization (PSO) and gravitational search algorithm (GSA) to solve combined economic and emission dispatch (CEED) problem considering wind power availability for the wind-thermal power system. The proposed algorithm shows an interesting hybrid strategy and perfectly integrates the collective behaviors of PSO with the Newtonian gravitation laws of GSA. GPSOA updates particle's velocity caused by the dependent random cooperation of GSA gravitational acceleration and PSO velocity. To describe the stochastic characteristics of wind speed and output power, Weibull-based probability density function (PDF) is utilized. The CEED model employed consists of the fuel cost objective and emission-level target produced by conventional thermal generators and the operational cost generated by wind turbines. The effectiveness of the suggested GPSOA is tested on the conventional thermal generator system and the modified wind-thermal power system. Results of GPSOA-based CEED problems by means of the optimal fuel cost, emission value, and best compromise solution are compared with the original PSO, GSA, and other state-of-the-art optimization approaches to reveal that the introduced GPSOA exhibits competitive performance improvements in finding lower fuel cost and emission cost and best compromise solution.

## 1. Introduction

The classical economic dispatch (ED) problem is to determine the optimal active power allocation from all the involved units to minimize the total operating cost regardless of emissions produced while satisfying all units and system constraints [1]. However, with increasing seriousness of energy crisis and growing public awareness of environmental protection, high-efficiency utilization for renewable energy sources such as wind, as well as reduction of pollutant emission derived from fossil fuels, has been paid more attention all over the world. In this circumstance, modifying the existing allocation technology strategies to reduce both fuel cost and emission level of pollutants have become a hot and urgent research issue. Accordingly, a new dispatch approach, known as the combined economic and emission dispatch (CEED) problem has been presented to pursue both

the least emission level and lowest generation cost of operation of a power system [2]. To find quality solution of the CEED problem, different optimization approaches have been developed. The classical optimization approaches such as linear programming (LP) [3] and recursive quadratic programming (RQP) [4] have been proposed by researchers. However, the practical CEED problem is a nonlinear and nonsmooth constrained optimization problem with complex and nonconvex features, which is regarded as a challenge for seeking the global optimal solution. Therefore, some traditional gradient information-based optimization methods fail to solve efficiently the CEED problem. In recent decades, as an alternative to the traditional optimization approaches, various population-based nature-inspired heuristic techniques have been extensively introduced for solving many complex optimization problems in the real world such as feature selection [5, 6], image processing [7],

robotic path planning [8], neural networks training [9], and electric power system planning [10]. Without a doubt, some heuristic approaches have been also reported in the literature to solve the CEED problems. Among these heuristic techniques such as evolutionary programming (EP) [11], refined genetic algorithm (RGA) [12], nondominated sorting genetic algorithms (NSGA) [13], particle swarm optimization (PSO) [14–17], differential evolution (DE) [18], gravitational search algorithm (GSA) [19, 20], ant colony optimization [21], bacterial foraging algorithm [22], opposition-based harmony search [23], biogeography-based optimization algorithm [24], artificial physical optimization [25], and glowworm swarm optimization [26] have been widely investigated to find the optimal solution of the CEED problem.

However, the above-mentioned CEED problem only depends on how best to decrease the pollutant emission in fossil-fuel power industry by help of regulating the existing dispatch strategies. At the moment, renewable energy such as wind energy in power sector has gained wide attention due to its prominent advantage with low fuel cost and zero emission. Hence, the ED or CEED model with incorporating wind power has been proposed to obtain feasible scheduling solution by researchers to realize the goal of emission reduction. In [27], an economic dispatch problem incorporating wind power was firstly proposed and different coefficients in the model on the effect of optimal outputs were discussed. Also, a minimum emission dispatch model considering the constraints of wind power availability for the power system was presented in [28, 29]. Multiobjective economic and emission load dispatch problem including wind power penetration using GSA was proposed by handling both the fuel cost and emission objectives [30]. To establish a more practical dispatch scenario, a probabilistic multiobjective economic and emission problem by taking the uncertainty of wind speed and load demand into account was proposed in [31]. From another point of view, powerful heuristic methods are of great importance for solving the CEED problem including wind power availability. Several available optimization methodologies such as bipopulation chaotic differential evolution algorithm (BPCDE) [32], chaotic quantum genetic algorithm (CQGA) [33], covariant matrix adaptation with evolution strategy (CMA-ES) [34], hybrid flower pollination algorithm (HFPA) [35], series PSO-DE [36], hybrid firefly algorithm (FFA) [37], decomposition-based multiobjective evolutionary algorithm (MOEA) [38], and hybrid imperialist competitive-sequential quadratic programming (HIC-SQP) [39] have been proved effective to solve wind power-integrated CEED problems. However, there is still a lot of room for improvement in obtaining better scheduling schemes for the wind-thermal power system although the current optimization algorithms have been successfully employed to solve CEED problem in the presence of wind power availability.

In this paper, in an attempt to take full advantage of the search behavior of PSO and GSA, a novel modified hybrid optimization approach integrating the GSA into the PSO, namely, gravitational particle swarm optimization algorithm (GPSOA), is firstly proposed for solving the CEED problem of wind-thermal power system considering wind power

penetration. The main target of the proposed GPSOA is to promote the optimization capability of the original PSO and GSA by incorporating the exploration advantage in PSO with the exploitation advantage of GSA to overcome their individual weaknesses. The proposed approach embodies different interesting concepts, e.g., the cooperation behaviors of the PSO and the acceleration mechanisms of the GSA. GPSOA simultaneously updates particle position through the dependent stochastic configuration of PSO velocity and GSA acceleration to increase its diversity. Therefore, the probability of finding global solution and the capability of accelerating convergence rate in GPSOA have been significantly improved. To demonstrate the optimization performance of the suggested GPSOA, the conventional IEEE 30-bus test system and modified wind-thermal power system were employed as the benchmark. Results obtained verify the feasibility and effectiveness of the GPSOA according to superior solution quality and convergence performance when compared with GSA, PSO, and other state-of-the-art optimization approaches.

Thus, the main objectives of the current article may be noted as follows:

- (a) The performance of the newly proposed GPSOA, as an optimization tool in solving wind power-integrated CEED problems, is investigated on different conventional and wind-thermal power test systems and the obtained results are presented.
- (b) The best results obtained from the solution of the CEED problems of test systems by adopting this proposed approach are compared to those published in the recent literature.

The rest of this paper is organized as follows. In Section 2, the mathematical formulation of the CEED problem including wind power availability is firstly established. The suggested GPSOA optimization approach is introduced in Section 3. Specific solution procedure by using the GPSOA approach for the CEED problem is presented in detail in Section 4. In Section 5, numerical examples and simulation results validate the competitive performance of the GPSOA for solving traditional thermal and modified wind-thermal power test systems. Finally, the conclusions are covered in Section 6.

## 2. Economic and Emission Dispatch Model considering Wind Power Availability

In this section, the economic and emission dispatch model considering wind power penetration is established to find the optimal dispatch by conducting simultaneous minimization of the two competing objectives, i.e., economic dispatch problem including wind power and emission dispatch problem. In the model, the stochastic characteristics of wind speed and output power are described by a Weibull-based probability density function (PDF) in Section 2.1. Thus, the operational cost caused by underestimation and overestimation of wind power is computed in Section 2.2 using a closed-form equation by means of the incomplete gamma

function (IGF). Finally, the objective formulation of the CEED problem with wind power incorporation and its constraints are described in the following.

**2.1. Probability Analysis of Wind Power.** A major challenge to the integration of wind output power into power network is its uncertainty, fluctuation, and intermittent nature. Hence, it is indispensable that the output of wind power should be expressed as a stochastic variable by means of a transformation function from wind speed to power output. When ignoring some minor nonlinear factors, a simplified linear piecewise function is given to describe the actual relationship between them, as shown in the following equation:

$$w = \begin{cases} 0, & v < v_{\text{in}} \text{ or } v \geq v_{\text{out}}, \\ w_r \left( \frac{v - v_{\text{in}}}{v_r - v_{\text{in}}} \right), & v_{\text{in}} \leq v < v_r, \\ w_r, & v_r \leq v < v_{\text{out}}, \end{cases} \quad (1)$$

where  $v$  is the current wind speed in m/s;  $v_r$ ,  $v_{\text{out}}$ , and  $v_{\text{in}}$  are rated, cut-out and cut-in wind speeds, respectively; and  $w_r$  is the rated output power.

Generally, it is pointed out that the stochastic description of wind speed is defined by two-dimensional variable Weibull distribution [27]. The probability density function  $f_V(v)$  of wind speed  $v$  can be expressed as follows:

$$f_V(v) = \frac{k}{c} \left( \frac{v}{c} \right)^{k-1} \exp \left[ - \left( \frac{v}{c} \right)^k \right]. \quad (2)$$

As you can see the relationship between output power and wind speed, the probability density function  $f_W(w)$  of output power of wind turbine can be computed by equations (3) and (4). Due to a piecewise function in equation (1), the cumulative probability is given while  $w$  equals 0 or rated power  $w_r$ :

$$\begin{aligned} \Pr_W(w = 0) &= \Pr_W(v < v_{\text{in}}) + \Pr_W(v \geq v_{\text{out}}) \\ &= 1 - \exp \left( - \left( \frac{v_{\text{in}}}{c} \right)^k \right) + \exp \left( - \left( \frac{v_{\text{out}}}{c} \right)^k \right), \end{aligned} \quad (3)$$

$$\begin{aligned} \Pr_W(w = w_r) &= \Pr_W(v_r \leq v < v_{\text{out}}) \\ &= \exp \left( - \left( \frac{v_r}{c} \right)^k \right) - \exp \left( - \left( \frac{v_{\text{out}}}{c} \right)^k \right). \end{aligned} \quad (4)$$

The probability density function  $f_W(w)$  while  $w$  is between 0 and  $w_r$  is

$$f_W(w) = \frac{khv_{\text{in}}}{c} \left[ \frac{(1+h\lambda)v_{\text{in}}}{c} \right]^{k-1} \times \exp \left\{ - \left[ \frac{(1+h\lambda)v_{\text{in}}}{c} \right]^k \right\},$$

$$0 < w < w_r,$$

$$h = \frac{v_r - v_{\text{in}}}{v_{\text{in}}},$$

$$\lambda = \frac{w}{w_r}, \quad (5)$$

where  $c$  is the scale parameter and  $k$  shape parameter of Weibull distribution. Apparently, the probability density function of output power is more complicated for wind turbine. It contains discrete and continuous output power. Moreover, the total cumulative probability reaches 1.

## 2.2. Objective Formulation of Combined Economic and Emission Dispatch including Wind Power

### 2.2.1. Operational Cost of Wind Power Availability.

When considering the influence on power network resulting from the uncertainty of wind speed, the operational cost of wind turbine can be calculated in three parts: overestimated unbalance cost of wind power  $\text{WPCost}_{\text{oe}}$ , underestimated unbalance cost of wind power  $\text{WPCost}_{\text{ue}}$ , and direct cost of wind power  $\text{WPCost}_{\text{dir}}$ . Thus, the operational cost of wind turbine  $y_w$  is given in equation (6), which can be derived from [27]

$$\begin{aligned} y_w &= \sum_{j=1}^{N_w} y_{wj} = \sum_{j=1}^{N_w} (\text{WPCost}_{\text{oe},j} + \text{WPCost}_{\text{ue},j} + \text{WPCost}_{\text{dir},j}) \\ &= \sum_{j=1}^{N_w} (C_{\text{r}w_j} E(Y_{\text{oe},j}) + C_{\text{p}w_j} E(Y_{\text{ue},j}) + g_j w_j), \end{aligned} \quad (6)$$

where  $N_w$  is the number of wind power generator.  $\text{WPCost}_{\text{oe},j}$  represents the overestimated unbalance cost for the  $j$ th wind turbine. The actual output power of wind turbine is less than the scheduled output power. At this point, the overestimation case occurs. Hence, the power network system must purchase output power from other resources to meet system requirements.  $C_{\text{r}w_j}$  represents the cost coefficient of the  $j$ th wind generator under overestimation case;  $E(Y_{\text{oe},j})$  represents the desired value of the  $j$ th wind generator under overestimation case [28]. Hence, it can be computed using a closed-form expression (equation (7)) by means of the incomplete gamma function (IGF).

$$\begin{aligned}
E(Y_{oe,j}) &= w_j \times \Pr_W(w=0) + \int_0^{w_j} (w_j - w) f_W(w) dw \\
&= w_j \times \left[ 1 - \exp\left(-\left(\frac{v_{in,j}}{c_j}\right)^{k_j}\right) + \exp\left(-\left(\frac{v_{out,j}}{c_j}\right)^{k_j}\right) \right] \\
&\quad + \left( \frac{w_{r,j} v_{in,j}}{(v_{r,j} - v_{in,j}) + w_j} \right) \left[ \exp\left(-\left(\frac{v_{in,j}}{c_j}\right)^{k_j}\right) \right. \\
&\quad \left. - \exp\left(-\left(\frac{v_{1,j}}{c_j}\right)^{k_j}\right) \right] \\
&\quad + \left( \frac{w_{r,j} c_j}{(v_{r,j} - v_{in,j})} \right) \left\{ \Gamma \left[ 1 + \frac{1}{k_j}, \left(\frac{v_{1,j}}{c_j}\right)^{k_j} \right] \right. \\
&\quad \left. - \Gamma \left[ 1 + \frac{1}{k_j}, \left(\frac{v_{in,j}}{c_j}\right)^{k_j} \right] \right\}, \tag{7}
\end{aligned}$$

where  $v_{1,j} = v_{in,j} + (v_{r,j} - v_{in,j})w_j/w_{r,j}$ ,  $w_j$  and  $w_{r,j}$  represent the practical active power and the rated output power of the  $j$ th wind turbine, respectively.  $c_j$  and  $k_j$  denote the scale factor and shape factor of the  $j$ th wind turbine, respectively.  $v_{in,j}$ ,  $v_{out,j}$ , and  $v_{r,j}$  are cut-in speed, cut-out speed, and rate speed of the  $j$ th wind turbine, respectively.  $\Gamma(\cdot)$  is the incomplete gamma function.

$WPCost_{ue,j}$  is the underestimated unbalance cost for the  $j$ th wind turbine. The actual output power of wind turbine is more than the scheduled output power. At this time, the redundant output power is wasted and the power network system must compensate the wind turbine supplier's operational cost.  $C_{pwj}$  is the cost coefficient of underestimation case for the  $j$ th wind turbine.  $E(Y_{ue,j})$  represents the expected value of underestimation case for the  $j$ th wind turbine [28]. Then, it is also computed as a mathematical expression (equation (8)) depending on the IGF.

$$\begin{aligned}
E(Y_{ue,j}) &= (w_{r,j} - w_j) \times \Pr_W(w = w_{r,j}) + \int_{w_j}^{w_{r,j}} (w - w_j) f_W(w) dw \\
&= (w_{r,j} - w_j) \left[ \exp\left(-\left(\frac{v_{r,j}}{c_j}\right)^{k_j}\right) - \exp\left(-\left(\frac{v_{out,j}}{c_j}\right)^{k_j}\right) \right] \\
&\quad + \left( \frac{w_{r,j} v_{in,j}}{(v_{r,j} - v_{in,j}) + w_j} \right) \left[ \exp\left(-\left(\frac{v_{r,j}}{c_j}\right)^{k_j}\right) \right. \\
&\quad \left. - \exp\left(-\left(\frac{v_{1,j}}{c_j}\right)^{k_j}\right) \right] \\
&\quad + \left( \frac{w_{r,j} c_j}{(v_{r,j} - v_{in,j})} \right) \left\{ \Gamma \left[ 1 + \frac{1}{k_j}, \left(\frac{v_{1,j}}{c_j}\right)^{k_j} \right] \right. \\
&\quad \left. - \Gamma \left[ 1 + \frac{1}{k_j}, \left(\frac{v_{r,j}}{c_j}\right)^{k_j} \right] \right\}, \tag{8}
\end{aligned}$$

$WPCost_{dir,j}$  represents the direct cost for the  $j$ th wind turbine. Its calculated value is proportional to the available wind power. Then, it can be written as follows:

$$WPCost_{dir,j} = g_j w_j, \tag{9}$$

where  $g_j$  represents the direct cost coefficient.

### 2.2.2. Economic Dispatch Problem including Wind Power.

The economic dispatch objective including wind power is to minimize the total fuel cost of thermal generators and wind turbines while satisfying all the constraints. That is to say, it can be composed of the fuel cost of thermal units and the operational cost of wind power availability. Then, the objective function can be represented as follows:

$$F_T = \sum_{j=1}^{N_w} y_{wj} + \sum_{i=1}^{N_g} F_i(P_{Gi}), \tag{10}$$

$$F_i(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \sin \left[ e_i \times (P_{Gi}^{\min} - P_{Gi}) \right] \right|, \tag{11}$$

where  $F_T$  is the total fuel cost.  $y_{wj}$  represents the operational cost of the  $j$ th wind generator.  $F_i$  is the fuel cost of the  $i$ th thermal generator including valve point effect.  $a_i$ ,  $b_i$ , and  $c_i$  are the fuel cost coefficients for the  $i$ th thermal unit, respectively.  $d_i$  and  $e_i$  are the fuel cost coefficients for the  $i$ th thermal unit with valve point effect, respectively.  $P_{Gi}$  and  $P_{Gi}^{\min}$  are the output power and its lower limit of the  $i$ th thermal generator, respectively.

**2.2.3. Emission Dispatch Problem.** The objective of emission dispatch model can be described as minimization of the total pollutant emission level produced by the consumption of fossil fuels in the conventional power system. Since wind power belongs to nonpollution renewable energy, the pollutant emission level is usually regarded as zero. Hence, the total pollutant emission level for power system including wind power is equal to that of the classical power system of the thermal generator. The pollutant emission released by fossil fuel consumption is defined as the sum of an exponential function and a quadratic function. Then, mathematically the emission dispatch function can be expressed as follows [40]:

$$E_T = \sum_{i=1}^{N_g} \left[ 10^{-2} (\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) + \xi_i \exp(P_{Gi} \lambda_i) \right], \tag{12}$$

where  $E_T$  is the emission release and  $\alpha_i$ ,  $\beta_i$ ,  $\gamma_i$ ,  $\xi_i$ , and  $\lambda_i$  are the pollution coefficients of the  $i$ th thermal generating unit.

### 2.2.4. Problem Constraints

(1) *Power Balance Constraints.* For a wind-thermal power system, the total generated thermal power and wind power should be equal to the total real power loss  $P_L$  in the

transmission lines plus the total load demand  $P_D$ . Then, the active power balance constraints can be given as follows:

$$\sum_{i=1}^{N_g} P_{Gi} + \sum_{j=1}^{N_w} w_j = P_D + P_L. \quad (13)$$

The transmission loss  $P_L$  depends on the output of each generated unit, grid structure, and line parameter. Generally, the power system loss is defined as a function of active power at each power unit, and then, the resultant calculation formula is expressed as follows [17]:

$$P_L = \sum_{i=1}^{N_g+N_w} \sum_{j=1}^{N_g+N_w} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{N_g+N_w} B_{i0} P_{Gi} + B_{00}, \quad (14)$$

where  $B_{ij}$ ,  $B_{i0}$ , and  $B_{00}$  are the line loss coefficients (the  $P_{Gi}$  in the formula should be replaced by  $w_j$  when the generated power is from wind turbine).

(2) *Generation Capacity Limits.* The active power output of each unit should be limited in the range of its minimum and maximum values. The generation capacity limits for each generated power unit are given in the following equations:

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max}, \quad i = 1, 2, \dots, N_g, \quad (15)$$

$$0 \leq w_j \leq w_{r,j}, \quad j = 1, 2, \dots, N_w, \quad (16)$$

where  $P_{Gi}^{\min}$  and  $P_{Gi}^{\max}$  are the minimum and maximum of power output for the  $i$ th thermal generator, respectively.

**2.2.5. Overall Objective Function for Combined Economic and Emission Dispatch Problem.** It is pointed that the two objectives such as economic dispatch and emission dispatch are actually incompatible in essence. Hence, the objective of combined economic and emission dispatch problem is to balance between the fuel cost economy and the pollutant emission level, which should be regarded as a multiobjective optimization problem. As a matter of fact, the optimal solution to the multiobjective problem does not exist. A Pareto-optimal solution obtained is the best solution vector out of several numbers of solution vectors that could be achieved without disadvantaging other objectives. Hence, for the multiobjective CEED problem, Pareto-optimal solution is also the best dispatch out of set of solution vectors that can be achieved without disadvantaging both fuel cost minimization and emission minimization. However, the multiobjective optimization problem is converted into a single objective one by an effective evaluation function, and a significant optimal solution is found by means of proposed algorithms. In this paper, a linear weighting-sum evaluation method is employed to find the optimal solution and reduce the computing effort. To be specific, the above multiobjective optimization problem can be converted into a single objective optimization problem by applying an equivalent factor such as price penalty factor (PPF) [30]. The PPF value is to give equal importance weight of the emission cost with the fuel cost. Therefore, the overall objective function for a wind-thermal power system can be described as follows:

$$\text{minimize} \quad TC(P_D) = F_T(P_{Gi}, w_j) + Pf(P_D) \times E_T(P_{Gi}), \quad (17)$$

where  $TC(P_D)$  is the total cost in \$/h and  $Pf(P_D)$  is the price penalty factor in \$/ton. Also, the CEED problem in a wind-thermal power network is subject to constraints shown in equations (13) to (16). For calculating the  $Pf$  value for a given load demand  $P_D$ , the detailed calculation steps were employed in [30].

However, the CEED problem can also be regarded as a multiobjective optimization problem using a particular weight factor  $\lambda$ . Accordingly, the overall objective function for the CEED problem is formulated and optimized. As a result, the Pareto-optimal solutions, known as the Pareto-optimal front, can be generated using a weight coefficient  $\lambda$ . Changing weight factor  $\lambda$  means varying the different levels of importance of one objective with respect to another objective. Hence, if the economic dispatch and emission-level dispatch problems are considered together, the overall mathematical formulation of multiobjective problem is expressed as follows:

$$\text{minimize} \quad TC(P_D) = \lambda \times F_T(P_{Gi}, w_j) + (1 - \lambda) \times Pf(P_D) \times E_T(P_{Gi}), \quad (18)$$

where  $\lambda$  represents the weight factor. Generally, it varies uniformly from 0 to 1. In the experiment, it is increased in steps of 0.033 from 0 up to 1. Thus, a group of nondominated solutions is obtained by 30 intervals.

For the multiobjective dispatch problem, the overall objective equation (18) is minimized for varying weights of each objective when the  $Pf$  value for a given load is obtained. In this case, a group of nondominated solutions in the repository are obtained. As a result, the best compromise solution is determined by using fuzzy-based decision maker. The detailed fuzzy decision method is presented in [14].

### 3. Gravitational Particle Swarm Optimization Algorithm (GPSOA)

**3.1. Particle Swarm Optimization.** Particle swarm optimization is a swarm-based metaheuristic optimization approach [41]. It is biologically inspired by intelligent social behaviors like a flock of birds. In recent decades, PSO is widely applied to optimization solution in terms of its efficiency, simplicity, and effectiveness [5, 6, 8, 14–18]. In the basic PSO, the population consists of a group of particles which represent potential solutions to the given problem moving through the  $D$ -dimensional searching space. Each particle in PSO is associated with two components, namely, position vector and velocity vector. During the searching course, each particle flies through its previous personal best performance called  $pbest$  and the global best performance obtained far from the global swarm called  $gbest$  in the decision space. To be specific, the PSO particle's velocity and its new position at the iteration  $t+1$  are updated by the following equations:

$$v_i^d(t+1) = w(t)v_i^d(t) + c_1r_1(pb_{i^d} - x_i^d(t)) + c_2r_2(gbest^d - x_i^d(t)), \quad (19)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1), \quad (20)$$

$$w(t) = \text{rand} \frac{t}{t_{\max}} (w_{\max} - w_{\min}) + w_{\min}, \quad (21)$$

where  $v_i^d(t)$  and  $x_i^d(t)$  represent the velocity and position of particle  $i$  in the  $d$ th dimension at time  $t$ , respectively. The coefficients  $c_1$  and  $c_2$  are two acceleration factors that control the influence of personal best experience  $pb_{i^d}$  and global best experience  $gbest^d$  in the search process, respectively.  $r_1$  and  $r_2$  are two random values in the range of  $[0,1]$ .  $pb_{i^d}$  represents the optimal position found so far by particle  $i$ , and  $gbest^d$  represents the optimal position in the entire swarm.  $w(t)$  represents the inertia weight value defined by using equation (21), where  $w_{\min}$  and  $w_{\max}$  represent the maximum and minimum value of  $w(t)$ , and its target is to impose the influence of the previous velocity on the current velocity. Hence, the balance of the exploration and exploitation capability of the PSO can be adjusted by the inertia weight.  $t_{\max}$  represents the maximum number of iterations.  $t$  represents the current number of iterations.

**3.2. Gravitational Search Algorithm.** GSA is also a newly developed population-based metaheuristic optimization approach inspired by the Newton physics law of gravitation and mass interactions between agents [42]. In GSA, each agent is considered as the position of the mass, and its performance is associated with a fitness of a problem. Each agent attracts each other in the universe. The gravity force between any two agents is directly proportional to the product of their masses. However, it is inversely proportional to the square of the gap between them. Hence, all the agents in the population move towards the heaviest mass under the gravitational force through the Newtonian physics law. The heaviest agent that corresponds to the best solution flies more slowly than the lightest one during the search process. The heaviest mass that presents the optimal solution in a multidimensional search space can be attracted by masses. It was shown in [7, 9, 19, 20, 43] that the algorithm is competent to handle large-scale nonlinear optimization problems. The main steps and structure of the GSA approach are summarized as follows:

Step 1: initialize the population

Suppose that there is a population with  $N$  agents. First, initialize randomly agents' positions which correspond to a set of solution of the problem in the search domain as follows:

$$X_i = (x_i^1, \dots, x_i^d, \dots, x_i^D), \quad i = 1, 2, \dots, N, \quad (22)$$

where  $x_i^d$  denotes the position of the  $i$ th mass in the  $d$ th dimension, which represents a candidate solution to the optimization problem,  $D$  denotes the dimension of the

search space, and  $N$  is the total number of agent in the entire population.

Step 2: compute fitness value

Compute the fitness value of all agents at iteration  $t$  and also evaluate the *best* and *worst* fitness in terms of equations (23) and (24), respectively (without loss of generality, a minimization optimization problem is defined in this paper):

$$best(t) = \min_{j \in \{1, \dots, N\}} fit_j(t), \quad (23)$$

$$worst(t) = \max_{j \in \{1, \dots, N\}} fit_j(t), \quad (24)$$

where  $fit_j(t)$  denotes the objective fitness of the  $j$ th agent at generation  $t$ .  $best(t)$  and  $worst(t)$  denote the best and worst objective fitness in the swarm at time  $t$ , respectively.

Step 3: compute gravitational constant  $G(t)$

The gravitational constant  $G(t)$  at time  $t$  is calculated as follows:

$$G(t) = G_0 \exp\left(-\alpha \frac{t}{t_{\max}}\right). \quad (25)$$

Apparently,  $G(t)$  is reduced with iteration to adjust search accuracy.  $G_0$  represents the initial value of  $G(t)$  and is set to 100.  $\alpha$  is a constant term and is set to 20 [42].  $t_{\max}$  is the maximum number of iterations, and  $t$  is the current number of iterations.

Step 4: update gravitational and inertial masses

The updated gravitational and inertial masses  $i$  at iteration  $t$  are expressed as follows:

$$M_{ai} = M_{pi} = M_{ii} = M_i, \quad i = 1, 2, \dots, N, \quad (26)$$

$$q_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)}, \quad (27)$$

$$M_i(t) = \frac{q_i(t)}{\sum_{j=1}^N q_j(t)},$$

where  $M_i(t)$  denotes the mass of the  $i$ th agent at time  $t$ .

Step 5: calculate acceleration

The gravitational force acting on mass “ $i$ ” from mass “ $j$ ” in the  $d$ th dimension is as in equation (28). Apparently, the gravity acts between separated agents without delay and intermediary. The total gravitational force that acts on agent  $i$  in the  $d$ th dimension is a randomly weighted sum of the forces exerted from other agents, and then, the gravitational acceleration  $a_i^d(t)$  is given in equation (29) based on the Newton gravitational law:

$$F_{ij}^d = G(t) \frac{M_{pi}(t) * M_{aj}(t)}{R_{ij}(t) + \epsilon} (x_j^d - x_i^d), \quad (28)$$

$$a_i^d(t) = \sum_{j \in kbest, j \neq i} \text{rand}_j G(t) \frac{M_j(t)}{R_{ij}(t) + \varepsilon} (x_j^d - x_i^d),$$

$$d = 1, 2, \dots, D, j = 1, 2, \dots, N, \quad (29)$$

where  $a_i^d(t)$  is the acceleration of the mass  $i$  in the  $d$ th dimension at time  $t$ .  $\varepsilon$  denotes a small constant term.  $\text{rand}_j$  is the uniform stochastic value in the range  $[0,1]$ , which can increase the search diversity in the search process.  $R_{ij}(t)$  represents the Euclidean norm both  $i$ th and  $j$ th agents.  $kbest$  is the group of initial  $K$  agents with best solutions and heaviest mass. It is defined as a function of time according to the rule of linear decrease. In this way, at the beginning of the optimization process, all agents contribute the forces and the algorithm presents the exploration capability to avoid trapping in a local optimum. As time passes,  $kbest$  is linearly reduced to 1 and the exploitation performance is reinforced. Finally, only one mass is forced on the others.

Step 6: update agent velocity and position

Finally, the  $i$ th agent velocity at next time ( $t+1$ ) and its updated position can be computed as the following equations, respectively:

$$v_i^d(t+1) = \text{rand}_i v_i^d(t) + a_i^d(t), \quad (30)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1). \quad (31)$$

Step 7: repeat from Steps 2 to 6 until the maximum iteration  $t_{\max}$  is reached or the termination criterion is satisfied. Then, the optimal objective function value (best fitness) and the corresponding best position (global optimal solution) for optimization problem are obtained.

### 3.3. Gravitational Particle Swarm Optimization Algorithm.

The key operation of swarm-based metaheuristic optimization algorithms is how to keep a better tradeoff between exploitation and exploration abilities in the searching process. A good algorithm should have the capability of these two abilities to seek the globally optimal solution. For instance, the exploitation ability basically depends on  $gbest$  and the exploration ability primarily relies on  $pbest$  in PSO. Meanwhile, the exploration ability of GSA can be assured by means of suitable parameters such as  $G_0$  and  $\alpha$ , and the exploitation ability depends on reducing participant agents and slow movement of heavier agents [43]. However, some algorithms present more outstanding advantage on one of these abilities. For instance, PSO has a tendency to global exploration in a multivariable optimization problem. By comparison, GSA's exploitation performance is particularly conspicuous. Hence, PSO and GSA approaches possess respective advantages and potentialities. It encourages us to develop an appropriate hybridization technique to improve the original algorithm and obtain a superior optimization performance.

Inspired by above-mentioned ideas, the simple strategy to incorporate GSA with PSO is to carry out their respective search process successively in a sequence mode. That is to say, they run one by one to generate new particles and superior solutions are replaced. However, this hybridization mode is difficult to obtain an excellent optimization capability. Unlike two population-based GA and DE algorithms, GSA and PSO approaches have some similarities in evolutionary process. For example, they are population-based metaheuristic algorithms and the updated equations of both algorithms are highly similar in terms of velocity and position vector. In [9], a hybrid PSOGSA method for solving feed-forward networks was proposed. PSOGSA combines the social thinking ability ( $gbest$ ) of PSO with the local exploitation capability of GSA. In this hybrid strategy, GSA operator is embedded into the PSO algorithm, and the particle velocity updation is added to the acceleration of the GSA. Hence, PSOGSA does not take full use of the personal learning strategy of a particle that governs the exploration search in PSO. That is to say, the social experience learning mechanism in PSO is only for use in the PSOGSA. In this case, PSOGSA lacks the exploration search ability of PSO and is likely to cause premature convergence. Thus, in this article, another way to integrate PSO with GSA is proposed to design a parallel mode different from a sequence mode. Coevolutionary technique is applied in the hybridization of PSO and GSA. Each particle in the new population is simultaneously affected by PSO and/or GSA. So, each agent in the suggested algorithm updates its velocity by means of the cooperative effect on PSO and GSA.

To this end, a novel hybrid optimization method using cooperative evolutionary of both PSO velocity and GSA acceleration, namely, gravitational particle swarm optimization algorithm (GPSOA), is proposed to significantly improve the optimization performance of the original algorithm. So, the velocity formulation of the particle  $i$  in the  $d$ th dimension at time  $t+1$  in GPSOA is updated as follows:

$$v_i^d(t+1)_{\text{GPSOA}} = c_3 r_3 (1 - r_4) \left[ w(t) v_i^d(t) + c_1 r_1 \cdot (pbest_i^d - x_i^d(t)) + c_2 r_2 (gbest^d - x_i^d(t)) \right] + c_4 r_4 (1 - r_3) \left[ \text{rand}_i v_i^d(t) + a_i^d(t) \right]. \quad (32)$$

Apparently, the GPSOA velocity expression (equation (32)) is a close combination of PSO velocity expression of equation (19) and GSA velocity expression of equation (30), of which,  $c_3$  and  $c_4$  are acceleration factors generated in the range  $[0, 1]$ , which control the influence degree of both PSO velocity and GSA acceleration on GPSOA. It is pointed out that when  $c_3$  or  $c_4$  is equal to zero, GPSOA can be transformed into the original PSO or GSA and when  $c_3$  and  $c_4$  are set to 1.0, GPSOA is affected by equal influence of GSA and PSO.  $r_3$  and  $r_4$  are dependent random variables generated uniformly in the range  $[0,1]$ . In this case, the stochastic influence of GSA and PSO on GPSOA to improve the global searching ability is provided. Based on the updated velocity, the corresponding position is calculated as follows:

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1)_{\text{GPSOA}} \quad (33)$$

#### 4. Solution Procedure of the CEED Problem considering Wind Power Availability

In this section, the implementation of the proposed GPSOA to solve a CEED problem is presented in detail for all the generated units including wind power units. The basic decision variables of a CEED problem are active power output of all the generators. In GPSOA, the  $i$ th decision variables, i.e., the position of any individual/agent  $X_i$  which denotes a potential solution to a given CEED problem can be defined as follows:

$$X_i = x_i^1, x_i^2, \dots, x_i^d, \dots, x_i^{N_g + N_w}, \quad i = 1, 2, \dots, N, \quad (34)$$

where  $x_i^d$  (the position of the  $i$ th particle/agent in the  $d$ th dimension) represents the real power output of the generated unit. Furthermore, all the candidate solutions are composed of vectors  $\{X_1, X_2, \dots, X_N\}$  generated using the following equation:

$$\begin{cases} P_{Gi} = P_{Gi}^{\min} + \text{rand}(P_{Gi}^{\max} - P_{Gi}^{\min}), & i = 1, 2, \dots, N_g, \\ w_j = \text{rand} \cdot w_{r,j}, & j = 1, 2, \dots, N_{w-1}, \end{cases} \quad (35)$$

where  $\text{rand}$  represents a uniform random value in the range  $[0,1]$ . Also, the output of the  $N_w$ th wind turbine can be achieved by using the following equation:

$$w_{N_w} = P_D + P_L - \sum_{i=1}^{N_g} P_{Gi} - \sum_{j=1}^{N_w-1} w_j, \quad (36)$$

$$w_{N_w} = \begin{cases} 0, & \text{if } w_{N_w} < 0, \\ w_{r,N_w}, & \text{if } w_{N_w} > w_{r,N_w}. \end{cases}$$

Accordingly, the agent matrix  $\mathbf{X}$  consists of a set of positions of all particles together, which can be shown as follows:

$$\mathbf{X} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} P_{G1}^1 & P_{G1}^2 & \dots & P_{G1}^d & \dots & P_{G1}^{N_g} & w_1^1 & w_1^2 & \dots & w_1^d & \dots & w_1^{N_w} \\ P_{G2}^1 & P_{G2}^2 & \dots & P_{G2}^d & \dots & P_{G2}^{N_g} & w_2^1 & w_2^2 & \dots & w_2^d & \dots & w_2^{N_w} \\ \vdots & \vdots \\ P_{Gi}^1 & P_{Gi}^2 & \dots & P_{Gi}^d & \dots & P_{Gi}^{N_g} & w_i^1 & w_i^2 & \dots & w_i^d & \dots & w_i^{N_w} \\ \vdots & \vdots \\ P_{GN}^1 & P_{GN}^2 & \dots & P_{GN}^d & \dots & P_{GN}^{N_g} & w_N^1 & w_N^2 & \dots & w_N^d & \dots & w_N^{N_w} \end{bmatrix}, \quad (37)$$

where  $P_{Gi}^d$  and  $w_i^d$  are the actual output power of the  $i$ th agent in the  $d$ th thermal generator and wind turbine,

respectively.  $N$  represents the total agent in the population.  $N_g$  represents the total number of thermal generator.  $N_w$  is the total number of wind turbine. Each row of matrix  $\mathbf{X}$  represents a candidate solution vector. The element of the matrix is the real output power of the generated unit, which is subjected to the generator limit constraint.

The proposed GPSOA-based CEED solution procedure is illustrated as follows:

Step 1: specify the GPSOA parameters and test system data

In this procedure, first, some parameters of wind generator are specified. For instance, total number of wind turbines and parameters of wind turbine like cut-in speed, cut-out speed, rated speed, rated power, and active power limits are given. Weibull probability distribution function parameters such as shape factor and scale factor are also listed. Cost coefficients of overestimation case, cost coefficients of underestimation case, and coefficients of direct cost for wind turbine are presented. Second, the number of thermal generating units, capacity constraints, and cost coefficients of the thermal generator are determined, and emission coefficients of the thermal generator, real power load, and transmission loss matrix  $B$ -coefficients are given. Third, key parameters of the proposed GPSOA such as inertia weight, acceleration coefficients, gravitational constant, and population size are selected. Finally, the total iteration is specified.

Step 2: set initial decision variables

Set initial decision variables using equations (35) and (36) as the initial population of all agents. Each element in the population should satisfy generator-operating constraints through equations (15) and (16). For each set, the line transmission loss can be calculated by employing the Newton-Raphson program. The old agent set is deleted, and the new agent set is randomly reinitialized through the operating limit constraints if the slack generator may satisfy the power balance constraint given by equation (13). The process proceeds until all the available agents are generated. Additionally, the rows of the matrix should satisfy power balance constraint given by equation (13). So far, each element of the matrix is qualified to be a candidate solution to a given CEED problem. Meanwhile, the initial velocity  $V_i$  of each set can be selected through  $V_i = 0.1 \times X_i$ .

Step 3: increase the iteration counter

Step 4: compute the objective function fitness values  $F_T$  and  $E_T$

First,  $\text{WPCost}_{\text{oe},j}$ ,  $\text{WPCost}_{\text{ue},j}$ , and  $\text{WPCost}_{\text{dir},j}$  for wind turbines are computed from equation (7) to equation (9). Second, the operational cost  $\gamma_w$  of the wind turbine for each set  $X_i$  is calculated through equation (6). Meanwhile, the fuel cost  $F_i$  of the thermal generator is calculated using equation (11). Then, the total fuel cost  $F_T$  of each set is obtained

using equation (10). Additionally, the amount of emission  $E_T$  of the agent set using equation (12) is calculated. When considering a biobjective CEED problem, go to Step 5 to assess the overall objective fitness; otherwise, go to Step 6.

Step 5: evaluate the overall objective function fitness value TC

The overall objective function fitness value TC is evaluated for each agent set of matrix  $\mathbf{X}$  by means of the price penalty factor Pf.

Step 6: update  $pbest$ ,  $gbest$ ,  $best$ ,  $worst$ , and  $M_i$ .

According to the overall objective function fitness value, the  $pbest$ ,  $gbest$ ,  $best$ , and  $worst$  are chosen. Then, the masses of each agent set  $M_i$  are calculated by directly using equation (27).

Step 7: update inertia weight  $w$  and gravitational constant  $G$

Step 8: update acceleration  $a$ , velocity  $v$ , and position  $x$

First, calculate acceleration  $a$  and modify velocity  $v$  for each agent set using equations (29) and (32). Then, new agent position is updated using equation (33).

Step 9: check all the constraints of the updated agent

In this step, an important task is to check all the operational constraints of a CEED problem; that is, the updated position solution obtained by the GPSOA should be verified. First, the discarding strategy was proposed in [44] to handle the inequality constraints of the CEED problem. This strategy maintains the randomness and stochastic features of the algorithm. For instance, the generation capacity limits should be handled. An agent is available, if each agent of the matrix satisfies the generator capacity constraints (equations (15) and (16)). If an updated agent violates its boundary limits, the agent is fixed at the limit hit through equation (38).

$$P_{Gi} = \begin{cases} P_{Gi}^{\min}, & \text{if } P_{Gi} < P_{Gi}^{\min}, \\ P_{Gi}^{\max}, & \text{if } P_{Gi} > P_{Gi}^{\max}, \\ 0, & \text{if } w_j < 0, \\ w_{r,j}, & \text{if } w_j > w_{r,j}, \end{cases} \quad (38)$$

Second, the Newton–Raphson (NR) program for each set is performed. The line transmission loss is computed to satisfy the actual power balance constraints (equation (13)). Generally, the equality constraints can be repaired by the penalty function method after dealing with the inequality conditions [22]. In this article, a simple and effective heuristic approach is applied to handle the equality constraints [14, 43, 45].

Function *HANDLE\_CONSTR* is proposed to deal with the equality conditions of a CEED problem. For an agent set  $X_i$ , the availability of  $X_i$  can be checked by the difference value  $Err$  between  $P_D + P_L$  and the sum of all elements of  $X_i$ . If the absolute value of  $Err$  is greater than a

small constant  $\sigma$  (we set  $\sigma = 10^{-3}$  in this paper), then all elements of  $X_i$  are modified in turn from their  $d$ th dimension until  $X_i$  satisfies the corresponding constraints, where  $d$  selects a random integer within  $[1, N_g + N_w]$ . Also, the new position vector of  $X_i$  should meet the capacity of power units. Hence, the availability of the updated position is ensured.

Function *HANDLE\_CONSTR*: Op = *HANDLE\_CONSTR*( $X_i, P_G^{\min}, P_G^{\max}, w_r$ )

// $X_i$ : the current particle;  $P_G^{\min}$ ,  $P_G^{\max}$ , and  $w_r$ : the boundary limits of thermal generator and wind turbine//

1.  $Err = P_L + P_D - \text{sum}(X_i)$ //Compute the difference between  $P_D + P_L$  and the total of all agents of  $X_i$ //

2.  $d = \text{rand}(1, N_g + N_w)$ //Select a stochastic integer between 1 to  $N_g + N_w$ //

3. **WHILE** ( $|Err| > \sigma$ )//Verify the availability of position vector  $X_i$ //

3.1  $x_i^d \leftarrow x_i^d + Err$

3.2 **If**  $x_i^d$  may violate the capacity limits equations (15) and (16), **THEN**  $x_i^d$  is corrected by equation (38)

3.3  $Err = P_L + P_D - \text{sum}(X_i)$

3.4  $d = \text{mod}(d, N_g + N_w) + 1$ //Choose another dimension of the agent position variable, modulo  $N_g + N_w$ //

**END WHILE**

4.  $Op \leftarrow X_i$ //Output the new agent//

Step 10: terminate the process

If the termination criterion is satisfied, the iterative is terminated. When economic dispatch and emission dispatch problems are simultaneously performed, the results obtained, known as Pareto-optimal set, are stored in an array. Otherwise, repeat **Steps 3–9**.

Step 11: constitute the repository

For the biobjective CEED problem as per equation (18), the weight factor is increased in steps of 0.033 and the algorithm steps are repeated starting from Step 2 to Step 10, until the weight factor value is not more than 1. Then, the nondominated solutions found are stored in the repository.

Step 12: select the optimal compromise solution

In the repository stored, a fuzzy ranking decision operator is applied on Pareto-optimal solutions found based on fuzzy set theory and the optimal compromise solution is selected. The solution procedure of a fuzzy ranking decision maker can be found in [14, 38].

## 5. Simulation Results

5.1. *Description of the Case Study*. In this section, the proposed GPSOA is carried out to comprehensively investigate

the CEED problem of three different test cases, and they are given as follows:

*Case 1.* The conventional IEEE 30-bus test system including six thermal generators and neglecting wind power penetration was studied as the benchmark to verify the performance of the proposed GPSOA. The system transmission loss  $P_L$  is considered. The results are compared with those obtained by the existing algorithms to demonstrate the superiority performance of the suggested algorithm. The line data, bus data, and fuel cost and emission coefficients for standard IEEE 30-bus test systems are taken from [46, 47] and the  $B$ -loss coefficients from [48].

*Case 2.* A modified wind-thermal test system consisting of six thermal generators and two wind turbines was employed to assess the property of the suggested GPSOA to solve the CEED problem considering wind power availability. Also, the system transmission loss in this test case is neglected and considered as a lossless system. Two wind generators are installed on nodes no. 26 and no. 30 in the power network and become an indispensable part of the grid-connected power system [30]. Active power ranges of two wind power generators are 0 pu to 0.8 pu. The Weibull distribution parameters for wind turbine are given in  $c_1 = c_2 = 15$  and  $k_1 = k_2 = 2.2$ , which are taken from [28]. Other parameters are listed as  $w_{r,1} = w_{r,2} = 0.8$ ,  $v_{r,1} = v_{r,2} = 15$ ,  $v_{in,1} = v_{in,2} = 5$  and  $v_{out,1} = v_{out,2} = 45$ , respectively. The direct cost factors are set as  $g_1 = 120$  and  $g_2 = 150$ , respectively. The overestimation factor and underestimation coefficient are selected in terms of the conclusions given in [27]. As is well known, an increase in overestimation coefficient leads to decrease the output of scheduled wind power. In this case, it becomes more costly to overestimate the output of available wind power. Similarly, an increase in underestimation coefficients leads to increase in the output of scheduled wind power, because it becomes more costly to underestimate the output of available wind power. Hence, to increase the output of available wind power, the overestimation coefficient is chosen as larger value compared to the underestimation coefficient. In this paper, the overestimation and underestimation coefficients are given as  $C_{rw1} = C_{rw2} = 310$  and  $C_{pw1} = C_{pw2} = 100$ , respectively [28].

*Case 3.* The similar wind-thermal test system was regarded as Case 3 for simulation. The difference is that the system transmission loss in Case 3 is considered. In this circumstance, more active power must be supplied to meet the power balance constraints. Parameters in this system are also the same as parameters given in Case 2.

*5.2. Parameter Settings.* The GPSOA has been carried out in MATLAB 7.0.1 and executed on Pentium-IV, 3 GHz personal computer with 2 GB RAM for solving the CEED problem. The total real load demand  $P_D = 2.834$  p.u. In all of the simulation runs, the common parameter setup for the proposed algorithm is given. For instance, the number of

agents in the population is set 30. The maximum iteration is set 100 for three test systems. Each algorithm is required to independently perform 30 trails to record the statistical results in all experiments. The best solutions gained in terms of each performance criterion are bold faced in the respective tables for all the test cases considered.

As mentioned above, the performance of the GPSOA depends on the settings of different parameters. Hence, two important parameters such as  $c_3$  and  $c_4$  are required to be discussed and the optimal settings were obtained by the simulations. For simplicity, 30 different trails have been conducted on Case 1 with 100 iterations per trail. Different acceleration factor values tried are 0.1, 0.5, and 0.9, respectively. For each value of  $c_3$ , the value of  $c_4$  is increased successively as shown in Table 1. The results obtained from Table 1 show  $c_3 = 0.5$  and  $c_4 = 0.5$  are the optimal parameter settings for GPSOA. Other parameters such as  $w_{max} = 0.9$ ,  $w_{min} = 0.4$ ,  $c_1 = c_2 = 2.0$ ,  $\alpha = 20$ , and  $G_0 = 100$  are selected from [42, 43].  $kbest$  is selected for the total agents  $N = 30$  in the beginning and it decreases to 2% of all agents with lapse of iteration.

The simulation experiments were performed to evaluate the GPSOA optimization performance based on the extreme points of optimal fuel cost and emission level and the optimal compromise solution of the CEED problem of the power system. First, two objective functions like economic cost and emission level were individually solved to obtain two extreme values (optimal economic cost and emission-level objectives). The results gained by GPSOA and other state-of-the-art optimization approaches are given in Tables 2–5. Second, the overall objective function for the CEED problem simultaneously considering the two contradictory objectives by using a varying weight factor was optimized to obtain a group of nondominated solutions known as Pareto-optimal front. Finally, a fuzzy ranking decision approach was employed to gain the best compromise solution from the Pareto set [38]. The best compromise results obtained by GPSOA and other variants are presented in Tables 6 and 7.

Note that some definitions of cost are described as follows:

Fuel cost (FC) is the fuel cost of all participated power generators. For conventional power system, FC is represented as the fuel cost of thermal power generators in Case 1. For the wind-thermal test system, it includes the economic cost of thermal power units and the operating cost of wind turbines in Cases 2 and 3.

Emission cost (EC) is the emission level by thermal power plants.

Wind power cost (WPC) is the cost of wind power generators.

Total cost (TC) is the sum of fuel cost and the equivalent cost of emission level by using the PPF.

### 5.3. Computational Results and Discussion

*5.3.1. Case 1: Conventional Test System.* The performance of the GPSOA is compared with that of other reported

TABLE 1: Influence of GPSOA parameters on minimum economic cost (\$/h) for Case 1.

Acceleration factor	$c_4$		
$c_3$	0.1	0.5	0.9
0.1	605.62	601.04	606.26
0.5	601.22	<b>600.29</b>	602.01
0.9	603.31	601.46	602.52

TABLE 2: Comparison of best solution for fuel cost minimization offered by different algorithms for Case 1.

Generation (pu)	MBFA [22]	OHS [23]	FCPSO [22]	BB-MOPSO [14]	TV-MOPSO [14]	OGSA [20]	PSO	GSA	PSOGSA	GPSOA
$G_1$	0.1141	0.1156	0.1130	0.1229	0.1011	0.1336	0.1349	0.0951	0.1156	0.1129
$G_2$	0.3108	0.3039	0.3145	0.2880	0.2883	0.3201	0.3094	0.2389	0.2861	0.2995
$G_3$	0.5994	0.5316	0.5826	0.5792	0.5852	0.6414	0.5536	0.6746	0.5133	0.5266
$G_4$	0.9816	1.0199	0.9860	0.9875	0.9832	0.8430	1.0104	1.0158	1.0252	1.0169
$G_5$	0.5048	0.5124	0.5264	0.5255	0.5271	0.5730	0.4615	0.4224	0.5373	0.5268
$G_6$	0.3559	0.3579	0.3450	0.3564	0.3749	0.3338	0.3721	0.3953	0.3651	0.3595
TG (pu)	2.8666	2.8413	2.8675	2.8596	2.8598	2.8459	2.8419	2.8421	2.8426	2.8422
TL (pu)	0.0326	0.0073	0.0335	0.0256	0.0258	0.0119	0.0079	0.0081	0.0086	0.0082
FC (\$/h)	607.67	600.83	607.79	605.98	606.11	601.63	600.57	602.23	600.44	<b>600.29</b>
EC (ton/h)	0.2198	0.2221	0.2201	0.2202	0.2205	0.2168	0.2208	0.2255	0.2230	0.2221
CPU time (s)	NR	1.9956	NR	NR	0.8814	0.1136	0.0259	0.1038	0.1156	0.1062

NR means not reported in the referred literature.

TABLE 3: Comparison of best solution for emission minimization offered by different algorithms for Case 1.

Generation (pu)	MBFA [22]	OHS [23]	FCPSO [22]	BB-MOPSO [14]	TV-MOPSO [14]	OGSA [20]	PSO	GSA	PSOGSA	GPSOA
$G_1$	0.4055	0.4063	0.4063	0.4103	0.4188	0.4371	0.3382	0.4365	0.3931	0.4062
$G_2$	0.4609	0.4586	0.4586	0.4661	0.4582	0.4386	0.4667	0.4979	0.4673	0.4595
$G_3$	0.5444	0.5510	0.5510	0.5432	0.5530	0.5336	0.5358	0.4087	0.5339	0.5432
$G_4$	0.3986	0.4084	0.4084	0.3883	0.3803	0.4516	0.4562	0.3873	0.4023	0.3860
$G_5$	0.5440	0.5432	0.5432	0.5447	0.5345	0.5296	0.5308	0.5414	0.5403	0.5364
$G_6$	0.5134	0.4974	0.4974	0.5168	0.5251	0.4625	0.5168	0.5724	0.5072	0.5122
TG (pu)	2.8668	2.8649	2.8649	2.8693	2.8698	2.8530	2.8445	2.8442	2.8441	2.8435
TL (pu)	0.0328	0.0309	0.0309	0.0353	0.0358	0.0190	0.0105	0.0102	0.0101	0.0095
FC (\$/h)	644.43	642.89	642.89	646.48	647.66	640.26	630.03	644.64	636.52	638.48
EC (ton/h)	<b>0.1942</b>	<b>0.1942</b>	<b>0.1942</b>	<b>0.1942</b>	<b>0.1942</b>	<b>0.1942</b>	0.1947	0.1954	<b>0.1942</b>	<b>0.1942</b>
CPU time (s)	NR	1.9976	NR	NR	0.8846	0.1106	0.0263	0.1057	0.1142	0.1069

NR means not reported in the referred literature.

TABLE 4: Best fuel cost and best emission level of different methods for Case 2.

Output solutions	Minimum fuel cost					Minimum emission level				
	GA	PSO	GSA	PSOGSA	GPSOA	GA	PSO	GSA	PSOGSA	GPSOA
$G_1$	0.0402	0.0226	0.0263	0.0361	0.0326	0.3662	0.4092	0.4921	0.3522	0.3165
$G_2$	0.1238	0.1614	0.1135	0.1425	0.1516	0.4258	0.4561	0.4621	0.5023	0.4522
$G_3$	0.2831	0.2603	0.0502	0.2254	0.2801	0.3031	0.2372	0.3669	0.3144	0.4249
$G_4$	0.5626	0.7468	0.3816	0.7192	0.7268	0.3136	0.3460	0.3332	0.2642	0.3837
$G_5$	0.2652	0.2362	0.1533	0.3212	0.1822	0.5344	0.5141	0.4377	0.4821	0.4342
$G_6$	0.2332	0.1626	0.5968	0.2016	0.1826	0.4352	0.5096	0.5351	0.5211	0.4762
$w_1$	0.6226	0.6297	0.7737	0.6056	0.6498	0.0224	0.0212	0.0016	0.0341	0.0307
$w_2$	0.7023	0.6144	0.7386	0.5824	0.6283	0.4333	0.3406	0.2053	0.3636	0.3156
FC (\$/h)	422.64	288.11	324.39	286.52	<b>285.61</b>	665.82	650.40	661.23	656.14	661.34
EC (ton/h)	0.2618	0.2428	0.2317	0.2421	0.2426	0.1972	0.1945	0.1967	<b>0.1941</b>	<b>0.1941</b>
WPC (\$/h)	137.85	136.81	141.66	136.53	136.81	166.65	165.17	168.85	163.08	164.46
CPU time (s)	6.2632	2.3218	3.8598	3.5416	2.3957	8.2613	2.1273	3.8993	4.6252	4.1148

NR means not reported in the referred literature.

TABLE 5: Best fuel cost and best emission level of different methods for Case 3.

Output solutions Generation (pu)	Minimum fuel cost					Minimum emission level				
	GA	PSO	GSA	PSOGSA	GPSOA	GA	PSO	GSA	PSOGSA	GPSOA
$G_1$	0.0342	0.0212	0.0201	0.0261	0.0200	0.4216	0.4114	0.4403	0.4620	0.4206
$G_2$	0.2306	0.1588	0.1302	0.1543	0.1523	0.5662	0.4262	0.5562	0.4756	0.4606
$G_3$	0.0814	0.0784	0.2767	0.0802	0.0832	0.5842	0.5424	0.3635	0.5422	0.5524
$G_4$	0.7552	0.7273	0.8532	0.7442	0.7195	0.4154	0.3556	0.5227	0.4356	0.3925
$G_5$	0.2123	0.2453	0.0500	0.2221	0.2776	0.4615	0.5342	0.4841	0.4066	0.5271
$G_6$	0.1825	0.1763	0.0318	0.1536	0.1831	0.3801	0.5061	0.4561	0.4682	0.5076
$w_1$	0.6825	0.7256	0.7753	0.7341	0.7153	0.0026	0.0212	0.0046	0.0304	0.0224
$w_2$	0.6626	0.7032	0.6999	0.7216	0.6851	0.0211	0.0620	0.0122	0.0326	0.0143
TG (pu)	2.8413	2.8361	2.8372	2.8362	2.8361	2.8527	2.8591	2.8397	2.8532	2.8975
TL (pu)	0.0073	0.0021	0.0032	0.0022	0.0021	0.0187	0.0251	0.0057	0.0192	0.0635
FC (\$/h)	306.15	288.52	296.85	288.24	<b>286.02</b>	646.02	655.56	652.68	661.42	665.30
EC (ton/h)	0.2462	0.2430	0.2546	0.2279	0.2425	0.1970	0.1944	0.1969	0.1943	<b>0.1941</b>
WPC (\$/h)	142.78	141.45	146.36	141.52	141.62	158.52	158.86	162.06	160.61	161.23
CPU time (s)	6.2683	2.3025	3.7881	2.4238	2.3864	8.6236	4.1873	3.9552	4.4861	4.2428

TABLE 6: Comparison of best compromise solution offered by different algorithms for Case 1.

Generation (pu)	MBFA [22]	OHS [23]	FCPSO [22]	BB-MOPSO [14]	TV-MOPSO [14]	OGSA [20]	PSO	GSA	PSOGSA	GPSOA
$G_1$	0.2595	0.2121	0.1501	0.1322	0.0812	0.1168	0.2873	0.5000	0.2886	0.2966
$G_2$	0.3769	0.3066	0.2489	0.2142	0.3288	0.4049	0.3816	0.4644	0.4211	0.3948
$G_3$	0.5636	0.6886	0.7812	0.8406	0.4865	0.6105	0.7136	0.5349	0.7104	0.5432
$G_4$	0.6759	0.6794	0.7282	0.6964	0.9364	0.7348	0.6277	0.2333	0.6875	0.6246
$G_5$	0.5499	0.5822	0.6026	0.6253	0.4877	0.5562	0.3756	0.6131	0.2661	0.5295
$G_6$	0.4344	0.3869	0.3528	0.3452	0.5392	0.4272	0.4639	0.5002	0.4682	0.4512
TG (pu)	2.8602	2.8538	2.8638	2.8539	2.8598	2.8504	2.8497	2.8549	2.8419	2.8408
TL (pu)	0.0262	0.0198	0.0298	0.0199	0.0258	0.0164	0.0157	0.0209	0.0079	0.0068
FC (\$/h)	616.50	614.42	612.81	615.68	614.68	612.83	615.29	618.44	615.62	615.38
EC (ton/h)	0.2002	0.2034	0.2109	0.2082	0.1982	0.1983	0.1979	0.1981	0.1979	0.1978
PPF (\$/ton)					5928.7134					
TC (\$/h)	1803.43	1820.32	1863.18	1850.04	1789.75	1790.95	1789.98	1792.92	1788.91	<b>1788.41</b>
CPU time (s)	NR	NR	0.0922	0.1466	0.1862	0.1146	0.0271	0.1054	0.116	0.1078

NR means not reported in the referred literature.

TABLE 7: Best compromise solution of different methods for Cases 2 and 3.

Output solutions Generation (pu)	Case 2					Case 3				
	GA	PSO	GSA	PSOGSA	GPSOA	GA	PSO	GSA	PSOGSA	GPSOA
$G_1$	0.1605	0.2086	0.1512	0.2122	0.2103	0.2824	0.2671	0.2749	0.2453	0.2066
$G_2$	0.2431	0.2869	0.3713	0.2641	0.2785	0.2263	0.1855	0.2385	0.1824	0.2808
$G_3$	0.2841	0.3078	0.3162	0.3112	0.3031	0.2485	0.3491	0.2616	0.3162	0.3133
$G_4$	0.2252	0.2055	0.3479	0.2036	0.2251	0.3261	0.2306	0.3445	0.2845	0.2354
$G_5$	0.1632	0.3151	0.1101	0.3162	0.3018	0.2783	0.3007	0.2762	0.3082	0.3031
$G_6$	0.3622	0.3034	0.1221	0.2861	0.3016	0.2407	0.3356	0.2355	0.2641	0.3036
$w_1$	0.6426	0.6224	0.6143	0.6254	0.6088	0.5428	0.5241	0.4236	0.6423	0.6185
$w_2$	0.7531	0.5843	0.8000	0.6152	0.6048	0.7225	0.6634	0.8000	0.6122	0.5943
TG (pu)	2.8340	2.8340	2.8340	2.8340	2.8340	2.8676	2.8561	2.8548	2.8552	2.8547
TL (pu)						0.0336	0.0221	0.0208	0.0212	0.0207
FC (\$/h)	402.35	391.47	387.28	368.62	363.71	411.03	407.18	387.45	360.15	357.12
EC (ton/h)	0.2206	0.2084	0.2117	0.2092	0.2088	0.2126	0.2051	0.2111	0.2069	0.1887
WPC (\$/h)	139.52	138.84	142.61	138.82	138.06	161.83	160.51	164.07	161.35	162.05
PPF (\$/ton)			5928.7134					5928.7134		
TC (\$/h)	1710.22	1627.01	1642.39	1608.91	<b>1601.63</b>	1671.47	1623.16	1639.00	1586.81	<b>1475.87</b>
CPU time (s)	6.521	3.1091	3.2023	3.2166	3.2017	6.4833	3.0375	3.0539	3.4412	3.2278

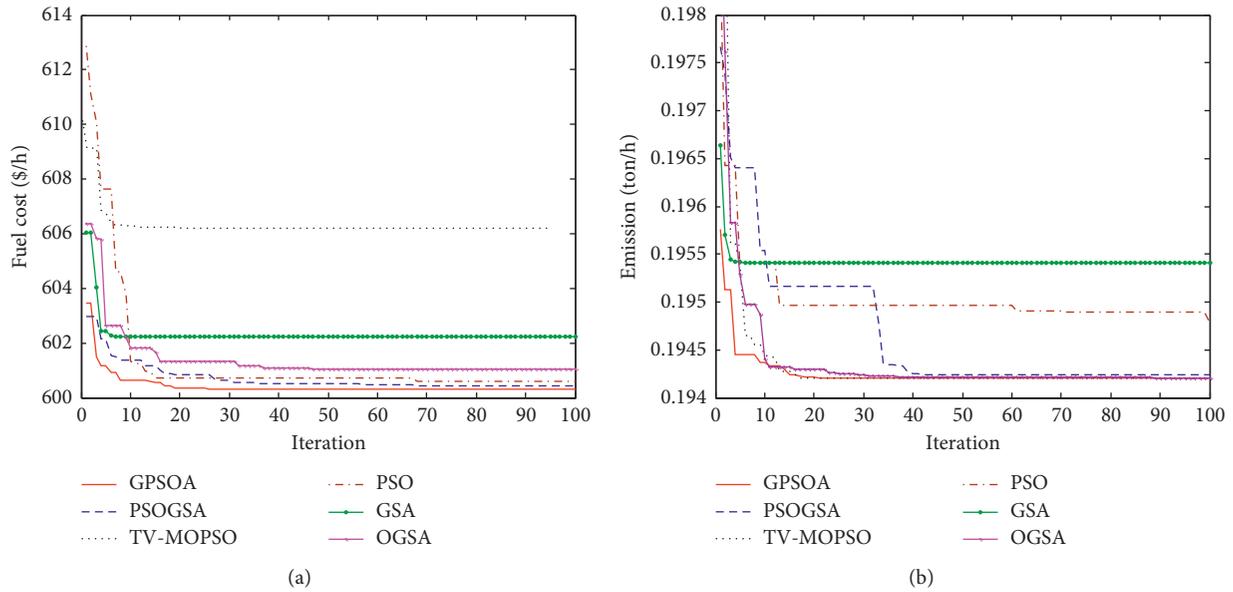


FIGURE 1: Convergence curves of various algorithms for Case 1.

approaches for the conventional thermal test system. The best solutions obtained by the GPSOA, PSOGSA, PSO, GSA, and other optimization algorithms for economic cost minimization and emission-level minimization are listed in Tables 2 and 3, respectively. From Table 2, it can be seen that the GPSOA obtains optimal economic cost than those reported in the literature like MBFA [22], OHS [23], FCPSO [22], BB-MOPSO [14], TV-MOPSO [14], and OGSA [20]. The minimum fuel cost by the suggested algorithm is found to be 600.29 \$/h. The corresponding emission level is 0.1942 ton/h. On the other hand, the optimal solutions for emission-level minimum objective obtained by GPSOA and other well-known approaches are provided in Table 3. It is observed that the best emission solution of 0.1942 ton/h obtained by the proposed algorithm is very similar to that of MBFA, OHS, FCPSO, BB-MOPSO, TV-MOPSO, OGSA, and PSOGSA algorithms and much less than that of PSO and GSA as presented in Table 3. It is important to note that the GPSOA is efficient in terms of the CPU times compared to OHS, TV-MOPSO, OGSA, and PSOGSA from Tables 2 and 3.

The convergence curves of the best solution for GPSOA, PSOGSA, OGSA, TV-MOPSO, GSA, and PSO for economic cost and emission-level objectives are presented in Figure 1(a) and 1(b), respectively. From Figure 1, it can be seen that the GPSOA converges faster and has a superior performance. The fuel cost and emission-level objective function values obtained by GPSOA are lower than those of PSO and GSA. The conclusion can also be found in Tables 2 and 3.

In order to gain the optimal compromise solution of the CEED problem, the fuzzy ranking decision maker was applied in this case and corresponding results are provided in Table 6. The Pareto-optimal front and best compromise solution obtained by GPSOA are also shown in Figure 2. From Table 6, it is revealed that the best compromise solutions with fuel cost 615.38 \$/h and emission content 0.1978 ton/h obtained by GPSOA satisfy both the two objectives by

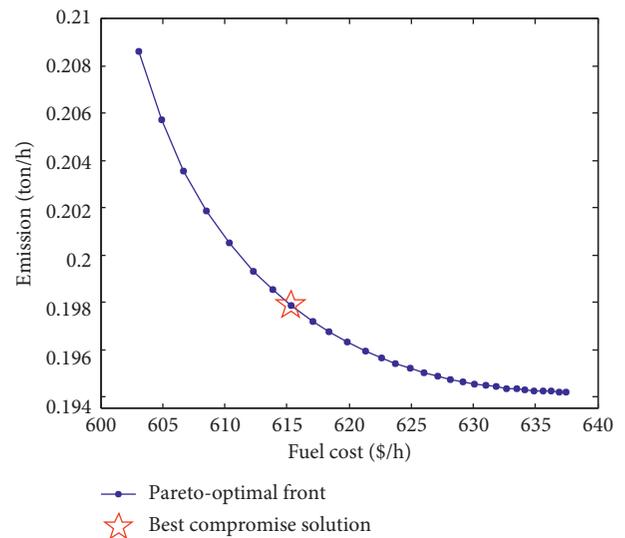


FIGURE 2: Pareto-optimal front and best compromise solution obtained by GPSOA for Case 1.

the maximum membership in the fuzzy set. It is important to note that the original emission level is converted into equivalent cost by multiplying emission level with the corresponding PPF value. Hence, the total fuel cost was computed by adding equivalent cost. Apparently, it can be seen that the minimum total cost 1788.41 \$/h obtained by GPSOA is slightly similar to that of PSOGSA and is least compared with those of MBFA, OHS, FCPSO, BB-MOPSO, TV-MOPSO, PSO, GSA, and OGSA for the biobjective CEED problem.

5.3.2. Case 2: Lossless Wind-Thermal Test System. For simplicity, the transmission loss has been neglected in this case. The GPSOA was implemented successfully to find the

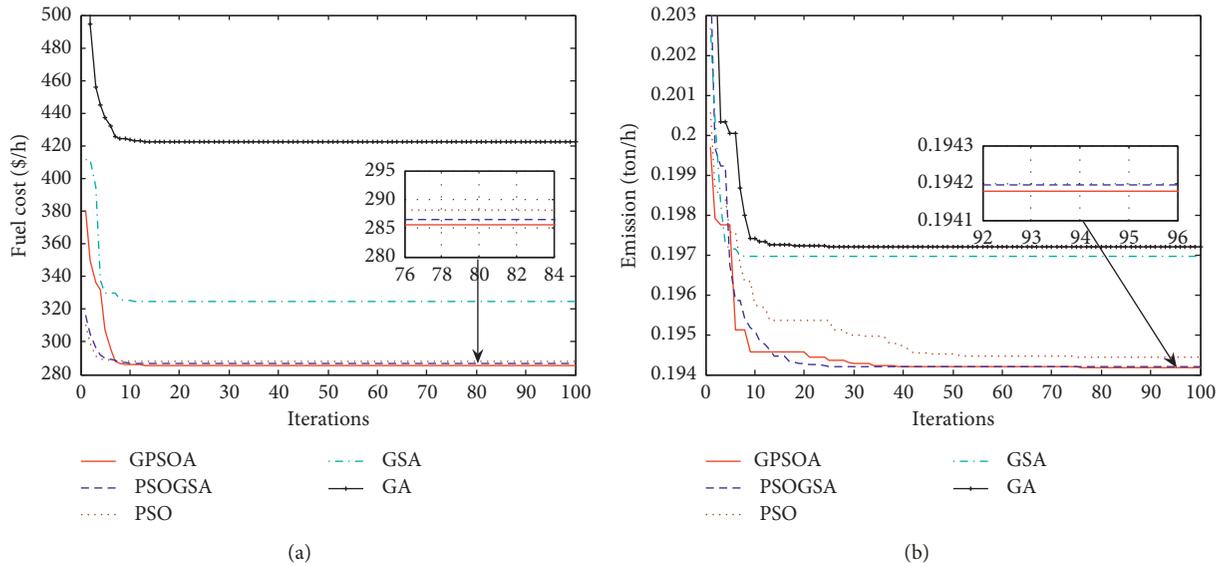


FIGURE 3: Convergence curves of various algorithms for Case 2.

solution of the lossless wind-thermal test system. The economic dispatch given by using equation (10) and the emission dispatch given by using equation (12) were individually optimized, and the optimal results for Case 2 obtained by GPSOA, PSO, GSA, and GA have been given in Table 4. In consideration of the economic cost objective, the minimum economic cost and corresponding emission level yielded by GPSOA are reported as 285.61 \$/h and 0.2426 ton/h, respectively. Similarly, the economic cost values and optimal emission level yielded by GPSOA are listed as 661.34 \$/h and 0.1941 ton/h, respectively, for the emission-level minimization problem. It is clear that GPSOA obtains lower fuel cost and emission-level values as compared to PSO, GSA, and GA from Table 4.

The convergence curves of the best solution yielded by GPSOA, PSO, GSA, and GA methods on fuel cost and emission level for Case 2 are presented in Figures 3(a) and 3(b), respectively. From Figure 3, it is observed that the fuel cost and emission level obtained by GPSOA converge smoothly to the minimum solution. Also, it is concluded that GPSOA and PSO present the similar optimization result. Moreover, the GSA and GA approaches quickly fall into local convergence after ten iterations because of premature convergence. It can be shown that GPSOA can get the best results with quickly convergence speed.

While considering the multiobjective optimization problem of the lossless wind-thermal test system, the best compromise solution and total cost found by GPSOA, PSO, GSA, and GA using the fuzzy ranking decision maker are presented in Table 7. The Pareto-optimal front and best compromise solution obtained by GPSOA are shown in Figure 4. It is clear that GPSOA shows best solutions in terms of total cost 1601.63 \$/h. Furthermore, the decrease cost obtained by GPSOA is larger than 26 \$/h when compared to GA, PSO, and GSA.

5.3.3. *Case 3: Wind-Thermal Test System with Loss.* The suggested wind-thermal test system is considered as Case 3 but transmission loss is taken into account. The transmission loss value can be computed by using the Newton–Raphson procedure. While individually optimizing the economic cost objective and the emission level for this case, the optimal results such as the generated schedule, the economic cost, and the emission level obtained by GPSOA, PSO, GSA and GA are listed in Table 5. While optimizing the economic cost objective, the optimal economic cost value and corresponding emission level obtained by GPSOA are reported as 286.02 \$/h and 0.2425 ton/h, respectively. Similarly, the economic cost value and optimal emission level generated by GPSOA are listed as 665.30 \$/h and 0.1941 ton/h, respectively, for the emission-level dispatch problem. It is clear from Table 5 that GPSOA obtains few fuel cost and emission level as compared to PSO, GSA, and GA when considering single fuel cost or emission objective problem. Apparently, GPSOA has a strong optimization ability to seek better quality solution.

The convergence curves of the fuel cost and emission objectives of different algorithms are given in Figures 5(a) and 5(b), respectively. The evolving of the algorithm represents its convergence behavior throughout the iterations. Also, it shows the convergence speed of the algorithm. It can be seen from Figure 5 that GPSOA converges rapidly to the best fuel cost and emission solution as compared to PSO, GSA, and GA.

While simultaneously considering multiobjective optimization problems like fuel cost and emission level, the best compromise solution and total cost obtained by GPSOA and other methods are given in Table 7. Moreover, the Pareto-optimal front and best compromise solution obtained by GPSOA are also shown in Figure 6. It is obvious that GPSOA obtains very superior result with total cost 1475.87 \$/h. Hence, the total cost found by GPSOA is reduced by 13.25%, 9.95%, 9.07%, and 7.52%, as compared

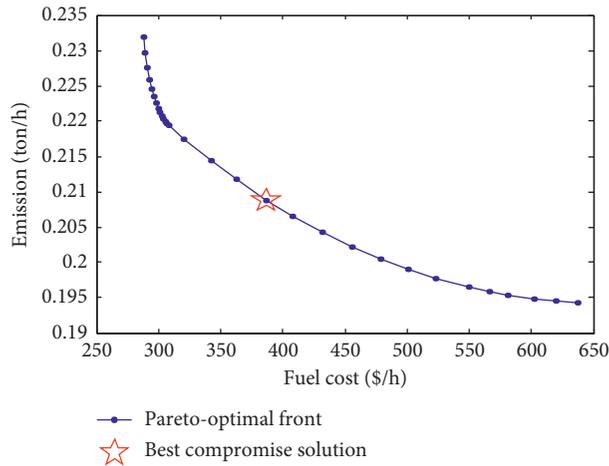


FIGURE 4: Pareto-optimal front and best compromise solution obtained by GPSOA for Case 2.

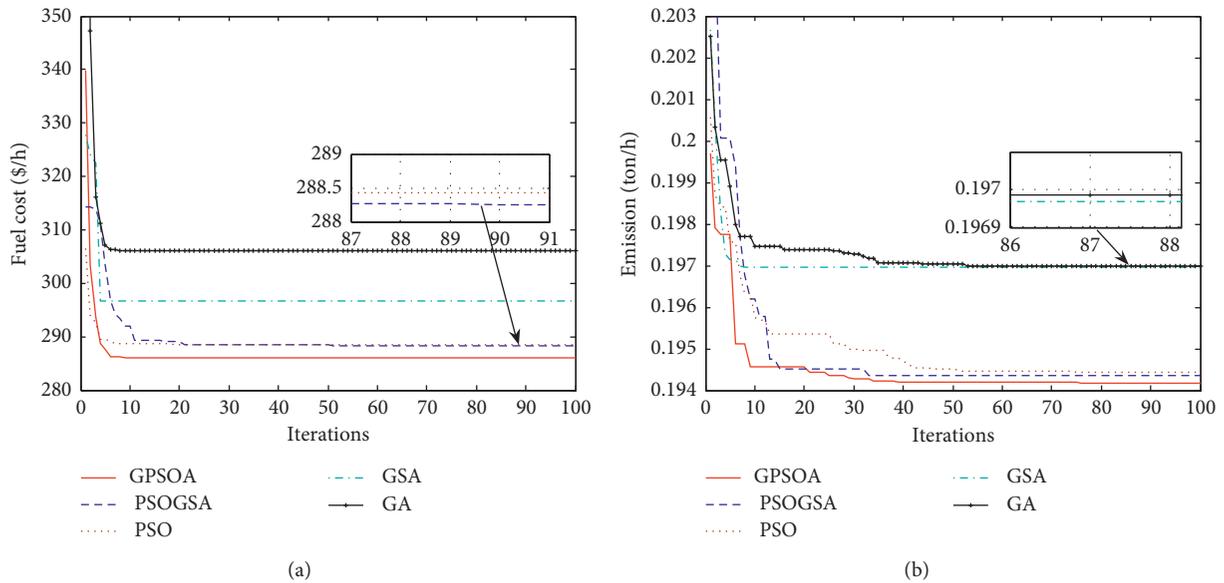


FIGURE 5: Convergence curves of various algorithms for Case 3.

to the result obtained by GA, GSA, PSO, and PSO GSA, respectively.

**5.4. Comparative Analysis.** The comparative conclusions of the proposed GPSOA on three cases are drawn in this section. First, for Case 1 (conventional thermal test system along with transmission loss) and Case 3 (modified wind-thermal test system with loss), it is obvious from Tables 2 and 5 that the fuel cost for economic dispatch is sharply reduced from 600.29 \$/h to 286.02 \$/h. From Tables 3 and 7, the emission level obtained by the GPSOA for emission dispatch is decreased from 0.1942 ton/h to 0.1941 ton/h. In addition, it is clear in Tables 6 and 7 that the total cost for the biobjective CEED problem of the wind-thermal test system is dropped by 17.5% from the thermal power system without wind turbine, implying that the total cost is sharply fallen from 1788.41 \$/h to 1475.87 \$/h. Hence, it can be concluded that

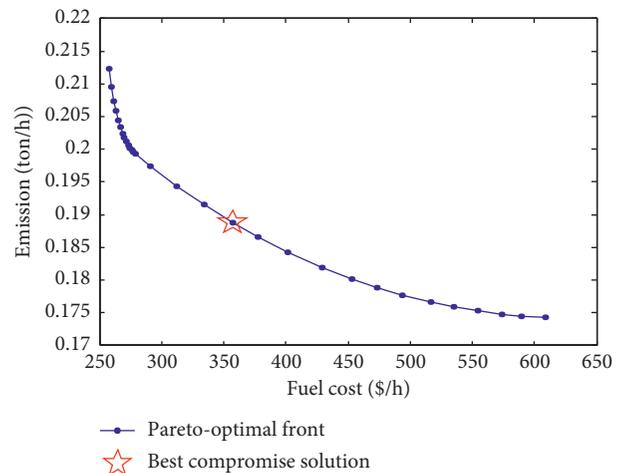


FIGURE 6: Pareto-optimal front and best compromise solution obtained by GPSOA for Case 3.

TABLE 8: Statistical results of the minimum fuel cost, minimum emission, and best compromise solution by different algorithms on three cases.

Algorithm	Minimum fuel cost				Minimum emission level				ASD values for best compromise solution			
	Best	Worst	Average	Std.	Best	Worst	Average	Std.	Best	Worst	Average	Std.
<i>Case 1 (conventional thermal test system)</i>												
GPSOA	600.29	600.31	600.29	2.5601e-03	0.1942	0.1942	0.1942	4.0891e-09	0.8203	0.5809	0.7016	6.8199e-03
PSOGSA	600.44	601.02	600.96	2.7367e-02	0.1942	0.1942	0.1942	5.7842e-08	0.8065	0.5296	0.7045	4.6413e-03
TV-MOPSO	605.06	608.57	606.35	3.5274e-00	0.1942	0.1943	0.1942	5.6532e-04	0.7632	0.6534	0.6962	3.7624e-03
PSO	600.57	607.13	603.13	1.5618e-00	0.1947	0.1990	0.1964	1.1037e-03	0.7477	0.5876	0.6896	7.2215e-03
GSA	602.23	615.30	609.05	3.4189e-00	0.1954	0.2057	0.2004	2.6205e-03	0.7327	0.5164	0.6587	1.0174e-02
OGSA	601.02	604.73	601.53	2.6352e-01	0.1942	0.1944	0.1942	6.5624e-04	0.7524	0.6028	0.6835	4.6441e-03
<i>Case 2 (lossless wind-thermal test system)</i>												
GPSOA	<b>285.61</b>	285.61	<b>285.61</b>	<b>4.8224e-08</b>	<b>0.1941</b>	0.1942	<b>0.1942</b>	<b>7.2534e-07</b>	<b>0.6751</b>	0.6011	<b>0.6356</b>	<b>5.0026e-03</b>
PSOGSA	286.52	286.82	286.66	3.6226e-06	0.1941	0.1944	0.1943	3.6518e-02	0.6624	0.5628	0.6164	2.7538e-03
PSO	288.12	289.69	288.62	1.4625e-02	0.1945	0.1947	0.1946	1.0231e-04	0.6630	0.6026	0.6268	5.0167e-03
GSA	324.40	419.02	366.44	2.6899e+01	0.1967	0.2156	0.2063	4.6911e-03	0.6598	0.4353	0.5794	4.8831e-02
GA	422.64	462.62	436.62	3.3943e+01	0.1972	0.2208	0.2176	2.7521e-02	0.5873	0.4261	0.5207	8.7264e-02
<i>Case 3 (wind-thermal test system with loss)</i>												
GPSOA	<b>286.02</b>	286.05	<b>286.03</b>	<b>4.5555e-03</b>	<b>0.1941</b>	0.1943	<b>0.1942</b>	<b>4.9695e-05</b>	<b>0.7466</b>	0.6052	0.6318	<b>4.9998e-03</b>
PSOGSA	288.24	290.51	289.43	2.7536e-02	0.1943	0.1950	0.1946	1.6253e-02	0.6825	0.5844	0.6275	6.6253e-02
PSO	288.52	289.15	288.07	3.6977e-02	0.1944	0.1948	0.1945	1.6181e-04	0.6748	0.5964	<b>0.6423</b>	5.5679e-03
GSA	296.85	324.92	367.50	6.1065e+01	0.1969	0.2145	0.2070	4.1027e-03	0.6647	0.4831	0.6163	3.6581e-02
GA	306.15	384.63	326.73	1.6259e+02	0.1970	0.2186	0.2092	3.0726e-03	0.6026	0.4222	0.5726	5.7529e-02

TABLE 9: Ranking results of algorithms on the basis of average solutions for three cases.

Algorithm	Minimum fuel cost			Minimum emission level			ASD values for best compromise solution			Average rank	Overall rank
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3		
GA	—	5	4	—	5	5	—	5	5	4.83	7
PSO	4	3	2	5	3	2	4	2	1	2.89	3
TV-MOPSO	5	—	—	1	—	—	3	—	—	3	4
GSA	6	4	5	6	4	4	6	4	4	4.77	6
OGSA	3	—	—	1	—	—	5	—	—	3	4
PSOGSA	2	2	3	1	2	3	2	3	3	2.44	2
GPSOA	1	1	1	1	1	1	1	1	2	1.11	1

the integration of wind turbine into the conventional power system greatly improves the load dispatch management level and a lot of operating cost is saved. Actually, the operator in power plants can choose the appropriate dispatch solution in terms of the priorities of minimizing cost and/or emission. Second, Tables 2 to 7 show that GPSOA obtains less fuel cost and emission level as compared to PSOGSA, PSO, and GSA. Also, the total cost obtained by GPSOA is minimal compared with that of PSOGSA, PSO, GSA, and GA. So it can be seen that GPSOA has an excellent optimization performance to seek better quality solution in the power system. Finally, from Tables 2 to 7, it is obvious that the average times of CPU running required by PSO among time-boxed iterations are less as compared to GPSOA, PSOGSA, GSA, and GA. However, GPSOA shows fast convergence speed during optimization process. When the stopping criterion of simulation experiment is set to convergence precision value, it can be concluded that GPSOA is computationally efficient because of the fast convergence rate of the GPSOA from Figures 1 and 3.

5.5. *Statistical Tests.* In this section, to assess the robust performance of the GPSOA approach to solve the problem, 30 independent experiments were executed to grasp tendencies of three objectives: the minimal economic cost, the minimal emission level, and the best compromise result. The standard deviation and the worst, the best and the average values of the fuel cost and emission-level results of among 30 runs are easily obtained from the experiments. For the changes of the best compromise solutions in all the 30 simulations, the mean satisfactory degree (MSD) using the fuzzy ranking decision approach based on compromise result is defined and computed in terms of the maximum and minimum of each objective function [14]. For a best compromise solution  $\vec{X}_{\text{com}}$ , its MSD value is defined as follows:

$$\vec{\mu}_{\text{com}} = \frac{1}{M} \sum_{i=1}^M \mu_i^{\text{com}}. \quad (39)$$

Apparently, the MSD value can be utilized to observe changes in best compromise results, even if it is probable that

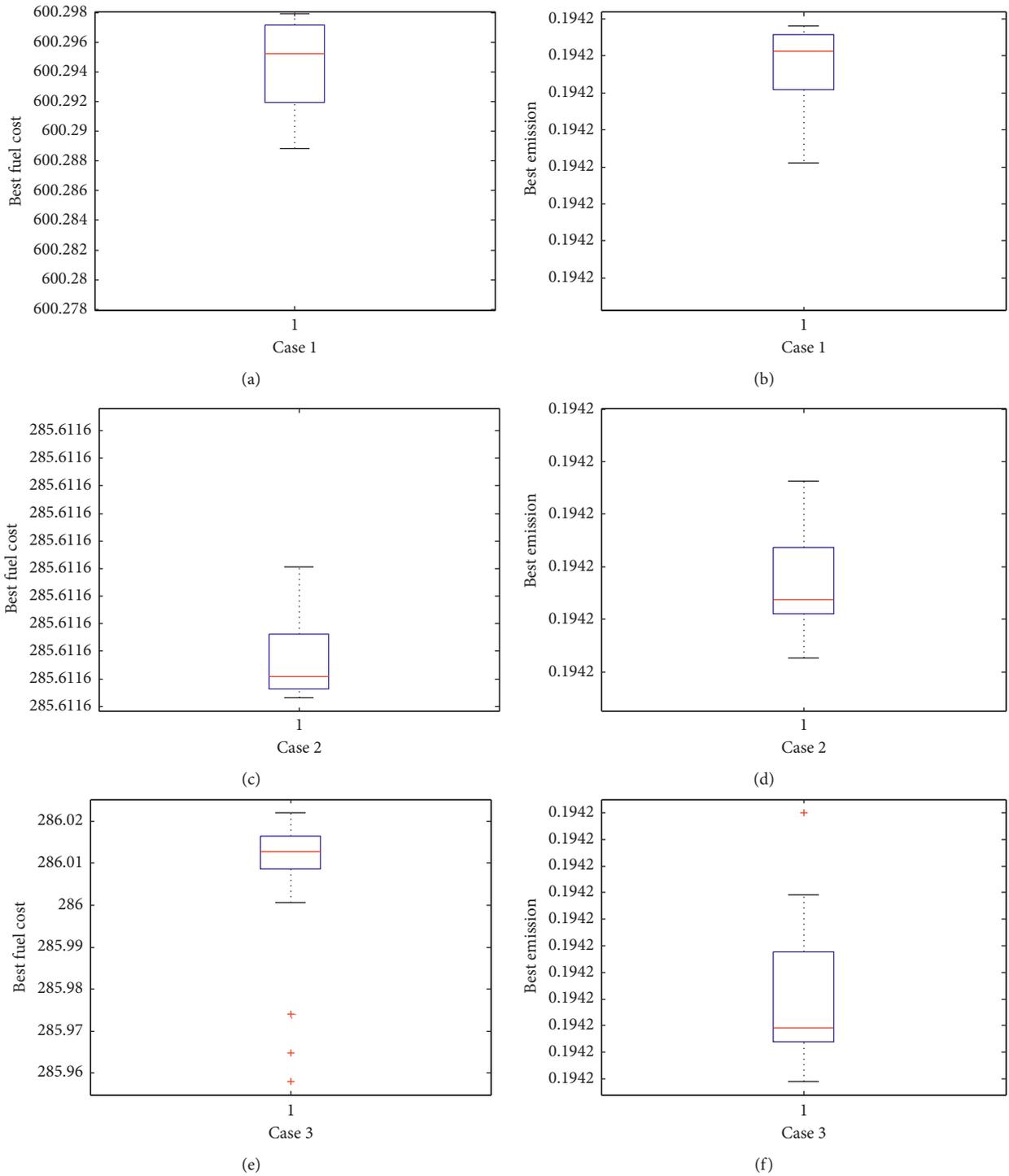


FIGURE 7: Box plot-distributed results obtained by GPSOA in 30 trails for different cases.

the same MSD value denotes different best compromise results.

The statistical results obtained by different algorithms are presented in Table 8. It is clear from Table 8 that the standard deviations of the GPSOA are the minimal. It is indicated that GPSOA shows strong robustness. It is not sensitive to initial variables and parameters setting for optimizing the

CEED problem. To better evaluate the significance of the proposed GPSOA, we have also ranked the algorithms from minimum mean solutions to maximum solutions for different cases. The algorithm that is not statistically different to each other is presented the equal rank. The algorithm that is statistically different to more than one algorithm is shown the lower rank. The overall rank and the average

rank of the algorithms in terms of the average solutions from Table 8 are shown in Table 9, respectively. It is evident that the related algorithms can be arranged in terms of the average rank. The rank is given as follows: GPSOA, PSOGSA, PSO, TV-MOPSO, OGSA, GSA, and GA.

That is to say, GA ranks the worst, whereas GPSOA ranks the best. It can be deduced that GPSOA has better performance on solving the CEED problems. Figure 7 describes the distributed outlines of the optimal fuel cost and emission-level solutions based on box plot. It can be concluded that the objective function value of each run is nearly close to the best result for each test system.

## 6. Conclusion

In this paper, the fuel cost and emission level of thermal generators and the operational cost caused by wind turbines are comprehensively considered here, and then, the CEED model to coordinate the active power output generated from the thermal and wind turbine is established. To solve the proposed model, a novel GPSOA which adopts coevolutionary technique to update its particle in the population with the cooperation contributions of PSO velocity and GSA acceleration is firstly proposed and has been successfully implemented to solve the CEED problem for the conventional test system and modified wind-thermal test system. Simulation results show that GPSOA is apt to converge to optimal solution and achieves certain superior performance as compared to other evolutionary approaches. It has been concluded that the suggested GPSOA approach is a viable choice for solving multiobjective optimization problems. So in the future, GPSOA seems to become a competitive tool to solve complex dynamic multiobjective optimization, optimal power flow problem, and system identification fields in search of better-quality results.

## Data Availability

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

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

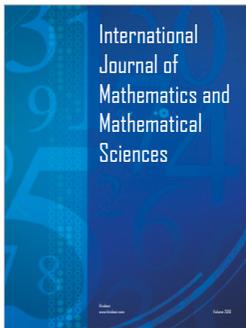
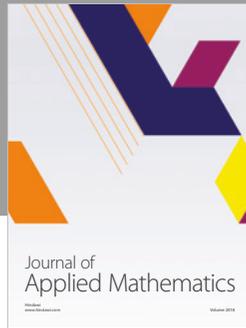
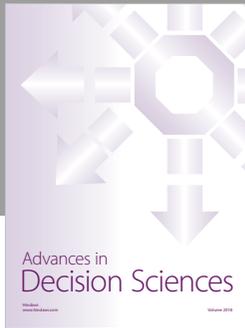
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