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An Elitist Multi-Objective Particle Swarm Optimization Algorithm for Sustainable Dynamic Economic Emission Dispatch Integrating Wind Farms

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Abstract: In recent years, wind energy has been widely used as an alternative energy source as it is a clean energy with a low running cost. However, the high penetration of wind power (WP) in power networks has created major challenges due to their intermittency. In this study, an elitist multi-objective evolutionary algorithm called non-dominated sorting particle swarm optimization (NSPSO) is proposed to solve the dynamic economic emission dispatch (DEED) problem with WP. The proposed optimization technique referred to as NSPSO uses the non-dominated sorting principle to rank the non-dominated solutions. A crowding distance calculation is added at the end of all iterations of the algorithm. In this study, WP is represented by a chance-constraint which describes the probability that the power balance cannot be met. The uncertainty of WP is described by the Weibull distribution function. In this study, the chance constraint DEED problem is converted into a deterministic problem. Then, the NSPSO is applied to simultaneously minimize the total generation cost and emission of harmful gases. To proof the performance of the proposed method, the ten-unit and forty-unit systems—including wind farms—are used. Simulation results obtained by the NSPSO method are compared with other optimization techniques that were presented recently in the literature. Moreover, the impact of the penetration ratio of WP is investigated.

Keywords: dynamic dispatch; wind power; chance-constraint problem; PSO; pareto front

1. Introduction

1.1. Research Background

In recent years, power system operators have been advised to use non-conventional energy sources such as wind energy and solar energy. Although renewable energy sources have positive environmental impacts, their exact output power is not evident to predict. For this reason, these sources are mostly integrated with conventional sources, such as thermal units, to meet the balance between load demand and power generation. However, mismanagement of thermal generating units leads to high operation cost and unacceptable emission level. Moreover, high penetration of renewable energy, especially wind energy, into the power system caused major challenges due to their intermittent outputs. As countermeasures, decision makers in the power sector should use an optimal power dispatch under wind power (WP) uncertainty for reducing both operational cost and emission. Due to the dynamic characteristic of today's network loads, it is necessary to schedule the generation units according to power demand variations. To achieve the aforementioned tasks, the dynamic economic emission dispatch (DEED) problem incorporating wind energy has become a key issue for power system operators. The purpose of the DEED problem is to minimize simultaneously the total fuel cost and total emission by finding the power production of thermal power plants according to the predicted load demands [1,2]. The DEED problem is equivalent to the static economic emission dispatch (SEED) at each time interval mostly of one hour. Several constraints may be considered in the resolution of the DEED problem, such as generator ramp-rate limits (RRL), prohibited operating zones (POZ) and valve-point loading effects (VPLE). Unfortunately, POZ constraints, due to the vibrations in the shaft bearing, cause discontinuities in the objective functions [3]. Moreover, VPLE constraints make fuel cost function with ripples [2,3].

1.2. Related Works

In several works, classical methods—including dynamic programming [4], linear programming [5], and interior point [6] methods—have been used to solve both SEED and DEED problems. However, these techniques require initialization and are iterative and, as a result, the search process may converge into local optima. Moreover, the quality of optimal solutions is affected by the differentiability and continuity of the objective function. Metaheuristic-based techniques, such as genetic algorithm [7], particle swarm optimization (PSO) [8], artificial bee colony (ABC) [9], bacterial foraging [10], simulated annealing [11] and differential evolution (DE) [12] have been also suggested as other alternative methods to handle the complexity of the DEED problem. In fact, metaheuristic algorithms offer the possibility of modifying their control parameters, taking into account the complexity of the problem to be solved. These algorithms derive their efficiency from the fact that they can escape local optima, which are the main handicap in optimization problems.

In recent years, the uncertainty of wind power has been studied in many optimal dispatch problems [13–18]. However, it has been seen that wind energy has barely been employed for minimizing both the fuel cost and emission at the same time. The recent developments of the renewable energy sources encouraged power system operators to seek suitable incorporation of wind energy for optimum load dispatch. Hetzer et al. [13] developed an economic dispatch model incorporating WP where the random characteristic of WP output is described by the Weibull probability distribution function (PDF). In [15], the stochastic availability of WP output is described by penalty costs corresponding to the overestimation and underestimation of the actual wind energy. Generally, these penalty costs are added to the total production cost. In [19], the overestimation and underestimation costs of WP availability are combined with the total fuel cost of thermal generators and then a hybrid PSO and artificial physics optimization (APO) algorithm is used for minimization of the total cost. An improved version of the chemical reaction optimization method is proposed in [3] for the SEED problem incorporating penalty costs associated with wind energy availability. In [20], a scenario-based stochastic framework was established for describing the stochastic DEED problem considering WP. Biswas et al. [21] presented also a scenario-based method to model the randomness of WP in the optimal reactive power dispatch problem. Unfortunately, scenario-based methods need a large number of scenarios for increased accuracy of results. Some techniques presented in the literature for handling the power dispatch problems are listed in Table 1.

Chance-constraint programming has been also presented in the literature as suitable approaches for solving stochastic optimization problems such as dispatch power problems, including WP [16–18]. Zhu et al. [16] formulated the SEED problem with WP as a chance-constraint problem (CCP) and then a multi-objective evolutionary algorithm was used for its resolution. Hu et al. [18] developed the chance-constraint model for the economic dispatch problem integrating thermal units, wind farm and energy storage system. A CCP-based method was developed in [17] for handling with the DEED in presence of wind energy. The total production cost and emission were combined in a single objective function and then the problem was solved using GAMS software. However, the application of metaheuristic techniques may provide more accurate solutions for this kind of problem. Jadhav et al. proposed an improved version of the ABC algorithm for solving the SEED problem incorporating WP, where the emission was converted to a carbon tax and then it was combined with the fuel cost to form the single objective function [22]. The economic emission dispatch problem was converted into a mono-objective problem in [23] in order to apply new global particle swarm optimization (NGPSO) for its solution. Hagh et al. [24] used an exchange market algorithm method for solving the stochastic economic emission dispatch problem, where the fuel cost, penalty costs of WP and emission were combined in one objective function. Unfortunately, most of the aforementioned methods did not necessarily provide the real Pareto front and the compromise solution which are frequently requested for the decision making. In addition, the solution programs need to run several times to get the non-dominated solutions. In consequence, several multi-objective optimization algorithms such as NSGA-II (non-dominated sorting genetic algorithm-II), MOPSO (multi-objective PSO) and MODE (multi-objective DE) were used for solving this kind of problem [25]. These algorithms are mainly based on the non-dominance principle and may provide the Pareto front in a single run. However, some works demonstrated that MOPSO-based algorithms provide frequently the more accurate Pareto front [25]. In fact, MOPSO adopts the non-dominated sorting principles to improve the solution diversity. In addition, PSO and its variants use the experience acquired during the search for the optimum solution in order to best guide the search process. Unlike GA and DE, PSO does not have mutation and crossover operators, but it emulates the social behavior of organisms, which enables the PSO-based techniques to efficiently provide the local solutions.

Table 1. List of some techniques used for dispatch problems.

Techniques	Dispatch Problems
Dynamic programming [4]	Static economic dispatch problem without valve-point loading effects (VPLE) constraints
Interior point method [6]	Nonlinear optimal power flow
Particle swarm optimization (PSO) [8]	Static economic dispatch with VPLE constraints
Artificial bee colony (ABC) [9]	
Genetic algorithm [7]	Dynamic economic dispatch problem with VPLE constraints
Bacterial foraging [10]	Dynamic economic emission dispatch (DEED) problem with VPLE constraints
Simulated annealing [11]	
Differential evolution (DE) [12]	
Here-and-now approach [14]	Static economic dispatch problem including wind power and without VPLE
Stochastic optimization technique [15]	Static economic emission dispatch (SEED) problem considering wind power
Chance-constraint programming [16]	SEED problem considering wind power
Chance-constraint programming [17]	DEED problem considering wind power
Chance-constraint programming [18]	Static economic dispatch considering wind power and without VPLE
Scenario-based approach [20]	DEED problem considering wind power
Scenario-based approach [21]	Reactive power dispatch considering renewable energy sources and with uncertainties in loads.

1.3. Aims and Contributions

Within this context, this paper presents an elitist multi-objective method to solve the DEED for the wind-thermal system. In the optimization process, all cited operating constraints are considered and the stochastic characteristic of the WP is represented by a chance-constraint which describes the probability that the power balance cannot be met. The stochastic constraint is incorporated in the system constraints in order to mitigate the penalty costs of WP. The resolution of the problem is carried out mainly in two steps. Firstly, the stochastic problem is converted into a deterministic problem by representing the random characteristic of the wind speed by the Weibull PDF. Then, the problem is solved by an elitist multi-objective evolutionary algorithm. The proposed optimization technique, called non-dominated PSO algorithm (NSPSO), uses a crowding distance comparison at the end of iterations of the classic PSO in order to facilitate the convergence to the real Pareto front. The Pareto front is generated in one run of the solution program. The proposed method is tested on the ten-unit and forty-unit systems including the wind energy source.

2. Materials and Methods

2.1. Chance-Constrained DEED Problem

In the literature, the DEED problem was considered as a bi-objective optimization problem. It aims to minimize simultaneously the total fuel cost and total emission by finding the power production of thermal units according to the predicted load demands. The resolution of the DEED problem can be accomplished by solving the SEED problem over a certain period of time subdivided into smaller time intervals. The total fuel cost and emission over time horizon of T hours are described, respectively [2], by Equations (1) and (2). In this study, T = 24 h.

$$C_T = \sum_{t=1}^{T}\sum_{i=1}^{N} a_i + b_i P_i^t + c_i\left(P_i^t\right)^2 + \left|d_i \sin\left\{e_i\left(P_i^{\min} - P_i^t\right)\right\}\right| \tag{1}$$

$$E_T = \sum_{t=1}^{T}\sum_{i=1}^{N} \alpha_i + \beta_i P_i^t + \gamma_i\left(P_i^t\right)^2 + \eta_i \exp\left(\lambda_i P_i^t\right) \tag{2}$$

The two objective functions will be minimized subject to the constraints given in Equations (3)–(7). Inequality (3) is the chance-constraint describing the stochastic characteristic of WP. It represents the probability to meet the system load requirement at time t. Real power losses P_{loss}^t are calculated using the B-loss formula [2]. In practice, the power generation of each unit i during two successive time periods is confronted by its RRLs defined by Inequalities (4) and (5). The POZ constraints are described as given in Equation (6). Maximum and minimum generations of both thermal units and the wind energy source are stated in Equations (7) and (8), respectively.

$$\Pr\left(\sum_{i=1}^{N} P_i^t + P_w^t \le P_{ld}^t + P_{loss}^t\right) \le \alpha \tag{3}$$

$$P_i^{t-1} - P_i^t \le R_i^{down} \tag{4}$$

$$P_i^t - P_i^{t-1} \le R_i^{up} \tag{5}$$

$$P_i^t \in \begin{cases} P_i^{\min} \le P_i^t \le P_{i,1}^{down} \\ P_{i,k-1}^{up} \le P_i^t \le P_{i,k}^{down}, \ k = 2, \ldots, z_i \\ P_{i,z_i}^{up} \le P_i^t \le P_i^{\max} \end{cases} \tag{6}$$

$$P_i^{\min} \le P_i^t \le P_i^{\max} \tag{7}$$

$$0 \le P_w^t \le P_{wr} \tag{8}$$

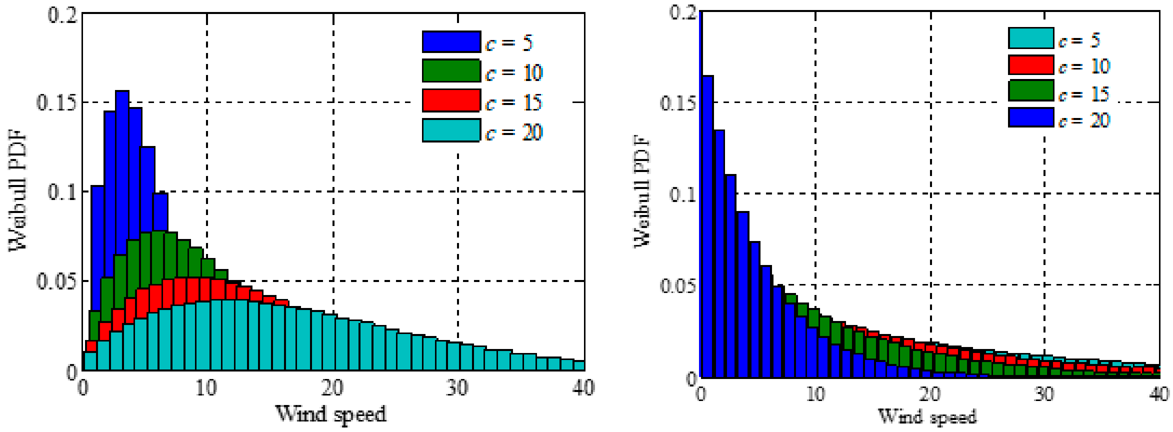
2.2. Probability Model of WP Output

The high penetration of WP into power networks has created major challenges due to the intermittency of the wind speed. From the literature review, it is found that the wind speed is widely described by two-parameter Weibull PDF [17]. The Weibull PDF and cumulative distribution function are given, respectively, in Equations (9) and (10) [17].

$$f_V(v) = (k/c)(v/c)^{k-1} \exp\left[-(v/c)^k\right] \tag{9}$$

$$F_V(v) = \int_0^v f_V(\tau)\, d\tau = 1 - \exp\left(-(v/c)^k\right),\ v \geq 0 \tag{10}$$

Parameters c and k in Equation (9) depend on the wind farm location. Mostly, they are in the range of (5.0, 20.0) and (1.0, 3.0), respectively. Figure 1 depicts the impact of parameters c and k on the Weibull PDF. It can be seen that the curve shape is influenced by the value of parameter k. It is noteworthy also that if c increases, the curves move toward higher wind speed.



(a) (b)

Figure 1. Weibull probability distribution function (PDF): (**a**) For k = 1.7; (**b**) For k = 1.

In this paper, WP output as a function of the wind speed is described by the following equation.

$$P_w = \varphi(v) = \begin{cases} 0, & v < v_{in} \text{ or } v \geq v_{out} \\ w_r \frac{v - v_{in}}{v_r - v_{in}}, 0 \leq w < w_r, & v_{in} \leq v < v_r \\ w_r, & v_r \leq v < v_{out} \end{cases} \tag{11}$$

The cumulative distribution function (CDF) of the random P_w may be calculated as follows.

$$F_W(P_w) = \Pr(w \leq P_w) = \begin{cases} 0, & (P_w < 0) \\ 1 - \exp\left\{-\left(\frac{\left(1 + \frac{hP_w}{w_r}\right)v_{in}}{c}\right)^k\right\} + \exp\left(-\left(\frac{v_{out}}{c}\right)^k\right), & 0 \leq P_w < w_r \\ 1, & (P_w \geq w_r) \end{cases} \tag{12}$$

Thus, constraint (3) can be modified as follows.

$$\Pr\left\{P_w^t \leq P_{ld}^t + P_{loss}^t - \sum_{i=1}^{N} P_i^t\right\} = F_W\left(P_{ld}^t + P_{loss}^t - \sum_{i=1}^{N} P_i^t\right) \leq \alpha \tag{13}$$

where $h = \frac{v_r - v_{in}}{v_{in}}$.

2.3. Implementation of the Non-Dominated Sorting PSO Algorithm

The PSO algorithm emulates the social behavior of organisms [26]. In the PSO algorithm, the i-th individual, called particle, is represented at each iteration k by its position $X_i^k = \left(X_{i1}^k, \ldots, X_{in}^k\right)$ and its velocity $V_i^k = \left(V_{i1}^k, \ldots, V_{in}^k\right)$.

From iteration k to the next iteration (k + 1), position and velocity are updated as given in the two following equations.

$$V_i^{k+1} = wV_i^k + c_1 r_1\left(pbest_i^k - X_i^k\right) + c_2 r_2\left(gbest^k - X_i^k\right) \tag{14}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{15}$$

where w, c_1 and c_2 are the PSO parameters; r_1 and r_2 are random numbers in the range [0, 1]; $pbest_i^k$ and $gbest^k$ are the best solution of the i-th particle and the best solution in the overall population at the k-th iteration, respectively.

In order to adopt the PSO algorithm for multi-objective problems, several modifications of the original PSO have been developed in the literature [27–30]. In this study, the non-dominated sorting concept suggested by Deb et al. [28] for the non-dominated sorting genetic algorithm is incorporated in the classical PSO algorithm.

At each generation t, an offspring population Q_t is generated from the parent population P_t. The two populations are combined in one population R_t as in Equation (16). Then, the obtained population is sorted into different non-domination levels F_j as given in Equation (17). This process is shown in Figure 2 and it is detailed in [28].

$$R_t = P_t \cup Q_t \tag{16}$$

$$R_t = \cup_{j=1}^{r}\left(F_j\right) \tag{17}$$

where r is the number of fronts.

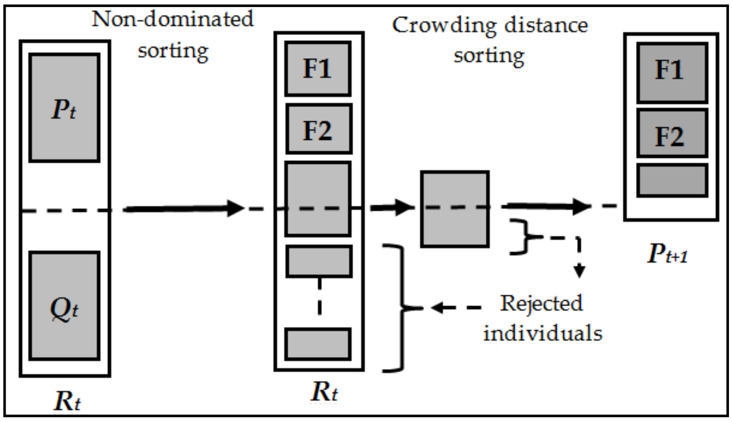


Figure 2. Non-dominated sorting concept.

3. Results and Discussion

The performance of the proposed method for solving the DEED of a wind-thermal system is verified by using two test systems which are the standard ten-unit 39-bus New England power system and the forty-unit system. The single line diagram of the first system is shown in Figure 3. All aforementioned constraints are considered for both systems. Generator cost and emission coefficients of system 1 are shown in Table A1 in the Appendix. Generation limits and RRLs of all units of this system are given in Table A2. All data of system 2 are taken from [24,25]. The hourly variation of the load is given in Table A3.

Three cases are considered in this section.

(i) SEED problem without wind power.
(ii) DEED problem without wind power.
(iii) DEED problem with wind power.

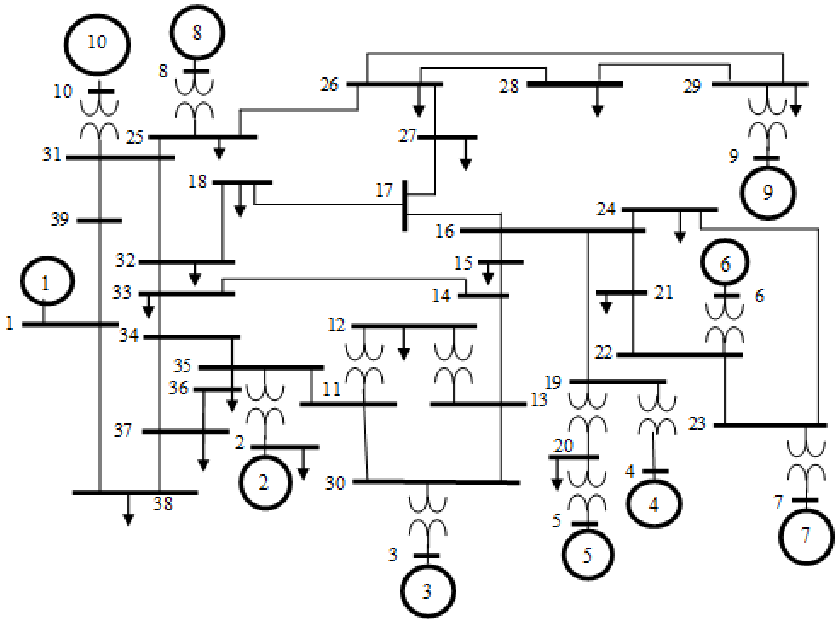


Figure 3. Single-line diagram of the studied system.

3.1. Case 1: SEED Problem without Wind Power

To prove the superiority of the proposed technique, the fuel cost and the emission are minimized for the forty-unit system with VPLE. In this case, the total load is 10,500 MW. The optimization results are shown in Table A4 in the Appendix. As seen in Table A4, the minimum fuel cost and emission provided by NSPSO are USD 121,153/h and 389,953 ton/h, respectively. It is clear that these values are better than those obtained by using the classical PSO algorithm. In addition, it can be verified easily that all constraints are satisfied.

3.2. Case 2: DEED Problem without Wind Power

In this case, the performance of the proposed optimization algorithm NSPSO is tested on the DEED problem without incorporation of WP. Initially, the NSPSO is applied to the ten-unit system with constant load P_{ld} = 1700 MW and a comparison with the classical PSO is provided. The convergence and the Pareto set of solutions of both algorithms are shown in Figures 4 and 5, respectively. From Figures 4 and 5, it is clear that the proposed NSPSO provides the best results compared to the PSO algorithm. It is noticed that the minimum cost and the minimum emission achieved by NSPSO for the static problem are 9.9334 × USD 10^4/h and 1.1158 × 10^4 ton/h while are 9.9555 × USD 10^4/h and 1.1233 × 10^4 ton/h for the PSO algorithm, respectively. From Figure 5, it is obvious that fuel cost and emission are conflicting objective functions. In other words, if a power system operator or decision maker wants lower production cost, more emissions of harmful gases will be emitted and vice versa.

To further study the effectiveness of the NSPSO, it is executed for the classical DEED problem and obtained results are compared with other optimization techniques, such as improved bacterial foraging algorithm (IBFA) and non-dominated sorting genetic algorithm (NSGA-II), used in other research works for solving the same problem. The comparison results shown in Table 2 confirm that the NSPSO outperforms these techniques despite POZ constraints not being taken into account in some of them. The minimum total cost and minimum total emission achieved by the proposed technique are USD 2,474,472.8 and 293,416.3 ton, respectively.

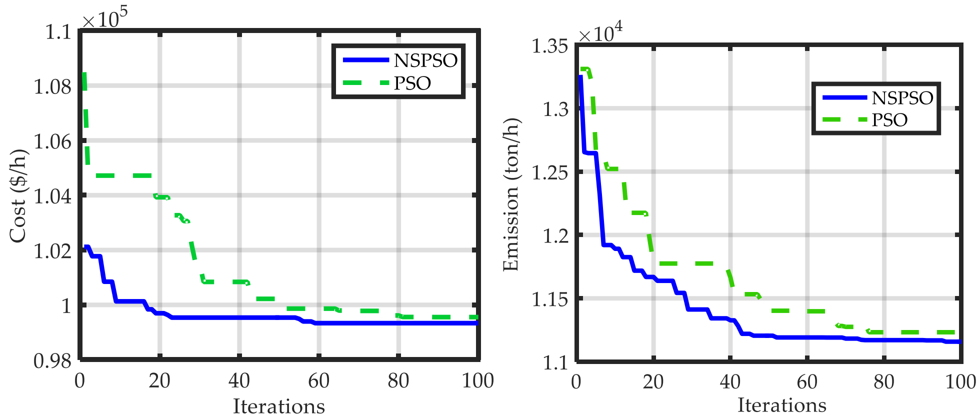


Figure 4. Convergence of the non-dominated sorting particle swarm optimization (NSPSO) and PSO.

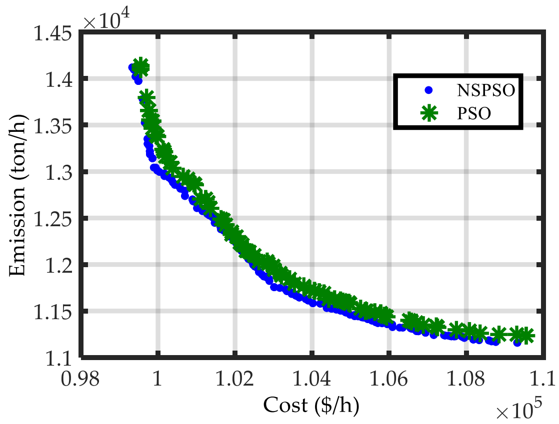


Figure 5. Pareto fronts.

Table 2. Comparison of the NSPSO with other meta-heuristic techniques.

Method	Minimum Total Cost (USD)	Minimum Total Emission (ton)
NSPSO	2,474,472.8	293,416.3
PSO	2,491,480.2	2.97696
IBFA [1]	2,481,733.3	295,833.0
NSGAII [2]	2.5168×10^6	3.1740×10^5

3.3. Case 3: DEED with Wind Power

In this case, the effect of the incorporation of wind energy into the power system is studied through the DEED problem. The problem is solved by using the proposed method for various values of the threshold tolerance. Due to the space limit, just the optimum solutions for $\alpha = 0.25$ are presented. Tables 3–5 show the optimum solutions for the dynamic economic dispatch, dynamic emission dispatch and the DEED compromise solution, respectively. It is worth noting that the compromise solution is provided using a fuzzy-based approach described in [2]. It is clear from these tables that the optimum solutions respect the required constraints such as the generation limits and the ramp rate limits. Nevertheless, the total cost and emission are reduced, respectively, from USD 2,474,472.8 and 293,416.3 ton (Table 2) to USD 2,433,467.20 (Table 3) and 283,538.16 ton (Table 4), when WP is considered.

Table 3. Optimum solution for the dynamic economic dispatch (α = 0.25).

Hour	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	WP
1	152.19	135.00	143.75	60.00	73.00	160.00	130.00	98.50	25.23	46.13	30.89
2	150.07	137.64	191.51	60.00	121.47	152.07	130.00	120.00	20.00	16.13	32.42
3	152.45	135.00	271.51	110.00	171.47	145.20	130.00	120.00	20.00	12.62	17.80
4	154.32	135.00	268.30	145.34	217.31	155.92	123.12	119.74	50.00	39.69	31.44
5	153.35	136.00	297.97	168.14	227.50	160.00	130.00	118.81	49.26	44.39	32.52
6	196.18	135.00	329.35	218.14	243.00	144.52	130.00	120.00	71.22	55.00	32.33
7	151.82	199.68	340.00	255.06	237.69	160.00	123.16	120.00	80.00	55.00	30.84
8	166.04	226.41	340.00	300.00	243.00	160.00	130.00	120.00	80.00	53.27	14.60
9	224.73	306.41	340.00	300.00	243.00	160.00	130.00	120.00	80.00	55.00	32.63
10	252.51	386.41	340.00	300.00	243.00	160.00	130.00	120.00	80.00	54.27	32.46
11	272.99	466.41	340.00	300.00	243.00	160.00	130.00	120.00	80.00	46.38	32.33
12	308.76	470.00	340.00	300.00	243.00	160.00	130.00	120.00	80.00	55.00	32.49
13	272.91	463.03	327.97	300.00	232.48	160.00	130.00	103.97	79.81	55.00	29.48
14	195.22	383.58	311.62	300.00	243.00	159.38	129.81	119.01	76.49	42.81	31.80
15	152.33	303.58	301.25	300.00	243.00	129.41	130.00	120.00	78.15	44.18	31.32
16	161.55	223.58	221.25	250.00	233.79	160.00	130.00	120.00	55.00	14.18	27.29
17	150.68	145.58	218.55	239.01	243.00	144.51	129.86	119.07	51.30	44.18	32.04
18	151.05	213.33	297.55	249.74	232.67	154.08	126.38	117.79	54.29	45.89	31.88
19	178.47	293.33	300.00	299.74	243.00	160.00	130.00	87.79	53.17	55.00	32.57
20	212.61	373.33	340.00	300.00	243.00	160.00	130.00	117.79	80.00	55.00	32.50
21	231.14	308.96	339.73	299.43	243.00	160.00	125.76	119.94	76.99	54.78	32.20
22	152.08	232.02	262.12	249.43	239.68	160.00	130.00	120.00	52.59	44.88	31.91
23	153.27	152.02	182.12	235.39	189.68	110.00	100.00	120.00	80.00	14.88	25.64
24	152.08	135.00	117.01	185.39	156.80	100.04	130.00	90.00	80.00	31.39	30.48
Cost (USD)						2,433,467.20					
Emission (ton)						331,251.40					

Table 4. Optimum solution for the dynamic emission dispatch (α = 0.25).

Hour	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	WP
1	165.58	135.60	88.56	73.46	133.09	119.92	92.78	92.31	78.23	54.01	21.60
2	165.52	136.28	95.30	91.47	136.97	132.32	100.62	116.64	79.97	55.00	21.75
3	165.70	157.99	115.67	117.19	163.79	159.98	129.38	119.54	79.96	54.98	21.76
4	195.69	197.85	138.87	139.11	203.33	160.00	130.00	120.00	80.00	54.95	21.69
5	216.08	213.04	149.59	155.70	219.00	160.00	129.69	120.00	79.93	55.00	21.62
6	245.43	250.33	182.85	189.66	242.54	159.60	129.70	119.86	79.89	55.00	21.76
7	265.32	270.48	202.15	209.58	241.34	160.00	130.00	120.00	80.00	55.00	21.73
8	284.88	287.09	225.55	227.96	242.92	160.00	129.76	119.96	79.97	55.00	21.71
9	326.49	317.64	268.44	277.96	243.00	157.18	130.00	120.00	80.00	54.67	18.91
10	340.26	355.82	340.00	268.08	243.00	160.00	130.00	120.00	80.00	51.92	11.95
11	384.79	366.58	340.00	300.00	243.00	160.00	130.00	120.00	78.17	55.00	14.91

Table 4. *Cont.*

Hour	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	WP
12	394.93	395.50	340.00	300.00	243.00	160.00	130.00	120.00	80.00	55.00	21.77
13	356.63	356.77	332.55	299.30	242.81	159.97	129.92	120.00	79.87	54.87	21.76
14	323.38	324.57	265.26	272.00	242.98	159.96	129.66	119.67	79.89	55.00	21.76
15	287.40	287.15	224.63	226.75	243.00	160.00	129.69	119.79	79.84	55.00	21.61
16	234.54	235.52	170.56	176.75	238.93	160.00	130.00	120.00	55.00	55.00	21.75
17	218.58	217.50	160.73	158.17	224.54	159.47	129.03	119.99	54.93	55.00	21.71
18	253.80	256.98	191.47	190.38	242.58	159.98	130.00	120.00	54.89	55.00	21.69
19	293.70	291.55	231.14	234.04	243.00	159.96	129.96	119.98	54.95	54.95	21.73
20	301.23	340.24	311.14	284.04	243.00	160.00	130.00	120.00	80.00	55.00	20.92
21	322.36	316.67	269.77	275.90	242.94	159.92	130.00	119.88	79.79	54.99	21.76
22	244.56	236.67	189.77	225.90	243.00	160.00	100.00	120.00	80.00	55.00	21.62
23	165.11	157.07	109.77	175.90	193.00	160.00	125.62	120.00	80.00	55.00	21.75
24	170.50	137.02	116.29	125.90	143.00	148.23	107.99	104.65	80.00	55.00	20.17
Cost (USD)	2,552,118.86										
Emission (ton)	283,538.16										

It is clear from Tables 3 and 4 that the production cost is USD 2,466,582.70 for dynamic economic dispatch and it is increased to USD 2,552,118.86 for dynamic emission dispatch, while emission is 331,251.40 ton under dynamic economic dispatch, and it decreases to 283,538.16 ton under dynamic emission dispatch. It is worth noting that the minimization of emission under economic dispatch is not considered and economic aspects are not considered under emission dispatch. To avoid the above-mentioned conflicts, the compromise solution given in Table 5 may be selected as the optimum solution.

Table 5. Best compromise solution for the DEED problem (α = 0.25).

Hour	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	WP
1	150.11	135.64	77.13	113.31	123.76	125.26	94.02	86.25	64.89	52.62	31.51
2	150.13	135.00	83.51	110.89	167.96	128.21	95.09	94.21	78.68	55.00	32.57
3	151.74	138.19	130.19	125.09	172.81	159.16	124.66	119.95	76.13	55.00	32.23
4	155.27	144.41	176.07	172.92	222.81	154.32	130.00	120.00	80.00	55.00	29.37
5	166.61	189.98	188.18	184.09	219.69	159.73	128.33	119.41	80.00	49.56	32.59
6	208.48	220.78	203.56	225.51	243.00	159.56	128.76	119.74	80.00	53.65	32.10
7	255.24	245.79	220.35	275.51	243.00	129.32	130.00	89.74	80.00	55.00	30.94
8	220.71	300.02	277.02	269.20	243.00	157.83	100.00	119.74	80.00	37.67	28.59
9	274.93	289.02	326.95	294.78	243.00	155.08	129.49	117.97	80.00	48.61	32.35
10	298.85	369.02	310.79	300.00	243.00	160.00	130.00	120.00	80.00	55.00	32.26
11	287.06	449.02	340.00	300.00	243.00	160.00	130.00	120.00	80.00	55.00	27.25
12	338.40	463.32	334.81	297.73	239.12	157.06	128.35	118.05	77.85	54.55	30.57
13	312.20	383.32	340.00	300.00	243.00	159.68	129.85	120.00	79.20	53.61	32.44
14	274.94	310.29	295.01	293.28	242.08	159.90	130.00	119.61	80.00	54.76	32.49
15	225.34	250.11	288.03	262.93	242.66	160.00	121.27	119.74	80.00	53.24	29.71

Table 5. *Cont.*

Hour	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	WP
16	150.21	203.99	251.89	232.77	228.27	153.00	126.88	116.35	51.72	55.00	26.48
17	159.48	168.06	203.71	195.09	243.00	160.00	129.39	116.88	55.00	55.00	32.33
18	210.39	236.26	241.82	243.83	232.79	153.36	130.00	86.88	55.00	54.52	30.67
19	248.46	249.38	264.83	293.83	243.00	160.00	130.00	110.55	55.00	55.00	23.65
20	290.34	310.01	340.00	293.29	243.00	157.66	130.00	120.00	74.49	55.00	30.54
21	285.72	296.94	302.19	293.47	242.59	159.99	130.00	119.57	79.11	54.62	28.42
22	213.06	223.41	222.19	243.47	213.47	160.00	129.62	117.53	80.00	41.53	30.95
23	156.28	143.41	184.23	193.47	163.47	160.00	99.62	120.00	80.00	37.35	24.93
24	151.87	135.00	115.93	145.17	182.97	133.97	129.62	90.00	50.00	43.52	30.02
Cost (USD)						2,466,582.70					
Emission (ton)						298,159.46					

Table 6 shows the effect of the threshold probability α on the minimum production cost, the minimum emission and compromise solution of the DEED problem incorporating wind energy. It is clear that the minimums of the two objective functions decrease as the probability α, that power balance described by Equation (13) cannot be met, increases, because the larger α signifies using more WP and reducing the demand of thermal energy.

Table 6. Effect of the threshold tolerance.

α	Dynamic Economic Dispatch		Dynamic Emission Dispatch		Compromise Solution	
	Cost ($\times 10^6$ (USD))	**Emission ($\times 10^5$ ton)**	**Cost ($\times 10^6$ (USD))**	**Emission ($\times 10^5$ ton)**	**Cost ($\times 10^6$ (USD))**	**Emission ($\times 10^5$ ton)**
0.25	2.433467	3.31251	2.552118	2.83538	2.466582	2.98159
0.3	2.376280	3.07791	2.506736	2.70929	2.427758	2.80227
0.35	2.360207	3.02358	2.470134	2.65313	2.394421	2.72884

The penetration ratio of WP is investigated also in this study. The maximum value of WP penetration is given as follows.

$$P_w^{\max} = \eta P_D \tag{18}$$

where P_D is the total demand power and η is the ratio of WP penetration.

Table 7 shows the effect of WP penetration ratios on the total fuel cost and the total emission for total demand power equal to 1500 MW. It is clear that if the ratio increases, fuel cost and emission decrease due to the reduction in outputs of thermal units.

Table 7. Effect of wind power (WP) penetration ratio on the SEED (P_D = 1500 MW).

Ratio η	5%	10%	15%	20%
Cost (USD/h)	83,865	82,007	80,312	78,579
Emission (ton/h)	7570	7190	6818	6481

4. Conclusions

In this study, a PSO-based multi-objective optimization technique is proposed to solve the DEED problem incorporating wind energy. To avoid the penalty costs corresponding to the overestimation and underestimation of the wind farm output, the uncertain characteristic of the wind power is represented by a chance-constraint in the DEED model. The latter describes the probability that energy balance cannot be met. In order to adopt the PSO algorithm for the multi-objective DEED problem, the non-dominated sorting concept is incorporated in the classical PSO method. The proposed method referred to as NSPSO is successfully tested for the static economic emission dispatch problem. Then, its effectiveness for solving the stochastic DEED problem is evaluated. The fuel cost with VPLE and emission is minimized simultaneously where all constraints cited in the problem formulation are considered. Simulation results show that NSPSO outperforms other optimization techniques used for solving the same problem. Moreover, the effect of the penetration ratio on the objective functions is studied.

It can be concluded that the proposed algorithm can provide a variety of solutions for the decision makers in a single run. The NSPSO algorithm has the ability to optimize simultaneously more than two objective functions. Therefore, other functions can be added to the problem, e.g., total losses and voltage deviation.

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Nomenclature

C_T	Total fuel cost in USD
E_T	Total emission in ton
N:	Number of thermal units
a_i, b_i, c_i, d_i and e_i	Cost coefficients
α_i, βi, γ_i, η_i, and λI	Emission coefficients
P_i^t	Generation in MW of unit i at time t
P_{ld}^t	Total demand power in MW at time t
$\Pr(\bullet)$	Probability of event $(\bullet)$
α	Probability that the energy balance constraint cannot be met
P_w^t	Wind power output at time t
P_{loss}^t	Total losses in MW at time t
N	Number of thermal units
$P_i^{\min}$ and $P_i^{\max}$	Minimum and maximum limits of generation of unit i, respectively
R_i^{down} and R_i^{up}	Down-ramp and up-ramp limits of the of the i-th unit in MW
$P_{i,k}^{down}$ and $P_{i,k}^{up}$	Down and up limits of the k-th POZ of unit i, respectively
z_i	Number of POZ for the i-th unit
$f_V(\bullet)$	Probability density function (PDF)
$F_V(\bullet)$	Cumulative distribution function (CDF)
v	Wind speed in m/s
V and P_W	Wind speed and wind power random variables
k and c	Shape and scale factors of the Weibull distribution function, respectively
v_{in}, v_{out} and v_r	Cut-in, cut-out and rated wind speeds in m/s, respectively
w_r	Rated wind power output in MW

Appendix A

Table A1. Generator cost and emission coefficients.

Unit	a_i	b_i	c_i	d_i	e_i	α_i	β_i	γ_i	η_i	λ_i
1	786.7988	38.5397	0.1524	450	0.041	103.3908	−2.4444	0.0312	0.5035	0.0207
2	451.3251	46.1591	0.1058	600	0.036	103.3908	−2.4444	0.0312	0.5035	0.0207
3	1049.9977	40.3965	0.0280	320	0.028	300.3910	−4.0695	0.0509	0.4968	0.0202
4	1243.5311	38.3055	0.0354	260	0.052	300.3910	−4.0695	0.0509	0.4968	0.0202
5	1658.5696	36.3278	0.0211	280	0.063	320.0006	−3.8132	0.0344	0.4972	0.0200
6	1356.6592	38.2704	0.0179	310	0.048	320.0006	−3.8132	0.0344	0.4972	0.0200
7	1450.7045	36.5104	0.0121	300	0.086	330.0056	−3.9023	0.0465	0.5163	0.0214
8	1450.7045	36.5104	0.0121	340	0.082	330.0056	−3.9023	0.0465	0.5163	0.0214
9	1455.6056	39.5804	0.1090	270	0.098	350.0056	−3.9524	0.0465	0.5475	0.0234
10	1469.4026	40.5407	0.1295	380	0.094	360.0012	−3.9864	0.0470	0.5475	0.0234

Table A2. Unit operating limits in MW.

Unit	$P_i^{\min}$	$P_i^{\max}$	R_i^{down}	R_i^{up}
1	150	470	80	80
2	135	470	80	80
3	73	340	80	80
4	60	300	50	50
5	73	243	50	50
6	57	160	50	50
7	20	130	30	30
8	47	120	30	30
9	20	80	30	30
10	10	55	30	30

Table A3. Hourly loads.

Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Load (MW)	1036	1110	1258	1406	1480	1628	1702	1776	1924	2022	2106	2150
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	2072	1924	1776	1554	1480	1628	1776	1972	1924	1628	1332	1184

Table A4. Optimum generation in MW (case 1).

Units	**Best Cost**		**Best Emission**	
	NSPSO	**PSO**	**NSPSO**	**PSO**
1	113.9975	113.6956	444.5290	439.2442
2	111.2700	108.5791	118.8684	118.8350
3	97.7987	97.5901	119.5250	119.1685
4	78.6822	180.8286	120.0000	120.0000
5	87.7614	89.4804	171.0041	171.3165

Table A4. *Cont.*

Units	Best Cost		Best Emission	
	NSPSO	PSO	NSPSO	PSO
6	39.3092	135.9100	99.6506	100.0000
7	61.0281	262.3170	126.4088	123.6008
8	84.7192	286.7468	293.3165	293.0055
9	282.9047	289.1561	298.0365	298.3546
10	129.1357	128.6181	296.4214	297.2705
11	165.2336	165.0649	136.1537	137.1096
12	94.1237	95.2535	298.0555	298.7171
13	125.0462	127.4267	300.0000	299.9239
14	393.5936	393.9443	435.5130	437.5409
15	304.3556	303.7451	428.8594	428.4812
16	395.9528	392.3604	424.3950	425.0628
17	489.8036	486.7798	418.5687	420.6127
18	489.6818	480.9941	438.3276	438.2479
19	512.0610	517.3487	441.5894	443.2781
20	512.6642	511.1498	437.8936	436.2938
21	523.1834	523.5155	433.7515	434.5389
22	523.1455	532.7049	432.6224	431.5904
23	521.7535	536.3904	432.0455	431.4084
24	523.5970	528.3499	437.9027	439.7005
25	525.0606	523.1002	433.8896	434.0663
26	535.5420	546.2872	437.0916	435.3730
27	11.6919	13.9834	440.2194	439.3075
28	10.0623	18.6982	28.2081	27.6326
29	10.0201	13.3795	28.3884	27.9565
30	95.7998	83.7703	28.3276	30.0000
31	199.9715	182.6645	98.9027	99.7623
32	200.0000	196.3166	171.4707	170.4029
33	200.0000	199.0675	171.9558	171.7829
34	203.7138	186.6948	169.5057	169.1000
35	170.1866	181.6321	200.0000	200.0000
36	202.3923	195.0869	200.0000	199.8316
37	120.0000	119.0675	200.0000	199.9375
38	113.7251	114.3643	102.1179	103.9197
39	120.0000	108.4289	103.8253	103.8042
40	521.0316	529.5086	102.6590	103.8210
Cost (USD/h)	121,153	122,362	129,911	129,945
Emission (USD/h)	389,953	4.10112	176,299	176,305

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