An Improved Non-dominated Sorting Genetic Algorithm for the Optimal Economic Emission Dispatch Problem with Wind Power Sources

Imene Khenissi
LETI Laboratory, National Engineering School of Sfax, University of Sfax, Tunisia
imen.khenissi@enis.tn

Sultan M. Alotaibi
Department of Electrical Engineering, College of Engineering, University of Ha'il, Ha'il 55476, Saudi Arabia
sultan3tibi@gmail.com

Muhammad Tajammal Chughtai
Department of Electrical Engineering, College of Engineering, University of Ha'il, Ha'il 55476, Saudi Arabia
mt.chughtai@uoh.edu.sa

Tawfik Guesmi
Department of Electrical Engineering, College of Engineering, University of Ha'il, Ha'il 55476, Saudi Arabia
tawfik.guesmi@istmt.rnu.tn

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ABSTRACT

This study proposes a novel multi-objective technique for the Stochastic Economic Emission Dispatch Problem (SEEDP) integrating wind energy sources. To do this, the SEEDP is first formulated as a Chance Constrained Programming (CCP) problem where the randomness of the Wind Power (WP) output is obtained with the Weibull distribution function. Nevertheless, the chance constraint is employed to describe the fulfillment of the power balance constraint. In fact, after applying the probability theory, the proposed CCP issue is converted into a deterministic optimization problem. Moreover, the impact of WP penetration on the optimal solutions is investigated. To resolve the proposed multi-objective approach, the second version of the Non-dominated Sorting Genetic Algorithm (NSGAII) is applied. Moreover, to test the robustness of the proposed strategy, a ten-unit system is used and the acquired results are compared with those of other optimization techniques.

Keywords-economic emission dispatch; dhance constrained programming; pareto solution; non-dominated sorting genetic algorithm

I. INTRODUCTION

The main objective of the Economic Emission Dispatch (EED) problem is to simultaneously minimize the total fuel cost and the emissions of harmful gases generated by thermal generating units. To reach these goals, various constraints should be satisfied, such as power balance constraints, Valve Point Loading Effects (VPLEs) [1], and generation limits. VPLEs happen during the control of the steam valve of the turbines in thermal units through separate nozzles. VPLEs are modeled by adding sinusoidal functions to the original quadratic fuel cost function, which gives rise to a non-convex EED problem. Other constraints due to Prohibited Operating Zones (POZs) can also be considered in the EED problem model. In fact, the inclusion of POZ constraints can lead to input-output generation characteristic discontinuities. Due to the aforementioned constraints, the EED problem can be considered a discontinuous, nonlinear and non-convex optimization problem. From the literature review, it is found that various traditional approaches, such as linear programming [2], lambda iteration [3], dynamic programming [4], and interior point [5] have been applied to deal with this issue.

Nevertheless, the total cost and emission functions have been investigated using quadratic functions, whereas the VPLEs have been completely neglected. Moreover, the traditional techniques need an initial solution and are iterative methods, which may affect their convergence rate and result accuracy.

In the past two decades, meta-heuristic techniques have been presented as alternative optimization methods for handling the EED problem. For instance, an improved version of the Bacterial Foraging Algorithm (BFA) has been deployed in [6] for the combined EED problem. In [7], VPLEs have been considered in the EED problem and a differential evolution-based method was introduced for the problem solution. Authors in [8] applied the Simulated Annealing (SA) algorithm to solve this problem using a mono-objective function based on the Price Penalty Factor (PPF), the cost, and emission functions. It should be noted that the aforementioned methods are single objective optimization methods. Thus, these algorithms must be run several times to provide non-dominated solutions. The EED problem is categorized as a multi-objective optimization problem involving the simultaneous optimization of two conflicting objective functions with different units. This situation gave rise to an ensemble of optimal solutions known as non-dominated solutions or Pareto optimal solutions instead of a unique optimal solution. Multi-objective heuristic techniques, like multi-objective Particle Swarm Optimization (PSO) [9] and multi-objective evolutionary algorithms [10] have been proposed. In these techniques, a non-dominated sorting mechanism has been used to extract the best Pareto solutions.

In recent years, power decision makers have introduced Renewable Energy Sources (RESs) to deal with power scheduling problems due to their economic and environmental benefits. Unfortunately, RESs have intermittent outputs due to the random weather changes. Many research works describe the intermittent characteristics of these sources [11-14]. For instance, due to the underestimation and overestimation of the available Wind Power (WP), penalty costs have been considered in various research works to model the stochastic dispatch problem with wind farms [15-17]. In this context, when the predicted WP is less than the actual WP, underestimation cost will occur and when the actual WP is less than the predicted WP, overestimation cost will occur. A new methodology has been suggested in [16] to model and solve the stochastic economic dispatch problem utilizing RESs. In this method, penalty costs have been considered in the operating cost along with the total fuel cost. Added to that, the improved fireworks algorithm was put into service to minimize the objective function. An evolutionary algorithm based on decomposition has been employed in [11] to solve the combined EED incorporating wind turbine, where the Weibull Probability Distribution Function (PDF) was introduced to model the randomness of WP. In [13], a chemical reaction optimization-based method was suggested for solving the wind-based combined EED problem using a mono-objective function based on cost and emission functions. In order to avoid underestimation and over estimation costs, the randomness of RES outputs was modeled by chance constraint programming [14, 18]. In [18], a Chance Constrained Programming (CCP)-based dynamic economic dispatch modeling was presented and an improved PSO has been employed to reduce the total production cost. In [14], the EED with WP was also modeled as a CCP problem and then a chaotic-based sine-cosine technique was developed for its solution.

This study proposes an efficient and robust methodology for solving the combined EED problem integrating WP sources. The considered problem is converted into a multi-objective optimization problem where the total cost and emissions are taken as the objective functions. To increase the practical relevance of this study, all operating constraints such as, generation capacity, power balance constraint, ramp rate limits and POZs are incorporated into the problem formulation. Moreover, the intermittency characteristic of the WP source is described by a chance constraint. To deal with this issue, the second version of the Non-dominated Sorting Genetic Algorithm (NSGAII) is introduced to simultaneously reduce the cost and emission functions without combining them into one function. This multi-objective optimization algorithm is deployed to mitigate limitations of weighted sum approaches such as the non-diversity of the non-dominated solutions. Besides, unlike weighted sum approaches, the recommended NSGII-based method can provide the Pareto solutions in a single run. In order to reach the best compromise solution, a fuzzy based approach is adopted. The validity and efficiency of the proposed strategy are demonstrated based on the ten-unit system.

II. THE NSGAII ALGORITHM

NSGAII is a modified version of the NSGA algorithm [19]. It is a fast and elitist approach that has been proposed to overcome the criticism addressed to the NSGA method. The NSGAII algorithm is mainly based on the non-dominated sorting mechanism. The main principle of this algorithm is to randomly generate a population P_0 of N known individual solutions, according to (1). In this study, decision variables are represented by real coded numbers to reduce the computation time.

$$S_j^i = S_j^{min} + \theta\left(S_j^{max} - S_j^{min}\right) \quad (1)$$

where $\theta \in (0,1)$ is a uniformly distributed random number, $S^i = \left[S_1^i, S_2^i, \cdots, S_V^i\right]$ is the *i*-th vector of decision variables, V is the decision variable number, $i \in \{1, \cdots, N\}$, $j \in \{1, \cdots, V\}$, and S_j^{min} and S_j^{max} are the lower and upper limits of the *j*-th decision variable.

At each iteration t, a new population Q_t is produced from the actual population P_t by applying the genetic operators crossover and mutation. To accomplish this, objective functions for all individuals in the population P_t are calculated. Then, a tournament selection of candidate solutions from the population P_t is performed. Each selected couple of solutions (S^i, S^j) will undergo a crossover operation to create two new solutions $\tilde{S}^i$ and $\tilde{S}^j$ [20]. In this study, the non-uniform arithmetic crossover is deployed. Thus, $\tilde{S}^i$ and $\tilde{S}^j$ can be obtained by using (2) as follows:

$$\begin{cases} \tilde{S}^i = \varphi S^i + (1-\varphi)X^j \\ \tilde{S}^j = \varphi S^j + (1-\varphi)X^i \end{cases} \quad (2)$$

where $\varphi \in (0,1)$ is a random number.

After generating N new individuals using the crossover operator, the mutation operation is applied for each individual $\widetilde{S^i}$:

$$\tilde{S}_k^i = \begin{cases} \tilde{S}_k^i + h(t, S_k^{max} - S_k^{min}), x = 0 \\ \tilde{S}_k^i - h(t, \tilde{S}_k^i - S_k^{min}), x = 1 \end{cases} \quad (3)$$

where $h(t,z) = z\left(1 - n^{\left(1-\frac{t}{Iter_{max}}\right)^{\delta}}\right)$, n is a random number between 0 and 1, x is a random binary number, δ is called the shape parameter, and $Iter_{max}$ is the maximum number of iterations.

Once the offspring population Q_t is created, it will be combined with its parent population P_t to generate a new one R_t, as given in (4). The combined population R_t is sorted based on non-dominated sorting into fronts F_j, as given by (5):

$$R_t = P_t \cup Q_t \quad (4)$$

$$R_t = \cup_{j=1}^{n} F_j \quad (5)$$

The non-dominated sorting process starts by extracting the non-dominated solutions from the actual population P_t. These solutions will be removed from P_t and will be inserted in the first front F_1. Front F_2 is the set of the non-dominated solutions of the set $P_t \backslash F_1$ (i.e. P_t-F_1). This process continues until all solutions are assigned to a front. The NSGAII pseudo-code is illustrated in Algorithm 1.

```
Algorithm 1: NSGAII pseudo-code
Initialize NSGAII parameters
Read network data
t ← 0
Initialize population P0 according to (1).
Q0 ← genetic operators(P0) according to
(2) and (3)
While t < Itermax do
Rt = Pi ∪ Qt
(Fj)j=1,⋯,n ← non_dominated_sorting (Rt)
Pt+1 ← 0
j ← 0
While dim(Pt+1) + dim(Fj) ≤ N do
Pt+1 ← Pt+1 ∪ Fj
j ← j+1
End while
Fj ←crowing_distance (Fj)
Pt+1 ← Pt+1 ∪ Fj(1: N − |Fj|)
Qt+1 ←genetic_operators (Pt+1)
t ← t + 1
End while
```

III. ECONOMIC EMISSION DISPATCH PROBLEM MODELING

The EED problem can be considered a multi-objective problem that aims to minimize both fuel cost and gas emissions. In this study, the total fuel cost based on the VPLE and total emission functions can be written as presented in (6) and (7), respectively [6,10,11].

$$C_T = (\textstyle\sum_{i=1}^{NG} a_i + b_i P_i + c_i P_i^2 + \left|d_i sin\{e_i(P_i^{min} - P_i)\}\right|) \quad (6)$$

$$E_T = \textstyle\sum_{i=1}^{NG} \alpha_i + \beta_i P_i + \gamma_i P_i^2 + \eta_i exp(\lambda_i P_i) \quad (7)$$

where a_i, b_i, c_i, d_i, and e_i are the cost coefficients of unit i, NG is the number of thermal units, and α_i, β_i, γ_i, η_i, and λ_i represent the emission coefficients of unit i.

In this study, the objective functions C_T and E_T are reduced, taken into account the following constraints. It can be noted that (8)-(10) represent power balance constraints, generation capacity of unit i, and POZ constraints corresponding to the i-th unit, respectively.

$$\textstyle\sum_{i=1}^{NG} P_i - P_D - P_L = 0 \quad (8)$$

$$P_i^{min} \le P_i \le P_i^{max}, \quad i = 1, \cdots, NG \quad (9)$$

$$P_i \in \begin{cases} P_i^{min} \le P_i \le P_{i,1}^{down} \\ P_{i,k-1}^{up} \le P_i \le P_{i,k}^{down}, k = 2, \cdots, z_i \\ P_{i,z_i}^{up} \le P_i \le P_i^{max} \end{cases} \quad (10)$$

where P_i is the output of unit i, P_D is the total load, P_L is the total real power losses, P_i^{max} and P_i^{min} represent the upper and lower and limits of P_i, respectively, $P_{i,k}^{down}$ and $P_{i,k}^{up}$ represent the down and up bounds of POZ number k, and z_i defines the i-th unit of the POZ number .

Total real losses denoted by P_L can be calculated by [21-22]:

$$P_L = \textstyle\sum_{i=1}^{NG}\sum_{j=1}^{NG} P_i B_{ij} P_j + \sum_{i=1}^{NG} B_{oi} P_i + B_{oo} \quad (11)$$

where B_{ij}, B_{oi}, and B_{oo} are the B-loss coefficients.

The randomness of WP generation is mainly caused by the intermittent wind speed changes. The expression of the WP output (W) based on the wind speed (V) can be written as [14]:

$$W = \begin{cases} 0, if\ V < v_{in} \text{ or } V > v_{out} \\ \frac{(V - v_{in}) w_r}{v_r - v_{in}}, \quad \text{if } v_{in} \le V < v_r \\ w_r, \text{if } v_r \le V < v_{out} \end{cases} \quad (12)$$

where w_r is the rated power of the wind turbine and v_r, v_{in}, and v_{out} are rated cut-in, and cut-out wind speeds, respectively.

In this study, the randomness of wind speed is described by the two-parameter Weibull distribution function, expressed by:

$$f_V(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^k\right] \quad (13)$$

Therefore, the Cumulative Distribution Function (CDF) can be written as:

$$F_V(v) = \int_0^v f_V(\tau) d\tau = 1 - exp\left[-\left(\frac{v}{c}\right)^k\right], \ v \ge 0 \quad (14)$$

where v is the wind speed, k is the scale factor, and c is the shape factor.

Referring to (12)-(14) and applying probability theories, it can be found that the CDF of the WP output, which is $Pr(W \leq w)$, can be presented using (15)- (17) as [14]:

$$F_W(w) = 1 - exp\left\{-\left[\frac{\left(1+\frac{hw}{w_r}\right)v_{in}}{c}\right]^k\right\} + exp\left[-\left(\frac{v_{out}}{c}\right)^k\right],$$
$$0 \leq w < w_r \quad (15)$$

$$F_W(w) = 0, \quad w < 0 \quad (16)$$

$$F_W(w) = 1, \quad w \geq w_r \quad (17)$$

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

Therefore, the incorporation of WP into the EED problem can be considered by transforming the power balance constraint (8) into (18):

$$Pr\left\{W \leq P_D + P_L - \sum_{i=1}^{NG} P_i\right\} = F_W\left(P_D + P_L - \sum_{i=1}^{NG} P_i\right) \leq \sigma \quad (18)$$

where $\sigma \in (0,1)$ represents the tolerance that power balance constraint is unable to reach.

IV. SIMULATION RESULTS

To demonstrate the efficiency and applicability of the proposed strategy, a ten-unit system incorporating wind energy resources is introduced. The single line diagram of this test system is illustrated in Figure 1. The total system load is 2000 MW [14]. The parameters of the wind turbine adopted in this study are tabulated in Table I. The performance and robustness of the proposed NSGAII based strategy are evaluated for two cases:

- Case 1: EED problem without WP.
- Case 2: stochastic EED problem incorporating WP.

The proposed NSGAII parameters values are tabulated in Table II.

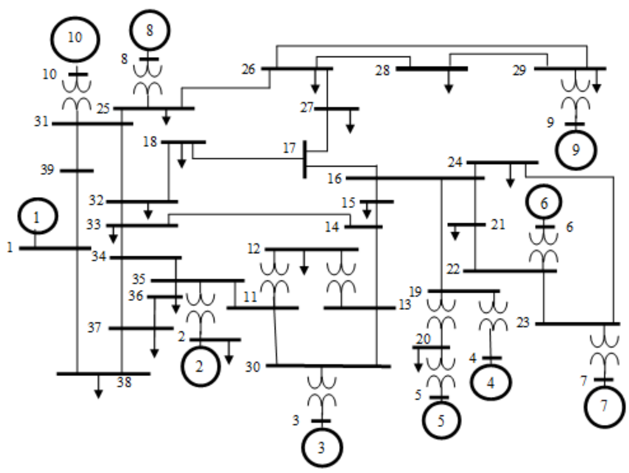

Fig. 1. The studied ten-unit system

TABLE I. WIND TURBINE PARAMETERSS

K	*C*	V_{in}	v_{out}	v_r
1.7	15	5	45	15

TABLE II. NSGAII PARAMETERS.

Parameter	Value
Maximum number of Iterations ($Iter_{max}$)	200
Population size (N)	200
Crossover probability	0.7
Mutation probability	0.1

A. *EED Problem without Inclusion of WP*

In this section, the EED problem is solved without WP. The convergence curves of the proposed NSGAII for best cost and best emission are provided in Figures 2 and 3, respectively. It can be seen that the optimization algorithm converges to the optimum cost and optimum emission after 48 and 47 iterations, correspondingly.

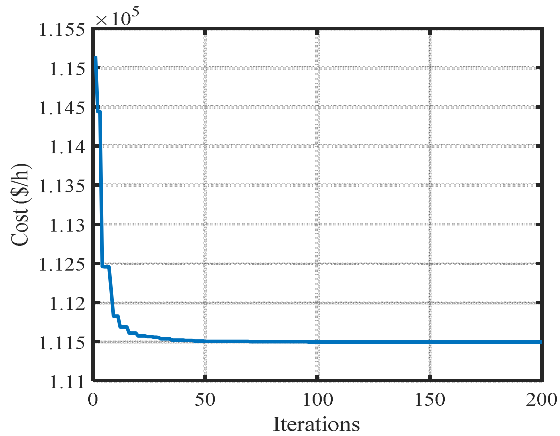

Fig. 2. Convergence characteristics of the best cost using the NSGII algorithm- case 1.

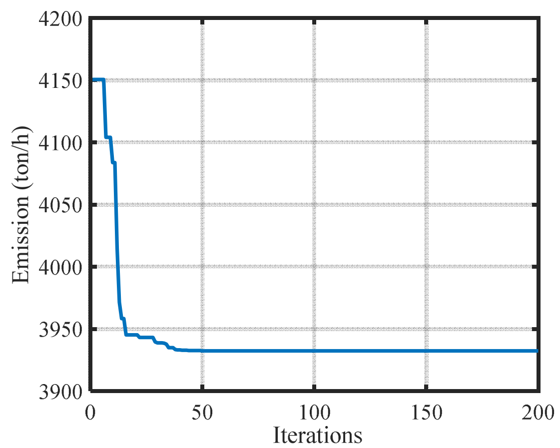

Fig. 3. Convergence characteristics of the best emissions using the NSGII algorithm- case 1.

Table III portrays the optimum solutions for the minimum cost and minimum emissions, which are 111497.63 $/h and 3932.24 ton/h, respectively.

TABLE III. OPTIMAL SOLUTIONS IN MW FOR CASE 1.

Unit	Economic dispatch	Emission dispatch
P_1	55.0000	55.0000
P_2	80.0000	80.0000
P_3	106.9408	81.1394
P_4	100.5756	81.3666
P_5	81.5017	160.0000
P_6	83.0207	240.0000
P_7	300.0000	294.4853
P_8	340.0000	297.2669
P_9	470.0000	396.7628
P_{10}	470.0000	395.5738
C_T ($/h)	111497.63	116412.46
E_T (ton/h)	4572.19	3932.24
P_L (MW)	87.0388	81.5949

To further demonstrate the effectiveness of the proposed method, a comparison with other optimization techniques, such as PSO [15], Firefly Algorithm (FA) [15], and Differential Evolution (DE) [15] is investigated. Table IV displays the optimal economic dispatch and emission dispatch problems provided by the NSAGII and the compared methods. It can be clearly seen that NSGAII achieves the best results. The non-dominated solutions sets, also called Pareto fronts, using the proposed NSGAII and the classical GA are demonstrated in Figure 4.

TABLE IV. ECONOMIC DISPATCH AND EMISSION DISPATCH WITH VARIOUS METHODS FOR CASE 1

Methods	Economic dispatch		Emission dispatch	
	Cost ($/h)	Emissions (ton/h)	Cost ($/h)	Emissions (ton/h)
NSGAII	111497.63	4572.19	116412.46	3932.24
PSO [15]	111498.49	4567.27	116412.49	3932.24
DE [15]	111565.71	4572.68	116418.34	3946.24
FA [15]	111500.79	4581.00	116443.05	3932.62

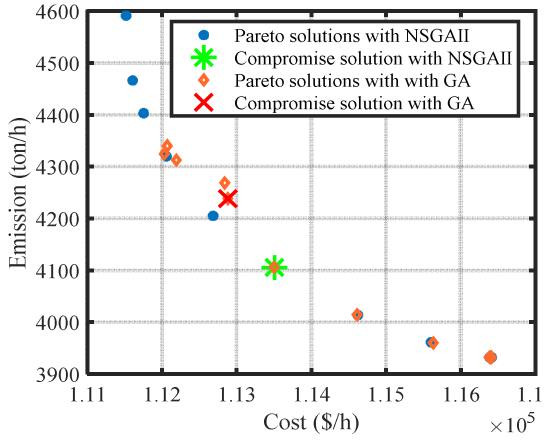

Fig. 4. Pareto front.

It is clear that fuel cost and emission functions are conflicting objectives, i.e. the more the fuel cost decreases, the more the emissions increase and vice-versa. Moreover, it can be noted that the Pareto solutions obtained using NSGAII are better distributed throughout the Pareto front compared with the classical GA. Figure 4 also discloses that the compromise solution and Pareto solutions corresponding to GA are dominated by many Pareto solutions of the NSGAII method.

TABLE V. COMPROMISE SOLUTIONS IN MW FOR CASE 1.

Units	NSGAII	GA	PSO [15]
P_1	54.9999	55	55.0000
P_2	79.9990	77.3539	80.0000
P_3	84.7558	81.2254	84.7423
P_4	83.3894	73.6333	83.4244
P_5	143.6979	115.9185	143.7728
P_6	164.3373	166.5706	164.2697
P_7	299.6464	260.2005	299.5123
P_8	315.4158	328.0858	315.4370
P_9	427.7569	458.0062	427.8233
P_{10}	429.7959	469.664	429.8128
C_T ($/h)	113505.05	112884.91	113504.92
E_T (ton/h)	4105.66	4238.54	4105.6762
P_L (MW)	83.7944	85.6583	83.7950

The compromise solutions obtained using NSGAII and the classical GA are tabulated in Table V. Note that the optimal solution of the combined EED is the compromise solution extracted from the non-dominated solutions set by deploying a fuzzy based mechanism presented in [22]. As given in Table V, the optimal total cost attained using the NSGAII is 113505.05 $/h. Nevertheless, the optimal total emissions are around 4105.66 ton/h.

B. EED Problem with the Inclusion of WP

In this subsection, a wind turbine (for parameters, see Table I) is added to the studied system. The convergence characteristics of the suggested algorithm when applied for the EED problem incorporating WP are shown in Figures 5-6. The presented results in these Figures are acquired for σ = 0.35. These results reveal that fuel cost and emissions are significantly decreased, after the integration of wind turbine, from 111497.63 $/h and 3932.24 ton/h to 107495.63 $/h and 3699.48 ton/h, respectively. This is due to the contribution of the WP source and the reduction of the total output of the thermal units.

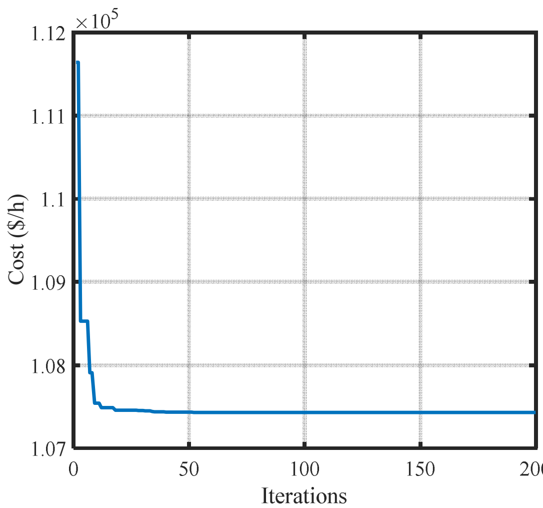

Fig. 5. Convergence characteristics of best cost using the NSGII algorithm- case 2.

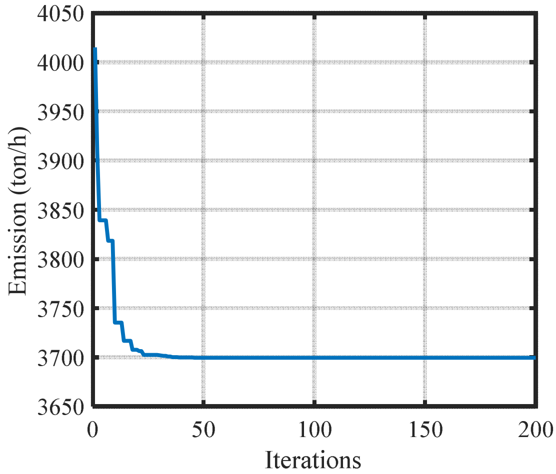

Fig. 6. Convergence characteristics of best emissions using the NSGIIalgorithm- case 2.

To study the tolerance σ effect on the appropriate solution, the EED problem with WP source is resolved for different tolerance values. The optimal compromise solutions for those values are illustrated in Table VI. According to this table, it is clear that the more the tolerance increases, the more the injected WP increases, which leads to the total fuel cost and emissions reduction.

TABLE VI. COMPROMISE SOLUTIONS FOR EED WITH WP (CASE 2).

Units	$\sigma = 0.27$	$\sigma = 0.35$	$\sigma = 0.4$
P1	55.0000	55.0000	55.0000
P2	79.9999	80.0000	78.9252
P3	82.8077	80.7472	81.3160
P4	81.3517	82.3995	80.4182
P5	138.3661	140.3117	137.8204
P6	157.8475	151.7227	155.7896
P7	299.8699	287.5884	282.0385
P8	305.6136	307.4437	300.5149
P9	420.4973	414.1958	415.3891
P10	420.6774	417.5370	414.0629
W	38.53	61.66	76.11
CT ($/h)	110874.56	109354.89	108483.45
ET (ton/h)	3969.38	3884.60	3824.94

V. CONCLUSION

Renewable energy ισ embedded in various power grids to decrease the reliance on fossil fuels and reduce the environmental impacts of conventional generating units. Unfortunately, RESs, such as wind turbine systems, are intermittent and their outputs depend on weather changes. Within this context, this study proposes a meta-heuristic technique-based method to deal with the combined EED problem incorporating a wind turbine. In this strategy, the randomness of the WP output is described by the Weibull distribution function and the deterministic power balance constraint is converted into a chance constraint. Other operating constraints such as, generation limits, ramp rate limits, and POZ constraints are considered. Due to the complexity, nonlinearity, and non-convexity of this problem, an elitist optimization method, called NSGAII, is applied to obtain the optimal solutions. The effectiveness of the recommended strategy is demonstrated using a ten-unit system. The obtained results were compared with those of other optimization techniques

The suggested strategy can be extended for the hybrid EED problem incorporating various RESs, involving wind farms and PV systems.

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