A New Particle Swarm Optimization Based Strategy for the Economic Emission Dispatch Problem Including Wind Energy Sources

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Abstract-Power dispatch has become an important issue due to the high integration of Wind Power (WP) in power grids. Within this context, this paper presents a new Particle Swarm Optimization (PSO) based strategy for solving the stochastic Economic Emission Dispatch Problem (EEDP). This problem was solved considering several constraints such as power balance, generation limits, and Valve Point Loading Effects (VPLEs). The power balance constraint is described by a chance constraint to consider the impact of WP intermittency on the EEDP solution. In this study, the chance constraint represents the tolerance that the power balance constraint cannot meet. The suggested framework was successfully evaluated on a ten-unit system. The problem was solved for various threshold tolerances to study further the impact of WP penetration.

Keywords-economic emission dispatch; wind energy; stochastic optimization; particle swarm optimization

I. INTRODUCTION

Wind energy has expanded rapidly the recent years at a global level. Wind power is becoming more and more economically competitive compared to conventional energy production methods due to improvements in turbine efficiency and rising fuel prices [1]. In addition, wind energy sources are growing at a rapid pace reaching a technical maturity that allows them to become important components of the energy industry. On the other hand, the inclusion of wind energy in power grids introduced new challenges. The high penetration of wind energy has a significant impact on system security due to its intermittent characteristics [2]. One of these challenges is the power dispatch problem. In general, the dispatch problem aims to find the optimal generation of all generators and sources minimizing energy production cost and system losses. In addition, global warming and increased initiatives to protect the environment are forcing producers to reduce the gas emissions produced by fossil fuel combustion in power stations. The fuels used in thermal power stations (coal, fuel oil, natural gas, etc.) produce harmful gases like carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NO_x) which are toxic and cause the greenhouse effect. Thus, the reduction of the emission of these gases during electricity production has become a primordial task [3].

Several studies combined the economic and environmental aspects in one problem called Economic Emission Dispatch Problem (EEDP) [4-5], considering several constraints such as generation capacity, power balance, and Valve Point Loading Effects (VPLE) [4-5]. Various methods have been suggested in the past two decades to solve this nonlinear and nonconvex problem. For instance, classical techniques such as dynamic programming [6], linear programming [7], lambda iteration [8], and interior-point [9] have been widely used for solving the dispatch problem. However, in these techniques, the fuel cost was approximated by a quadratic, and VPLE constraints were neglected. In addition, these conventional methods were iterative and required an initial solution which may affect the convergence of the employed method and produce only local solutions. Various intelligent optimization methods were presented to overcome the limitations of classical methods, like the Genetic Algorithm (GA) [10], Artificial Bee Colony (ABC) [11], Bacterial Foraging Algorithm (BFA) [12], Particle Swarm Optimization (PSO) [13], Differential Evolution (DE) [14], and Simulated Annealing (SA) [15]. In general, these meta-heuristic techniques have achieve good results in solving

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various engineering problems. However, the aforementioned techniques minimized fuel cost and emissions by seeking the optimal production of the existing thermal units. At the moment, wind energy has attracted much attention in the power sector due to its zero fuel cost and emissions. Hence, the inclusion of wind power in the EEDP formulation has gained wide attention.

In [16], a new mathematical formulation was developed based on the here-and-now approach for the stochastic EEDP integrating WP sources. The intermittency of wind power was described by the Weibull distribution function. The same approach was extended for the dynamic EEDP in [17]. Various fuzzy membership functions were suggested in [18], taking into account that system security may be affected by the randomness of wind power, to describe the dispatcher's attitude regarding WP penetration. Two objective functions, based on operational cost and risk level, were considered and minimized using a PSO-based method, but emissions were not included in the problem formulation. The risk level of WP uncertainty was considered in [19], incorporating VPLE in the cost function. Fuzzy quadratic functions that described dispatcher's attitudes were investigated in [20] to determine the quantity of additional WP to minimize generation cost without affecting system security. The effect of fluctuations of WP on the EEDP was modeled in [21] by over- and under-estimation costs of available WP, where a hybrid algorithm combining PSO and gravitational search was used to minimize the objective functions. In [22], the under- and over-estimation costs of uncertain WP were also included in the total production cost, using an improved fireworks algorithm to find the optimal generation. The randomness of WP was modeled by a chance constraint in the dispatch problem formulation to avoid the over- and under-estimation costs in [23], where WP was represented by a Weibull distribution function, and the impact of WP penetration on the total fuel cost and emissions was studied and analyzed.

In recent years, PSO-based techniques have been favored by researchers due to their low parameter number, convergence rate, and easy implementation. PSO was introduced in [24] as an efficient optimization tool for complex optimization problems. This study presents a new PSO-based strategy for solving the stochastic EEDP incorporating a wind farm. At first, the problem is formulated as a stochastic optimization problem. Then, the stochastic constraint, which describes power balance, was converted to a deterministic constraint. The Weibull distribution function was used to describe the randomness of WP. The PSO algorithm was used to solve the obtained deterministic problem. The effectiveness of the proposed method was tested on a 10-unit system, investigating the cases with and without WP sources. Moreover, the impact of WP penetration rate was studied.

II. PROBLEM FORMULATION

The EEDP is treated as a multi-objective mathematical programming problem that attempts to minimize both cost and emissions simultaneously while satisfying equality and inequality constraints. The following objectives and constraints were taken into account in the EEDP problem formulation:

A. Objective Functions

The thermal units with multi-steam admission valves that work sequentially to cover the ever-increasing generation increase the nonlinearity order of the total fuel cost due to the VPLE, as illustrated in Figure 1.

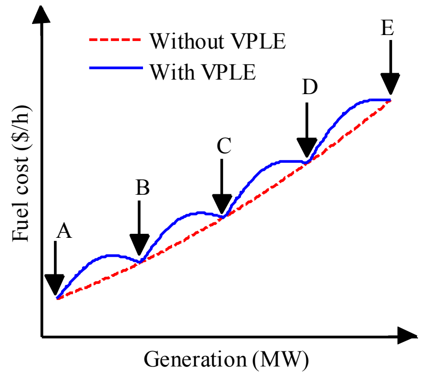

Fig. 1. Fuel cost function with five valves (A, B, C, D, E).

The fuel cost function of a thermal generator, considering the VPLE, is expressed as the sum of a quadratic and a sinusoidal function. Thus, the total fuel cost in terms of real power output can be expressed as [23]:

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

where a_i, b_i, c_i, d_i, and e_i are the cost coefficients of the i-th unit, P_i is the output power in MW, and the total cost C_T is in $/h. The second objective function considered is the atmospheric pollutants such as sulfur (SO_x) and nitrogen oxides (NO_x) caused by fossil-fueled generator units. This can be modeled as the summation of a quadratic polynomial and an exponential function [23]:

$$E_T = \sum_{i=1}^{N} \alpha_i + \beta_i P_i + \gamma_i (P_i)^2 + \eta_i \exp(\xi_i P_i) \quad (2)$$

where a_i, β_i, γ_i, η_i , and ξ_i are the emission coefficients, and the total emission is in ton/h. In several works, the bi-objective EEDPs were converted into a mono-objective optimization problem [3], and the Price Penalty Factor (PPF) based method was adopted. Thus, the combined economic-emission objective function can be described by:

$$F_T = \mu C_T + (1-\mu)\lambda E_T \quad (3)$$

where, $\mu = \text{rand}(0,1)$, F_T will be minimized for each generated value of μ to obtain the optimal solution that can be a nominee solution in the Pareto front, and λ is the average of the PPF thermal units. As shown in (4), the PPF of the i-th unit is the rate between its fuel cost and its emission for maximum generation capacity, and (5) gives the expression of λ.

$$\lambda_i = \frac{C_{i_{max}}}{E_{i_{max}}} \quad (4)$$

$$\lambda = \frac{1}{N} \sum_{i=1}^{N} \lambda i \quad (5)$$

B. Problem Constraints

The EEDP can be solved by minimizing the F_T defined in (3) for the following constraints [23]:

- Generation Capacity: Because of the unit design, the real power output of each unit i should be within its minimum P_i^{min} and maximum limit P_i^{max}:

$$P_i^{min} \leq P_i \leq P_i^{max} \quad i = 1, \dots, N \quad (6)$$

- Real power balance constraints: The total of real power generation must balance the predicted power demand P_d plus the real power losses P_L in the transmission lines, at each time interval over the scheduling horizon:

$$\sum_{i=1}^{N} P_i^t - P_D^t - P_L^t = 0 \quad t = 1, \dots, T \quad (7)$$

P_L can be calculated using a constant loss formula [4]:

$$P_L^t = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \quad (8)$$

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

- Prohibited Operating Zones (POZ) constraints: The POZ constraints are described as:

$$P_i^t \in \begin{cases} P_i^{min} \leq P_i \leq P_{i,1}^{down} \\ P_{i,k-1}^{up} \leq P_i \leq P_{i,k}^{down} & ,k = 2, \dots, z_i \\ P_{i,z_i}^{up} \leq P_i \leq P_i^{max} \end{cases} \quad (9)$$

where $P_{i,k}^{down}$ and $P_{i,k}^{up}$ are the down and up bounds of POZ number k, and z_i is the number of POZ for the i-th unit due to the vibrations in the shaft or other mechanical faults. Therefore, the machine has discontinuous input-output characteristics [4].

C. Description of WP Randomness

A major challenge in integrating wind power output into a power network is its uncertainty, fluctuation, and intermittent nature. Hence, WP output should be expressed as a stochastic variable utilizing a transformation from wind speed to power output. A simplified linear piecewise function can describe the actual relationship between them when ignoring some minor nonlinear factors. This study adopts the two-factor Weibull distribution [16]. The main advantage of this distribution type is that if its parameters are specified at a given altitude, they can be found for another one. The Probability Density Function (PDF) and the Cumulative Distribution Function (CDF) of wind speed are described by (10) and (11), respectively:

$$f_V(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^k\right] \quad (10)$$

$$F_V(v) = \int_0^v f_V(\tau)\, d\tau = 1 - exp\left(-\left(\frac{v}{c}\right)^k\right), \quad v \geq 0 \quad (11)$$

where, k and c are positive parameters called shape and scale factors for a given location, respectively. The speed-power characteristic of the wind turbine can be described by:

$$W = \phi(V) = 0, \text{ if } V < v_{in} \text{ or } V > v_{out} \quad (12)$$

$$W = \phi(V) = \frac{(V - v_{in}) w_r}{v_r - v_{in}} \text{ if } v_{in} \leq V < v_r \quad (13)$$

$$W = \phi(V) = w_r, \text{ if } v_r \leq V < v_{out} \quad (14)$$

Based on probability theories, the CDF corresponding to the WP can be described by:

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

where, $h = \frac{v_r - v_{in}}{v_{in}}$. Taking into account the intermittency characteristic of WP, the power balance constraint given by (7) can be modified as:

$$Pr\{\sum_{i=1}^{N} P_i + W \leq P_D + P_L\} \leq \sigma\} \quad (16)$$

where $P_r(x)$ is the probability of event x, W is the WP output of the wind farm, and σ is the tolerance that power balance between total generation, load, and total system losses cannot meet.

III. THE PSO ALGORITHM

PSO is considered an efficient and robust method that can be applied to nonlinear optimization problems and more particularly on electrical systems [25-26]. This algorithm ignores several conditions, such as differentiability and continuity regardless of the objective functions and the constraints to be optimized or respected. For an optimization problem with n decision variables, the i-th particle at iteration k is presented by its position $X_i^k = (X_{i1}^k, \dots, X_{in}^k)$ that is considered as a candidate solution and velocity $V_i^k = (V_{i1}^k, \dots, V_{in}^k)$. At the next generation $k+1$, the velocity and the position of this particle will be updated according to:

$$\begin{aligned} V_i^{k+1} = wV_i^k + c_1 r_1 (pbest_i^k - X_i^k) \\ + c_2 r_2 (gbest^k - X_i^k) \end{aligned} \quad (17)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (18)$$

where, w, c_1, and c_2 are the PSO parameters, r_1 and r_2 are random numbers in the range [0,1], and $pbest_i^k$ and $gbest^k$ are the best solution of the i-th particle and the overall population at the k-th iteration respectively. At each iteration k, the inertia weight w used for balancing between local and global searches can be calculated as:

$$w = w^{max} - \frac{w^{max} - w^{min}}{k^{max}} * k \quad (19)$$

where k^{max} is the maximum number of iterations, and w^{max} and w^{min} are the upper and lower bounds of w. From (19), it is clear that w^{max} is the initial value of the inertia weight while w^{min} is its final value.

IV. SIMULATION AND RESULTS

Two cases were studied to verify the effectiveness of the suggested strategy for solving the EEDP including a wind farm. Simulations were carried out on MATLAB R2009a installed on a PC with an i7-4510U@2.60GHz CPU. The studied cases were: A ten-unit system without a wind farm

(Case 1) and a ten-unit system with a wind farm (Case 2). All data of both systems were taken from [3, 23]. The wind parameters are shown in Table I.

TABLE I. WIND PARAMETERS

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

A. Case 1

Since the EEDP is a multi-objective optimization problem, a set of non-dominated solutions is required. Table II shows a list of non-dominated solutions obtained for various values of μ ranging from 0 to 1. From Table II, it can be noted that as μ increases, the total production cost decreases and the total emissions increase. The convergence characteristics of the proposed PSO-based technique for the economic (μ=*1*) and the emission (μ=*0*) dispatch problems are shown in Figure 2. The Pareto-front resulted from the PSO-based strategy is depicted in Figure 3. The best economic dispatch solution correspond to 111498.49$/h fuel cost and 4567.27ton/h total emissions, while the best emission dispatch solution corresponds to 3932.24ton/h total emissions and 116412.49 $/h total fuel cost. To further test the effectiveness of the proposed method, the simulation results obtained using the proposed PSO-based method were compared with various algorithms. From Table III, it is clear that the proposed PSO method outperforms the others in solving power dispatch problems.

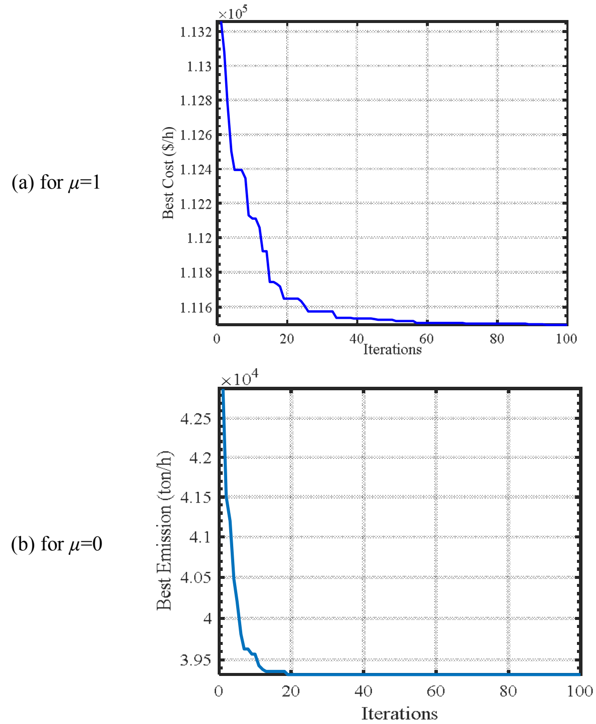

Fig. 2. Convergence characteristics of the proposed method (case 1).

TABLE II. PARETO SOLUTIONS FOR VARIOUS VALUES OF μ (CASE 1).

λ	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
P_1	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	54.9736
P_2	80.0000	80.0000	79.9999	80.0000	80.0000	80.0000	80.0000	80.0000	80.0000	79.9980	80.0000
P_3	81.1292	81.1079	81.0693	81.8332	83.0377	84.7423	86.7683	88.4989	90.57678	98.1322	106.2337
P_4	81.3701	81.1322	80.8085	81.2860	82.1286	83.4244	84.9239	85.9500	87.2575	93.1849	100.3274
P_5	160.0000	160.0000	160.0000	160.0000	160.0000	143.7728	126.1284	109.9550	96.7236	88.4957	82.5885
P_6	240.0000	240.0000	240.0000	219.5599	189.0966	164.2697	142.7271	121.8599	103.5178	92.2169	82.98739
P_7	294.4776	292.2409	289.7346	291.3277	294.5846	299.5123	300.0000	300.0000	300.0000	299.9786	299.9923
P_8	297.2982	296.9563	296.5578	300.8168	307.3015	315.4370	321.2987	327.2378	333.8038	340.0000	340.0000
P_9	396.7566	398.0034	399.4279	406.0273	415.3302	427.8233	442.3925	456.2269	469.9842	470.0000	469.9574
P_{10}	395.5627	397.2015	399.1011	406.2881	416.3488	429.8128	445.6171	461.2196	469.9878	469.9907	469.9736
C_T	116412.49	116399.01	116384.25	115599.76	114608.47	113504.92	112644.77	112023.28	111650.66	111530.31	111498.49
E_T	3932.2432	3932.3162	3932.5799	3961.3722	4014.4321	4105.6762	4210.6645	4325.7406	4434.2593	4501.6670	4567.2691
P_L	81.5947	81.6424	81.6993	82.1394	82.8283	83.7950	84.8563	85.9483	86.8517	86.9972	87.0343

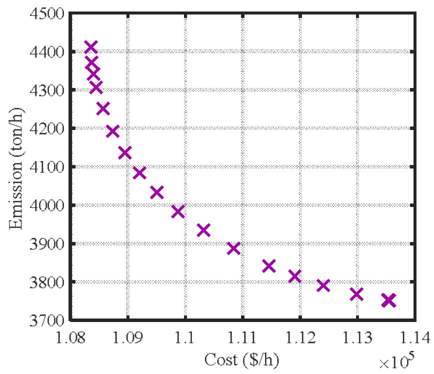

Fig. 3. Pareto-front (case 1).

TABLE III. SIMULATION RESULTS OBTAINED FOR CASE 1.

	Best cost		Best emission	
	Cost ($/h)	**Emission (ton/h)**	**Cost ($/h)**	**Emission (ton/h)**
PSO	111498.49	4567.27	116412.49	3932.24
DE	111565.71	4572.68	116418.34	3946.24
FA	111500.79	4581.00	116443.05	3932.62

B. Case 2

In this case, a wind farm with a rated power of w_r=*1.0*pu on a 100MVA base was incorporated in the ten-unit system. The problem was solved for various values of the tolerance σ to investigate the impact of the penetration level of WP on the EEDP solutions. Figure 4 shows the convergence characteristics of production cost (μ=*1*) and emissions (μ=*0*) for σ=*0.3*.

TABLE IV. PARETO SOLUTIONS FOR VARIOUS VALUES OF μ (CASE 2 – σ = 0.3).

λ	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
P_1	55.0000	55.0000	55.0000	54.9927	54.9975	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000
P_2	79.3793	79.0572	79.2443	80.0000	79.9935	80.0000	80.0000	80.0000	80.0000	80.0000	79.9671
P_3	79.2368	79.1410	79.1944	95.6866	89.4404	87.6390	86.3276	84.6486	83.0527	81.3265	80.1881
P_4	79.4393	78.8639	79.1835	87.6092	85.3617	84.0826	83.7210	82.7481	81.6908	80.3916	79.6187
P_5	160.0000	160.0000	160.0000	71.2762	80.4537	91.7389	105.7879	120.9868	138.6410	158.8935	160.0000
P_6	240.0000	240.0000	240.0000	70.2414	82.0695	97.1504	116.1033	135.7649	157.5176	180.8750	210.0817
P_7	283.2762	278.7705	281.1587	299.6879	296.3502	294.8372	296.4263	2.9430731	290.9290	285.5700	282.3278
P_8	285.6298	285.0466	285.3679	337.1601	327.7143	319.2092	316.2059	314.8193	306.9338	297.6583	291.2683
P_9	384.6910	387.3684	385.9387	470.0000	469.9934	459.1521	444.9970	431.0097	418.3983	405.4202	396.0864
P_{10}	383.5466	387.0554	385.1589	469.9973	469.9908	466.8807	450.0184	434.2659	420.3902	406.4300	396.3520
C_T	113553.68	113527.38	113541.18	108361.08	108398.65	108566.61	108947.91	109504.42	110317.96	111457.33	112401.88
E_T	3752.5080	3752.8219	3752.5756	4411.1741	4341.4299	4251.0979	4136.8332	4033.7302	3934.7089	3841.9554	3791.0480
P_L	77.4441	77.5478	77.4915	83.8963	83.6103	82.9351	81.8324	80.7956	79.7983	78.8100	78.1351

(a) μ=1

(b) μ=0

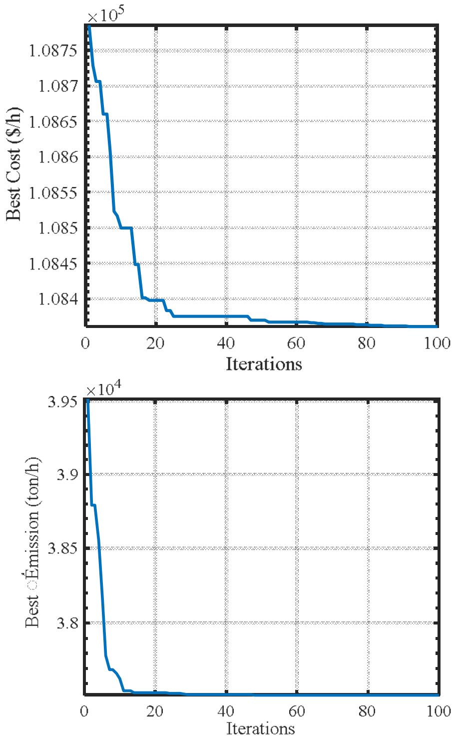

Fig. 4. Convergence characteristics for case 2 (σ=0.3).

The Pareto solutions for various values of the weight factor, ranging from 0 to 1, are presented in Table IV. Meanwhile, the Pareto-front for this case is shown in Figure 5. Figure 6 illustrates the impact of the variation of the tolerance on the minimum fuel cost and the total emission functions. From this Figure, it is obvious that the more the tolerance that power balance constraint cannot meet is, the less the cost and emissions are because the more the tolerance is, the more the WP penetration is.

V. CONCLUSION

This study presented a PSO-based strategy for solving the multi-objective EEDP incorporating wind energy sources. The power balance constraint was converted into a chance constraint and the intermittency of WP was described by the Weibull distribution to consider the stochastic characteristic of WP. This chance constraint represents the probability that the power balance constraint cannot meet.

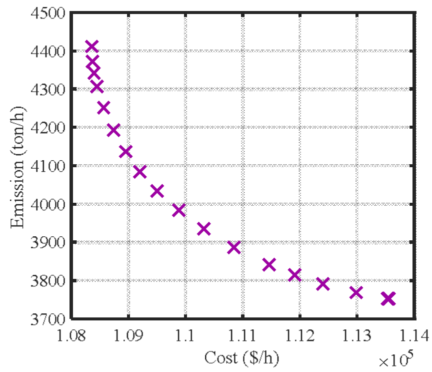

Fig. 5. Pareto-front for case 2 (σ=0.3).

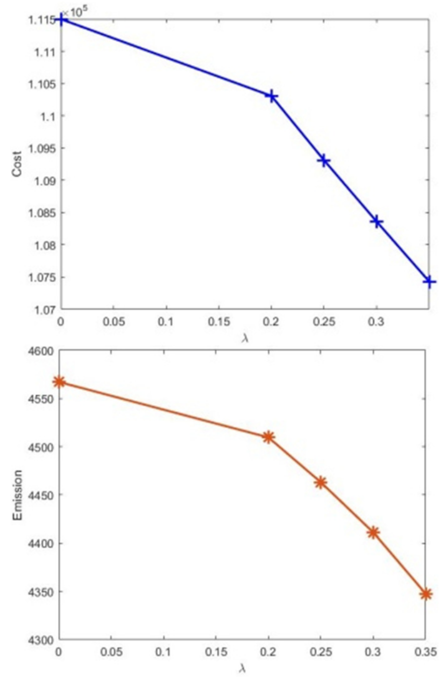

Fig. 6. Impact of the tolerance on the EEDP solutions (case 2).

The EEDP was solved using a PSO-based method depending on several operating constraints such as generators, limits, valve point loading effects, and real power losses. Simulation results, performed on a 69-bus ten-unit system, showed that the level of available wind power (WP) was highly dependent on the threshold tolerance. The results also showed the effectiveness of the proposed optimization method for solving the non-convex EEDP.

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