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 in 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 (VPLEs). 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 metaheuristic techniques have achieve good results in solving...
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:

\[ C_T = \sum_{i=1}^{N} \alpha_i + b_i P_i + c_i P_i^2 + d_i \sin\left(\epsilon_i \left( P_{i}^{\min} - P_i \right) \right) \] (1)

\[ E_T = \sum_{i=1}^{N} \frac{a_i}{\beta_i} + \frac{\gamma_i}{\eta_i} \left( P_i \right)^2 + \xi_i \exp\left( \zeta_i P_i \right) \] (2)

where, \(a_i, b_i, c_i, d_i, \) and \(\epsilon_i\) 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\(_2\)) 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]:

\[ F_T = \mu C_T + (1 - \mu)\lambda E_T \] (3)

where, \(\mu = \text{rand}(0,1)\), \(F_T\) will be minimized for each generated value of \(\mu\) to obtain the optimal solution that can be a nominee solution in the Pareto front, and \(\lambda\) 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 \(\lambda_i\).

\[ \lambda_i = \frac{C_{i\text{max}}}{E_{i\text{max}}} \] (4)

\[ \lambda = \frac{1}{N} \sum_{i=1}^{N} \lambda_i \] (5)

B. Problem Constraints

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

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.

![Fuel cost function with five valves (A, B, C, D, E).](image)

Fig. 1. Fuel cost function with five valves (A, B, C, D, E).
• Generation Capacity: Because of the unit design, the real power output of each unit \( i \) should be within its minimum \( P_{i, \text{min}} \) and maximum limit \( P_{i, \text{max}} \):

\[
P_{i, \text{min}} \leq P_i \leq P_{i, \text{max}} \quad i = 1, ..., N \quad (6)
\]

• Real power balance constraints: The total of real power must balance the predicted power demand \( P_L \) plus the real power losses \( P_L \) in the transmission lines, at each time interval over the scheduling horizon:

\[
\Sigma_{i=1}^{N} P_i^t - P_i^t - P_L^t = 0 \quad t = 1, ..., T \quad (7)
\]

where \( P_L^t \) can be calculated using a constant loss formula [4]:

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

where \( B_{oo} \) is the real power losses also called \( B \)-coefficients.

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

\[
P_i^t \in \left\{ \begin{array}{ll}
P_{i, \text{min}} \leq P_i \leq P_{i, \text{down}} & \\
P_{i, \text{up}} \leq P_i \leq P_{i, \text{down}} & k = 2, ..., z_i \end{array} \right. \quad (9)
\]

where \( P_{i, \text{down}} \) and \( P_{i, \text{up}} \) 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, the wind 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:

\[
f_v(v) = \frac{k}{\lambda} (\frac{v}{\lambda})^{k-1} \exp \left( -\left(\frac{v}{\lambda}\right)^k \right) \quad (10)
\]

\[
F_v(v) = \int_0^v f_v(t) dt = 1 - \exp \left( -\left(\frac{v}{\lambda}\right)^k \right), \quad v \geq 0 \quad (11)
\]

where, \( k \) and \( \lambda \) 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:

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

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

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

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

\[
F_W(w) = Pr(W \leq w) = 1 - \exp \left( -\left(\frac{v_{in}}{w} \right)^k \right) \quad (15)
\]

\[
+ \exp \left( -\left(\frac{v_{out}}{w} \right)^k \right), \quad 0 \leq w < w_r.
\]

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

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

where, \( P_i(x) \) is the probability of event \( x \), \( W \) is the WP output of the wind farm, and \( \sigma \) 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 \( X_i^k = (X_{i1}^k, ..., X_{in}^k) \) that is considered as a candidate solution and velocity \( V_i^k = (V_{i1}^k, ..., V_{in}^k) \). At the next generation \( k+1 \), the velocity and the position of this particle will be updated according to:

\[
V_{ik}^{k+1} = wV_{ik}^k + c_1r_1(p_{best}^k - X_i^k) + c_2r_2(g_{best}^k - X_i^k) \quad (17)
\]

\[
X_{ik}^{k+1} = X_{ik}^k + V_{ik}^{k+1} \quad (18)
\]

where, \( w, c_1, \) and \( c_2 \) are the PSO parameters, \( r_1, r_2 \) are random numbers in the range \([0, 1]\), and \( p_{best}^k \) and \( g_{best}^k \) 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:

\[
w = w_{max} - \frac{w_{max} - w_{min}}{k_{max}} \ast k \quad (19)
\]

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...
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 $\mu$ ranging from 0 to 1. From Table II, it can be noted that as $\mu$ increases, the total production cost decreases and the total emissions increase. The convergence characteristics of the proposed PSO-based technique for the economic ($\mu=1$) and the emission ($\mu=0$) 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.

B. Case 2

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

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**Table I. Wind Parameters**

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**Table II. Pareto Solutions for Various Values of $\mu$ (Case 1).**

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**Table III. Simulation Results Obtained for Case 1.**

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

Fig. 3. Pareto-front (case 1).
T able IV. Pareto solutions for various values of $\mu$ (Case 2–$\sigma = 0.3$).

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<td>80.1881</td>
<td>79.6187</td>
<td>218.6410</td>
<td>198.6410</td>
<td>230.8750</td>
<td>291.2683</td>
<td>396.0864</td>
<td>396.3520</td>
</tr>
</tbody>
</table>

WP. This chance constraint represents the probability that the power balance constraint cannot meet.

Fig. 4. Convergence characteristics for case 2 ($\sigma = 0.3$).

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 ($\sigma = 0.3$).

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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