OPTIMAL COST OF POWER SYSTEM INCORPORATING WIND ENERGY USING HERE-AND-NOW APPROACH

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ABSTRACT

In this paper, a new approach for the economic environmental dispatch (EED) problem with both wind turbines and thermal generators is presented. The here-and-now (HN) strategy is used in the problem formulation by incorporating the stochastic characteristic of the wind power (WP) in the system constraints. Weibull probability distribution function (PDF) is employed to describe the WP. An elitist optimization approach based on particle swarm optimization and the non-dominated sorting concept is applied to solve the stochastic and non-smooth EED problem. The suggested framework is successfully evaluated on the 69-bus ten-unit system.

Keywords: economic environmental dispatch, wind power, weibull distribution, her-and-now (HN) strategy.

INTRODUCTION

In electrical power system, the need to reduce the environmental emission and to minimize the total fuel cost of the generation, require a review of energy strategies. Renewable energies and especially wind power (WP) technology has attracted much attention as a promising renewable energy resource.

In electrical networks, generally the integration of wind energy sources (WES) is accompanied by several difficulties. The stochastic availability of wind energy is the first factor in this problem of difficulties. That’s it there, to solve such problems scientific research and technological developments appeal to the load distribution problem as best solution to this problem.

In the literature, several approaches have been proposed to describe the impact of the wind power (WP) output of the WES on power systems [1-2]. An economic dispatch (ED) model incorporating WP is proposed in [1-8]. Where, the stochastic wind speed characteristics were described based on the Weibull probability distribution function (PDF) and included in the total cost function. Reference [7] presents the ED problem for thermal units combined and the wind farm with the integration of PDF Weibull in the total production cost.

The same distribution function was used in [1] for solving the ED. The here-and-now (HN) strategy was used to model the problem by incorporating the probabilistic characteristics in the problem constraints. This stochastic characteristic is described by the tolerance that power balance constraint cannot be satisfied. Due to the increase of the environmental requirements, several works have combined the emission and the economic dispatch problems in one problem called economic emission dispatch (EED) problem [8-11]. In the most research works, EED problem has been formulated as a multi-objective optimization problem (MOP).

Within this context that takes place this study. Where a new approach based on the HN strategy is used for modeling the EED problem including WES. Two objective functions that are total production cost and emission have been minimized simultaneously subject to several operating constraints such as generation limits, valve point loading effects (VPLE) and real power balance constraints. In addition, power losses calculated using the B-loss formula has been considered in the problem formulation.

To overcome drawbacks of conventional methods such as Newton methods, lambda iteration and linear programming, numerous intelligent optimization techniques, such as genetic algorithms (GA), particle swarm optimization (PSO), bacterial foraging, artificial bee colony (ABC) and simulated annealing have been proposed recently for solving the EED problem whether with or without WP [12-15].

In recent years, PSO algorithms have attracted much attention for solving several problems related to power systems [16-17]. This heuristic technique was introduced by Kennedy and Eberhart [18]. It emulates the social behavior of organisms such as flocking of birds and schooling of fish. However, conventional PSO was criticized for its premature convergence while the problem has multiple minima and with nonconvex objective functions. Thus, several works have suggested modifications in the classic PSO algorithm. Reference [17] presents a review of PSO application in power dispatch problems. Unfortunately, these modified PSO approaches have been tested only for single objective problems. Therefore, if it is a MOP, all objectives are weighted as per the importance and added together to form a single objective function. Thus, there is a loss of diversity in Pareto optimal solutions.

To overcome these problems, this study presents a PSO-based technique called non-dominated sorting PSO (NSPSO) algorithm for solving the non convex EED problem. This technique incorporates the non-dominated sorting mechanism used in the NSGAI approach [19], into the original PSO algorithm. A fuzzy set theory [20] is used to extract the best compromise solution, from the
Pareto-optimal solutions, for the decision makers. The proposed approach was tested on the tree-unit and the ten-unit systems. Total production cost in $/h and total emission in ton/h have been minimized simultaneously subject to several operating conditions such as, generation limits, VPLE and real power balance constraints. In addition, power losses calculated using the B-loss formula has been considered in the problem formulation.

The main contributions of this work are summarized as follows:

- An existing HN-based strategy used for modeling the ED [1] was extended for the EED with WES;
- A new elitist PSO-based optimization technique was proposed for solving the non convex probabilistic EED problem.

The rest of this paper is organized as follows. Section 2 provides the basic formulation of the probabilistic EED problem. WP characteristics described by Weibull distribution is presented in section 3. The proposed optimization algorithm is detailed in section 4. Simulation results and discussion are conducted in section 5. Finally, conclusion and future work are included in section 6.

**PROBLEM FORMULATION**

The EED problem is a MOP that aims to provide the optimum generation of thermal units for minimum production cost and minimum emission of harmful gases such as CO, CO2, NOx.

In practical cases, valve-point loading effects (VPLE) should be considered in the EED problem. Thus, a sinusoidal form will be added to the quadratic cost function and the problem will be with higher order nonlinearity. Thus, total fuel cost and total emission constraints describe the stochastic characteristic of the wind speed. The wind is never stable at any point. It is influenced by several factors depending on the geographical location. To evaluate its variations over a period, a probability distribution function can be used. Moreover, power balance constraint was replaced by the following equation.

\[
\sum_{i=1}^{N} P_i + W - P_D - P_L = 0
\]

Finally, the EED problem taking into account of generation limits of all thermal units and WES can be described as given in equation (5).

\[
\begin{align*}
\text{minimize } & (C_T, E_T) \\
\text{s.t. } & \quad P_i^{\min} \leq P_i \leq P_i^{\max}, \quad i = 1, 2, \ldots, N \\
& \quad 0 \leq W \leq w_r \\
& \quad \Pr \left( \sum_{i=1}^{N} P_i + W \leq P_D + P_L \right) \leq P_a \\
& \quad \sum_{i=1}^{N} P_i + W - P_D - P_L = 0
\end{align*}
\]

Where, \( P_i^{\min} \) and \( P_i^{\max} \) are lower and upper limits of the generated power of the \( i \)-th unit. \( w_r \) is the is the rated power of the WES.

**WIND POWER CHARACTERISTICS**

Wind speed is the most critical data needed to evaluate the potential power of a wind site because of the power-speed relationship. The wind is never stable at any point. It is influenced by several factors depending on the geographical location. To evaluate its variations over a period, a probability distribution function can be used. The variation of the wind speed \( V \) (m/s) that is a random variable can be described by the Weibull probability distribution function. The Weibull distribution with two parameters is the most used. The probability that the wind speed will be \( v \) and the corresponding cumulative distribution function (CDF) are described by respectively equations (6) and (7).
\[ f_v(v) = \frac{k}{c} \left( \frac{v}{c} \right)^{k-1} \exp \left[ -\left( \frac{v}{c} \right)^k \right] \]  \hspace{1cm} (6)

\[ F_v(v) = \int_0^v f_v(\tau) d\tau = 1 - \exp \left( -\left( \frac{v}{c} \right)^k \right), \quad v \geq 0 \]  \hspace{1cm} (7)

Where, \( k \) and \( c \) are positive parameters called shape factor and scale factor for a given location, respectively.

Figure-1 shows the Weibull PDF as a function of wind speed and scale factor for \( k \) factors of 1 and 2. It is clear that the shape of the curve is influenced by the value of parameter \( k \).

Moreover, Figure-2 shows the variation of Weibull PDF as a function of wind speed and shape factor for \( c \) factors of 10 and 20. It is noteworthy that if \( c \) increases, the curves move toward higher wind speed.

To characterize the relationship between WP and wind speed, the following simplified model cited in references[1-3] can be used.

\[
W = \begin{cases} 
0, & \text{if } V < v_{in} \text{ or } V > v_{out} \\
\frac{(V - v_{in})w_r}{v_r - v_{in}}, & \text{if } v_{in} \leq V < v_r \\
w_r, & \text{if } v_r \leq V < v_{out}
\end{cases}
\]  \hspace{1cm} (8)

**Figure-1.** Three-dimensional Weibull PDF vs. wind speed and scale factor (1 mph = 0.446 m/s).

**Figure-2.** Three-dimensional Weibull PDF vs. wind speed and shape factor.
where, \( w_r \) is the rated power of the WPG, \( v_r \), \( v_{in} \) and \( v_{out} \) are rated, cut-out and cut-in wind speeds respectively.

Based on probability theories, the combined discrete/continuous characteristic of the WP can be described by its CDF given in the following equation [1].

\[
F_{W}(w) = \begin{cases} 
0, & (w < 0) \\
1 - \exp \left( \left( \frac{\ln \left( \frac{v_r}{w} \right)}{c} \right)^{m} \right), & 0 \leq w < v_r \\
1, & (w \geq v_r) 
\end{cases}
\]

Where,

\[
h = \frac{v_r}{v_{in}} - 1
\]

Using equation (9), inequality (3) can be rewritten as below.

\[
F_W \left( P_D + P_L - \sum_{i=1}^{N} P_i \right) \leq P_a
\]

For feasibility of the problem, tolerance \( P_a \) should verify the following inequality [1].

\[
Pr(W = 0) \leq P_a < 1
\]

For example if \( c = 15, v_{in} = 5, v_{out} = 45 \) and \( k = 1.7 \cdot P_a \in [0.1447, 1] \)

**PROPOSED NSPSO-LS**

PSO algorithm firstly proposed by in [18], emulates the social behavior of organisms. Each swarm represents a population. For an optimization problem with \( n \) decision variables, the \( i \)-th particle at iteration \( k \) is presented by its position \( X_i^k = (X_i^k, \ldots, X_{n_i}^k) \) that is considered as a candidate solution and velocity \( V_i^k = (V_i^k, \ldots, V_{n_i}^k) \). At the next generation \((k+1)\), velocity and position of this particle will be updated according to equations (13) and (14).

\[
V_i^{k+1} = wV_i^k + c_1P_1 (pbest_i^k - X_i^k) + c_2P_2 (gbest^k - X_i^k)
\]

\[
X_i^{k+1} = X_i^k + V_i^{k+1}
\]

Where, \( w \), \( c_1 \) and \( c_2 \) are the PSO parameters. \( \eta_1 \) and \( \eta_2 \) 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.

Unfortunately, PSO was proposed initially for single objective problem. Thus, several multi-objective PSO (MOPSO) algorithms have been proposed in recent years [13, 21].

Within this context, an improved version of PSO algorithm with local search is illustrated in the rest of this section. This multi-objective optimization technique symbolized by NSPSO-LS is based on the non-dominated sorting concept proposed in [19].
Set generation counter \( k = 0 \)

- Initialize population \( P^k \) of size \( N \) with random position \( X_{ij}^k \) and velocity \( V_{ij}^k \) vectors within their limits for each particle \( i \).
- Set \( gbest^k = X_{best}^k \)

Execute non-dominated sorting and crowding distance ranking of the entire population

Select randomly the global best position \( gbest^k \) from the 5% of the top crowded solutions of front 1

Update particle position and velocity according to equations (13) and (14)

Set \( R = P^k \cup F^{k+1} \)

Sort \( R \) according to non-domination levels

Fill \( P^{k+1} \) with the first \( N \) individuals of \( F_j \) according to their levels and crowding distances.

Generate the non-dominated set \( REP \) of the new population \( p^{k+1} \)

Apply local search procedure to \( P^{k+1} \) and \( REP \)

Termination criterion is satisfied

Stop

- \( k = k + 1 \)

**Figure-4.** Flowchart of the proposed algorithm.

At each iteration \( k \), this elitist approach combines population \( P^k \) with \( N \) particles and the offspring population \( Q^k \) having the same number \( N \) of particles.

The combined population \( R^k = P^k \cup Q^k \) of size \( 2N \) will be sorted into different non-domination levels \( F_j \). Therefore, we can write:

\[
R^k = \bigcup_{j=1}^{r} F_j \quad (15)
\]

Where, \( r \) is the number of fronts.

The flowchart of the local search algorithm applied for an iteration \( k \) is shown in Fig. 3. However, the basic steps of the proposed NSPSO-LS are illustrated in Figure-4.

**RESULTS AND DISCUSSIONS**

The effectiveness of the proposed strategy has been tested on the ten-unit system. Generators’ data taken from [22] are given in Table-1. A wind farm has been incorporated in the system with rated power of \( w_r = 1.0 \text{ pu} \) with a base of 100 MVA. Wind parameters are listed in Table-2. The B-loss matrix of the system is given below. The proposed optimization technique NSPSO-LSO has been compared with the NSGAII. For more detail on the NSGAII, see [19]. The EED problem has been solved for the two cases without and with WES.

The total demand power was fixed on \( P_{D} = 2000 \text{ MW} \) for the two cases. Simulation results were performed on MATLAB R2009a installed on a PC with i7-4510U CPU @ 2.60 GHz, 64 bit. NSPSO-LS parameters were chosen to be as given below:

\[
R = 10^{-11}
\]

Table-1. Wind parameters.

<table>
<thead>
<tr>
<th>( k )</th>
<th>( c )</th>
<th>( v_{in} )</th>
<th>( v_{out} )</th>
<th>( v_r )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.7</td>
<td>15</td>
<td>5</td>
<td>45</td>
<td>15</td>
</tr>
</tbody>
</table>

**Case 1: Without WES**

To demonstrate the effectiveness of the proposed optimization algorithm, the EED problem is solved without WES subject to all generator limits. Obtained results were compared with those obtained using NSGAII. For fair comparisons, the initial population is randomly generated for the two methods with the same population size \( N = 400 \) and maximum number of iterations \( I_{max} = 200 \). Convergence characteristics obtained using these two algorithms are compared in figure 5 and figure 6 . It is clear that NSPSO-LS provides the minimum fuel cost and emission that are respectively, 111510.91 $/h and 3935.80 ton/h with NSPSO-LS and are111721.40 $/h and 3968.81 ton/h for NSGAII. Since EED problem is a MOP, it is interesting to provide a set of non-dominated solutions called Pareto solutions for the decision making. Figure-7 depicts a list of Pareto solutions obtained at the last iteration of the NSPSO-LS algorithm. It can be clearly seen that when total cost in $/h is minimized, the total emission is at its maximum value and vice versa.
Case 2: With WES

In this subsection, the WES is incorporated in the test system. Thus, the Weibull PDF of the WP described in (3) was included in EED problem and the real power balance constraint of the conventional problem was modified as given in (4). The Pareto solutions as well as the compromise solution obtained using NSPSO-LS algorithm for two different tolerances $P_\alpha = 0.2$ and $P_\alpha = 0.25$, are depicted in Figure-8.
Table-2. Comparison of results for the EED without WES.

<table>
<thead>
<tr>
<th></th>
<th>Best cost</th>
<th></th>
<th></th>
<th>Compromise solution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NSPSO-LS</td>
<td>NSGAII</td>
<td>NSPSO-LS</td>
<td>NSGAII</td>
</tr>
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<td>$P_1$</td>
<td>54.8895</td>
<td>54.2210</td>
<td>54.9758</td>
<td>52.2571</td>
</tr>
<tr>
<td>$P_2$</td>
<td>79.8484</td>
<td>80.0000</td>
<td>79.0703</td>
<td>68.4707</td>
</tr>
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<td>$P_3$</td>
<td>105.4088</td>
<td>83.9099</td>
<td>83.0234</td>
<td>81.1908</td>
</tr>
<tr>
<td>$P_4$</td>
<td>101.4115</td>
<td>130.0000</td>
<td>83.9107</td>
<td>90.3707</td>
</tr>
<tr>
<td>$P_5$</td>
<td>86.3021</td>
<td>82.6766</td>
<td>160.0000</td>
<td>160.0000</td>
</tr>
<tr>
<td>$P_6$</td>
<td>80.7400</td>
<td>89.5583</td>
<td>238.2799</td>
<td>240.0000</td>
</tr>
<tr>
<td>$P_7$</td>
<td>299.6468</td>
<td>300.0000</td>
<td>290.4281</td>
<td>300.0000</td>
</tr>
<tr>
<td>$P_8$</td>
<td>339.5175</td>
<td>326.2673</td>
<td>296.8293</td>
<td>261.2193</td>
</tr>
<tr>
<td>$P_9$</td>
<td>469.9862</td>
<td>470.0000</td>
<td>391.9239</td>
<td>429.5232</td>
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<tr>
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<td>403.1708</td>
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</tr>
<tr>
<td>Cost</td>
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<td>116447.81</td>
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<tr>
<td>Emission</td>
<td>4562.54</td>
<td>4608.77</td>
<td>3935.80</td>
<td>3968.81</td>
</tr>
<tr>
<td>Losses</td>
<td>86.9948</td>
<td>86.6331</td>
<td>81.6122</td>
<td>81.9995</td>
</tr>
</tbody>
</table>

To show the effect of the threshold tolerance on the optimum solutions, the problem has been solved for various values of $P_a$. best solutions for minimum cost, minimum emission and best compromise solution are shown in Tables 3-5, respectively. It is evident that optimum cost and emission decrease as the tolerance increases. Since, more WP will be used for higher tolerance and vice versa. Moreover, it is clear that the WES cannot contribute in the system for $P_a$ lower than 0.14 which confirms equation (12). For that condition the WP is nil and optimum generation of thermal plants are same as provided for the EED without WES.

Table-3. Cost minimization.

<table>
<thead>
<tr>
<th>$P_a$</th>
<th>0.14</th>
<th>0.15</th>
<th>0.2</th>
<th>0.25</th>
<th>0.3</th>
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<td>54.4231</td>
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</tr>
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</tr>
<tr>
<td>$P_4$</td>
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<tr>
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<td>75.2036</td>
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</tr>
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<td>$P_6$</td>
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<td>WP</td>
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<tr>
<td>Cost</td>
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<td>116330.76</td>
<td>116447.81</td>
<td>112956.10</td>
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<tr>
<td>Emission</td>
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<td>4608.77</td>
<td>3935.80</td>
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<td>4168.39</td>
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<tr>
<td>Losses</td>
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Table-4. Emission minimization.

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<th>$P_a$</th>
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Table-5. Compromise solution.

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<th>0.3</th>
</tr>
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CONCLUSIONS

This paper expands the conventional multi-objective EED problem by incorporating wind energy sources in power network. The well-known here-and-mow strategy is used for modeling this probabilistic EED problem. Where, the stochastic wind speed characteristics described based on the Weibull distribution is included in the problem constraints. Then, an elitist multi-objective optimization algorithm is proposed for solving the problem subject to several operating constraints such as, generators’ limits, valve point loading effects and real power losses. Simulation results, performed on the 69-bus ten-unit system, showed that the level of available wind power (WP) is highly dependent on the threshold tolerance that the power balance constraint cannot be verified. Results also showed the effectiveness of the proposed NSPSO-LS for solving non convex problems with any number of conflicting objectives, since they are optimized independently. For future work, other objective functions corresponding to overestimation and underestimation of the available WP can be added to the problem; extend the problem formulation for the case with multiple renewable energy sources.
REFERENCES


