An Improved Particle Swarm Optimization Technique for Combined Economic and Environmental Power Dispatch Including Valve Point Loading Effects

Badr M. Alshammari, T. Guesmi

Abstract—In recent years, the combined economic and emission power dispatch is one of the main problems of electrical power system. It aims to schedule the power generation of generators in order to minimize cost production and emission of harmful gases caused by fossil-fueled thermal units such as CO, CO₂, NOₓ, and SO₂. To solve this complicated multi-objective problem, an improved version of the particle swarm optimization technique that includes non-dominated sorting concept has been proposed. Valve point loading effects and system losses have been considered. The three-unit and ten-unit benchmark systems have been used to show the effectiveness of the suggested optimization technique for solving this kind of nonconvex problem. The simulation results have been compared with those obtained using genetic algorithm based method. Comparison results show that the proposed approach can provide a higher quality solution with better performance.

Keywords—Power dispatch, valve point loading effects, multiobjective optimization, Pareto solutions.

I. INTRODUCTION

The economic environmental dispatch (EED) problem has received in the two past decades much attention. It aims to provide the optimum generation schedule for minimum production cost and minimum emission of harmful gases caused by fossil-fueled thermal units [1]-[3]. Within this context, several research works have been proposed to solve this problem. Various studies have considered the traditional EED problem where the production cost function of each thermal unit is approximated by a quadratic function [4]-[6]. Unfortunately, practical EED problem incorporates the valve-point loading effects (VPLE) in the production cost. These additional constraints make the problem with high nonlinear functions. Thus, traditional optimization techniques, such as Newton methods [5], lambda iteration, and linear programming [6] cannot provide the best solution. In recent years, numerous intelligent optimization techniques, such as genetic algorithms (GA), particle swarm optimization (PSO), bacterial foraging, artificial bee colony (ABC), and simulated annealing have been used to solve this non-convex EED problem [7], [8].

In recent years, PSO algorithms have attracted much attention for solving EED problem [9], [10]. This heuristic technique was introduced by Kennedy and Eberhart [11]. 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 [10] presents a review of PSO application in economic dispatch problems. Unfortunately, these modified PSO approaches have been tested only for single objective problems. Therefore, if it is a multi-objective optimization problem (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 nonconvex EED problem. This technique incorporates the non-dominated sorting mechanism used in the NSGAII approach [12], into the original PSO algorithm.

A fuzzy set theory [2] 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 have been considered in the problem formulation.

Simulation results show that this new algorithm proved a very competitive performance in finding much better spread of solutions and better convergence near the true Pareto-optimal solutions compared to the NSGAII method.

II. PROBLEM FORMULATION

The EED problem is formulated as MOP. Two objective functions are considered in this study to simultaneously minimize the total fuel cost and total emission of the thermal units under several operating conditions.

A. Objective Functions

Considering a power system with N generators, its total fuel cost function $C_T$ in ($$/h$) with VPLE and emission in (ton/h) is respectively given by the following equations [13].

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

Badr M. Alshammari and T. Guesmi are with the Electrical Engineering Department, College of Engineering, University of Hail, Saudi Arabia (e-mail: badr_ms@hotmail.com, t.guesmi@uoh.edu.sa).
where $a_i$, $b_i$, $c_i$, $d_i$, and $e_i$ are the cost coefficients of the $i^{th}$ unit, while $\alpha_i$, $\beta_i$, $\gamma_i$, $\eta_i$ and $\Delta_i$ are the emission coefficients of the $i^{th}$ unit. $P_i$ is the generation of the $i^{th}$ unit.

**B. Problem Constraints**

Total cost and emission functions will be minimized subject to the following constraints.

- **Generation limits**
  
  \[ P_{i, \text{min}} \leq P_i \leq P_{i, \text{max}}, \ i = 1, \ldots, N \]  

  (3)

  where $P_{i, \text{min}}$ and $P_{i, \text{max}}$ are the lower and upper power generation limits of the $i^{th}$ unit.

- **Power balance constraints**
  
  For a given total demand power $P_D$, the generation schedule should verify the following equality.

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

  (4)

  where $PL$ is the total losses in MW.

  The total transmission losses can be calculated using the following equation [13].

  \[ P_L = \sum_{j=1}^{N} P_j B_{ij} + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \]  

  (5)

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

**III. PROPOSED ALGORITHM**

PSO is firstly presented by Kennedy and Eberhart. It emulates the social behavior of organisms such as flocking of birds and schooling of fish.

In a physical-dimensional search space with the dimension $n$, the $i^{th}$ particle at iteration $k$ is presented by its position $X_i^k = (X_{i,1}^k, \ldots, X_{i,n}^k)$ and velocity $V_i^k = (V_{i,1}^k, \ldots, V_{i,n}^k)$. The updated velocity and position of this particle at the next generation $(k+1)$ can be governed, respectively, by the following equations

\[ V_{i, \text{new}}^{k+1} = w V_i^k + c_1 \eta (p_{\text{best}} - X_i^k) + c_2 \phi (g_{\text{best}} - X_i^k) \]  

(6)

\[ X_i^{k+1} = X_i^k + V_{i, \text{new}}^{k+1} \]  

(7)

where $w$ is the inertia weight factor, $c_1$ and $c_2$ are the acceleration constants. The coefficients $w$, $c_1$, and $c_2$ can be determined according to [11]. $r_1$ and $r_2$ are two random numbers between 0 and 1. $p_{\text{best}}^k$ and $g_{\text{best}}^k$ are the best position of the $i^{th}$ particle achieved based on its own experience and the best position among all the particles in the swarm at the $k^{th}$ iteration, respectively.

Several research works have been proposed to adopt the PSO algorithm for MOP, such as in [14].

In this study, a PSO-based MOP algorithm symbolized by NSPSO is presented for solving the EED problem. The proposed NSPSO algorithm is based on the non-dominated sorting concept presented by [12].

The non-dominated sorting concept, has been developed in this paper and used for solving the EED problem. At each iteration $k$, this elitist approach extends the basic form of PSO by combining the $p_{\text{best}}$ of $N$ particles $P^k$ and the $N$ particles offspring $Q^k$. The combined population $R^k = P^k \cup Q^k$ of size $2N$ will be sorted into different non-domination levels $F_j$ [13]. Therefore, we can write.

\[ R^k = \bigcup_{j=1}^{r} F_j \]  

(8)

where $r$ is the number of fronts.

Once the non-dominated sorting is completed, a crowding distance, as given in [13], is assigned to each solution of the combined population $R^k$ to provide an estimate of the density of solutions surrounding that solution in the same front $F_j$.

Thus, every solution in $R^k$ has two indices, non-domination level and crowding distance. Then, particles of the next population $P^{k+1}$ will be the first $N$ individuals of the subsequent non-dominated fronts in the order of their levels, i.e. members of $F_1$ have priority to will be in $P^{k+1}$ followed by members from $F_2$, and so on until the number of these individuals is greater than or equal to $N$. Let us consider that $F_j$ is the last non-dominated set. Then, individuals of $F_j$ will be selected to fill $P^{k+1}$ according to their crowding distance in the descending order. The global best position is selected randomly from the 5% of the top crowded solutions of $F_1$.

**IV. SIMULATION RESULTS**

Two test systems with different complexities have been used to demonstrate the effectiveness of the proposed NSPSO technique. The compromise solutions were extracted from the Pareto front using the fuzzy based membership function value assignment method [2].

**A. Case 1: Three-Unit System**

In this case, the three-unit system is used to prove the feasibility of the proposed technique. The unit data taken from [15] are shown in Table I. The B-loss matrix is given below.
The Pareto set and the compromise solution obtained using the NSPSO algorithm for three load levels are given in Fig. 1. Optimum solutions are illustrated in Table II. It is clear that total cost and emission are monotonically increasing functions with respect to the total demand power.

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**Fig. 1 Pareto front for the three-unit system:** (a) for \( P_D = 300 \) MW (b) for \( P_D = 350 \) MW (c) for \( P_D = 400 \) MW

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**Table I**

<table>
<thead>
<tr>
<th>Unit</th>
<th>( P_{\text{min}} )</th>
<th>( P_{\text{max}} )</th>
<th>( a )</th>
<th>( B )</th>
<th>( C )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>250</td>
<td>328.13</td>
<td>8.663</td>
<td>0.00525</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>150</td>
<td>136.91</td>
<td>10.04</td>
<td>0.00609</td>
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<tr>
<td>3</td>
<td>15</td>
<td>100</td>
<td>59.16</td>
<td>9.76</td>
<td>0.00592</td>
</tr>
</tbody>
</table>

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**B. Case 2: Ten-Unit System**

For this test system, the VPLE is considered for all units. The B-loss matrix is given below. The generator data taken from [16] are illustrated in Table III.

\[
B = \begin{bmatrix}
0.000136 & 0.000175 & 0.000184 \\
0.000175 & 0.000154 & 0.000283 \\
0.000184 & 0.000283 & 0.00165
\end{bmatrix}
\]

---

The Pareto solution set and the compromise solution obtained using the NSPSO for total demand power of 1500 MW, are given in Fig. 2.

To demonstrate the effectiveness of the proposed approach, a comparison with GA based method called NSGAII is investigated. Table IV shows that the NSPSO outperforms NSGAII in providing the best results for both minimum cost
and minimum emission.

### TABLE II
**OPTIMUM SOLUTIONS FOR CASE 1**

<table>
<thead>
<tr>
<th>$P_0$ (MW)</th>
<th>$P_1$ (MW)</th>
<th>$P_2$ (MW)</th>
<th>$P_3$ (MW)</th>
<th>$C_T$ ($/h$)</th>
<th>$E_T$ (ton/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Best cost</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>300</td>
<td>207.6346</td>
<td>87.2951</td>
<td>15.0000</td>
<td>9.9297</td>
<td>3619.8606</td>
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<tr>
<td>350</td>
<td>235.8080</td>
<td>112.2470</td>
<td>15.0000</td>
<td>13.0549</td>
<td>4210.5345</td>
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<tr>
<td>400</td>
<td>249.9331</td>
<td>150.0000</td>
<td>16.7696</td>
<td>16.7028</td>
<td>4825.6814</td>
</tr>
<tr>
<td><strong>Best emission</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>300</td>
<td>96.3336</td>
<td>135.9757</td>
<td>100.0000</td>
<td>32.3092</td>
<td>3920.4545</td>
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<tr>
<td>350</td>
<td>136.7485</td>
<td>150.0000</td>
<td>100.0000</td>
<td>36.7484</td>
<td>4485.2530</td>
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<tr>
<td>400</td>
<td>191.4945</td>
<td>150.0000</td>
<td>100.0000</td>
<td>41.4945</td>
<td>5053.8599</td>
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<td><strong>Compromise solution</strong></td>
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<tr>
<td>300</td>
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<td>127.7517</td>
<td>44.3052</td>
<td>14.6857</td>
<td>3692.6519</td>
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<tr>
<td>350</td>
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<td>143.5784</td>
<td>46.8624</td>
<td>18.9131</td>
<td>4274.9795</td>
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<tr>
<td>400</td>
<td>218.4445</td>
<td>150.0000</td>
<td>57.6805</td>
<td>26.1250</td>
<td>4351.6210</td>
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</tbody>
</table>

### TABLE III
**UNIT DATA FOR THE TEN-UNIT SYSTEM**

<table>
<thead>
<tr>
<th>Unit</th>
<th>$P_{\text{min}}$</th>
<th>$P_{\text{max}}$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\gamma$</th>
<th>$\delta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<td>470</td>
<td>38.5397</td>
<td>0.1524</td>
<td>0.041</td>
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<td>2</td>
<td>135</td>
<td>451.3251</td>
<td>46.1591</td>
<td>0.1058</td>
<td>0.036</td>
<td>103.3908</td>
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<tr>
<td>3</td>
<td>73</td>
<td>340</td>
<td>1049.9977</td>
<td>0.0280</td>
<td>0.028</td>
<td>300.3910</td>
</tr>
<tr>
<td>4</td>
<td>60</td>
<td>300</td>
<td>1243.5311</td>
<td>0.0354</td>
<td>0.052</td>
<td>260.0006</td>
</tr>
<tr>
<td>5</td>
<td>73</td>
<td>243</td>
<td>1658.5696</td>
<td>0.0211</td>
<td>0.063</td>
<td>280.0006</td>
</tr>
<tr>
<td>6</td>
<td>57</td>
<td>160</td>
<td>1356.6592</td>
<td>0.179</td>
<td>0.048</td>
<td>320.0006</td>
</tr>
<tr>
<td>7</td>
<td>20</td>
<td>130</td>
<td>1450.7045</td>
<td>0.0121</td>
<td>0.086</td>
<td>300.0006</td>
</tr>
<tr>
<td>8</td>
<td>47</td>
<td>120</td>
<td>1450.7045</td>
<td>0.0121</td>
<td>0.082</td>
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</tr>
<tr>
<td>9</td>
<td>20</td>
<td>80</td>
<td>1455.6056</td>
<td>0.1099</td>
<td>0.098</td>
<td>350.0006</td>
</tr>
<tr>
<td>10</td>
<td>10</td>
<td>55</td>
<td>1469.4026</td>
<td>0.1295</td>
<td>0.380</td>
<td>360.0012</td>
</tr>
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</table>

### TABLE IV
**OPTIMUM SOLUTION FOR CASE 2 ($P_0 = 1500$ MW)**

<table>
<thead>
<tr>
<th>$P_0$ (MW)</th>
<th>$P_1$ (MW)</th>
<th>$P_2$ (MW)</th>
<th>$P_3$ (MW)</th>
<th>$C_T$ ($/h$)</th>
<th>$E_T$ (ton/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Best cost</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>151.0699</td>
<td>150.3148</td>
<td>222.1862</td>
<td>212.3576</td>
<td>158.4670</td>
<td>153.8185</td>
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<tr>
<td>135.0000</td>
<td>135.0000</td>
<td>225.0995</td>
<td>228.9496</td>
<td>184.9382</td>
<td>234.6255</td>
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<tr>
<td>256.2241</td>
<td>186.2797</td>
<td>160.4036</td>
<td>160.4766</td>
<td>195.4399</td>
<td>184.5578</td>
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<tr>
<td>240.2177</td>
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<td>184.9382</td>
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<td>231.0923</td>
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<td>129.8012</td>
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<td>120.0000</td>
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<td>79.0047</td>
<td>79.5426</td>
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<tr>
<td>45.4832</td>
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<td>55.0000</td>
<td>54.9215</td>
<td>54.8865</td>
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<tr>
<td><strong>Cost ($/h)</strong></td>
<td><strong>85466.98</strong></td>
<td><strong>85466.91</strong></td>
<td><strong>91736.17</strong></td>
<td><strong>91736.17</strong></td>
<td><strong>88627.74</strong></td>
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<tr>
<td><strong>Emission (ton/h)</strong></td>
<td><strong>7959.50</strong></td>
<td><strong>7959.50</strong></td>
<td><strong>7977.11</strong></td>
<td><strong>7977.11</strong></td>
<td><strong>8597.81</strong></td>
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<tr>
<td><strong>Losses (MW)</strong></td>
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<td><strong>6199.85</strong></td>
<td><strong>6211.90</strong></td>
<td><strong>6211.90</strong></td>
<td><strong>6223.93</strong></td>
</tr>
</tbody>
</table>

### V. CONCLUSION

In this study, a new PSO-based optimization technique symbolized by NSPSO is proposed for solving the non-convex economic-environmental dispatch (EED). The EED problem has been formulated as an MOP. Several operating constraints have been considered such as generation limits, valve point loading effects and real power balance constraints. The proposed NSPSO technique incorporates the non-dominated sorting mechanism to adopt the original PSO algorithm for MOP. The effectiveness of the proposed optimization technique is tested on the three-unit and ten-unit systems. Simulations results have demonstrated that NSPSO can provide acceptable optimum solutions for the EED problem with different complexities.
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REFERENCES