Solving Economic Emissions Load Dispatch problem by using Hybrid ACO-MSM approach

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Abstract- This paper introduces a solution of the economic emissions load dispatch (EELD) problem using a hybrid approach of ant colony optimization (ACO) and modified simplex method (MSM). The proposed approach combines and extends the attractive features of both ACO and MSM, where it is based on ACO to get approximate nondominated set of the problem followed by MSM to improve the solution. The proposed approach has been applied in two test examples and the solution is then compared with that obtained by some other techniques to prove the superiority and effectiveness of the proposed algorithm.

Keywords- Multiobjective Decision Making problem, Pareto optimal, Ant Colony Optimization, Modified Simplex method, economic emissions load dispatch problem.

I. INTRODUCTION

The objective of the Economic Emission Load Dispatch (EELD) problem of electric power generation is to schedule the committed generating units outputs to meet the required load demand at minimum operating cost with minimum emission while satisfying all units and system equality and inequality constraints. EELD problem is one of the mathematical optimization issues in power system operation attracting many researchers’ interests. EELD problem is a multiobjective mathematical programming problem which is concerned with the attempt to obtain the optimal solution which simultaneously optimizes two conflicting objectives.

Many approaches and methods were proposed to solve multiobjective economic emission load dispatch problems [4, 7, 10]. The use and development of metaheuristics-based multiobjective optimization techniques have significantly grown. Partial swarm algorithm is one of the most recent metaheuristic algorithms that have been applied in optimization tasks such as EELD problem [3, 7, 12, 13]. Ant colony optimization (ACO) is one of the most recent metaheuristic techniques for approximate optimization so we used it to solve this problem.

The first ACO algorithms were introduced by Marco Dorigo and colleagues as a novel nature-inspired metaheuristic for the solution of hard combinatorial optimization (CO) problems in the early 1990’s [1,5,6]. ACO belongs to the class of metaheuristics [2], which are approximate algorithms used to obtain good enough solutions to hard CO problems in a reasonable amount of computation time. It is inspired by the ants foraging behavior, at the core of this behavior is the indirect communication between the ants by means of chemical pheromone trails, which enables them to find short paths between their nest and food sources.

II. MULTIOBJECTIVE DECISION MAKING PROBLEM FORMULATION

A multiobjective decision making problem (MODM) can be defined as the problem of finding a vector of decision variables which satisfies constraints and optimizes (minimize or maximize) a vector function whose elements represent the objective functions. The mathematical formulation of a MODM problem is to optimize k different objective functions -usually in conflict with each other- subject to a set of system constraints [9].

\[
\text{optimize } \mathbf{f}(\mathbf{x}) = (f_1(x), f_2(x), \ldots, f_k(x))' \\
\text{subject to } \mathbf{x} = (x_1, x_2, \ldots, x_n)' \\
G_j(x) \geq 0 \quad j = 1, 2, \ldots, J \tag{1}
\]

where \( \mathbf{x} \) is an \( n \) dimensional vector of decision variables and also is called the decision space or search space, \( G_j, j = 1, 2, \ldots, J \) are inequality constraints. For a problem having more than one objective function (say, \( f_j, j = 1, 2, \ldots, k > 1 \)), any two solutions \( x_1 \) and \( x_2 \) can have one of two possibilities, one dominates the other or nondominates the other. A solution \( x_1 \) is said to dominate the other solution \( x_2 \), if both the following condition are true:

1. The solution \( x_1 \) is no worse than \( x_2 \) in all objectives, or \( f_j(x_1) \neq f_j(x_2) \) for all \( j = 1, 2, \ldots, k \) objectives.
2. The solution \( x_1 \) is strictly better than \( x_2 \) in at least one objective, or \( f_j(x_1) < f_j(x_2) \) for at least one \( j \in [1, 2, \ldots, k] \).

Definition 1 [9]: (Pareto optimal solution): \( x^* \) is said to be a Pareto optimal solution of multiobjective optimization problem if there exists no other feasible \( x \) (i.e., \( x \in X \)) such that \( f_j(x) \leq f_j(x^*) \) for all \( j = 1, 2, \ldots, k \), and \( f_j(x) < f_j(x^*) \) for at least one objective \( j \).

III. ECONOMIC EMISSION LOAD DISPATCH

The economic emission load dispatch have two objective function fuel cost and emission objectives which are conflicting ones. The problem can be formulated as described below:

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• Objective Functions

Fuel cost objective: The classical economic dispatch problem of finding the optimal combination of power generation, which minimizes the total fuel cost while satisfying the total required demand can be mathematically stated as follows:

\[
    f_c(x) = \sum_{i=1}^{n} C_i (P_{gi}) = \sum_{i=1}^{n} (a_i + b_i P_{gi} + c_i P_{gi}^2) \text{ $/hr$} \tag{1}
\]

where \( C_i \) : Fuel cost of generator \( i \).
\( a_i, b_i, c_i \) : Fuel cost coefficients of generator \( i \).
\( P_{gi} \) : Out power (p.u) by generator \( i \). \( n \): number of generator.

• Emission objective:

The emission function can be presented as the sum of all types of emission considered, such as \( NO_x \), \( SO_x \), thermal emission, etc., with suitable pricing or weighting on each pollutant emitted. In the present study, only one type of emission \( NO_x \) is taken into account without loss of generality. The amount of \( NO_x \) emission is given as a function of generator output, that is, the sum of a quadratic and exponential function:

\[
    f_n(x) = \sum_{i=1}^{n} 10^{12} (a_i + b_i P_{gi} + c_i P_{gi}^2) + \alpha_i \exp(\beta_i P_{gi}) \text{ ton/hr} \tag{2}
\]

where \( \alpha_i, \beta_i, \gamma_i, \lambda_i \) : coefficients of the \( i \)th generator's \( NO_x \) emission characteristic.

• Constraints:

Power balance constraint: the total power generated must supply the total demand and the transmission losses

\[
    \sum_{i=1}^{n} P_{gi} = P_b + P_{trans} \tag{3}
\]

where \( P_b \) is load demand, \( P_{trans} \) is transmission losses.

\( P_{trans} \) can be calculated by

\[
    P_{trans} = \sum_{i=1}^{n} \sum_{j=1}^{n} P_{ij} B_{ij} P_j \tag{6}
\]

where \( B_{ij} \) are the elements of loss coefficient matrix \( B \).

• Generator capacity constraint:

For stable operation real power output of each generator is restricted by lower and upper limits as follows:

\[
    P_{lim} \leq P_{gi} \leq P_{Glim} \text{ \ \ \ \ \ \ \ \ i = 1, \ldots, N} \tag{4}
\]

• Security constraints:

A mathematical formulation of the security constrained EELD problem would require a very large number of constraints to be considered. However, for secure operation the transmission line loading \( S_{li} \) is restricted by its upper limit as:

\[
    S_{li} \leq S_{lim} \text{ \ \ \ \ \ \ \ \ i = 1, \ldots, n_L} \tag{5}
\]

\( n_L \) : The number of transmission lines.

IV. THE PROPOSED ALGORITHM

In this section, we present the proposed algorithm. Firstly ACO was implemented to get approximate nondominated set \( ND(\cdot) \). Secondly, modified simplex method MSM was used as a neighborhood search engine to improve the solution quality. The proposed algorithm is explained as follows.

• ACO Algorithm

The ACO algorithm has been used to find approximate nondominated solution set of MODM. The main characteristic features of this approach simulates parallel independent runs strategy [11], where we apply a sequence of \( M \) colonies constituting a chain one followed the other and each of them has own parameters. Also, it differs from other approaches in selection procedure in which, each ant colony construct its solutions based on a weight sum of multiobjective criteria, where the weight attached to multiobjective criteria is not constant but randomly generated.

\[
    w_j = \frac{\text{random}(\cdot)}{\sum_{i=1}^{k} \text{random}(\cdot)}, \text{ \ \ \ \ } i = 1, 2, \ldots, k \tag{6}
\]

where \( \text{random}(\cdot) \) is a non-negative random number. From equation (6) we can see that \( w_j \) is a real number in the closed interval \([0,1]\) and \( \sum_{i=1}^{k} w_i = 1 \). Every ant colony constructs its solutions based on different weight values newly generated by equation (6). The combined fitness function is defined as:

\[
    f = \sum_{j=1}^{k} w_j f_j(x) \tag{7}
\]

Save all the nondominated solution produced by all \( M \) colonies initially in the archive \( A^{\text{in}} = \{ ND(\cdot) \} \). Update archive, Algorithm 1 is used to update the archive.

Till this moment we get an approximate Pareto solution, we seek to improve the solution quality by getting solutions more close to the true Pareto optimal solution; we implement local search technique as a neighborhood search engine. The procedure of MSM is described in the following subsection.

Algorithm 1: Archive Update

1. INPUT \( A, X \)
2. If \( \exists X' \in A \mid X \text{ dominates } X' \text{ then} \)
3. \( A' \leftarrow A \)
4. Else if \( \exists X' \in A \mid X \text{ dominates } X' \text{ then} \)
5. \( A' \leftarrow A \cup \{X\} \setminus \{D\} \)
6. Else if \( \exists x \in A \mid X \text{ dominates } X' \text{ then} \)
7. \( A' \leftarrow A \cup \{X\} \)
8. end if
9. OUTPUT : \( A' \)

• Modified Simplex Algorithm

This section is concentrate in describing one of local search technique used in nonlinear programming [9] and its modified form to be suitable to multiobjective optimization problems. The basic idea in the simplex method is to compare the values of the objective function at the \((n + 1)\) vertices of a general simplex and move the simplex gradually toward the optimum during the iterative process. There are three operations, known as reflection, contraction, and expansion. Our method tries to improve a set of points to get nondominated solution.
close to true Pareto optimal solution. Assume the obtained approximate nondominated set is represented by ND().

**Reflection:** To explain this method, assume there are three points \( \{X_1, X_2, X_3\} \subset ND \) and assume these points are arranged according to one of the objective functions \( \{X_1, X_2, X_3\} \). A new point \( X_n \), obtained by reflecting the point \( X_m \) (subscript \( m \) indicate the middle point) in the opposite face to have new value. Mathematically, the reflected point \( X_n \) is given by

\[
X_n = (1 + \alpha)X_m - aX_m
\]

(8)

\( x_0 \) is the centroid of all points \( X_i \), except \( i = m \)

\[
x_0 = \frac{1}{m} \sum_{i=1}^{m} X_i
\]

(9)

\( \alpha > 0 \) is called the reflection coefficient. Comparing the generated point \( X_n \), with the set of points \( \{X_1, X_2, X_3\} \), \( X_n \) is replaced by \( X_m \) if \( F(X_m) \) dominates \( F(X_n) \) and preserve its feasibility, else if \( F(X_m) \) and \( F(X_n) \) are nondominated to each other, then \( X_n \) are added to the set \( \{X_1, X_2, X_3\} \) producing the set \( \{X_1, X_2, X_3, X_n\} \). In the other hand if \( F(X_m) \) was dominated by \( F(X_n) \), the contraction process will be used to generate a new point. Algorithm 2 describes the main feature of the reflection process.

**Algorithm 2: Reflection process**

1. **INPUT** ND(X), X
2. If \( \exists X \in ND(X) \setminus \{X\} \) and go to Expansion process
3. \( A' \leftarrow ND(X) \cup \{X\} \) and go to Contraction process
4. else if \( \exists X \in ND(X) \setminus \{X\} \) and go to Contraction process
5. Replace all \( X \) by \( X/2 \)
6. \( A' \leftarrow ND(X) \cup \{X\} \)
7. end if
8. **OUTPUT** : A'  

**Expansion:** If a reflection process gives a point \( X_n \), for which \( F(X_n) \) dominates \( F(X_m) \), i.e. the resultant set is three points assumes it is namely as \( \{X_1, X_2, X_3\} \), so we can generally expect to get more accepted points by moving along the direction pointing from \( X_n \) to \( X_m \). Hence we expand \( X_n \) to \( X_m \) using the relation:

\[
X_m = \gamma X_n + (1 - \gamma)X_0
\]

(10)

**Algorithm 3: Expansion process**

1. **INPUT** ND(X), X
2. If \( \exists X \in ND(X) \setminus \{X\} \) and go to Expansion process
3. \( A' \leftarrow ND(X) \cup \{X\} \)
4. else if \( \exists X \in ND(X) \setminus \{X\} \) and go to Contraction process
5. Replace all \( X \) by \( X/2 \)
6. \( A' \leftarrow ND(X) \cup \{X\} \)
7. end if
8. **OUTPUT** : A'

where \( \gamma > 1 \) is called the expansion coefficient. Algorithm 3 describes the main feature of the expansion process.

**Contraction:** If a reflection process gives a point \( X_n \) for which \( X_n \) are dominated by any point in the set \( \{X_1, X_2, X_3\} \). In this case new point \( X_n \) are generated as follows:

\[
X_n = \beta X_n + (1 - \beta)X_0
\]

(11)

where \( \beta \) is called the contraction coefficient (\( 0 < \beta < 1 \)). Algorithm 4 describes the main feature of the contraction process.

**Algorithm 4: Contraction process**

1. **INPUT** ND(X), X
2. If \( \exists X \in ND(X) \setminus \{X\} \) then
3. \( A' \leftarrow ND(X) \cup \{X\} \)
4. else if \( \exists X \in ND(X) \setminus \{X\} \) then
5. Replace all \( X \) by \( X/2 \)
6. \( A' \leftarrow ND(X) \cup \{X\} \)
7. end if
8. **OUTPUT** : A'

The pseudo code of the proposed algorithm is shown in figure (2).

**ACO**

Construct M colonies.

Initialize the parameters for each ACO.

Initialize archive \( A^{+\theta} = [\emptyset] \)

For \( n = 1: M \)

While (Stop criterion has not been satisfied) do

Solution Construction ()

Pheromone Update ()

End

End

Archive A contain all generated approximated nondominated solutions, MSM

For \( i = 1: \text{size}(A) \) do

\( \forall (x_1, x_2, x_3) \in A \) if \( f_1(x_2, x_3), f_2(x_1, x_3), f_3(x_1, x_2) \) are descending w.r.t any \( f_j \)

While (the algorithm do not produce new points) do

Generate X

If (Reflection process is succeeded)

Expansion process

If else (Contraction process is succeeded)

If (Reflection process is succeeded)

Expansion process

End

Generate new set of points \( (x_1, x_2, x_3) \)

End

**V. IMPLEMENTATION OF THE PROPOSED APPROACH**

The techniques and all simulations developed in this study were implemented on 3.0 GHz PC using MATLAB language.
The algorithm developed in the previous section has been implemented to the standard IEEE 30-bus 6-generator test system. The values of fuel cost and emission coefficients are given in Table (1). To demonstrate the potential of the proposed approach for different problem complexities and trade-off surfaces, two different cases have been considered as follows. Case (A), for comparison purposes with the reported results, the system is considered as lossless and the security constrain is released. Convergence of fuel cost and emission objectives are shown in figure (3).

Case (B), in this case, the power loss has been taken into account. The transmission loss B-coefficients are specified in [3]. Convergence of fuel cost and emission objectives when optimized are shown in figure (4). The values of the best cost and the best emission objectives with the proposed approach are given in Tables (2).

Table (1): Generator cost, capacities and emission coefficients of test system.

<table>
<thead>
<tr>
<th>Case</th>
<th>G1</th>
<th>G2</th>
<th>G3</th>
<th>G4</th>
<th>G5</th>
<th>G6</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>100</td>
<td>120</td>
<td>40</td>
<td>60</td>
<td>40</td>
<td>100</td>
</tr>
<tr>
<td>b</td>
<td>200</td>
<td>150</td>
<td>180</td>
<td>100</td>
<td>180</td>
<td>150</td>
</tr>
<tr>
<td>c</td>
<td>10</td>
<td>10</td>
<td>20</td>
<td>10</td>
<td>20</td>
<td>10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Emission</th>
<th>Cost</th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>α</td>
<td>4.091</td>
<td>2.543</td>
<td>4.258</td>
<td>5.326</td>
</tr>
<tr>
<td>β</td>
<td>-5.554</td>
<td>-6.047</td>
<td>-5.094</td>
<td>-3.55</td>
</tr>
<tr>
<td>γ</td>
<td>6.490</td>
<td>5.638</td>
<td>4.586</td>
<td>3.38</td>
</tr>
<tr>
<td>ζ</td>
<td>2E-4</td>
<td>5E-4</td>
<td>1E-6</td>
<td>2E-3</td>
</tr>
<tr>
<td>λ</td>
<td>2.857</td>
<td>3.333</td>
<td>8</td>
<td>2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Pₐₐₓ</th>
<th>P₆ₐₓ</th>
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</thead>
<tbody>
<tr>
<td>Power</td>
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<td>0.05</td>
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<td></td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>0.05</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Table (2): Solutions compromising minimum fuel cost and emission

Table (3): Generator cost, capacities and emission coefficients of test system.

The second test system consists of three plants and six generators. The test system considered was derived from [7]. The generation data are given in Tables (3). The system load was 900 mw. Two different cases have been considered as test system 1. Convergence of fuel cost and emission objectives are shown in figure (5) for case (A) and figure (6) for case (B). The values of the best cost and the best emission objectives with the proposed approach are given in Tables (4).

Figure (3): Case (A), Results of test system 1

In this subsection, a comparative study has been carried out to assess the proposed approach concerning quality of the Pareto set. On the first hand, evolutionary techniques suffer from the quality of the Pareto set. Therefore the proposed approach has been used to increase the solution quality by combing the two merits of two heuristic algorithms. However, the goal is not only to increase the solution quality, but also to generate a representative subset, which maintains the characteristics of the general set and take the solution diversity into consideration. On the other hand, classical techniques aim to give single point at each iteration of problem solving by converting the multiobjective problem to a single objective problem by linear combination of different objectives as a weighted sum. On the contrary, the proposed approach is a heuristics-based multiobjective optimization technique where, it uses a population of solutions in their search, multiple Pareto-optimal solutions can, in principle, be found in one single run.

Figure (4): Case (B), Results of test system 1

Table (4): Generator cost, capacities and emission coefficients of test system.
\[ \begin{bmatrix} 0.000091 & 0.000031 & 0.000029 \\ 0.000031 & 0.000062 & 0.000028 \\ 0.000029 & 0.000028 & 0.000072 \end{bmatrix} \]

Proposed algorithm [7]

\begin{tabular}{lcccc}
& Case(A) & Case(B) & Case(A) & Case(B) \\
\hline
G1 & 33.88 & 48.57 & 32.50 & 51.82 \\
G2 & 13.33 & 39.06 & 10.82 & 38.64 \\
G3 & 152.96 & 180.91 & 143.64 & 248.73 \\
G4 & 142.24 & 114.66 & 143.03 & 122.14 \\
G5 & 278.16 & 296.42 & 287.10 & 252.01 \\
G6 & 279.69 & 259.88 & 282.90 & 223.57 \\
\hline
Cost & 45480.96 & 47581.23 & 45463.42 & 47804.55 \\
Emission & 784.17 & 823.2 & 795.00 & 843.42 \\
Losses & ---- & 38.77 & ---- & 36.90 \\
\end{tabular}

Table 4: Solutions compromising minimum fuel cost and emission

\begin{center}
\includegraphics[width=0.5\textwidth]{figure5.png}
\end{center}

Figure (5): Case (A), Results for test system 2

\begin{center}
\includegraphics[width=0.5\textwidth]{figure6.png}
\end{center}

Figure (6): Case (B), Results of test system 2

V. CONCLUSION

In this paper, we present a new approach for solving EELD. The methodology combines and extends the attractive features of both ACO and MS. The algorithm presents a new selection procedure based on a combined fitness function and empirical results show that our approach is very efficient to find the true Pareto optimal solutions for EELD and may be very helpful in studying optimization problems in power systems.

REFERENCES