Hybrid Ant Optimization System for Multiobjective Optimal Power Flow Problem Under Fuzziness

A. A. Galal\textsuperscript{a}, A. A. Mousa\textsuperscript{a, b}, B. N. AL-Matrafi\textsuperscript{c}

\textsuperscript{a} Department of Mathematics and Statistics, Faculty of sciences, Taif University, Taif, El-Haweiah, P.O. Box 888, Zip Code 21974, Saudi Arabia.

\textsuperscript{b} Department of Basic Engineering Science, Faculty of Engineering, Menoufia University, Egypt.

\textsuperscript{c} Physics and Engineering Mathematics Department, Faculty of Engineering, Tanta University, Egypt.

(Received 8/1/2013, Accepted 9/3/2013)

Abstract In this paper, a new hybrid optimization system is presented. Our approach integrates the merits of both ant colony optimization and steady state genetic algorithm and it has two characteristic features. Firstly, Since there is instabilities in the global market and the rapid fluctuations of prices, a fuzzy representation of the optimal power flow problem has been defined, where the input data involve many parameters whose possible values may be assigned by the expert. Secondly, by enhancing ant colony optimization through steady state genetic algorithm, a strong robustness and more effectively algorithm was created. Also, stable Pareto set of solutions has been detected, where in a practical sense only Pareto optimal solutions that are stable are of interest since there are always uncertainties associated with efficiency data. Moreover to help the decision maker DM to extract the best compromise solution from a finite set of alternatives a TOPSIS (Technique for Order Performance by Similarity to Ideal Solution) method is adopted. It is based upon simultaneous minimization of distance from an ideal point (IP) and maximization of distance from a nadir point (NP). The results on the standard IEEE systems demonstrate the capabilities of the proposed approach to generate true and well-distributed Pareto optimal nondominated solutions of the multiobjective OPF.

Keywords: Ant colony; Genetic Algorithm; fuzzy numbers; optimal power flow.
1. Introduction

The OPF optimizes a power system operating objective function (such as the operating cost of thermal resources) while satisfying a set of system operating constraints, including constraints dictated by the electric network. OPF has been widely used in power system operation and planning. In its most general formulation, the OPF is a non-linear, non-convex, large-scale, static optimization problem with both continuous and discrete control variables. Even in the absence of non-convex unit operating cost functions, unit prohibited operating zones, and discrete control variables, the OPF problem is nonconvex due to the existence of the nonlinear (AC) power flow equality constraints. The presence of discrete control variables, such as switchable shunt devices, transformer tap positions, and phase shifters, further complicates the problem solution [1,2,3]. Since there is instabilities in the global market, implications of global financial crisis and the rapid fluctuations of prices, for this reasons a fuzzy representation of the multiobjective optimal power flow has been defined, where the input data involve many parameters whose possible values may be assigned by the experts. In practice, it is natural to consider that the possible values of these parameters as fuzzy numerical data which can be represented by means of fuzzy subsets of the real line known as fuzzy numbers. Mathematical programming approaches, such as nonlinear programming, quadratic programming and linear programming, have been used for the solution of the OPF problem [4,5]. Unfortunately, the OPF problem is a highly nonlinear and a multimodal optimization problem. Therefore, conventional optimization methods that make use of derivatives and gradients, in general, not able to locate or identify the global optimum. On the other hand, many mathematical assumptions such as analytic and differential objective functions have to be given to simplify the problem. Furthermore, this approach does not give any information regarding the trade-offs involved.

The development of meta-heuristic optimization theory has been flourishing. Many meta-heuristic paradigms such as genetic algorithm, simulated annealing, and tabu search have shown their efficacy in solving computationally intensive problems [6,7,8,9]. The studies on heuristic algorithms over the past few years have shown that these methods can be efficiently used to eliminate most of difficulties of classical methods. Since they are population–based techniques, multiple Pareto-optimal solutions can, in principle, be found in one single run.

Recently, to meet the ever increasing demands in the design problems, a new evolutionary algorithm called ant colony optimization algorithm have all been used successfully to mimic the corresponding natural, or physical, or social phenomena [10,11,12]. Ant colony optimization (ACO) is a metaheuristic inspired by the shortest path searching behavior of various ant species. Since the initial work of Dorigo, Maniezzo, and Colomi on the first ACO algorithm, the ant system [13], several researchers have designed ACO algorithms to deal with multiobjective problems. The set of solutions achieved by a multiobjective evolutionary algorithm is required to satisfy both convergence and diversity criteria [14].
This paper intends to present a new hybrid algorithm for solving optimal power flow under fuzziness. The proposed approach integrates the merits of both ACO and GA and it has two characteristic features. Firstly, a fuzzy representation of the optimal power flow problem has been defined. Secondly, by enhancing ACO through GA, a strong robustness and more effectively algorithm was created. Several optimization runs of the proposed approach will be carry out on the standard IEEE systems to verify the validity of the proposed approach.

This paper is organized as follows. In section 2, MOO is described. Section 3, provides a Multi-objective Formulation of ELD Problem. In section 4, the proposed algorithm is presented. Implementation of the proposed approach is presented in section 5. Results and discussion are given in section 6. Finally, section 7 gives a conclusion about this study.

2. MULTIOBJECTIVE OPTIMIZATION

A Multi-objective Optimization Problem (MOP) can be defined as determining a vector of decision variables within a feasible region to minimize a vector of objective functions that usually conflict with each other. Such a problem takes the form:

\[
\begin{align*}
\text{Minimize} & \quad \{f_1(X), f_2(X), \ldots, f_m(X)\} \\
\text{subject to} & \quad g(X) \leq 0,
\end{align*}
\]

where \(X\) is vector of decision variables; \(f_i(X)\) is the \(i\)th objective function; and \(g(X)\) is constraint vector. A decision vector \(X\) is said to dominate a decision vector \(Y\) (also written as \(X \succ Y\)) iff:

\[
f_i(X) \leq f_i(Y) \quad \text{for all} \quad i \in \{1, 2, \ldots, m\} \quad \text{and} \quad f_i(X) < f_i(Y) \quad \text{for at least one} \quad i \in \{1, 2, \ldots, m\}
\]

All decision vectors that are not dominated by any other decision vector are called nondominated or Pareto-optimal. These are solutions for which no objective can be improved without detracting from at least one other objective.

3. MULTIOBJECTIVE FORMULATION OF ELD PROBLEM

The economic emission load dispatch involves the simultaneous optimization of fuel cost and emission objectives which are conflicting ones. The deterministic problem is formulated as described below.

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(\cdot) = C_i = \sum_{i=1}^{n} C_i (P_{Gi}) = \sum_{i=1}^{n} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \text{$/hr}$

Where

- \( C \): total fuel cost ($$/hr), \( C_i \): is fuel cost of generator \( i \)
- \( a_i, b_i, c_i \): fuel cost coefficients of generator \( i \),
- \( P_{Gi} \): power generated (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_2(\cdot) = E_{NO_x} = \sum_{i=1}^{n} \left[ 10^{17} (\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) + \xi_i \exp(\lambda_i P_{Gi}) \right] \text{ton$/hr}$

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

**Constraints:** The optimization problem is bounded by the following constraints:

- **Power balance constraint.** The total power generated must supply the total load demand and the transmission losses.

\[ \sum_{i=1}^{n} P_{Gi} - P_D - P_{Loss} = 0 \]

Where \( P_D \): total load demand (p.u), and \( P_{Loss} \): transmission losses (p.u).

The transmission losses are given by[15]:

\[ P_{Loss} = \sum_{i=1}^{n} \sum_{j=1}^{n} \left[ A_{ij} (P_i P_j + Q_i Q_j) + B_{ij} (Q_i P_j - P_i Q_j) \right] \]

Where \( P_i = P_{Gi} - P_{Gi} \), \( Q_i = Q_{Gi} - Q_{Gi} \), \( A_{ij} = \frac{R_y}{V_i V_j} \cos(\delta_i - \delta_j) \), \( B_{ij} = \frac{R_y}{V_i V_j} \sin(\delta_i - \delta_j) \)

- \( n \): number of buses
- \( \delta_i \): voltage angle at bus \( i \)
- \( R_y \): series resistance
- \( P_i \): real power injection at connecting buses \( i \) and \( j \)
$V_i$: voltage magnitude at bus $i$

$Q_i$: reactive power injection at bus $i$

- **Maximum and Minimum Limits Of Power Generation.** The power generated $P_{Gi}$ by each generator is constrained between its minimum and maximum limits, i.e.,

$$P_{Gi \, \text{min}} \leq P_{Gi} \leq P_{Gi \, \text{max}}; \quad Q_{Gi \, \text{min}} \leq Q_{Gi} \leq Q_{Gi \, \text{max}},$$

$$V_{i \, \text{min}} \leq V_i \leq V_{i \, \text{max}}, \quad i = 1, \ldots, n$$

where $P_{Gi \, \text{min}}$: minimum power generated, and $P_{Gi \, \text{max}}$: maximum power generated.

- **Security Constraints.** A mathematical formulation of the security constrained EELD problem would require a very large number of constraints to be considered. However, for typical systems the large proportion of lines has a rather small possibility of becoming overloaded. The EELD problem should consider only the small proportion of lines in violation, or near violation of their respective security limits which are identified as the critical lines. We consider only the critical lines that are binding in the optimal solution. The detection of the critical lines is assumed done by the experiences of the DM. An improvement in the security can be obtained by minimizing the following objective function.

$$S = f(P_{Gi}) = \sum_{j=1}^{k} (|T_j(P_{Gi})| / T_j^{\text{max}})$$

Where, $T_j(P_{Gi})$ is the real power flow $T_j^{\text{max}}$ is the maximum limit of the real power flow of the $j$ th line and $k$ is the number of monitored lines. The line flow of the $j$ th line is expressed in terms of the control variables $P_{Gi}$, by utilizing the generalized generation distribution factors (GGDF) [1] and is given below.

$$T_j(P_{Gi}) = \sum_{i=1}^{n} (D_{ji} P_{Gi})$$

where, $D_{ji}$ is the generalized GGDF for line $j$, due to generator $i$

For secure operation, the transmission line loading $S_j$ is restricted by its upper limit as

$$S_j \leq S_{j \, \text{max}}, \quad j = 1, \ldots, n_j$$

Where $n_j$ is the number of transmission line.

- **Multiobjective Formulation of EELD Problem.**
The multiobjective EELD optimization problem is therefore formulated as:

\[ \text{Min } f_1(x) = C_1 = \sum_{i=1}^{n_t}(a_i + b_i P_{Gi} + c_i P_{Gi}^2) \text{ } \$/\text{hr} \]

\[ \text{Min } f_2(x) = E_{\text{loss}} = \sum_{i=1}^{n_t}[10^{-7}(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) + \xi_i \exp(\lambda_i P_{Gi})] \text{ } \text{ton/}\text{hr} \]

s.t. \[ \sum_{i=1}^{n_t} P_{Gi} - P_D - P_{\text{Loss}} = 0, \]

\[ S_i \leq S_{(\text{max })}, \quad \ell = 1, \ldots, n_{\text{var}}, \]

\[ P_{G_{(\text{min })}} \leq P_{Gi} \leq P_{G_{(\text{max })}} \quad i = 1, \ldots, n \]

\[ Q_{G_{(\text{min })}} \leq Q_{Gi} \leq Q_{G_{(\text{max })}} \quad i = 1, \ldots, n \]

\[ V_{i_{(\text{min })}} \leq V_i \leq V_{i_{(\text{max })}} \quad i = 1, \ldots, n \]

4. THE PROPOSED APPROACH

with several objectives in ant colonies that use the principles of MACO necessitates to answer three questions: (1) how to globally update pheromone according to the performance of each solution based on each objective, where each colony having its own pheromone structure (2) how does a given ant locally selects a path, according to the visibility and the desirability, at a given step of the approach (3) how to build the Pareto front. The main steps of the MACO are summarized as follows

**Step 1:** Construct \( Q \) Colonies. In a multiobjective optimization problem, multiobjective functions \( F = \{f_1, f_2, \ldots, f_Q\} \) need to be optimized simultaneously, there does not necessarily exist a solution that is best with respect to all objectives because of incommensurability and confliction among objectives. For this step, the number of colonies is set to \( Q \) with its own pheromone structure, where \( Q = |F| \) is the number of objectives to optimize.

**Step 2:** Initialization. First, pheromones trails are initialized to a given value \( r^0_q, (q=1,2,\ldots,Q) \) where \( r^0_q \) is the pheromone information in the current iteration and Pareto set are initialized to an empty set.

Implementing the multipheromone ant colony optimization for a certain problem requires a representation of \( n \) variables for each ant, with each variable \( i \) has a set of \( m_i \) options(nodes) with their values \( l_{ij} \) which we generate(a fully connected graph \((n,n)\)), and their associated pheromone concentrations \( \{ r_{ij} \} \) (see figure 1); where \( i = 1,2,\ldots,n \), and \( j = 1,2,\ldots,n \). The process starts by generating \( m \) ants' position (solutions) from the population which is generated randomly, thus
each ant \( k, k \in \{1, 2, \ldots, m\} \) has a position with a selected value for each variable (\( l_y \mid i = 1, 2, \ldots, n \land j = 1, 2, \ldots, ni \)) according to the associated pheromone with this value. This process continues for each objective. Consequently, path of each ant was consisted of \( n \) nodes with a value \( l_y \) for each node.

**Step 3:** Evaluation. The MACO parameterized by the number of ant colonies \( Q \) and the number of associated pheromone structures. All the colonies have the same number of ants. Each colony \( k, k \in \{1, 2, \ldots, Q\} \) tries to optimize an objective considering the pheromone information associated for each colony, where each colony is determined knowing only the relevant part of a solution. This methodology enforces both colonies to search in different regions of the nondominated front.

![Fig. (1). Ant Representation.](image)

**Step 4:** Trail Update and Reward Solutions. When updating pheromone trails, one has to decide on which of the constructed solutions laying pheromone. The quantity of pheromone laying on a component represents the past experience of the colony with respect to choosing this component. Then, at each cycle every ant constructs a solution, and pheromone trails are updated. Once all ants have constructed their solutions, pheromone trails are updated as usually in equation 2: first, pheromone trails are reduced by a constant factor to simulate evaporation to prevent premature convergence; then, some pheromone is laid on components of the best solution. Accordingly, pheromone concentration \( (P^t \mid q = 1, 2, \ldots, Q \land i = 1, 2, \ldots, n \land j = 1, 2, \ldots, ni) \) associated with each possible route (variable value) is changed in a way to reinforce good solutions, as in equation 2 and the change in pheromone concentration \( \Delta r^t_\theta \) is expressed in equation
A possibility is to reward every nondominated solution of the current cycle as follows

\[ \Delta \tau_{ij}^q(t) \leftarrow (1-\rho)\tau_{ij}^q(t-1) + \Delta \tau_{ij}^q, \]

\[ b = 1,2,\ldots,B \quad B \subseteq ni \]

Where \( \tau_{ij}^q(t) \) the revised concentration of pheromone is associated with option \( b \in ni \) at iteration \( t \), \( \tau_{ij}^q(t-1) \) is the concentration of pheromone at the previous iteration \( (t-1) \); \( \Delta \tau_{ij}^q \) is change in pheromone concentration that can be determined according to equation 6; and \( B \) is the size of reward solutions

**Step 5:** Solution Construction. Once the pheromone is updated after an iteration, the next iteration starts by changing the ants’ paths (i.e. associated variable values) in a manner that respects pheromone concentration and also some heuristic preference. For each ant and for each dimension construct a new candidate group to replace the old one. As such, an ant \( k \) will change the value for each variable according to the transition probability. The transition probability is done for each colony \((p_{ij}^q(t), q = 1,2,\ldots,Q)\) as expressed in the following equation.

\[ p_{ij}^q(t) = \begin{cases} \left[ \frac{\tau_{ij}^q(t)}{\sum_{b \in ni} \tau_{ij}^q(t)} \right]^\alpha, & \forall j, h \in ni \\ 0, & \text{otherwise} \end{cases} \]

Where \( p_{ij}^q(t) \) is Probability that option \( l_{ij} \) is chosen by ant \( k \) for variable \( i \) at iteration \( t \).

**Step 6:** Nondominated Solutions. The set of nondominated solutions is stored in an archive. During the optimization search, this set, which represents the Pareto front, is updated. At each iteration, the current solutions obtained are compared to those stored in the Pareto archive; the dominated ones are removed and the nondominated ones are added to the set.

**Step 7:** Steady State Genetic Algorithm. Steady state genetic algorithm was implemented in such way that, two offspring are produced in each generation. Parents are selected to produce offspring and then a decision is made as to which individuals in the population to select for deletion to make room for the new offspring (figure 2). A replacement/ deletion strategy defines which member of the
population will be replaced by the new offspring. Steady state genetic algorithms overlapping systems, since parents and offspring compete for survival.

(i) Selections: Selection determines which individuals of the population will have all or some of their genetic material passed on to the next generation of individuals. The mechanism for selecting the parents is based on a tournament selection. Tournament selection operates by choosing some individuals randomly from a population and selecting the best from this group to survive into the next generation. For example, pairs of parents \((x^i, y^j)\) are randomly chosen from the initial population. Their fitness values are compared and a copy of the better performing individual becomes part of the mating pool. The tournament will be performed repeatedly until the mating pool is filled. That way, the worst performing parent in the population will never be selected for inclusion in the mating pool. Tournaments are held between pairs of individuals are the most common. In this way all parents necessary for a reproduction operator are selected.

(ii) Recombination through Crossover and Mutation: After selection has been carried out, then the mechanisms of crossover and mutation are applied to produce an offspring, the following subsection outlines these genetic operators.

Crossover: Once the parents are created, the crossover step is carried out by replacing the current value with a new one which produced stochastically with a probability proportional to the crossover probability. Suppose the crossover probability set by the system is \(p_c\). Generating a random number \(r \in [0,1]\), the crossover operation could be carried out only if \(r < p_c\). Suppose \(x^i\) and \(y^j\) are two parents and \(\alpha\) is a random number (i.e. \(\alpha \in [0,1]\)). The result of crossover operation \(x^i\) and \(y^j\) can be obtained by the following linear combination of \(x^i\) and \(y^j\):

\[
\begin{align*}
x'^i &= \alpha x^i + (1-\alpha)y^j \\
y'^j &= (1-\alpha)x^i + \alpha y^j
\end{align*}
\]

Mutation: Once the crossover is performed, the mutation step is carried out by replacing the current value with a new one which produced stochastically with a probability proportional to the mutation probability \(p_m\). Generating a random number \(r \in [0,1]\), the mutation operation is implemented only if \(r < p_m\). Suppose \(x(j)\) will be transformed into \(x'(j)\) after mutation as follows:

\[
x'(j) = L(j) + \lambda(U(j) - L(j)), \quad j=1,2,\ldots,n
\]

Where \(\lambda\) is a random number (i.e. \(\lambda \in [0,1]\)). Here \(L\) and \(U\) are the lower and upper bounds respectively.

(iii) Replacement / deletion strategy: A widely used combination is to replace the worst individual only if the new individual is better. In the paper, this strategy
will be suggested that the individual will be deleted if it was dominated by the new offspring as in algorithm 1.

Fig.(2). The Model for Steady State for Genetic Algorithms

Algorithm 1: The Strategy of Deletion

1. INPUT: $POP, x$
2. if $\exists x' \in POP \mid x' \succ x$, then
3. $POP' = POP$
4. else if $\exists x' \in POP \mid x \succ x'$, then
5. $POP' = POP \cup \{x\} / \{x'\}$
6. end if
7. Output: $POP'$

Step 8: Optimization of the above-formulated objective functions using multiobjective genetic algorithms yields not a single optimal solution, but a set of Pareto optimal solutions, in which one objective cannot be improved without sacrificing other objectives. For practical applications, however, we need to select one solution, which will satisfy the different goals to some extent. Such a solution is called best compromise solution. TOPSIS method given by Yoon and Hwang [16,17] has the ability to identify the best alternative from a finite set of alternatives quickly. It stands for "Technique for Order Preference by Similarity to the Ideal Solution" which based upon the concept that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest from the negative ideal solution. TOPSIS can incorporate relative weights of criterion importance. The idea of TOPSIS can be expressed in a series of steps.

1- Obtain performance data for $n$ alternatives over $M$ criteria $x_{ij}$ ($i=1,...,n$ $j=1,...,M$).

2- Calculate normalized rating (vector normalization is used) $r_{ij}$. 

...
3- Develop a set of importance weights $w_j$, for each of the criteria. The basis for these weights can be anything, but, usually, is adhoc reflective of relative importance.

$$V_{ij} = w_j J_{ij}$$

4- Identify the ideal alternative (extreme performance on each criterion) $S^+$. 

$$S^+ = \{ v_1^+, v_2^+, \ldots, v_j^+, \ldots, v_m^+ \} = \left\{ \left( \max_{v_j} \left| j \in J_1 \right) \right\} \left( \min_{v_j} \left| j \in J_2 \right) \right\} , i = 1,\ldots,n \}$$

Where $J_1$ is a set of benefit attributes and $J_2$ is a set of cost attributes.

5- Identify the nadir alternative (reverse extreme performance on each criterion) $S^-$. 

$$S^- = \{ v_1^-, v_2^-, \ldots, v_j^-, \ldots, v_m^- \} = \left\{ \left( \min_{v_j} \left| j \in J_1 \right) \right\} \left( \max_{v_j} \left| j \in J_2 \right) \right\} , i = 1,\ldots,n \}$$

6- Develop a distance measure over each criterion to both ideal ($D^+$) and nadir ($D^-$).

$$D^+_i = \sqrt{\sum_j (v_{ij} - v_{ij}^+)^2}$$

$$D^-_i = \sqrt{\sum_j (v_{ij} - v_{ij}^-)^2}$$

7- For each alternative, determine a ratio $R$ equal to the distance to the nadir divided by the sum of the distance to the nadir and the distance to the ideal.

$$R = \frac{D^-}{D^- + D^+}$$

8- Rank alternative according to ratio $R$ (in Step 7) in descending order.

9- Recommend the alternative with the maximum ratio

A relative advantage of TOPSIS is the ability to identify the best alternative from a finite set of alternatives quickly [16-18]. TOPSIS is attractive in that limited subjective input is needed from decision makers. The only subjective input needed is weights which reflect the degree of satisfactoriness of each objective.

5. IMPLEMENTATION OF THE PROPOSED APPROACH

The described methodology has been described for M-objective function, but it is applied to the standard IEEE 30-bus 6-generator test system with two objectives. The single-line diagram of this system is shown in figure 3 and the detailed data are given in [1,2]. The values of fuel cost and emission coefficients are given in Table 1. For comparison purposes with the reported results, the system is
considered as losses and the security constraint is released. The techniques used in this study were developed and implemented on 1.7-MHz PC using MATLAB environment. Table 2 lists the parameter setting used in the algorithm for all runs.

Table (1). Generator cost and emission coefficients

<table>
<thead>
<tr>
<th></th>
<th>G1</th>
<th>G2</th>
<th>G3</th>
<th>G4</th>
<th>G5</th>
<th>G6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost</td>
<td>a</td>
<td>10</td>
<td>10</td>
<td>20</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>b</td>
<td>200</td>
<td>150</td>
<td>180</td>
<td>100</td>
<td>180</td>
</tr>
<tr>
<td></td>
<td>c</td>
<td>100</td>
<td>120</td>
<td>40</td>
<td>60</td>
<td>40</td>
</tr>
<tr>
<td>Emission</td>
<td>α</td>
<td>4.091</td>
<td>2.543</td>
<td>4.258</td>
<td>5.426</td>
<td>4.258</td>
</tr>
<tr>
<td></td>
<td>β</td>
<td>-5.554</td>
<td>-6.047</td>
<td>-5.094</td>
<td>-3.550</td>
<td>-5.094</td>
</tr>
<tr>
<td></td>
<td>ζ</td>
<td>2.0E-4</td>
<td>5.0E-4</td>
<td>1.0E-6</td>
<td>2.0E-3</td>
<td>1.0E-6</td>
</tr>
<tr>
<td></td>
<td>λ</td>
<td>2.857</td>
<td>3.333</td>
<td>8.000</td>
<td>2.000</td>
<td>8.000</td>
</tr>
</tbody>
</table>

Table (2). Parameters for the Proposed Approach

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of objective function</td>
<td>2</td>
</tr>
<tr>
<td>Number of colonies</td>
<td>2</td>
</tr>
<tr>
<td>m</td>
<td>100</td>
</tr>
<tr>
<td>ρ</td>
<td>0.5</td>
</tr>
<tr>
<td>α</td>
<td>1</td>
</tr>
<tr>
<td>β</td>
<td>0</td>
</tr>
<tr>
<td>C</td>
<td>100</td>
</tr>
<tr>
<td>τ_0</td>
<td>10</td>
</tr>
<tr>
<td>p_c</td>
<td>0.85</td>
</tr>
<tr>
<td>p_m</td>
<td>0.02</td>
</tr>
</tbody>
</table>
Fig. (3). Single line diagram of IEEE 30-bus 6-generator test system.

Naturally, these data (cost and emission) involve many controlled parameters whose possible values are vague and uncertain. Consequently each numerical value in the domain can be assigned a specific "grade of membership" where 0 represents the smallest possible grade of membership, and 1 is the largest possible grade of membership. Thus fuzzy parameters can be represented by its membership grade ranging between 0 and 1.

![Fuzzy numbers diagram](image)

**Fig.(4). Fuzzy numbers of the effectiveness of resource**

The fuzzy numbers shown in figure 4 have been obtained from interviewing DMs or from observing the instabilities in the global market and rate of prices
fluctuations. The idea is to transform a problem with these fuzzy parameters to a crisp version using $\alpha$-cut level. This membership function can rewrite as follows:

$$
\mu(a_y) = \begin{cases} 
1, & a = a_y \\
\frac{20a_y - 19}{a_y} & 0.95a_y \leq a \leq a_y \\
21 - \frac{20a_y}{a_y} & a_y \leq a \leq 1.05a_y \\
0 & a < 0.95a_y \text{ or } a > 1.05a_y 
\end{cases}
$$

So, every fuzzy parameter $\tilde{a}_y$ can be represented using the membership function. By using $\alpha$-cut level, these fuzzy parameters can be transformed to a crisp one having upper and lower bounds $[a_y^L, a_y^U]$, which declared in figure 4. Consequently, each $\alpha$-cut level can be represented by the two end points of the alpha level.

6. RESULTS AND DISCUSSION

Here, the problem is how to determine the optimal power flow for considering the minimum cost and the minimum emission objectives simultaneously. In order to efficiently and effectively obtain the solution, the search for the optimal solution is carried out in two steps. Firstly, a set of nondominated solutions is obtained by exploring the optimal Pareto frontier using different $\alpha$ cut level. To study the influence of fuzzy parameters on the obtained Pareto optimal solutions, all the range of the parameter fluctuation were scanned, two bounds of Alpha value have been considered $\alpha = 0, 1$, and also we take some values between these bounds $\alpha = 0.2, 0.4, 0.6, 0.8$. Based on the definition of Pareto stability, the Pareto frontier may be reduced to a manageable size (i.e., Stable Pareto optimal solutions). MM-ACO is employed to deal with this problem. Graphical presentations of the experimental results are presented in figures (5-10) for six instances problems. It is obvious from figures (5-10) that the results maintain the diversity and convergence for all $\alpha$ cut level.
Fig. (5). Pareto optimal set for $\alpha$ cut level = 0.

Fig. (6). Pareto optimal set for $\alpha$ cut level = 0.2.

Fig. (7). Pareto optimal set for $\alpha$ cut level = 0.4.
Fig. (8). Pareto optimal set for $\alpha$ cut level = 0.6

Fig. (9). Pareto optimal set for $\alpha$ cut level = 0.8.

Fig. (10). Pareto optimal set for $\alpha$ cut level = 1.0.
Further we need to determine stable Pareto set solution, which is a Pareto optimal for all runs (different $\alpha$ cut level), there was 7 Pareto solution was detected as a stable Pareto solution. Table 3 lists the set of the stable set of optimal solution. On the basis of the application, we can conclude that the proposed method can provide a sound optimal power flow by simultaneously considering multiobjective problem.

### Table 3. The Stable optimal Pareto solutions by MM-ACO.

<table>
<thead>
<tr>
<th>Pareto index</th>
<th>$PG_1$</th>
<th>$PG_2$</th>
<th>$PG_3$</th>
<th>$PG_4$</th>
<th>$PG_5$</th>
<th>$PG_6$</th>
<th>Emission (ton/h)</th>
<th>Cost ($/h$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.2556</td>
<td>0.4041</td>
<td>0.5315</td>
<td>0.6798</td>
<td>0.5350</td>
<td>0.4271</td>
<td>0.1996</td>
<td>610.6031</td>
</tr>
<tr>
<td>2</td>
<td>0.2510</td>
<td>0.4035</td>
<td>0.5291</td>
<td>0.6827</td>
<td>0.5394</td>
<td>0.4274</td>
<td>0.1998</td>
<td>610.3254</td>
</tr>
<tr>
<td>3</td>
<td>0.2523</td>
<td>0.4023</td>
<td>0.5307</td>
<td>0.6848</td>
<td>0.5359</td>
<td>0.4272</td>
<td>0.1998</td>
<td>610.2686</td>
</tr>
<tr>
<td>4</td>
<td>0.2563</td>
<td>0.4055</td>
<td>0.5285</td>
<td>0.6743</td>
<td>0.5374</td>
<td>0.4312</td>
<td>0.1994</td>
<td>610.9785</td>
</tr>
<tr>
<td>5</td>
<td>0.2616</td>
<td>0.4079</td>
<td>0.5293</td>
<td>0.6632</td>
<td>0.5355</td>
<td>0.4355</td>
<td>0.1989</td>
<td>611.6744</td>
</tr>
<tr>
<td>6</td>
<td>0.2642</td>
<td>0.4080</td>
<td>0.5299</td>
<td>0.6594</td>
<td>0.5355</td>
<td>0.4360</td>
<td>0.1988</td>
<td>611.9128</td>
</tr>
<tr>
<td>7</td>
<td>0.2990</td>
<td>0.4336</td>
<td>0.5298</td>
<td>0.5914</td>
<td>0.5319</td>
<td>0.4476</td>
<td>0.1963</td>
<td>617.2925</td>
</tr>
</tbody>
</table>

Identifying a Satisfactory Solution

To select the best compromise solution, TOPSIS method is used. To show the effect of changing the weights on the best compromise solution, 3 cases are considered. In each case one weight is changed linearly taking 6 values. The other one are obtained using the relation $w_1 + w_2 = 1$. Tables (4) show the values of the weights in three cases. The objective functions obtained from the six solutions corresponding to the six weights are drawn versus weights for the six cases. The drawings are shown in Figures (3).

### Table 4: Different weights ($w_1$ is changed linearly)

<table>
<thead>
<tr>
<th>W2</th>
<th>W1</th>
<th>Run</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0.8</td>
<td>0.2</td>
<td>2</td>
</tr>
<tr>
<td>0.6</td>
<td>0.4</td>
<td>3</td>
</tr>
<tr>
<td>0.4</td>
<td>0.6</td>
<td>4</td>
</tr>
<tr>
<td>0.2</td>
<td>0.8</td>
<td>5</td>
</tr>
<tr>
<td>0.0</td>
<td>1.0</td>
<td>6</td>
</tr>
</tbody>
</table>
Therefore it can be said that TOPSIS method is attractive since limited subjective input (namely the weight values) is needed from the DM to get a satisfactory results from the Pareto set quickly. Also, this method can be classified as interactive approach, where the DM specifies input values according his needs.

7. CONCLUSIONS

Ant colony optimization has been and continues to be a fruitful paradigm for designing effective combinatorial optimization solution algorithms, in this paper; we proposed a new optimization system MM-ACO for solving multiobjective optimization with an application in optimal power flow considering two objective (cost and emission). Our approach has two characteristic features. Firstly, a set of nondominated solutions is obtained by exploring the optimal Pareto frontier using different $\alpha$-cut level and subsequently, based on the definition of Pareto stability, the Pareto frontier may be reduced to a manageable size (i.e., Stable Pareto optimal solutions). The main features of the proposed algorithm could be summarized as follows:

(a) The proposed technique has been effectively applied to solve the EELLD problem considering three objectives simultaneously, with the facility in handing more than two objectives.

(b) The non-dominated solutions in the obtained Pareto-optimal set are well distributed and have satisfactory diversity characteristics. This is useful in giving a reasonable freedom in choosing operating point from the available finite alternative.

(c) The proposed approach is efficient for solving nonconvex multiobjective optimization problems where multiple Pareto-optimal solutions can be found in one simulation run.
(d) This approach seems to be an interactive approach where the DM specifies the relative weights of criterion importance

(e) Simulation results verified the validity and the advantages of the proposed approach.

The performance improvement of ACO algorithm still remain in the experimental stage for lack of solid theoretical support; thus, for future work, we intend to test the algorithm on more complex real-world applications. Also, conduct research on the parallel mechanism of the ant colony optimization algorithms so that it improves the efficiency of the algorithm used in the intelligent systems.

8. REFERENCES


نظام أمثلية مستعمرة النمل الهجين لحل مشكلة السيران الأمل متعددة الأهداف ذات الطبيعة الضبابية

عبد الله عباس

الốt: ـ عبد الله موسيًـ! وقيت المطروث

قسم الرياضيات والإحصاء - كلية العلوم - جامعة الطائف
قسم العلوم الأساسية الهندسية - كلية الهندسة - جامعة الطائف
قسم الفيزياء والرياضيات الهندسية - كلية الهندسة - جامعة الطائف

(قدم لنشر: 8/13/2013م - وقيت لنشر: 9/2013م)

ملخص البحث: في هذه الورقة البحثية، يتم تقديم نظام أمثلية هجين جديد. وهذا النظام المقترح يجمع بين steady state genetic algorithm ويتنازل بإثنتين من النماذج المعروفة. أولاً، لأن هناك عدم استقرار في السوق العالمية والتنافس السريع للأسعار، تم تعريف (تقليل) لمشكلة تدفق الطاقة الأمل بصور ضبابية (غامضة)، حيث تشمل بيانات المدخلات الكثير من العوامل التي يقوم بتحديدها الخبراء. ثانياً، من خلال تجزي (تحسين) مستعمرة النمل من خلال الحوارم البيئية ذات الحالة المستقرة، تم بناء خوارزم جديد يمتاز بفترة وفاعلية عالية. أيضاً، تم الكشف عن مجموعة الحلول المستقرة "باريت" المستقرة من إجسام الحلول التي حصلنا عليها في حالات مختلفة، حيث أنه من التحديات العملية تعد تلك الحلول المستقرة ذات أهمية لأن هناك تطيات مربحة ككلية البيانات ومدى صحتها، وعلاوة على ذلك فقد تم توظيف تقنية TOPSIS لاستخراج أفضل حل توظيفي من مجموعة محدودة من البديل. وهي طريقة تعتمد مساعدة صانع القرار للاستخراج أفضل حل توظيفي من مجموعة محدودة من البديل. وهي طريقة تعتمد على تقييم المسافة من نقطة ثالثة (IP) ومعظم المسافة من نقطة ثالثة (NP). أظهرت النتائج على قدرات التهج (الطريقة) المفترضة توليد الحلول الباريتى مثالية وكذلك توزيع تلك الحلول لمشكلة تدفق الطاقة الأمل.