Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.12785/amis/080626

Best Compromise Alternative to EELD Problem using Hybrid Multiobjective Quantum Genetic Algorithm

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Received: 27 Oct. 2013, Revised: 25 Jan. 2014, Accepted: 26 Jan. 2014
Published online: 1 Nov. 2014

Abstract: A novel hybrid multiobjective quantum genetic algorithm (HM-QGA) for economic emission load dispatch (EELD) optimization problem is presented. The EELD problem is formulated as a nonlinear constrained multiobjective optimization problem with both equality and inequality constraints. HM-QGA are population based evolutionary algorithms that imitate quantum physics by introducing quantum bits for a basic probabilistic genotypic representation and hence better population diversity, and quantum gates for evolving the population of solutions. We use quantum genetic algorithm to exploits the power of quantum computing to speed up genetic algorithm procedure. We present methodology that allows the decision maker (DM) to be a partner in problem solving, where DM specifies input values (namely the weight values) according his needs. Simulation results on the standard IEEE 30-bus 6-generator test system show that the proposed algorithm outperforms other heuristic algorithms and is characterized by robustness, high success, fast convergence and excellent capability on global searching.

Keywords: Quantum computing, genetic algorithm, topsis, economic emission load dispatch

1 Introduction

Nowadays, the deregulated electricity market calls for robust economic load dispatch (ELD) tools that can reduce the costs of total generation and in same time can cope with the constraints of power system [1]. The ELD problem is a vital tool for economic operation of power system. The main target of ELD of electric power generation is to schedule the outputs of committed generating unit and to meet the load demand at a certain time at minimum operating cost while satisfying various system and generator constraints [2]. Therefore, the ELD problem is considered as a large-scale highly constrained nonlinear optimization problem.

The electricity generation by the use of fossil fuels can release several contaminants into the atmosphere. With rising concern over the environmental effect of fossil fuel and the passage of the Clean Air Act amendments of 1990, power utilities were forced to modify their operation strategies to consider a wide range of options which reduce pollution and atmospheric emissions of the thermal power plants [3]. Some strategies to reduce the atmospheric emission have been presented [4], [5]. Unfortunately, these strategies require modification of the existing equipment or installation of new equipment which involves considerable capital outlay. Therefore, the emission dispatch can be a more appropriate solution for reducing emission with respect to other methods [6]. In fact, including emission in the dispatching problem in which both emission and fuel cost is to be minimized turns the ELD problem into a multiobjective optimization problem which is more complicated rather than a single objective ELD problem. In last few years, this multiobjective optimization problem has received much attention [2].

In literature, various techniques have been addressed to environmental/economic dispatch (EELD) problem. In [7] the EELD problem has been converted to a single objective problem by treating the emission as a constraint. This method has a severe difficulty in getting the tradeoff relations between cost and emission. The quantum genetic algorithm exploits the power of quantum

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computing in order to speed up genetic algorithm procedure. A repair method is applied to repair illegal individuals. The idea of this technique is to separate any feasible individuals in a population from those that are infeasible by repairing infeasible individuals, hence more excellent individuals will appear in each evolutionary generation. Moreover to help the decision maker (DM) to extract the best compromise alternative from a finite set of alternatives, TOPSIS method is adopted.

In another research direction, the EELD problem is reduced to a single objective problem by a linear combination of different objectives as a weighted sum in which a set of non-inferior solutions can be obtained by varying the weights [8]. Unfortunately, this method has some drawbacks. It requires multiple runs equal to the desired optimal solutions. In addition, this method cannot be used to find optimal solutions if the objective functions are nonconvex or have a discontinuous-variable space [3]. Another method is presented in [9]. This method based on the ε-constraint method. This method optimizes the most preferred objective function when considering the other objectives as constraints bounded by some allowable levels (ε). The most observable drawbacks of this method are that it is time-consuming and tends to find weakly non-dominated solutions [3]. The new research direction is to handle both objective functions simultaneously. In last few years, the studies on evolutionary algorithms have shown that these algorithms can be efficiently used for solving the multi-objective optimization problems. Therefore, various papers proposed heuristic optimization algorithms to solve EELD problems.

Some of these algorithms are simulated annealing (SA) [10], genetic algorithm (GA) [11] and [12], particle swarm optimization [13,14,3], differential evolution [15], bacterial foraging [16], artificial immune system [17] and bee colony [18]. In these algorithms, multiple Pareto-optimal solutions can be found in one program run. This is due that these algorithms are population based techniques. In multi-objectives problems, the objectives are in conflict with each other, so a set of solutions can be obtained instead of one. This will lead to a difficult choice of the desired solution between them by power system decision makers [19]. One method to solve this problem is applying the fuzzy decision making method to the Pareto-optimal solution [20].

Recently, many hybrid algorithms [1,21,22,23,24] have been proposed and applied successfully to solve EELD problem. In [21] EELD problem is solved by using particle swarm optimization based on differential evolution (IMOPSO-DE) algorithm. In [22] an integrated approach combining an evolutionary programming based fuzzy coordination and an artificial neural network method along with a heuristic rule based search algorithm is proposed and applied to solve the multi-objective generation problem. Shubham et al. [24] applied particle swarm algorithm with fuzzy clustering algorithm to solve the multi-objective electric power dispatch with success. Zhou, et al [1] proposed a novel multiple group search optimizer (MGSO) to solve the highly constrained multiobjective power dispatch problem. An improved multi objective Interactive Honey Bee Mating Optimization (IHBMO) is proposed in [23] to find the feasible optimal solution of the Environmental/Economic Power Dispatch problem with considering operational constraints of the generators.

Enhancing genetic algorithm with Quantum computing [25]-[32] is adopted in this paper, the calculation of which is to borrow fully the concept and theory of Quantum computing (such as quantum bit and superposition of states of quantum mechanics) on top of the genetic algorithm. It uses quantum-bit to encode individual chromosome. What advantage is there to let the quantum-chromosome be evolved? Quantum chromosome is generated using quantum encoding. Because the quantum probability amplitude means that a quantum chromosome carries information about multiple states, a chromo-some will be in a quantum superposition state of many determined states before we make observation on it. Genetic algorithm with the qubit representation has a better characteristic of diversity than classical approaches, since it can represent superposition of states. And so it can bring a richer population than the simplistic application of genetic method. Also, it is quite easy to induce mutations with the in-formation of current best individual object so that the population will evolve toward a good schema with high probability to speed up the procedure convergence and, at the same time, prevent it from be-ing trapped in a local optimal solution effectively and prevent the premature phenomenon from occur-ring.

The paper is organized as follows: Section 2 reviews the economic emission load dispatch problem The multiobjective optimization is introduced in Section 3. Section 4 presents the hybrid multiobjective quantum algorithm HM-QGA. Experimental results and comparisons with other methods are presented in Section 5. Finally, Section 6 concludes the work.

2 Economic emission load dispatch (EELD)

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

2.1 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 [33] and [34]:

$$f_1(x) = C = \sum_{i=1}^{n} C_i(P_{Gi}) = \sum_{i=1}^{n} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \$/hr \quad (1)$$

where C is the total fuel cost ($\$/hr$), C_i is the fuel cost of generator i, a_i,b_i,c_i are the fuel cost coefficients of generator i, P_{Gi} is the power generated by generator i in p.u and n is the number of generators.

Emission objective. The emission function can be presented as the sum of all types of emission considered, such as NO_x, NO_2, 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 in ton/hr is given as a function of generator output, that is, the sum of a quadratic and exponential function:

$$f_2(x) = E_{NO_x} = \sum_{i=1}^{n} [10^{-2}(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) + \xi_i \exp(\lambda_i P_{Gi})] \quad (2)$$

where, $\alpha_i, \beta_i, \gamma_i, \xi_i, \lambda_i$ are the coefficients of the i^{th} generator's NO_x emission characteristic.

2.2 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.

$$\sum_{i=1}^{n} P_{Gi} - P_D - P_{Loss} = 0 \quad (3)$$

where P_D is the total load demand in p.u. and P_{loss} is the transmission losses in p.u.
The transmission losses are given by [35] and [36]:

$$P_{Loss} = \sum_{i=1}^{n_1} \sum_{j=1}^{n_1} [A_{ij}(P_i P_j + Q_i Q_j) + B_{ij}(Q_i P_j - P_i Q_j)] \quad (4)$$

And

$$P_i = P_{Gi} - P_{Di}, \quad Q_i = Q_{Gi} - Q_{Di}$$

$$A_{ij} = \frac{R_{ij}}{V_i V_j} \cos(\delta_i - \delta_j), \quad B_{ij} = \frac{R_{ij}}{V_i V_j} \sin(\delta_i - \delta_j)$$

where n_1 is number of buses, R_{ij} is series resistance connecting buses i and j, V_i is voltage magnitude at bus i, δ_i is voltage angle at bus i, P_i is real power injection at bus i and Q_i is 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.,

$$P_{Gi_{min}} \leq P_{Gi} \leq P_{Gi_{max}}.$$

Where $P_{Gi_{min}}$ and $P_{Gi_{max}}$ are the minimum and maximum power generated by generator i, respectively. Similarly,

$$Q_{Gi_{min}} \leq Q_{Gi} \leq Q_{Gi_{max}}, \quad V_{i_{min}} \leq V_i \leq V_{i_{max}}.$$

– **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 decision maker (DM). An improvement in the security can be obtained by minimizing the following objective function.

$$S = f(P_{Gi}) = \sum_{j=1}^{k} (|T_j(P_G)|/T_j^{max}) \quad (5)$$

Where, $T_j(P_G)$ is the real power flow, T_j^{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_{Gs}, by utilizing the generalized generation distribution factors (GGDF) [37] and [38] and is given below.

$$T_j(P_G) = \sum_{i=1}^{n} (D_{ji} P_{Gi}) \quad (6)$$

where, D_{ji} is the generalized GGDF for line j, due to generator i
For secure operation, the transmission line loading S_l is restricted by its upper limit as:

$$S_l \leq S_{l\ max}, \quad l = 1, \ldots, n_l$$

where n_l is the number of transmission lines.

3 Multiobjective optimization

Multiobjective optimization is the process of simultaneously optimizing two or more conflicting objectives subject to certain constraints. In many real world problems, there are situations where multiple objectives may be more appropriate rather than considering single objective. However, in such cases emphasis is on efficient solutions, which are optimal in a certain multiobjective sense [39]. Multi-objective optimization differs from the single objective case in several ways:

– The usual meaning of the optimum makes no sense in the multiple objective case because the solution optimizing all objectives simultaneously is, in general, impractical; instead, a search is launched for a feasible solution yielding the best compromise among objectives on a set of, so called, efficient solutions;
– The identification of a best compromise solution requires taking into account the preferences expressed by the decision-maker;
– The multiple objectives encountered in real-life problems are often mathematical functions of contrasting forms.
– A key element of a goal programming model is the achievement function; that is, the function that measures the degree of minimization of the unwanted deviation variables of the goals considered in the model.

A general multiobjective optimization (MOP) problem is expressed by: MOP:

$$\min \quad F(x) = (f_1(x), f_2(x), ..., f_m(x))^T \tag{7}$$

$$\text{subject to} \begin{cases} x \in S \\ x = (x_1, x_2, ..., x_n)^T \end{cases}$$

where $(f_1(x), f_2(x), ..., f_m(x))$ are the m objectives functions, $(x_1, x_2, ..., x_n)$ are the n optimization parameters, and $S \in R^n$ is the solution or parameter space. In real-world MOPs that usually involve conflicting objectives, there is no unique optimum, but rather a set of compromised solutions known as Pareto optimal solutions or non-dominated solutions [40] and [41]. These solutions distribute on the edge of the feasible region, showing the trade-off information between the conflicting objectives. **Definition 1.** (Pareto optimal solution): x^* is said to be a Pareto optimal solution of MOP if there exists no other feasible x (i.e., $x \in S$) such that $f_j(x) \leq f_j(x^*)$, for all $j = 1, 2, ..., m$ and $f_j(x) < f_j(x^*)$ for at least one objective function f_j.

4 Hybrid multiobjective quantum genetic algorithm (HM-QGA)

The purpose of this section is to informally describe the problem we are dealing with. To this end, let us first give a template for a large class of iterative search procedures which are characterized by the generation of a sequence of search points and a finite memory.

An abstract description of a generic iterative search algorithm is given in Figure 1. The integer t denotes the iteration count, the n-dimensional vector $f^{(t)} \in \mathbf{F}$ is the sample generated at iteration t and the set $\mathbf{A}^{(t)}$ will be called the archive at iteration t and should contain a representative subset of the samples in the objective space $\mathbf{F}$ generated so far. To simplify the notation, the samples are represented by n-dimensional real vectors f where each coordinate represents one of the objective values (Figure 2).

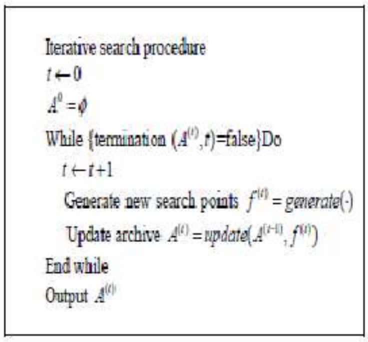

Fig. 1: Pseudo code of iterative search procedure.

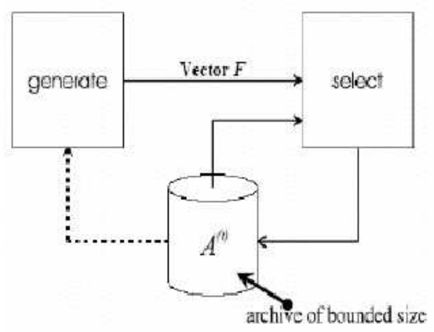

Fig. 2: Block diagram of Archive/selection strategy.

HM-QGA is based on the concepts of qubits and superposition of states of quantum mechanics. The smallest unit of information stored in a two- state quantum computer is called a quantum bit or qubit [42]-[45]. A qubit may be in the '1' state, in the '0' state, or in any superposition of the two. The state of a qubit can be represented as:

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{8}$$

Where α and β are complex numbers that specify the probability amplitudes of the corresponding states. $|\alpha|^2$ gives the probability that the qubit will be found in '0' state and $|\beta|^2$ gives the probability that the qubit will be found in '1' state. Normalization of the state to unity guarantees

$$|\alpha|^2 + |\beta|^2 = 1 \tag{9}$$

If there is a system of m-qubits, the system can represent 2^m states at the same time. However, in the act of observing a quantum gate, it collapses to a single state [42].

4.1 Representation

It is possible to use a number of different representations to encode the solutions onto chromosomes in evolutionary computation. The classical representations can be broadly classified as: binary, numeric, and symbolic [42]. HM-QGA uses a novel representation that is based on the concept of qubits. One qubit is defined with a pair of complex numbers, (α, β) as:

$$\begin{bmatrix} \alpha \\ \beta \end{bmatrix} \tag{10}$$

which is characterized by (8) and (9). And an m-qubits representation is defined as:

$$\left[\begin{array}{c|c|c|c} \alpha_1 & \alpha_2 & ..... & \alpha_m \\ \beta_1 & \beta_2 & ..... & \beta_m \end{array} \right] \tag{11}$$

where $|\alpha|^2 + |\beta|^2 = 1$, $i = 1, 2, \ldots, m$. This representation has the advantage that it is able to represent any superposition of states. If there is, for instance, a three-qubits system with three pairs of amplitudes such as:

$$\left[\begin{array}{c|c|c} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{3}} & \frac{1}{2} \\ \frac{1}{\sqrt{2}} & \sqrt{\frac{2}{3}} & \frac{\sqrt{3}}{2} \end{array} \right] \tag{12}$$

the state of the system can be represented as:

$$\frac{1}{2\sqrt{6}}|000\rangle + \frac{1}{2\sqrt{2}}|001\rangle + \frac{1}{2\sqrt{3}}|010\rangle + \frac{1}{2}|011\rangle + \frac{1}{2\sqrt{6}}|100\rangle + \frac{1}{2\sqrt{2}}|101\rangle + \frac{1}{2\sqrt{3}}|110\rangle + \frac{1}{2}|111\rangle \tag{13}$$

Note that the square of the above numbers are true probabilities, i.e., the above result means that the probabilities to represent the state $|000\rangle, |001\rangle, |100\rangle$ and $|010\rangle$ are $\frac{1}{24}, \frac{1}{8}, \frac{1}{24}$ and $\frac{1}{2}$, respectively. Consequently, the three-qubits system (12) has eight states information at the same time. Genetic algorithm with the qubit representation has a better characteristic of diversity than classical approaches, since it can represent superposition of states. Only one qubit chromosome such as (11) is enough to represent eight states, but in classical representation at least four chromosomes (000),(001),(100), and (101)) are needed. Convergence can be also obtained with the qubit representation. As $|\alpha|^2$ or $|\beta|^2$ approaches to 1 or 0. The qubit chromosome converges to a single state and the property of diversity disappears gradually. That is, the qubit representation is able to possess the two characteristics of exploration and exploitation, simultaneously. Population representation is a kind of data structure which represents the candidate solution of the problem in coding space. In order to form the appropriate design of individual using proposed algorithm, first consider that each individual consists of a sequence of m pairs of complex numbers, (α, β) (m is the length of m-qubit). Figure 3 illustrates the population structure by showing each individual armature.

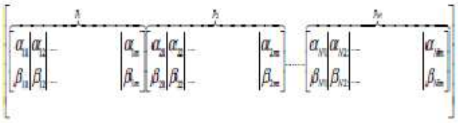

Fig. 3: Population structure.

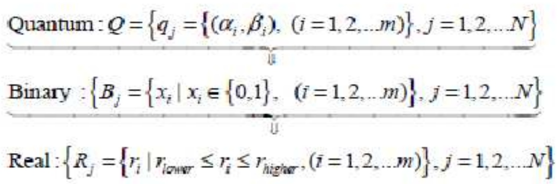

Fig. 4: The Evaluation process.

The length of m-qubit depends on the required precision (number of decimal places). Suppose that each variable x_i can take values from the domain $D_i = [a_i, b_i] \subseteq R$: suppose Q decimal places for the variables values is desirable. It is clear to achieve such precision each domain D_i should be cut into $(b_i - a_i).\ 10^Q$ equal size ranges. Let m_i be the smallest integer such that $(b_i - a_i).\ 10^Q \le 2^{m_i} - 1$

4.2 Evaluation

Binary string with length m is firstly constructed according to the probability amplitudes of individual $p_i (i = 1, 2, \ldots, N)$ with Q-bit representation as follows: For every bit $x_i (i = 1, 2, \ldots, m)$ of the string X, first generate a random number $\eta \in [0, 1]$. Second, transform the binary string to a real number vector R with every element in corresponding interval. Evaluation process is illustrated in Figure 4 and the pseudo code of evaluation algorithm is declared in Figure 5. Then a representation having each variable x_i coded as a binary string b_i of length m_i additionally, the following formula interprets each such string $r_i = a_i + decimal(1001....001_2).(b_i - a_i)/(2^{m_i} - 1)$.

4.3 Selection operator

Since our goal is to find new nondominated solutions, one simple way to combine multiple objective functions into a scalar fitness function [40]is the following weighted sum approach:

$$f(r) = w_1 f_1(r) + w_2 f_2(r) + \ldots + w_m f_m(r) = \sum_{j=1}^{m} w_i f_i(r) \tag{14}$$

```
Input p_i, i = 1,2,...N
 NV = number of variables
 i ← 1
While (i ≤ N) do
   Begin
  j ← 1
        While (j < m) do
        j ← j+1
        generate a random number η ∈ [0,1]
        If η > |α_i|^2
        Then x_i ← 1
        Else x_i ← 0
        End
  Transfom binary string X_i = {x_ij : (j = 1,2,...m)} to real number vector r_i
  i ← i+1
   End
  End
  Output R = {r_ij : i = 1,2,...NIND, j = 1,2,...NV}
```

Fig. 5: The pseudo code of evaluation algorithm.

Where r is a real string that represents each individual, $f(r)$ is a combined fitness function, $f_i(r)$ is the i-th objective function. When a pair of strings is selected for a crossover operation, we assign a random number to each weight as follows.

$$w_i = \frac{\text{random}_i(.)}{\sum_{j=1}^{m} \text{random}_j(.)} \qquad i = 1,2,\ldots,m \tag{15}$$

Calculate the fitness value of each string using the random weights w_i. Select a pair of strings from the current population according to the following selection probability $\beta(x)$ of a string x in the population P^t.

$$\beta(x) = \frac{f(x) - f_{min}(P^{(t)})}{\sum_{x\in P^{(t)}}\{f(x) - f_{min}(P^{(t)})\}} \tag{16}$$

where $f_{min}(P^{(t)}) = \min\{f(x)|x \in P^{(t)}\}$

This step is repeated for selecting $|p|/2$ pairs of strings from the current populations. For each selected pair apply crossover operation to generate two new strings, for each strings generated by crossover operation, apply a mutation operator with a prespecified mutation probability.

4.4 Crossover operation

One point crossover is implemented for Q-bit, which is illustrated as follows. In particular, one crossover position is randomly determined (e.g. position i), and then the Q-bits of the parents before position i are reserved while the Q-bits after position i are exchanged, which shown in Figure 6.

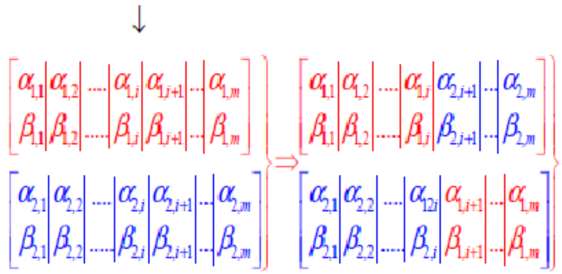

Fig. 6: Crossover operator.

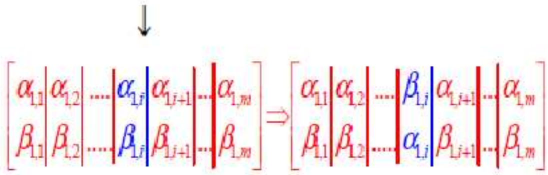

Fig. 7: Mutation operator.

4.5 Mutation operator

Mutation operator is done by randomly one position is selected (e.g. position i), and then the corresponding and are exchanged, which shown in Figure 7.

4.6 Rotation gate for Q-bit

A qubit chromosome Q_i is updated by using the rotation gate [46]:

$$U(\theta) = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \tag{17}$$

In such a way that the i-th qubit value (α_i, β_i) is updated as:

$$\begin{bmatrix} \alpha_i' \\ \beta_i' \end{bmatrix} = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \tag{18}$$

Where θ_i is the rotation angle. $\theta_i = s(\alpha_i, \beta_i)\Delta\theta_i$ where $s(\alpha_i, \beta_i)$ is the sign of θ_i that determines the direction, $\Delta\theta_i$ is the magnitude of rotation angle whose lookup table is shown in Table 1. In Table 1, b_i and r_i are the i-th bits of the best solution and the binary solution respectively. Here $f(.)$ is the fitness function given by (14)

The value of $\Delta\theta_i$ has an effect on the speed of convergence, but if it is too big the solution may diverge to a local optimum. The sign $s(\alpha_i, \beta_i$ determines the direction of convergence to a global optimum. The lookup table can be used as strategy for convergence this update procedure can be described as follows. The following pseudo in Figure 8, described the quantum updating procedure

Table 1: Lookup table is shown where b_i and r_i are the i-th bits of the best solution and the binary solution respectively.

r_i	b_i	$f(R) \geq f(B)$	$\Delta\theta_i$	$s(\alpha_i, \beta_i)$			
				$\alpha_i\beta_i > 0$	$\alpha_i\beta_i < 0$	$\alpha_i = 0$	$\beta_i = 0$
0	0	false	0	0	0	0	0
0	0	true	0	0	0	0	0
0	1	false	0	0	0	0	0
0	1	true	0.05π	-1	+1	± 1	0
1	0	false	0.01π	-1	+1	± 1	0
1	0	true	0.025π	+1	-1	0	± 1
1	1	false	0.005π	+1	-1	0	± 1
1	1	true	0.025π	+1	-1	0	± 1

Procedure update
($Q_j = \{q_i = (\alpha_i, \beta_i) : (i = 1, 2, \dots m)\}, j = 1, 2, \dots N$)
Begin
$i \leftarrow 0$
While $(i < m)$ do
$i \leftarrow i + 1$
Determine θ_i with the lookup table
Obtain (α'_i, β'_i) as
$[\alpha'_i, \beta'_i]^T = U(\theta_i)[\alpha_i, \beta_i]^T$
End
$q \leftarrow q'$
End

Fig. 8: The pseudo of update procedure.

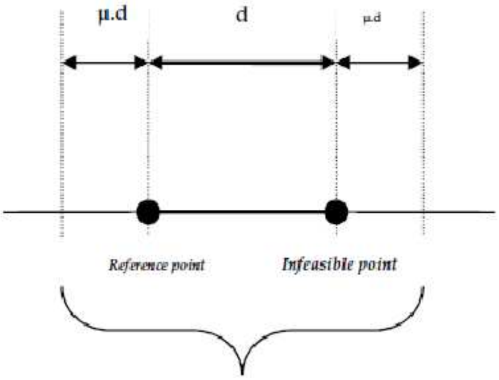

Fig. 9: Possible sampling region.

4.7 Repair procedure

Constraint handing techniques for evolutionary algorithms can be grouped into few categories [46]. One way is to generate solutions without considering the constraints then penalize them in the fitness function, this method have been used in many previous published work. Another category is based on the use of special mapping (decodes) which guarantee the generation of feasible solution or the use of problem specific operators which preserve the feasibility of the solution. The third category concentrates on the application of special repair algorithm to correct any infeasible solution so generated. The idea of this technique is to separate any feasible individuals in a population from those that are infeasible by repairing infeasible individuals. In this approach, feasible individuals (z) are generated on a segment defined by two points feasible individuals (i.e., initial reference point $\xi(t) \in F$) and infeasible individuals (w). But the segment may be extended equally on both sides determined by a user specified parameter μ. Thus, a new feasible individual is expressed as:

$$z_1 = \gamma.w + (1-\gamma).\zeta(t), \quad z_2 = (1-\gamma).w + \gamma.\zeta(t) \quad (19)$$

Where $\gamma = (1+2\mu)\delta - \mu$ and $\delta \in [0,1]$ is a random generated number. Figure **??** gives schematic view of possible sampling region. The interested reader is referred to [36] for further information. The pseudo code is presented in Figure 10. By using this function all individual are in the feasible space.

4.8 Archive updating

The size of archive, archive_size, can be adjusted according to the desired number of individuals to be distributed on the tradeoffs in the objective domain. The archive will be updated once a complete candidate solutions is formed. The idea is that ”*new solutions are only accepted in the archive if they are not dominated by any other element of the current archive*”. If a solution is accepted, all dominated solutions is removed. Pseudo code of the Archive updating are declared in Figure 11, where $a > b$ denoted that a dominate b.

Procedure Update
($Q_j = \{q_i = (\alpha_i, \beta_i) : (i = 1, 2, \ldots m)\}, j = 1, 2, \ldots N$)
Begin
$i \leftarrow 0$
While (q is infeasible) **do**
$i \leftarrow i+1$
Create new individual
$q_i = \gamma.\omega + (1-\gamma).\zeta(t)$,
If $q_i = \gamma.\omega + (1-\gamma).\zeta(t)$ is feasibile,
Continue.
Else
$q_i = (1-\gamma).\omega + \gamma.\zeta(t)$
End
Check feasibility
End
$q \leftarrow q'$
End

Fig. 10: The pseudo code of repair algorithm.

HM- QGA procedure
$t \leftarrow 0$
$A^0 \leftarrow \phi$
Create quantum population
$Q^0 = \{Q_j, j = 1, 2, \ldots N\} = \{\{q_i = (\alpha_i, \beta_i) \mid |\alpha_i|^2 + |\beta_i|^2 = 1, (i = 1, 2, \ldots m)\}, j = 1, 2, \ldots N\}$
While {termination (A^t, t) = false} Do
$t \leftarrow t+1$
Selection
Xover
Mutation
Evaluation: Quantum: $\{q_j\} \Rightarrow$ Binary: $\{B_j\} \Rightarrow$ Real: $\{R_j\}, j = 1, 2, \ldots N$
Archive update $A^{t+1} = U(A^t, R)$
Quantum Update
$Q^t = \{\{(\alpha_i, \beta_i) \mid [\alpha_i^t, \beta_i^t]^T = U(\theta_i)[\alpha_i, \beta_i]^T, (i = 1, 2, \ldots m)\}, j = 1, 2, \ldots N\}$
Evaluation: Quantum: $\{q_j\} \Rightarrow$ Binary: $\{B_j\} \Rightarrow$ Real: $\{R_j\}, j = 1, 2, \ldots N$
Archive update $A^{t+1} = U(A^t, R)$
End while

Fig. 12: The pseudo code of the proposed HM-QGA.

Input: Current archive A, new solution x
If $\{\exists x' \in A \mid x' \succ x\}$ *Do*
$A' \leftarrow A$
Else
$D = \{x' \in A \mid x \succ x'\}$
$A' = A \cup \{x\} \setminus D$
End
Output: A'

Fig. 11: Pseudo code of the Archive updating $A^{t+1}U(A^t, R)$.

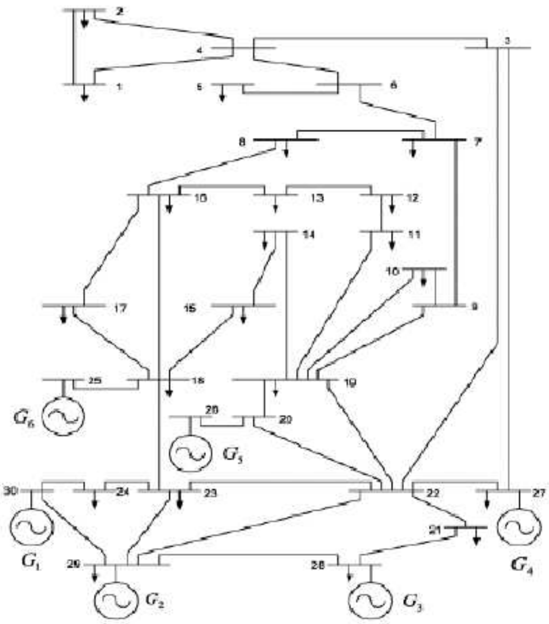

Fig. 13: Single line diagram of IEEE 30-bus 6-generator test system.

The pseudo code of the proposed algorithm is shown in Figure 12.

5 Implementation of the proposed approach

The described methodology is applied to the standard IEEE 30-bus 6-generator test system to investigate the effectiveness of the proposed algorithm. The single-line diagram of this system is shown in Figure 13 and the detailed data are given in [37] and [47]. The values of fuel cost and emission coefficients are given in Table 2. The techniques used in this study were developed and implemented on 1.7-MHz PC using MATLAB environment. Table 3 lists the parameter setting used in the algorithm for all runs.

5.1 Results and discussions

Figure 14 shows well-distributed Pareto optimal nondominated solutions obtained by the proposed algorithm after 200 generations.

Tables 4 and 5 show the best fuel cost and best emission obtained by proposed algorithm as compared to Nondominated Sorting Genetic Algorithm (NSGA) [48], Niched Pareto Genetic Algorithm (NPGA) [49], Strength

Table 2: Generator cost and emission coefficients.

		G1	G2	G3	G4	G5	G6
Cost	a	10	10	20	10	20	10
	b	200	150	180	100	180	150
	c	100	120	40	60	40	100
Emission	α	4.091	2.543	4.258	5.426	4.258	6.131
	β	-5.554	-6.047	-5.094	-3.550	-5.094	-5.555
	γ	6.490	4.638	4.586	3.380	4.586	5.151
	ζ	$2.0E-4$	$5.0E-4$	$1.0E-6$	$2.0E-3$	$1.0E-6$	$1.0E-5$
	λ	2.857	3.333	8.000	2.000	8.000	6.667

Table 3: GA parameters.

Population size (N)	50
Length of qubit m	14
No. of Generation	200
Crossover probability	0.90
Mutation probability	0.02
Selection operator	Dynamic selection
Crossover operator	Single point Crossover
Mutation operator	Single base substitution

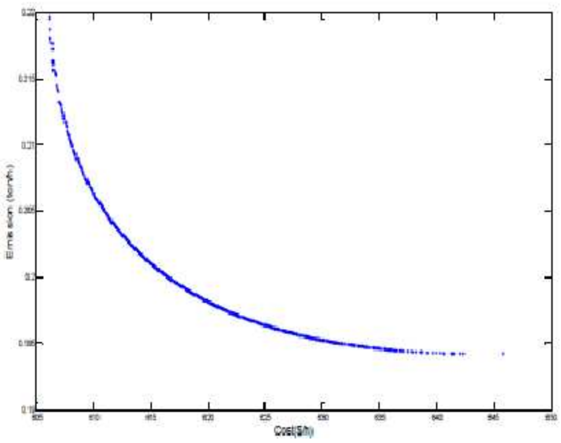

Fig. 14: Pareto-optimal front of the proposed approach.

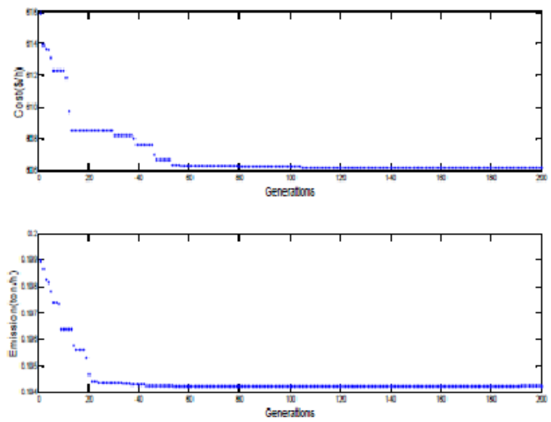

Fig. 15: Convergence of cost and emission objectives.

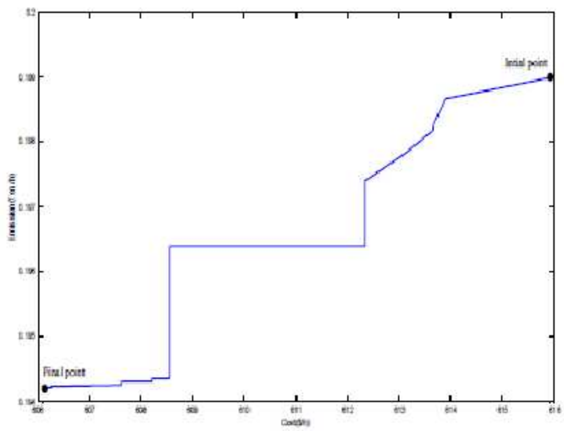

Fig. 16: Convergence of best compromise solution.

Pareto Evolutionary Algorithm (SPEA) [50], modified bacterial foraging algorithm MBFA [51], fuzzy clustering based particle swarm optimization (FCPSO) [52] and ε-dominance based evolutionary algorithm [34]. It can be deduced that the proposed algorithm finds comparable minimum fuel cost to the six evolutionary algorithms. Also it finds comparable minimum NO_x emission to the first five evolutionary algorithms, where ε-dominance approach finds minimum NO_x emission than our approach.

Convergence of fuel cost and emission objective functions are shown in Figure 15. Also, Figure 16 shows the convergence of best compromise solutions through the algorithm proceeding.

Table 4: Best fuel cost.

	NSGA [48]	NPGA [49]	SPEA [50]	MBFA [51]	FCPSO [52]	ε-dominance [34]	Proposed algorithm
P_{G1}	0.1168	0.1245	0.1086	0.1141	0.1130	0.1739	0.0741
P_{G2}	0.3165	0.2792	0.3056	0.3108	0.3145	0.3578	0.3026
P_{G3}	0.5441	0.6284	0.5818	0.5994	0.5826	0.5311	0.5452
P_{G4}	0.9447	1.0264	0.9846	0.9816	0.9860	0.9790	0.9456
P_{G5}	0.5498	0.4693	0.5288	0.5048	0.5264	0.4429	0.5975
P_{G6}	0.3964	0.39993	0.3584	0.3559	0.3450	0.3725	0.3482
Best Cost	**608.245**	**608.147**	**607.807**	**607.67**	**607.786**	**606.4533**	**606.1427**
Corresponding Emission	0.21664	0.22364	0.22015	0.2198	0.2201	0.2028	0.2197

Table 5: Best NO_x Emission.

	NSGA [48]	NPGA [49]	SPEA [50]	MBFA [51]	FCPSO [52]	ε-dominance [34]	Proposed algorithm
P_{G1}	0.4113	0.3923	0.4043	0.4055	0.4063	0.3885	0.4075
P_{G2}	0.4591	0.4700	0.4525	0.4609	0.4586	0.4984	0.4529
P_{G3}	0.5117	0.5565	0.5525	0.5444	0.5510	0.5167	0.5423
P_{G4}	0.3724	0.3695	0.4079	0.3986	0.4084	0.4502	0.3784
P_{G5}	0.5810	0.5599	0.5468	0.5440	0.5432	0.5205	0.5290
P_{G6}	0.5304	0.5163	0.5005	0.5134	0.4974	0.5005	0.5116
Best Emission	**0.1943**	**0.1942**	**0.1942**	**0.1942**	**0.1942**	**0.1882**	**0.1942**
Corresponding Cost	647.2510	645.9840	642.6030	**644.4300**	**642.8964**	642.8976	654.7809

5.2 Identifying a satisfactory operation point

For this practical application, we need to select one alternative, which will satisfy the different goals to some extent, such a solution is called best compromise solution. Or if there is a tax or penalty for exceeding the pollution limitations which controlled using environmental protection rules, or the generating cost must not exceeds allowable limitation. Optimization of the above-formulated problem using evolutionary based approaches yields not a single optimal solution, but a set of Pareto optimal solutions; however, we need to select one operating point, which will satisfy the different goals to some extent. Such a solution is called best compromise solution. TOPSIS method given by Yoon and Hwang [53] and [54] 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} $(i = 1,\ldots,n \text{and} j = 1,\ldots,M)$
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.

$$V_{ij} = w_j r_{ij} \tag{20}$$

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

$$\begin{aligned} S^+ &= \{v_1^+, v_2^+, \ldots, v_j^+, \ldots, v_m^+\} = \\ &= \{(\max v_{ij} | j \in J_1), (\min v_{ij} | j \in J_2), i = 1,..,n\} \end{aligned} \tag{21}$$

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^-

$$\begin{aligned} S^- &= \{v_1^-, v_2^-, \ldots, v_j^-, \ldots, v_m^-\} = \\ &= \{(\min v_{ij} | j \in J_1), (\max v_{ij} | j \in J_2), i = 1,..,n\} \end{aligned} \tag{22}$$

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

$$D_i^+ = \sqrt{\sum_j (v_{ij} - v_j^+)^2}, \qquad D_i^- = \sqrt{\sum_j (v_{ij} - v_j^-)^2} \tag{23}$$

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,

$$R = \frac{D^-}{D^- + D^+} \tag{24}$$

8. Rank alternative according to ratio R (in Step 7) in descending order.
9. Recommend the alternative with the maximum ratio.

Therefore it can be said that TOPSIS method is attractive since limited subjective input (namely the weight values which reflect the degree of satisfactory of each objective) 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. Here, DM plays an important role. The DM is expected to be an expert in the problem domain. The effect of changing the weights on the fuel cost and emission was studied. In each case one weight is changed linearly, and the other weight are generated in such a way that $w_1 + w_2 = 1$. In contrast, we observed the weights and the corresponding values of values of $f_1(.), f_2(.)$ to conclude best compromise operating point. In each case one weight is changed linearly taking 11 values as in Table 6, consequently the obtained solutions corresponding to these weights are drawn versus weights. The drawings are shown in Figure 17. From Figure 17 the following points may be concluded:

1. Depending on the user defined weights, one operation point has been selected.
2. The proposed algorithm has the ability to identify the best operating point from a finite set of alternatives quickly.
3. The proposed algorithm can identify best compromise solution, which will satisfy the different goals, given by the DM.
4. Increasing w_1 causing in approximately linearly decreasing in the cost function $f_1(.)$.
5. Increasing w_1 causing in approximately exponentially growth the Emission function $f_2(.)$.
6. The change of the cost corresponding to values of $w_1 < 0.6$ is approximately linearly increasing.

TOPSIS method has the ability to identify the best alternative from a finite set of alternatives quickly. it can incorporate relative weights of criterion importance according decision maker preference and environmental protection rules. Here, DM plays an important role. The DM is expected to be an expert in the problem domain.

Table 6: Different weights (w_1 is changed linearly).

Run	w_1	w_2
1	0.0	1.0
2	0.1	0.9
3	0.2	0.8
4	0.3	0.7
5	0.4	0.6
6	0.5	0.5
7	0.6	0.4
8	0.7	0.3
9	0.8	0.2
10	0.9	0.1
11	1.0	0.0

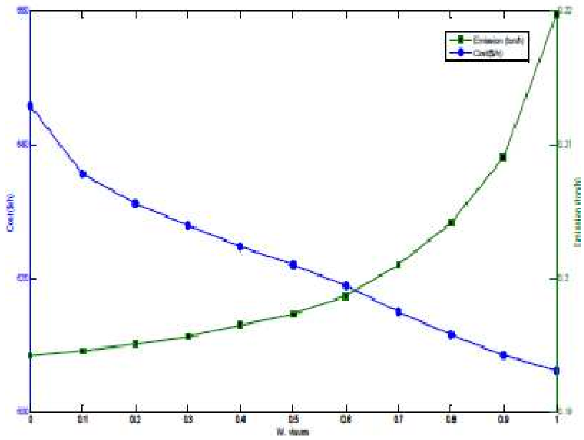

Fig. 17: Best compromise solution for different weights for cut level =0.

Comparative study has been carried out to assess the proposed approach concerning large size of the Pareto set, DM preference and computational time. On the first hand, evolutionary techniques suffer from the large size of the Pareto set, where the DM must identify one alternative solution. Therefore the proposed approach has been used to identify best compromise alternative form the finite Pareto set, which take the DM preference into consideration. On the other hand, classical techniques aim to give single point for each problem solving, which need to apply the method again and again to get another solution. Accordingly to DM preference, one single point has been selected. Accordingly it provides the facility to save computing time. Another advantage is that the simulation results prove superiority of the proposed approach to those reported in the literature.

6 Conclusions

The proposed algorithm in this paper was applied to economic emission load dispatch optimization problem formulated as multiobjective optimization problem with competing fuel cost, and emission. Optimization of EELD problem using evolutionary based approaches yields not a single optimal solution, but a set of Pareto optimal solutions; however, we need to select one operating point, which will satisfy the different goals to some extent. Such a solution is called best compromise solution. Consequently, TOPSIS method can incorporate the DM preference in the optimization process to identify such compromise solution. Also, this combination demonstrate how, instead of a Pareto set, a preferred can be found which give the ability to DM to select one operating point according to relative criterion importance. The main features of the proposed algorithm could be summarized as follows.

1. The proposed technique has been effectively applied to solve the EELD considering two objectives simultaneously, with no limitation in handing more than two objectives.
2. The proposed approach is efficient for solving nonconvex multiobjective optimization problems where multiple Pareto-optimal solutions can be found in one simulation run.
3. The trade-off 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.
4. With a number of trade-off solutions in the region of interests we have argued that the decision-maker would be able to make a better and more reliable decision using TOPSIS technique, without applying the method again and again.
5. Such methodology allows the DM to be a partner in problem solving, where the DM specifies input values (namely the weight values) according his needs.
6. On the basis of the application, we can conclude that the proposed method can provide a sound optimal power flow by simultaneously considering conflicting multiobjective functions.

This work may be very valuable for on-line operation of power systems when environmental constraints are also need to be considered. In addition to on-line operation, this work can be a part of an off-line planning tool when there are hard limits on how much emission is acceptable by a utility over a period of a month or a year. So, for future work, we intend to test the algorithm on more complex real-world applications.

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