APPLICATION OF MULTI-OBJECTIVE GENETIC ALGORITHM FOR SOLVING OPTIMAL POWER FLOW PROBLEM

Saket Gupta[1], Laxmi Srivastava[2]

Department of Electrical Engineering MITS, Gwalior, (India)

ABSTRACT

This paper presentsmulti-objective genetic algorithm for solving the optimal power flow (OPF) problem. The proposed method is employed for optimal adjustment of the power system control variables which involve continuous variables of the OPF problem namely active power generation at the PV buses except at the slack bus, voltage magnitude at PV buses, tap settings of transformer and shunt VAR compensation. Solution of multi-objective optimization problem providesa number of trade-off solutions. The decision maker has an option to choose a solution among the different trade-off solutions provided in the Pareto-optimal front.The proposed method is tested in standard IEEE 30-bus test system with different objective such as fuel cost minimization, voltage stability enhancement and transmission losses minimization. The numerical results clearly show that the proposed method is capable to produce true and well distributed Pareto-optimal solutions for multi-objective OPF problem.

Keywords*: *Multi-Objective Genetic Algorithm, Multi-Objective Optimization, Optimal Power Flow,Pareto-Optimal Front.

I. INTRODUCTION

The concept of the optimal power flow (OPF) was first proposed by Carpenters [1] in the early 1960's based on the economic dispatch problem. Optimal Power Flow problem is one of the fundamental issues of power system operation, designed and planning. The main purpose of an OPF algorithm is to find steady state operation point which minimizes objective function, while satisfying various operating constraints [2].

Early, several conventional optimization techniques where apply to solve OPF problem such as linear programming (LP), quadratic programming (QP), nonlinear programming (NPL), Mixed Integer Programming (MIP), interior point method (IP) and Newton-based method. Generally, most of these approaches have been applied to solve OPF problem assuming convex, analytic, differentiable and linear. But unfortunately, OPF problem is a highly non-linear and a multi-modal optimization problem, i.e. there exist more than one local optimum. Hence, conventional optimization techniques are not suitable for such a problem and conventional optimization methods that make use of derivatives and gradients are in general not able to locate or identify the global optimum [3]. Hence, it becomes essential to develop optimization techniques that are able to overcome these drawbacks and handling such difficulties. Complex constrained optimization problems have been solved by many evolutionary computational optimization techniques in the recent years. These techniques have been successfully applied to non-convex, non-smooth and non-differentiable optimization problems. Some of the set echniquesare genetic algorithm, simulated annealing, particle swarm optimization (PSO), evolutionary programming, hybrid evolutionary programming (HEP), chaotic ant swarm optimization (CASO), Bacteria foraging optimization (BFO), Teaching-Learning-Based Optimization (TLBO) [4, 5].

Genetic algorithm was first introduced based on Darwin's principle of evolution. GA is random search algorithms based on the principles of genetic variation and natural selection and is considered to offer a high probability of finding the global or near global optimum solution of difficult optimization problems. GA combine solution evaluation with stochastic genetic operator namely, selection, crossover and mutation to obtain near optimality. An optimization problemtreats simultaneously more than one objective function is called as multi-objective optimization problem. Multi-objective GAis an extension of classical GA. The main difference between a conventional GA and Multi-Objective Genetic Algorithm (MOGA) lies in the fitness assignment to an individual. The rest of algorithm issame as that in a classical GA.

The main aim of this paper is to apply the MOGA to solve the OPF problem.Multi-Objective Genetic Algorithm produces multiple solutions in one single simulation run for solving a multi-objective optimization problem. Genetic Algorithm toolbox of matlab has been used for solving Multi-Objectiveoptimal power flow(MO-OPF) problem.

II. PROBLEM FORMULATION

The main objective of OPF problem solution is to optimize a selected objective function such as fuel cost minimization, voltage stability enhancement and transmission losses minimizationvia optimal adjustment of the power system control variables, while at the same time satisfying various equality and inequality constraints. The problem can be described as follows [6]:

Mathematically,

Min F(x,u)(1)

Subject to: g(x,u) = 0(2)

h (x,u) ≤ 0 (3)

Where x is the vector of dependent variables or state variables; u is the vector of independent variables or control variables;F is the objective function to be optimized;g is the equality constraints representing nonlinear load flow Equations;h is the inequality constraints representing system operating constraints.

a. State Variables

In eq (1) – (3), x is the vector of dependent variables in a power system network that includes:

1. Slack bus generated active power P_{G_1}.
2. Load (PQ) bus voltageV_L.
3. Generator reactive power output Q_G .
4. Transmission line loading (line flow) S_l.

Hence, x can be expressed as:

$$\mathbf{x^T = [P_{G_1}, V_{L_1} \dots V_{L_{NL}}, Q_{G_1} \dots Q_{G_{NG}}, S_{l_1} \dots S_{l_{nl}}]} \quad \mathbf{(4)}$$

Where *NL*,*NG* and *nl* are denote the number of load buses,the number of generatorsunitand the number of transmission lines, respectively.

b. Control Variables

In eq (1) – (3), u denotes the independent or control variables of a power system network that includes:

1. Generator active power output P_G except at slack bus P_{G_1}.
2. Generator bus voltage V_G.
3. Transformer taps setting T.
4. Shunt VAR compensation Q_C.

Hence, u can be expressed as:

$$u^T = [P_{G_2} \dots P_{G_{NG}}, V_{G_1} \dots V_{G_{NG}}, T_1 \dots T_{NT}, Q_{C_1} \dots Q_{C_{NC}}] \quad (5)$$

Where *NG*, *NT* and *NC* are denote the number of generators unit, the number of regulating transformers and the number of shunt VAR compensators, respectively.

c. Objective function

In this paper, three different objective functions are considered. The objective functions are as follows:

1. Minimization of total fuel cost

In this case, the objective function $F_1(x,u)$ represents the total fuel cost, and it can be expressed asfollows [6]:

$$F_1(x,u) = \sum_{i=1}^{NG} f_i \ (\$/h) \quad (6)$$

Where, f_i is thetotal fuel cost of the ithgenerating unit.

The fuel cost characteristics is represented by quadratic functions as:

$$f_i = a_i + b_i P_{G_i} + c_i P_{G_i}^2 (\$/h) \quad (7)$$

Where a_i, b_i and c_i are the fuelcost coefficients of the ithgenerating unit and P_{G_i} is real power output of the ith generator.

2. Voltage stability enhancement

Voltage stability is one of the important issues in power system planning and operation. The static approach for voltage stability analysis involves determination of an index known as voltage collapse proximity indicator. This index is an approximate measure of closeness of the system operating point to voltage collapse. There are different type methods of determining the voltage collapse proximity indicator. One such method is the L-index of the load buses in theSystem proposed in[6]. It is based on power flow analysis and its value ranges from 0 (no load condition) to 1 (voltage collapse). The bus with the largest *L*-index value will be the most vulnerable bus in the system. The *L*-index determine for a power system is briefly discussed below [6, 7].

For a power system with *NB*, *NG* and *NL* buses representing thetotal number of buses, the total number of generator bus (or *PV* buses) and the total number of load buses (or *PQ* bus), respectively, we can separate buses into two parts: *PQ*buses at the head and *PV*buses at the tail as follows

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = [Y_{bus}] \begin{bmatrix} V_L \\ V_G \end{bmatrix} = \begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix} \quad (8)$$

Where, Y_{LL}, Y_{LG}, Y_{GL} and Y_{GG} are sub matrix of Y_{bus}.The following hybrid system of equations can be written:

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = [H] \begin{bmatrix} I_L \\ V_G \end{bmatrix} = \begin{bmatrix} H_{LL} & H_{LG} \\ H_{GL} & H_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \quad (9)$$

Where H matrix is generated by the partial inversion of Y_{bus} , H_{LL} H_{LG}, H_{GL} and H_{GG} are sub matrix of H, V_G , I_G , V_L and I_L are voltage and current vector of generator buses and load buses, respectively

The matrix H is given by:

$$[H] = \begin{bmatrix} Z_{LL} & -Z_{LL}Y_{LG} \\ Y_{GL}Z_{LL} & Y_{GG} - Y_{GL}Z_{LL}Y_{LG} \end{bmatrix} Z_{LL} = Y_{LL}^{-1} \qquad (10)$$

Therefore, the L-index denoted by L_j of bus j is represented as follows

$$L_j = \left| 1 - \sum_{i=1}^{NG} H_{LG_{ji}} \frac{V_i}{V_j} \right| \qquad j = 1, 2, 3 \ldots \ldots \ldots . NL \qquad (11)$$

For stable situations the condition $L_j \leq 1$ must not be violated for any of the buses j. Hence, a power system L-index describing the voltage stability of the complete subsystem is given by

$$F_2(x,u) = L_{max} = max\,(L_j), \ \ j = 1 \ldots \ldots . NL \qquad (12)$$

The lower value of L_{max} system ismore stable.

3. Minimization of total power losses

This objective is to minimize power transmission loss in the system. The power loss is a non- linear function of bus voltages. Total power loss in the transmission system can be mathematically represented as follows [6]:

$$F_3(x,u) = \sum_{k=1}^{NT} G_k \left| v_i^2 + v_j^2 + 2|V_i||V_j| \cos(\delta_i - \delta_j) \right| \qquad (13)$$

Where, G_k is the conductance of *kth* line connected between *ith* and *jth* buses: *NT* is the number of transmission lines: V_i is the voltage magnitude at bus *i*: V_j is the magnitude at bus j: δ_i is the voltage angles at bus *i*: δ_j is the voltage angles at bus *j*.

d. Constraints

OPF constraints can be classified into equality and inequality constraints, as detailed in given below:

A. . Equality Constraints

The equality constraints g represented by (2), are typical load flow equations which are defined as follows:

- Real Power Constraints

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\theta_{ij}) + B_{ij} \sin(\theta_{ij})] = 0 \qquad (14)$$

- Reactive Power Constraints

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\theta_{ij}) - B_{ij} \cos(\theta_{ij})] = 0 \qquad (15)$$

Where, $\theta_{ij} = \theta_i - \theta_j$, V_i and V_j are the voltage magnitudes at bus *i* and bus *j*respectively,*NB* is the number of buses, P_{Gi} is the active power generation at bus *i*,Q_{Gi} is the reactive power generation at bus *i*, P_{Di} is the active load demand at bus *i*, Q_{Di} is the reactive load demand at bus *i*, G_{ij} and B_{ij} are the elements of the admittance matrix ($Y_{ij} - G_{ij} + jB_{ij}$) representing the conductance and susceptance between bus *i* and bus *j*, respectively.

B. Inequality Constraints

The inequality constraints h represented are the power system operating limits includes:

i. Generator Constraints

For all generators including the slack: voltage, active and reactive outputs ought to be restricted by their lower and upper limits as follows:

$$V_{G_i}^{min} \leq V_{G_i} \leq V_{G_i}^{max} \quad i = 1 \ldots\ldots NG$$

(16)

$$P_{G_i}^{min} \leq P_{G_i} \leq P_{G_i}^{max} \quad i = 1 \ldots\ldots NG$$

(17)

$$Q_{G_i}^{min} \leq Q_{G_i} \leq Q_{G_i}^{max} i = 1 \ldots\ldots NG$$

(18)

ii. Transformer Constraints

Transformer taps have minimum and maximum setting limits as follows:

$$T_i^{min} \leq T_i \leq T_{G_i}^{max} \quad i = 1 \ldots\ldots NT$$

(19)

iii. Shunt VAR compensator constraints

Shunt VAR constraints must be restricted by their lower and upper limits as follows

$$Q_{C_i}^{min} \leq Q_{C_i} \leq Q_{C_i}^{max} \quad i = 1 \ldots\ldots NG$$

(20)

iv. Security Constraints

These contain the constraints of voltage magnitude at load buses and transmission line loadings. Voltage magnitude of each load bus must be prohibited within its lower and upper operating limits. Line flow through each transmission line ought to be restricted by its capacity limits. These constraints can be mathematically formulated as follows:

$$V_{L_i}^{min} \leq V_{L_i} \leq V_{L_i}^{max} \quad i = 1 \ldots\ldots NL$$

(21)

$$S_{l_i} \leq S_{l_i}^{max} \quad i = 1 \ldots\ldots nl$$

(22)

III. MULTI-OBJECTIVE GENETIC ALGORITHM

An optimization problem treats simultaneously more than one objective function is called as multi-objective optimization problem. Multi-Objective optimization Problem (MOP) can be mathematically presented as [8, 9]:

Min

$$[\,F(x) = f_1(x), \ldots\ldots f_n(x)] \quad (23)$$

Subject to: $$\begin{cases} g_j = 0 & j = 1, 2, \ldots\ldots M \\ h_k \leq 0 & k = 1, 2, \ldots\ldots N \end{cases} \quad (24)$$

Where *F(x)* consists of *n* conflicting objective functions, *x* is the decision vector, g_j is the *jth* equality constraint and h_k is the *kth* inequality constraint.

For a multi-objective optimization problem, any two solutions x_1 and x_2 can have any one of two possibilities, where one dominates other or not. In a minimization problem, without loss of generality, solution x_1 dominates x_2 if the following conditions are satisfied.

1. $\forall_i \in \{1,2,\ldots\ldots N\}: \quad f_i(x_1) \leq f_i(x_2)$ (25)
2. $\exists_j \in \{1,2,\ldots\ldots N\}: \quad f_j(x_1) < f_j(x_2)$ (26)

If any one of the above conditions is violated, then the solution x_1 does not dominate x_2. If x_2 dominates by the solution x_1, x_1 is called as the non-dominated solution. A solution is said to be Pareto optimal if it is not dominated by any other solution in the solution space. A Pareto optimalsolution cannot be refined with respect to any objective without worsening at least one other objective. The set of possible feasible non-dominated solutions in *X*is referred to as the Pareto optimal set, and for a given Pareto optimal set, the corresponding objective function values in the objective space is called the Pareto front. For several optimization problems,all Pareto optimal solutions are enormous (maybe infinite). The main goal of a multi-objective optimization algorithm is to identify solutions in the Pareto optimal set. However, searching the all Pareto optimal set, for many multi-objective problems, is practically impossible due to its size.

MOGA [9, 10]was the first multi-objective GA that explicitly used Pareto based ranking and niching techniques together to encourage the search toward the true Pareto front while maintaining diversity in the population. Once fitness has been assigned, selection can be performed and genetic operators are applied as usual. To a solution *i*, a rank equal to one plus the number of solutions η_i that dominate solution i is assigned:

$$r_i = 1 + \eta_i \quad (27)$$

The rank one is assigned to non-dominated solutions since no solution would dominate a non-dominated solution in a population. After ranking, raw fitness is assigned to each solution based on its rank by sorting the ranks in ascending order of magnitude. Then, a raw fitness is assigned to each solution by linear mapping function. Thereafter, solutions of each rank are considered at a time and their averaged raw fitness is called assigned fitness. Thus the mapping and averaging procedure ensures that the better ranked solutions have a higher assigned fitness. In order to maintain diversity in the population, niching among solutions of each rank are introduced. The niche count is calculated with following equation [9, 10, 11]:

$$nc_i = \sum_{j=1}^{\mu(r_i)} Sh(d_{ij}) \quad (28)$$

Where, $\mu(r_i)$ is the number of solutions in a rankand $Sh(d_{ij})$ is the sharing function value of two solution *i* and *j*.

The sharing function $Sh(d_{ij})$ is calculated by using objective function as distance metric as:

$$Sh(d_{ij}) = \begin{cases} 1 - \left(\frac{d_{ij}}{\sigma_{share}}\right)^{\alpha} & \text{if } d \leq \sigma_{share} \\ 0 & \text{otherwise} \end{cases} \quad (29)$$

The parameter *d* is the distance between any two solutions in the population and is σ_{share} the sharing parameter which signifies the maximum distance between any two solutions before they can be considered to be in the same niche. The above function takes a value in [0, 1] depending on the values of σ_{share} and d_{ij}. If $\alpha = 1$ is used, the effect linearly reduces from one to zero.

The normalized distance between any two solutions can be calculated as follows:

$$d_{ij} = \sqrt{\sum_{k=1}^{M}\left(\frac{f_k^{(i)} - f_k^{(j)}}{f_k^{max} - f_k^{min}}\right)^2} \quad (30)$$

Where f_k^{max} and f_k^{min} are the maximum and minimum objective function value of the *kth*objective.

In MOGA, the shared fitness is calculated by dividing the fitness of a solution by its niche count. Even though all solutions of any particular rank have the identical fitness, the shared fitness value of each solution residing in less crowded region has a better shared fitness which produces a large selection pressure for poorly represented solutions in any rank. The fitness of the solution is reduced by dividing the assigned fitness by the niche count. In order to keep the average fitness of the solutions in a rank same as that before sharing, the fitness values are scaled. This rule is continued until all ranks are processed. This paper, tournament selection, BLX- α crossover and non-uniform mutation operators are applied to create a new population [12].

Best Compromise Solution

Having obtained the Pareto optimal set, choosing a best compromise solution is important in decision making process. In this paper, fuzzy membership approach is used to find a best compromise solution. Due to imprecise nature of the decision maker'sjudgement the *ith* objective function F_i of individual *k* is represented by a membership function u_i^kdefined as

$$u_i^k = \begin{cases} 1 & F_i \geq F_i^{min} \\ \dfrac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}} & F_i^{min} < F_i < F_i^{max} \\ 0 & F_i^{max} \leq F_i \end{cases} \quad (31)$$

Where $F_i^{min}$and F_i^{max} are the minimum and maximum value of *ith* objective function among all non-dominated solutions, respectively. For each non-dominated solution *k*, the normalized membership function u^k is calculated as

$$\mu^k = \frac{\sum_{i=1}^{NO} \mu_i^{ko}}{\sum_{k=1}^{M}\sum_{i=1}^{NO} \mu_i^k} \quad (32)$$

Where, *M* is thetotal number of non-dominated solutions; *NO* is the number of objectives. Finally, the best compromise solution is the one achieving the maximum member ship function (μ^k).

IV. Numerical Results

The proposed MOGA algorithm is tested on the standard IEEE 30-bus test system [13]. This system consists of six generators at buses 1, 2, 5, 8, 11 and 13, four transformers with off-nominal tap ratio at lines 6–9, 6–10, 4–12 and 27–28 and addition, buses 10, 12, 15, 17, 20, 21, 23, 24 and 29 were selected as shunt VAR compensation buses for reactive power control. The complete system data with minimum and maximum limits of control variables are given in [13]. Bus 1 was taken as the slack bus. The proposed algorithm has been applied to solve the OPF problem for several cases with different objective functions. Before MOGA is applied to OPF problem, following parameters need to be defined. The number of population NP = 30 andthe number of variable = 24.

A. Case 1: Fuel cost Vs Transmission line Losses

In this case, two competing objectives, i.e. fuel cost and transmission linelosses were considered. This multi-objective optimization problem was solved by the proposed algorithm. The Pareto optimal solution obtained with the help of proposed MOGA algorithm is shown in Fig. 1. Pareto optimal solution, it is clear that the proposed MOGA method is giving well distributed solutions. The best compromise solution was found with the help of fuzzy membership approach. The best solution for minimum fuel cost and minimum loss and the compromise solutionare given in Table 1.

B. Case 2: Fuel cost Vs L-index

In this case, L-index is considered in place of transmission line losses. The L-index of a bus indicates the proximity of voltage collapse condition of that bus. It varies zero (no load case) to one (voltage collapse). These two competing objective functions were optimized by the proposed MOGA method. The Pareto optimal solution for this case is shown in Fig.2. The best compromise solution for minimum fuel cost and minimum L-index are given in Table 1.

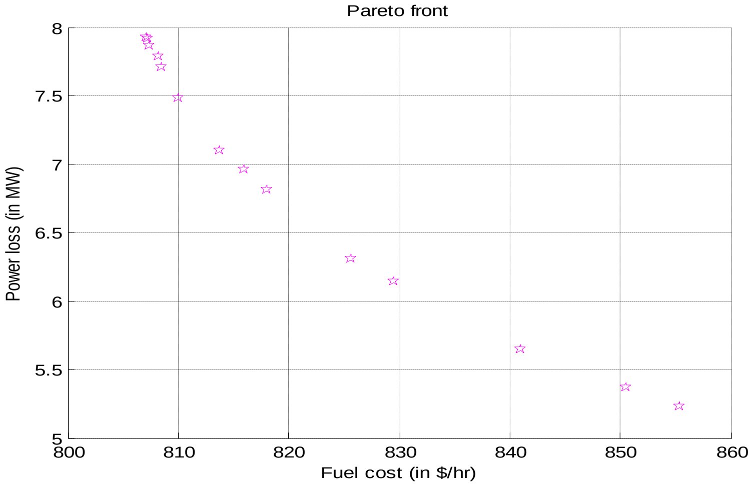

Fig.1. Pareto Optimal Solutions for Case 1

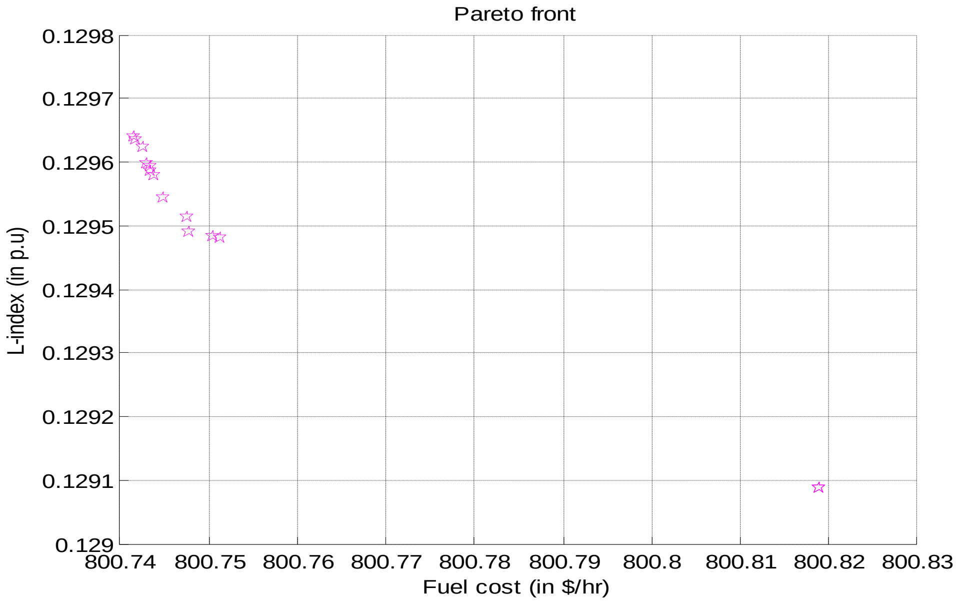

Fig.2. Pareto Optimal Solutions for Case 2

Table 1 Simulation Results for IEEE-30 Bus system

Control variable (p.u.)	Initial	Best Cost	Best Losses	Best Comp.	Best Cost	Best L-Index	Best Comp.
P2	.8000	.4897	.5895	.5675	.4894	.4928	.4900
P5	.5000	.2342	.3962	.3586	.2149	.2155	.2156
P8	.2000	.2409	.2877	.2742	.2022	.1967	.2012
P11	.2000	.1844	.2829	.2719	.1227	.1259	.1223
P13	.2000	.2030	.2361	.2371	.1201	.1237	.1201
V1	1.0500	1.0609	1.0508	1.0588	1.0806	1.0788	1.0806
V2	1.0400	1.0485	1.0207	1.0127	1.0190	1.0270	1.0190
V5	1.0100	1.0210	1.0162	1.0156	1.0266	1.0290	1.0265
V8	1.0100	1.0381	1.0349	1.0283	1.0456	1.0469	1.0456
V11	1.0500	1.0751	1.0433	1.0487	1.0664	1.0704	1.0664
V13	1.0500	1.0396	1.0504	1.0412	1.0723	1.0716	1.0723
T11	10780	.9986	1.0158	1.0120	1.0050	1.0036	1.0051
T12	1.0690	1.0007	1.0260	1.0172	.9925	.9906	.9926
T15	1.0320	1.0276	1.0233	1.0215	1.0110	1.0138	1.0110
T36	1.0680	.9793	.9836	.9851	.9701	.9732	.9700
Qc10	0.0	.0193	.0360	.0357	.0421	.0433	.0419
Qc12	0.0	.0224	.0304	.0239	.0497	.0499	.0498
Qc15	0.0	.0408	.0179	.0257	.0345	.0397	.0343
Qc17	0.0	.0285	.0229	.0232	.0409	.0408	.0409
Qc20	0.0	.0209	.0236	.0304	.0369	.0389	.0369
Qc21	0.0	.0154	.0254	.0276	.0500	.0500	.0500
Qc23	0.0	.0195	.0296	.0310	.0238	.0252	.0239
Qc24	0.0	.0423	.0329	.0260	.0500	.0500	.0500
Qc29	0.0	.0340	.0323	.0308	.0411	.0497	.0456
Fuel Cost($/h)	902.00	807.13	855.37	**841.05**	800.74	800.81	**800.75**
L_{max}	0.1772	-	-	-	.1296	.1291	**.1295**
P_{LOSS}	5.8423	7.930	5.228	**5.6482**	-	-	-

*Bold values represent the best values of the objective functions chosen and best comp.Indicate best compromise solution.

Table 2

The best compromise solution for case-1 using different multi objective algorithms.

Algorithms	Fuel cost ($/h)	Losses (MW)
MOSPEA [14]	847.01	5.666

NSGA-II [15]	823.88	5.7699
MOGA	841.05	5.6482

Table 3

The best compromise solution for case-2 using different multi objective algorithms.

Algorithms	Fuel cost ($/h)	L-index (p.u)
MOSPEA [14]	809.79	.1146
MOTLBO [16]	803.63	.1020
MOGA	800.75	.1295

V. CONCLUSIONS

In this paper a multi-objective genetic algorithm (MOGA) has been proposed to solve the multi-objective optimal power flow(MO-OPF) problem with many constraints in IEEE 30-bus system. The proposed approach successfully applied to solve various types of optimal power flow (OPF) problems with different objective function like fuel cost minimization, voltage stability enhancement and transmission losses minimization.The proposed approach results are compared with the results reported in the literature.The numerical results show that the proposed technique is efficient and outperforms for solving MO-OPF problem.

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