Multi Objective Harmony Search Algorithm For Optimal Power Flow

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***Abstract*—This paper proposes a multiobjective harmony search (MOHS) algorithm for optimal power flow (OPF) problem. OPF problem is formulated as a nonlinear constrained multiobjective optimization problem where different objectives and different constraints have been considered. Fast elitist non dominated sorting and crowding distance have been used to find and manage the Pareto optimal front. Finally, a fuzzy based mechanism has been used to select a compromise solution from the Pareto set. The proposed MOHS algorithm has been tested on IEEE 30 bus system with different objectives. Simulation results clearly show that the proposed method is able to generate true and well distributed Pareto optimal solutions for OPF problem.**

I. Introduction

In real world optimization problems, multiple competing objectives make us solve them simultaneously instead of solving them separately. This gives rise to a set of optimal solution (Largely known as Pareto optimal solution) rather than a single optimal solution. In the absence of a knowledge, it is not possible to find a better solution than others from the Pareto optimal solutions [1]. Because, one can not be better than other without any further information. Therefore, it is necessary to find as many Pareto optimal solutions as possible. Classical methods do convert the multi objective optimization problem to a single objective optimization problem by a suitable scaling/weighting factor method. This results in a single optimal solution. To obtain a Pareto optimal solutions, it should be run as many times as the number of solutions.

OPF problem is a nonlinear, constrained optimization problem where many competing objectives are present. Traditionally, OPF problem has been solved for different objectives as a single objective optimization problem [2]–[5]. This resulted in a optimal solution which satisfies one objective and not others. Therefore, to satisfy and find a compromise solution between two competing objectives, OPF problem is solved as a multiobjective optimization problem with different constraints.

Traditionally, multiobjective OPF problem has been solved by weighted sum and ϵ-constraint method [6]. The weighted sum method converts multiobjective optimization problem to a single objective optimization problem by giving suitable weights to the objectives. Whereas, ϵ-constraint method treats most preferred objectives for optimization and non preferred objective as a constraint in the allowable range ϵ. This range is further modified to obtain a Pareto optimal solution. These methods require multiple runs to obtain a Pareto optimal solution and need much computational time resulting in a weakly non-dominated solution.

Recently, multiobjective evolutionary algorithms have been reported to solve environmental/economic dispatch (EED), OPF and VAR dispatch problem [7]–[12]. These evolutionary algorithms are proved to be better than traditional method because of their ability to obtain a Pareto optimal solution in a single run. Since evolutionary algorithms use a population of solutions, they can be easily extended to maintain a diverse set of solutions in a single run. Most evolutionary algorithms reported for EED, OPF and VAR problems, use non dominated sorting , strength Pareto approach for maintaining a diverse Pareto optimal solutions. This paper considers the non dominated sorting and crowding distance method proposed by Deb [13] to maintain a well distributed Pareto optimal solutions.

Harmony search (HS) algorithm has been recently developed [14] in an analogy with improvisation process where musicians always try to polish their pitches to obtain a better harmony. Music improvisation process is similar to the optimum design process which seeks to find optimum solution. The pitch of each musical instrument determines the certain quality of harmony, just like the objective function assigned to the set of variables. In this paper, HS algorithm is extended using fast non dominated sorting and ranking procedure to find a Pareto optimal solutions for OPF problem with competing objectives. Finally a fuzzy based mechanism is used to find a compromise solution from the Pareto optimal solution. This multiobjective harmony search (MOHS) algorithm has been tested on a standard IEEE 30 bus test system for competing objectives. Simulation results clearly show the robustness of the MOHS method to obtain a well distributed optimal solutions.

II. Problem Formulation

The OPF problem is a non linear, non convex optimization problem which determines the optimal control variables for minimizing the certain objectives subject to the several equality and inequality constraints. The OPF problem is generally formulated as follows.

A. Objective functions

1) Fuel cost minimization: This objective is to minimize the total fuel cost F_T of the system. The fuel cost curves of the thermal generators are modeled as a quadratic cost curve and can be represented as

$$F_T = \sum_{i=1}^{N_G} (a_i P_i^2 + b_i P_i + c_i) \quad \$/hr \tag{1}$$

where a_i, b_i, c_i are the fuel cost coefficients of the ith generator, P_i is real power output of the ith generator and N_G is the total number of generators in the system.

2) Real power loss: This objective is to minimize the real power transmission line losses P_L in the system which can be expressed as follows.

$$P_L = \sum_{k=1}^{nl} g_k [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] \tag{2}$$

where g_k is the conductance of a transmission line k connected between i and jth bus, nl is the total number of transmission lines, V_i, V_j, δ_i and δ_j are the voltage magnitudes and phase angles of i and jth bus respectively.

3) L-Index: This objective is to maintain the voltage stability and move the system far away from the voltage collapse point. This can be achieved by minimizing the voltage stability indicator L-index [15], [16]and can be expresses as

$$L_{\max} = \max\{L_k, k = 1, 2, \cdots, nl\} \tag{3}$$

B. Constraints

1) Equality constraints: These constraints are typical load flow equations which can be described as follows

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{N_B} V_j (G_{ij} \cos\delta_{ij} + B_{ij} \sin\delta_{ij}) = 0 \quad i \in N_{PQ} \tag{4}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{N_B} V_j (G_{ij} \sin\delta_{ij} - B_{ij} \cos\delta_{ij}) = 0 \quad i \in N_G \tag{5}$$

where P_{Gi} is the real power generation at ith bus, P_{Di} is the real power demand at ith bus, Q_{Gi} is the reactive power generation at ith bus, Q_{Di} is the reactive power demand at ith bus, B_{ij} is the suceptance of the line connected between i and jth bus, N_B is the total number of buses, N_{PQ} is the number of load buses and N_G is the number of generator buses in the system.

2) Inequality constraints: These constraints represent the system operating limits as follows

1) Generation constraints: Generator voltages, real power outputs and reactive power outputs are restricted by their lower and upper bounds as follows:

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, \ i = 1, \cdots, N_G \tag{6}$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, \ i = 1, \cdots, N_G \tag{7}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, \ i = 1, \cdots, N_G \tag{8}$$

2) Transformer constraints: Transformer tap settings are restricted by their minimum and maximum limits as follows:

$$T_i^{\min} \le T_i \le T_i^{\max}, \ i = 1, \cdots, nt \tag{9}$$

3) Shunt VAR constraints: Reactive power injections at buses are restricted by their minimum and maximum limits as:

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max}, \ i = 1, \cdots, nc \tag{10}$$

4) Security constraints: These include the constraints of voltage magnitudes at load buses and transmission line loadings as follows:

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}, \ i = 1, \cdots, N_{PQ} \tag{11}$$

$$S_{li} \le S_{li}^{\max}, \ i = 1, \cdots, nl \tag{12}$$

III. Multiobjective Optimization

Many real world optimization problem involve simultaneous optimization of several conflicting objectives. Multiobjective optimization problems with such conflicting objectives give rise to a set of optimal solution, rather than a single optimal solution. Because, no solution can be considered to be better than other solutions with out a information. These set of optimal solutions are called as a Pareto optimal solutions.

A general multiobjective optimization problem consists of multiple objectives to be optimized simultaneously and the various equality and inequality constraints. This can be generally formulated as

$$\text{Min} \quad f_i(x), \quad i = 1, 2, \cdots, N \tag{13}$$

$$\text{Subject to}: \begin{cases} g_j(x) = 0, & j = 1, 2, \cdots, M \\ h_k(x) \le 0, & k = 1, 2, \cdots, K \end{cases} \tag{14}$$

where f_i is the ith objective function, x is a decision vector that represents a solution, N is the number of objective functions, M and K are the number of equality and inequality constraints respectively.

For a mutliobjective optimization problem, any two solutions x_1 and x_2 can have any one of two possibilities, one dominates other or none dominates other. In a minimization problem, with out loss of generality, solution x_1 dominates x_2 if the following conditions are satisfied.

$$1. \quad \forall i \in \{1, 2, \cdots, N\} : f_i(x_1) \le f_i(x_2) \tag{15}$$

$$2. \quad \exists j \in \{1, 2, \cdots, N\} : f_j(x_1) < f_j(x_2) \tag{16}$$

If any one of the above conditions is violated, then the solution x_1 does not dominate x_2. If x_1 dominates the solution x_2, x_1 is called as the non dominated solution. The solutions that are non dominated within the entire search space are denoted as Pareto optimal solutions.

IV. Harmony search algorithm

The harmony search (HS) algorithm, proposed by Geem [14], is a nature inspired algorithm, mimicking the improvisation of music players. The harmony in music is analogous to the optimization solution vector, and the musician's improvisations are analogous to the local and global search schemes in optimization techniques. The HS algorithm uses a stochastic random search, instead of a gradient search. This algorithm uses harmony memory considering rate and pitch adjustment rate for finding the solution vector in the search space.

The HS algorithm uses the concept, how aesthetic estimation helps to find the perfect state of harmony, to determine the optimum value of the objective function. The HS algorithm is simple in concept, few in parameters and easy in implementation. It has been successfully applied to various optimization problems. The optimization procedure of the HS algorithm is as follows:

1) Initialize the optimization problem and algorithm parameters.
2) Initialize the harmony memory.
3) Improvise a new harmony memory.
4) Update the harmony memory.
5) Check for stopping criteria. Otherwise, repeat step 3 to 4.

The detailed description of the above steps are given in [17]–[19] and the brief explanation is given in the following sections.

A. Initialization of problem and HS algorithm parameters

In this step, the optimization problem is specified as follows

$$\mathtt{Min} \quad f(x)$$

subject to

$$g(x) = 0$$
$$x_{k,\mathtt{min}} \leq x \leq x_{k,\mathtt{max}} \quad k = 1, 2, \cdots, N$$

where $f(x)$ is the objective function, $g(x)$ is the equality constraint, x is the set of decision variables, $x_{\mathtt{min}}$,$x_{\mathtt{max}}$ are minimum and maximum limits of decision variables and N is the number of decision variables. The HS algorithm parameter are also specified in this step. These are the harmony memory size (HMS) or the number of solution vectors in the harmony memory, harmony memory considering rate (HMCR), pitch adjustment rate (PAR), bandwidth rate (BW) and the number of improvisations (NI) or the stopping condition.

B. Initialization of harmony memory

The harmony memory (HM) is a memory location where all the solution vectors (sets of decision variables) are stored. The HM is similar to the number of population in other evolutionary algorithms. The HM matrix (17) is filled with as many randomly generated values between its minimum and maximum limits.

$$HM = \begin{pmatrix} x_1^1 & x_2^1 & \cdots & x_{N-1}^1 & x_N^1 \\ x_1^2 & x_2^2 & \cdots & x_{N-1}^2 & x_N^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^{\mathtt{HMS}-1} & x_2^{\mathtt{HMS}-1} & \cdots & x_{N-1}^{\mathtt{HMS}-1} & x_N^{\mathtt{HMS}-1} \\ x_1^{\mathtt{HMS}} & x_2^{\mathtt{HMS}} & \cdots & x_{N-1}^{\mathtt{HMS}} & x_N^{\mathtt{HMS}} \end{pmatrix} \quad (17)$$

C. Improvisation of a new harmony from the HM

A new harmony vector, $X' = (x'_1, x'_2, \cdots, x'_N)$ is generated based on three rules: 1) memory consideration, 2) pitch adjustment and 3) random selection. Generating a new harmony is called as improvisation.

In the memory consideration, the value of decision variables X' for the new vector are selected from $(x^1 - x^{\mathtt{HMS}})$. The harmony memory considering rate (HMCR), which varies between 0 and 1, is the rate of choosing one value from the historical values stored in HM, while (1-HMCR) is the rate of randomly selecting one value from the possible range of values as

$$x'_i = \begin{cases} x'_i \in \{x_i^1, x_i^2, \cdots, x_i^{\mathtt{HMS}}\} & \mathtt{if} \quad \mathtt{rand} \leq \mathtt{HMCR} \\ x'_i \in X_i & \mathtt{Otherwise} \end{cases} \quad (18)$$

where $\mathtt{rand}$ is the uniform random number in the range between 0 and 1 and X_i the set of possible range of values for each decision variable, that is $x_{i,\mathtt{min}} \leq X_i \leq x_{i,\mathtt{max}}$.

For example, a HMCR of 0.8 indicates that the HS algorithm will choose the decision variable from historically stored values in the HM with an 80% probability or from the possible range of values with a 20% probability. After the memory consideration, every component is examined to determine whether it should be pitch adjusted. This operation uses the PAR parameter, which is the rate of pitch adjustment as follows;

$$x'_i = \begin{cases} x'_i \pm \mathtt{rand} \times \mathtt{BW} & \mathtt{if} \quad \mathtt{rand} \leq \mathtt{PAR} \\ x'_i & \mathtt{Otherwise} \end{cases} \quad (19)$$

where $\mathtt{BW}$ is the arbitrary distance bandwidth.

To improve the performance of the HS algorithm, PAR and BW are changed during each generation as follows;

$$\mathtt{PAR}(g) = \mathtt{PAR}_{\mathtt{min}} + \frac{\mathtt{PAR}_{\mathtt{max}} - \mathtt{PAR}_{\mathtt{min}}}{\mathtt{NI}} \times g \quad (20)$$

where $\mathtt{PAR}(g)$ is the pitch adjusting rate of current generation, $\mathtt{PAR}_{\mathtt{min}}$ is the minimum pitch adjusting rate, $\mathtt{PAR}_{\mathtt{max}}$ is the maximum pitch adjusting rate, g is the current generation number and $\mathtt{NI}$ is the number of improvisations.

$$\mathtt{BW}(g) = \mathtt{BW}_{\mathtt{max}}\mathtt{exp}(\frac{\mathtt{Ln}(\frac{\mathtt{BW}_{\mathtt{min}}}{\mathtt{BW}_{\mathtt{max}}})}{\mathtt{NI}} \times g) \quad (21)$$

where $\mathtt{BW}(g)$ is the bandwidth rate of current generation, $\mathtt{BW}_{\mathtt{min}}$ is the minimum bandwidth rate and $\mathtt{BW}_{\mathtt{max}}$ is the maximum bandwidth rate.

D. Updating the harmony memory

Updating the harmony memory in HS algorithm for multi-objective optimization problem differs from that of basic HS algorithm. In this work, non dominated sorting and ranking scheme, proposed by Deb is used to find the Pareto optimal solutions. The new harmony memory, generated by improvisation process, is combined with the existing harmony memory to form $2 \times HMS$ solution vectors. Then non dominated sorting and ranking procedure is performed on the combined harmony memory. Once the ranking is assigned to all the solution vectors in the combined harmony memory, a diversity rank is assigned to the solution vectors, which are in the same non dominated front, using the crowding distance metric. The crowding distance is an indication of the density of the solution vectors surrounding a particular solution vector. The measure of crowding distance is generally based on the average distance of the two solution vectors on either side of a solution vector, along each of the objectives. Finally, the best HMS harmony memory is selected from the combined harmony memory in the order of their ranking for the next improvisation. To choose exactly HMS solution vectors from the last non dominated front, crowded comparison operator is used to select the best solutions needed to fill the HMS.

E. Stopping condition

The HS algorithm is stopped when the number of improvisations (NI) has been met. Otherwise sections IV-C and IV-D are repeated.

F. 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's judgment the ith objective function f_i of individual k is represented by a membership function μ_i^k defined as

$$\mu_i^k = \begin{cases} 1 & f_i \leq f_i^{\min} \\ \dfrac{f_i^{\max} - f_i}{f_i^{\max} - f_i^{\min}} & f_i^{\min} < f_i < f_i^{\max} \\ 0 & f_i \geq f_i^{\max} \end{cases} \qquad (22)$$

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 μ^k is calculated as

$$\mu^k = \frac{\sum\limits_{i=1}^{N} \mu_i^k}{\sum\limits_{k=1}^{P}\sum\limits_{i=1}^{N} \mu_i^k} \qquad (23)$$

where P is the total number of non dominated solutions. The best compromise solution is that having maximum value of μ^k.

V. Implementation of the Proposed Approach

The proposed approach to solve OPF problem is described in the following steps.

1) Input the system parameters, minimum and maximum limits of control variables.
2) Choose the harmony memory size HMS, pitch adjusting rate PAR, bandwidth BW and the maximum number of improvisations NI.
3) Initialize the harmony memory HM as explained in the section IV-B. While initializing, all the control variables are randomly generated with in their limits.
4) Start the improvisation.
5) For each solution vector in HM, evaluate the objective functions.
6) Improvise the new harmony memory as explained in the section IV-C.
7) Perform the non dominated sorting and ranking on the combined existing and new harmony memory.
8) Choose the best harmony memory from the combined solution vectors as given in the section IV-D for the next improvisation.
9) Check for stopping conditions. If the number of improvisations has been reached to the maximum, go to next step. Otherwise, go to step 5.
10) The non dominated solution vectors in the HM are Pareto optimal solutions.
11) Best compromise solution vector is taken from the Pareto optimal set using fuzzy membership approach.

VI. Simulation Results

In order to validate the robustness of the proposed MOHS method, a standard IEEE 30 bus system has been considered. This system consists of 6 generators at buses 1, 2, 5, 8, 11 and 13, 4 transformers with off-nominal tap ratio in the lines 6-9, 6-10, 4-12 and 27-28 and reactive power injection at the buses 10, 12, 15, 17, 20, 21, 23, 24 and 29. The complete system data with minimum and maximum limits of control variables are given in [2]. The network diagram of IEEE 30 bus system is shown in Fig 1. In this paper, three objectives, namely, fuel cost , losses and L-index have been considered.

Before MOHS is applied to OPF problem, following parameters need to be defined. They are, harmony memory size HMS = 50, harmony memory considering rate $HMCR$ = 0.85, pitch adjusting rate $PAR_{\min}$ = 0.2 and $PAR_{\max}$ = 2, bandwidth $BW_{\min}$ = 0.45 and $BW_{\max}$ = 0.9 and the number of improvisations NI = 500.

A. Case 1: Fuel cost Vs Losses

In this case, two competing objectives, i.e., fuel cost and losses, were considered. This multiobjective optimization problem was solved by the proposed approach. The Pareto optimal solution obtained using the proposed MOHS algorithm is shown in Fig. 2. From the Pareto optimal solution, it is clear that the proposed MOHS method is giving well distributed solutions. The compromise solution was found using the fuzzy membership approach. The best solution vectors for minimum

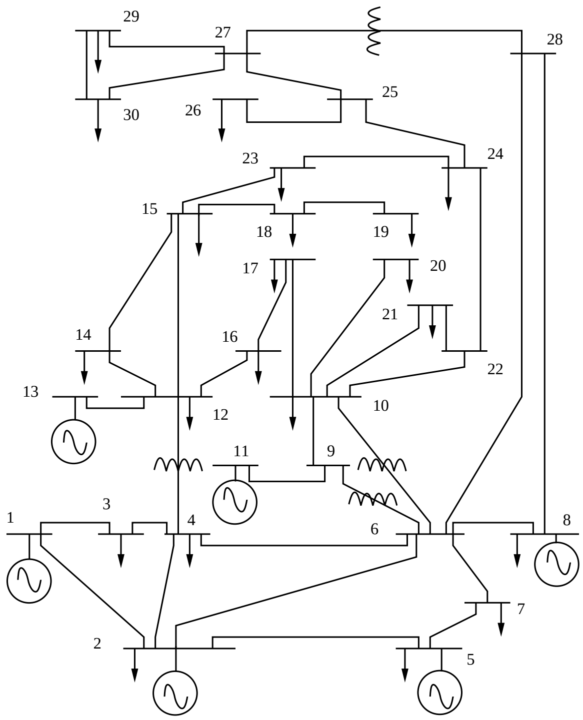

Fig. 1. Single Line Diagram of IEEE 30 Bus Test System

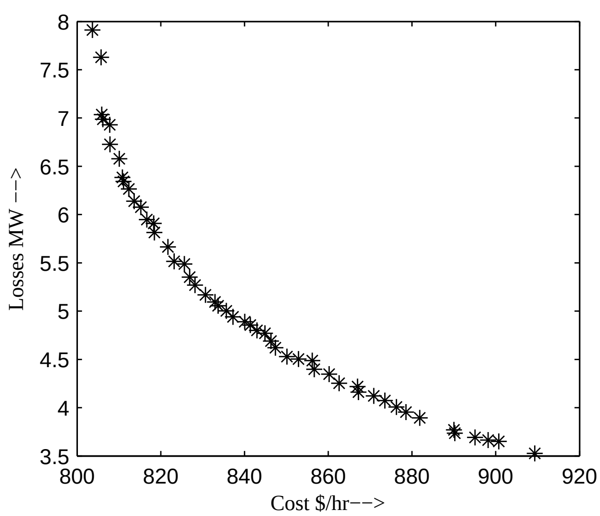

Fig. 2. Pareto Optimal Solutions For Case 1

cost, minimum loss and the compromise solution are given in Table I.

B. Case 2: Fuel cost Vs L-index

In this case, L-index is considered in place of transmission losses. L-index gives a scalar number to each load bus This index uses information on a normal power flow and is in the range zero (no load case) to one (voltage collapse). To maintain the voltage stability and move away from voltage collapse point, maximum value of L-index among load buses $L_{\max}$ must be minimized. These two competing objective

TABLE I
OPTIMAL SOLUTION FOR CASE 1

Variables	Best Cost	Best Losses	Best Compromise
P_{G1} MW	161.2088	84.6404	124.1938
P_{G2} MW	54.7416	52.3695	50.6518
P_{G5} MW	22.8866	47.9821	32.4311
P_{G8} MW	18.1654	34.6415	34.6415
P_{G11} MW	13.9513	29.0215	26.6144
P_{G13} MW	20.3588	38.1759	20.0232
V_1 (p.u)	1.0939	1.0914	1.0980
V_2 (p.u)	1.0820	1.0798	1.0826
V_5 (p.u)	1.0555	1.0555	1.0555
V_8 (p.u)	1.0661	1.0661	1.0661
V_{11} (p.u)	1.0958	1.0958	1.0946
V_{13} (p.u)	1.0949	1.0949	1.0997
T_{6-9}	1.0724	0.9628	0.9775
T_{6-10}	0.9181	1.0392	0.9647
T_{4-12}	0.9818	0.9818	0.9885
T_{28-27}	0.9699	0.9699	0.9709
Q_{c10} (p.u)	0.0137	0.0493	0.0288
Q_{c12} (p.u)	0.0344	0.0280	0.0497
Q_{c15} (p.u)	0.0347	0.0413	0.0474
Q_{c17} (p.u)	0.0367	0.0476	0.0365
Q_{c20} (p.u)	0.0459	0.0422	0.0484
Q_{c21} (p.u)	0.0485	0.0465	0.0470
Q_{c23} (p.u)	0.0383	0.0360	0.0425
Q_{c24} (p.u)	0.0447	0.0119	0.0411
Q_{c29} (p.u)	0.0430	0.0267	0.0355
Fuel cost $\$/hr$	**803.6838**	909.3377	**828.1713**
Loss	7.9123	**3.5258**	**5.2701**

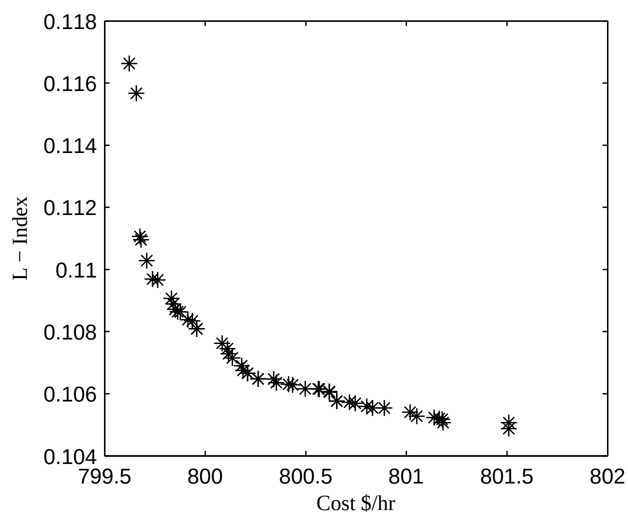

Fig. 3. Pareto Optimal Solutions For Case 2

functions were optimized by the proposed MOHS method. The Pareto optimal solution for this case is shown in Fig. 3. The best solution vectors are also given for minimum cost, minimum L-index and compromise case in Table II.

TABLE II
OPTIMAL SOLUTION FOR CASE 2

Variables	Best Cost	Best L-Index	Best Compromise
P_{G1} (MW)	176.4070	177.6569	176.4756
P_{G2} (MW)	48.1795	48.1795	48.1795
P_{G5} (MW)	21.9466	21.9466	21.9466
P_{G8} (MW)	21.3504	20.2148	21.3504
P_{G11} (MW)	11.7238	11.6816	11.7238
P_{G13} (MW)	12.4769	13.0176	12.4769
V_1 (p.u)	1.0999	1.0999	1.0999
V_2 (p.u)	1.0949	1.0976	1.0949
V_5 (p.u)	1.0767	1.0959	1.0767
V_8 (p.u)	1.0840	1.0995	1.0840
$V_1 1$ (p.u)	1.0985	1.0985	1.0990
$V_1 3$ (p.u)	1.0996	1.0996	1.0996
T_{6-9}	0.9022	0.9022	0.9400
T_{6-10}	1.0718	0.9007	0.9007
T_{4-12}	1.0156	0.9010	0.9213
T_{28-27}	0.9690	0.9157	0.9327
Q_{c10} (p.u)	0.0490	0.0490	0.0490
Q_{c12} (p.u)	0.0495	0.0495	0.0495
Q_{c15} (p.u)	0.0478	0.0478	0.0488
Q_{c17} (p.u)	0.0363	0.0478	0.0478
Q_{c20} (p.u)	0.0054	0.0493	0.0500
Q_{c21} (p.u)	0.0497	0.0497	0.0456
Q_{c23} (p.u)	0.0467	0.0467	0.0490
Q_{c24} (p.u)	0.0496	0.0496	0.0496
Q_{c29} (p.u)	0.0460	0.0483	0.0483
Fuel Cost $/hr	**799.6217**	801.5094	**799.8494**
L-Index	0.1166	**0.1049**	**0.1087**

VII. CONCLUSIONS

In this paper, different multi-objectives for OPF problem were formed. These multi-objectives have been solved by the proposed MOHS algorithm. Non-dominated sorting and ranking with crowded comparison operator were used to find and maintain the Pareto optimal solutions. Finally, a fuzzy membership approach has been used to identify the best compromise solution. From the simulation results, the proposed MOHS method is able to give well distributed Pareto optimal solutions for OPF problem with different objectives.

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