Analyzing effect of multi objective optimization using a novel e-constrained based approach

B.Sreenivasa Raju[1], Chintalapudi V Suresh[2], A.V.Naresh Babu[3]

***Abstract*—For power system effective control, operation, planning, and management it is necessary to solve multiple objectives simultaneously subjected to the requirements. In this paper, e-constrained optimization algorithm, one of the popular multi-objective optimization methods, is used to calculate the maximum possible load on a given system without violation of constraints in terms of loadability factor. There is a possibility in getting loadability on a given system by sacrificing some other objectives simultaneously. The used method can formulate multi-objective optimization function and can be solved by keeping other objective functions within its e-constrained values. Finally effective fuzzy decision making tool is used to select best optimal solution from the entire Pareto solutions generated. The complete working procedure is tested on the IEEE-30 bus system with supporting results.**

***Index Terms*—Multi-objective optimization, e-constrained approach, Generation Cost, Emission, Losses, Voltage Stability Index, Loadability.**

I. Introduction

POWER system effective planning includes optimal power generation, monitoring, controlling in different aspects. This can be performed by performing optimal power flow (OPF) on a given system [1, 2].

Power system engineers needs a lot of competence and specially designed tools to analyze and to control, power system operation, planning and management. Effective power system operation includes proper control over the system objectives, namely generation fuel cost, emission of generating units, real power loss, Voltage Stability Index (VSI) and system loadability etc. Generally, Optimal Power Flow (OPF) is used to analyze the power system, and to minimize/maximize any one of the above objectives subjected to equality and inequality constraints. The continuous and uncontrollable growth in demand for electricity needs construction of new transmission lines or extending the capacity of existing generating stations/substations. But these are very expensive and time consuming; hence there is a possibility to meet certain objectives in the system by sacrificing some other objectives simultaneously.

Optimal power flow problem with fuel cost function as an objective is being solved by developing real-coded genetic algorithm [3]. Same technique is used to solve OPF problem to improve system security [4]. A multi-objective optimization problem with four different objective functions namely, fuel cost, emission of the generators, real power loss in a transmission system and the security margin index is being solved by using evolutionary approaches [5]. Strength Pareto evolutionary algorithm is developed to solve multi-objective optimization problem with fuel cost and voltage stability index as the objectives [6]. Similar problem formulation with the same technique subjected to hard constraints is solved in [7]. A non-linear predictor-corrector primal-dual interior point method [8] and the environmental-economic planning problem is solved by forming multi-objective OPF [9]. Particle Swarm Optimization (PSO) based multi-objective optimization problem with transmission real power loss and voltage profile improvement as objectives via handling inequality constraints with the help of penalty method [10]. Three objective functions, fuel cost, power loss, and voltage deviation as objectives is being solved by developing enhanced PSO based multi-objective OPF problem [11]. In [12], bacteria foraging based algorithm is developed to solve multi-objective optimization problem with the loss and voltage stability limits are as objectives.

Then, there is need of optimal methodology to control some of the objectives based on the system requirements. This type of problem combines more than one objective function results many solutions instead of single optimal solution that simultaneously optimizes all the objective functions, the decision making tool is used for the "most preferred" solution in contrast to the optimal solution. In this type of problems, the concept of optimality is replaced by that of Pareto optimality that cannot be improved in one objective function without violating its performance in at least one of the rest. In this paper, the main objective is to propose a multi-objective solution methodology by using e-constraint approach and an effective decision making tool to select the good solution instead of local best solution. This Multi-Objective E-Constrained Optimization (MOECO) approach has been verified on the test systems. The analysis and the encouraging results gives support to handle multi-objective optimization problem with the proposed methodology.

II. E-constrained method

The e-constraint method optimizes one of the objective functions while the other objective functions are considered as constants [13-16].

$$\min \mathrm{F}_1(\mathrm{x})$$

Subjected to $\mathrm{F}_2(\mathrm{x}) \le \mathrm{e}_2, \mathrm{F}_3(\mathrm{x}) \le \mathrm{e}_3 \ldots \mathrm{F}_\mathrm{p}(\mathrm{x}) \le \mathrm{e}_\mathrm{p}$

Where, subscript p indicates the number of objective functions.

The significance of this method over the conventional methods is in terms of generating the most effective solution. It requires less number of runs to produce different effective solution with best Pareto front. This method overcomes the pitfall problem [17, 18], while the conventional methods cannot produce unsupported efficient solutions in multi-objective optimization problems. Scaling of the objective functions is not necessary [13]. The number of effective solutions can be controlled by adjusting interval of the objective functions range.

Bicriterian optimization problems based on e-constraint methodology has been studied in [19-21] to improve the performance and effectiveness of the solution.

Apart from all the discussions, this method needs the calculation of the objective functions range, number of intervals to get efficient solution, and the proper selection criteria to select better solution instead of best solution. The efficiency and effectiveness of the existing method is addressed.

III. STOCHASTIC PROBLEM FORMULATION

In general, aggregating the objectives and constraints, the OPF problem can be mathematically formulated as follows:

$$\text{minimize / maximize } F_n \qquad \forall\, n \in p$$
$$\text{subjected to } g(x,u) = 0$$
$$h(x,u) \leq 0$$

where 'p' indicates the number of objective functions, g(x,u) and h(x,u) are the set of equality and inequality constraints, respectively.

In this method single objective function is formulated to solve multi-objective optimization problem and penalty approach is used to handle inequality constraints.

In this paper, five objective functions considered and are generation fuel cost, emission, system power loss, voltage stability index and loadability. These objective functions are formulated as follows.

A. The generation fuel cost:

The objective function is used to minimize the total generation fuel cost and can be expressed as

$$F_1 = FC(P_{G_i}) = \sum_{i=1}^{N_G} a_i P_{G_i}^2 + b_i P_{G_i} + c_i \ \$/h \qquad (1)$$

where N_G is the number of generators, a_i, b_i and c_i are the cost coefficients and P_{G_i} is the real power output of i^{th} generator.

B. The emission:

Due to the limitations imposed by the Act 1990 [22], best feasible option is to operate the system as environmental friendly. The total ton/h atmospheric pollutants such as Sulpher oxides SO_x and Nitrogen oxides NO_x emitted by $E(P_{G_i})$ [5] is expressed as

$$F_2 = E(P_{G_i}) = \sum_{i=1}^{N_G} \left(\alpha_i + \beta_i P_{G_i} + \gamma_i P_{G_i}^2 + \xi_i \exp^{(\lambda_i P_{G_i})}\right) \ \text{ton/h} \qquad (2)$$

where $\alpha_i, \beta_i, \gamma_i, \xi_i$ and λ_i are emission coefficients of the i^{th} generator.

C. Real power losses:

In power system to enhance power delivery performance, one of the important issues to be considered is active power loss and can be calculated as

$$F_3 = \text{Losses } (L) \qquad (3)$$

$$= \sum_{i=1}^{N_{line}} g_i \left[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)\right] \text{MW}$$

where N_{line} is total number of transmission lines, g_i is the conductance of i^{th} line which connects buses i and j. V_i, V_j and δ_i, δ_j are voltage magnitude and angle of i^{th} and j^{th} buses.

D. Voltage Stability Index:

$L-$index (L_j) [2] of the load buses is considered to monitor the voltage stability in power system. The value of this $L-$index is in the range of '0' (no load on the system) to '1' (system voltage collapse). The voltage stability index at j^{th} bus and can be defined as

$$F_4 = L_j = \left|1 - \sum_{i=1}^{N_G} F_{ji}\frac{V_i}{V_j}\right|; \ j = N_G + 1, -- n \qquad (4)$$
$$[F] = -[Y_{LL}]^{-1}[Y_{LG}]$$

All quantities within the sigma in the RHS of L_j are complex quantities. The values $[F_{ji}]$ are obtained from Y bus matrix. At all load buses, VSI for the given load condition are computed and the maximum value of $L-$indices infers the proximity of the system to voltage collapse.

E. The system loadability:

This objective is used to maximize the system loadability that can be described as [23]

$$F_5 = \text{Loadability} = \lambda(x,u)$$

and λ can be obtained by assuming the constant power factor at each load in the real and reactive power balance equations as follows:

$$\sum_{\forall i} P_{G,i} - \sum_{\forall j}(1+\lambda)P_{Load,j} - \sum_{\forall k} P_{Losses,k} = 0 \quad --(5)$$
$$\sum_{\forall i} Q_{G,i} - \sum_{\forall j}(1+\lambda)Q_{Load,j} - \sum_{\forall k} Q_{Losses,k} = 0 \quad --(6)$$

$P_{Load,j}$ and $Q_{Load,j}$ are the real and reactive power loads at j^{th} bus under base case condition (λ=0), $P_{Losses,k}$ and $Q_{Losses,k}$ are real and reactive power losses in k^{th} transmission line

F. Equality constraints:

The equality constraints g(x,u) are the nonlinear power flow equations which are formulated as follows

Power balance constraint

$$\sum P_G = \sum P_{Load} + \sum P_{Losses}$$
$$\sum Q_G = \sum Q_{Load} + \sum Q_{Losses}$$

G. In-equality constraints:

The inequality constraints h(x,u) are limits of control variables and state variables. Generator active power(P_G), reactive power(Q_G), and Voltage (V_G) are restricted by their limits as follows:

$$P_{G_i}^{min} \leq P_{G_i} \leq P_{G_i}^{max}; \qquad \forall\, i \in N_G$$
$$Q_{G_i}^{min} \leq Q_{G_i} \leq Q_{G_i}^{max}; \qquad \forall\, i \in N_G$$
$$V_{G_i}^{min} \leq V_{G_i} \leq V_{G_i}^{max}; \qquad \forall\, i \in N_G$$

The constraints of voltages at load buses V_L and transmission loading S_L are represented as:

$$V_{L_{i,min}} \leq V_{L_i} \leq V_{L_{i,max}}; \qquad i = 1,2,3, \ldots \ldots . n_L$$

$$S_{L_i} \le S_{L_i}^{max}; \quad i = 1,2,3,\ldots\ldots n_l$$

where n_L is the number of transmission lines and n_l is the number of load buses.

The inequality constraints on control (independent) variable limits are given by

$$T_i^{min} < T_i < T_i^{max}; \; i = 1,2,3,\ldots\ldots n_t$$

$$Q_{C_i}^{min} < Q_{ci} < Q_{C_i}^{max}; \; i = 1,2\ldots\ldots n_c$$

where n_t is the number of tap changing transformers and n_c is the number of switchable VAr sources.

H. Constraints handling:

In this constraints handling method, the augmented function F(x) is defined as the sum of the objective function f(x) and a penalty term which depends on the constraint violation h(x).

$$F(x) = f(x) + \sum_{j=1}^{n} \lambda_j \left(h_j(x)\right)^2$$

where, 'n' is the number of inequality constraints, $h_j(x)$ values are the absolute values of the constraints. The parameter λ_j is the penalty coefficient of the jth inequality constraint and it is user defined parameter. In this problem, the equality constraints are met by the load flow solution, V_G, Q_C and Tap values are enforced during the population coding. Hence effectively, the inequality constraints to be handled here are slack bus real power generation ($P_{G,Slack}$), V_L, Q_G and S_L.

The penalized objective function can be written as the sum of unpenalized objective function (f(x)) plus penalty terms.

$$F_{aug}(x) = f(x) + \lambda_p \left(P_{G_{Slack}} - P_{G_{Slack}}^{\;limit}\right)^2 + \lambda_v \left(\sum_{i=1}^{n_L} \left(V_{L_i} - V_{L_i}^{\;limit}\right)^2\right) + \lambda_q \left(\sum_{i=1}^{N_G} \left(Q_{G_i} - Q_{G_i}^{\;limit}\right)^2\right) + \lambda_s \left(\sum_{i=1}^{n_l} \left(S_{L_i} - S_{L_i}^{\;limit}\right)^2\right)$$

where $\lambda_p, \lambda_v, \lambda_q$ and λ_s are respective penalty factors. Let x^{limit} is the limit value of the dependent variable 'x', given as

$$x^{limit} = \begin{cases} x^{max}, & x > x^{max} \\ x^{min}, & x < x^{min} \end{cases}$$

Since the order of magnitude violation is different for different constraints, it is difficult to find a unique value for $\lambda_p, \lambda_v, \lambda_q$ and λ_s. These can be fixed only by trial and error method and problem dependent [24].

IV. MULTI-OBJECTIVE E-CONSTRAINED APPROACH (MOECO)

This section describes the procedure to formulate multi-objective optimization problem.

A. Calculate individual objective functions

Initially, all the system objectives are solved individually based on their nature. i.e cost, emission, loss and VSI objective functions are minimized and the loadability objective is maximized. The corresponding values are tabulated in Table.1.

B. Create pay-off table

In order to properly handle this method, the range of every objective function at least for the 'p-1' objective functions are required that can be used as constraints. The range of these objective functions formulates pay-off table (the table with the results from the individual optimization of the 'p' objective functions).

C. Generate objective e-constrained values

The range of the j^{th} objective function is obtained among the minimum and maximum values of the j^{th} column of the payoff table that is divided into 'q' equal intervals using $(q-1)$ intermediate equidistant grid points. Thus, we have a total of $(q_j + 1)$ grid points for the j^{th} objective function. The density of the pareto optimal set representation can be controlled by properly assigning the values to the 'q'. The higher number of grid points leads to the denser representation of the Pareto optimal set but with the cost of higher computation time. In this paper, the number of intervals for the objective functions is selected to be 100.

D. Formulate multi-objective function

In order to deal with the multi-objective optimization problem can be formulated with five objective functions F1, F2, F3, F4, and F5 using e-constraint approach is as follows

$$\min F_1(x)$$

Subjected to $F_2(x) \le e_2, F_3(x) \le e_3, F_4(x) \le e_4$ and $, F_5(x) \le e_5$

$$e_{2,i}(x) = \max(F2) - \left(\frac{\max(F2) - \min(F2)}{\text{interval}}\right).i \quad \forall\, i = 0,1,2,\ldots\ldots,\text{interval}$$

$$e_{3,j}(x) = \max(F3) - \left(\frac{\max(F3) - \min(F3)}{\text{interval}}\right).j \quad \forall\, j = 0,1,2,\ldots\ldots,\text{interval}$$

$$e_{4,k}(x) = \max(F4) - \left(\frac{\max(F4) - \min(F4)}{\text{interval}}\right).k \quad \forall\, k = 0,1,2,\ldots\ldots,\text{interval}$$

$$e_{5,l}(x) = \min(F5) + \left(\frac{\max(F5) - \min(F5)}{\text{interval}}\right).l \quad \forall\, l = 0,1,2,\ldots\ldots,\text{interval}$$

where max(.) and min(.) represent the respective maximum and minimum values of the individual objective functions after optimization.

E. Solution using PSO

Here, the formulated multi objective optimized function is solved using PSO method [24, 25]. This method consists, initializing the population, weight updating, velocity updating, position updating, local best updating, global best updating.

The penalty functions are added to the formulated multi-objective optimized function to form augmented function to calculate fitness.

F. Generate Pareto front set

The final converged values correspond to the problem intervals are considered as the generated Pareto values. These are the best Pareto solutions from the generated solutions towards the problem optimization. Weightage to the objectives is assigned based on the requirements and the final selection is performed using fuzzy decision making tool.

G. Selection of best value

The decision maker needs to choose the optimal solution according to the requirement among all the Pareto optimal solutions. In this paper, a fuzzy decision making tool approach is proposed for the optimal selection of solution where a linear membership functions (μ_m) is defined for each objective function as follows:

$$\mu_m = \begin{cases} 1 & ; \text{for} \quad F_m \le F_m^{min} \\ \dfrac{F_m^{max} - F_m}{F_m^{max} - F_m^{min}} & ; \text{for} \quad F_m^{min} < F_m < F_m^{max} \\ 0 & ; \text{for} \quad F_m \ge F_m^{max} \end{cases}$$

for minimization of objectives and

$$\mu_m = \begin{cases} 0 & ; \text{for} \quad F_m \le F_m^{min} \\ \dfrac{F_m - F_m^{min}}{F_m^{max} - F_m^{min}} & ; \text{for} \quad F_m^{min} < F_m < F_m^{max} \\ 1 & ; \text{for} \quad F_m \ge F_m^{max} \end{cases}$$

for maximization of objective functions where F_m^n and μ_m^n are the value of the p^{th} objective function in the n^{th} Pareto solution. The membership functions are used to evaluate the optimality degree of the Pareto optimal solutions. The most preferred solution can be selected as follows:

The weight values can be selected by the power system dispatcher based on the importance of the objective aspects. Therefore, the optimal solution is obtained by adopting the proper weight factors to get best Pareto optimal solution.

For each solution in non dominated front set $'n'$, the normalized membership function μ_{opt}^n is calculated as

$$\mu_{opt}^n = \max \left\{ \frac{\sum_{i=1}^{N_{obj}} \omega_{p,i} \cdot \mu_{p,i}^n}{\sum_{p=1}^{M} \sum_{i=1}^{N_{obj}} \omega_{p,i} \cdot \mu_{p,i}^n} \right\} \qquad --(18)$$

where $'M'$ is the number of Pareto solutions. The best compromised solution is the one corresponds to the value of 'μ_{opt}^n'.

V. Results and Analysis

The developed algorithm is tested on IEEE-30 bus system and the corresponding results for single, three and five objectives only are given in the following three cases.

A. *Case – 1 (Single objective)*

The control variable variation corresponding to the multiple objectives is given in Table 1. It is observed that the minimization of cost function results in increase of the emission by a factor of 0.7904, losses by 1.9874 and VSI by 0.0448 (all factors are with respect to their minimized values). Table 1 reveals that the minimization of emission function results in increase of the cost by a factor of 0.1801, losses by 0.0709, and VSI by 0.0185. Minimization of losses in the system increases the cost by a factor of 0.2089, emission by 0.0119, and VSI by 0.1574. Similarly minimization of VSI results in increase of the cost by a factor of 0.01663, emission by 0.5745, and losses by 2.2839. In all the above cases there is no chance for getting loadability. But, from the last column of the Table 1, maximization of the loadability on a system results in increase of the cost by a factor of 0.7357, emission by 10.043, losses by 4.2387 and VSI by 0.59103. The important point is that, maximization of loadability on system increases the values of other objectives from their best values. The corresponding convergence patterns are shown in Fig 2.

Table 1. Control variables related to multiple objectives

	Cost, $/h	Emission, ton/h	Loss, MW	VSI	Loadability MW
Pg1, MW	177.2293	64.0087	51.3909	156.901	195.4534
Pg2, MW	48.5503	67.5944	80.0000	64.3043	80.00
Pg3, MW	21.4629	50.0000	50.0000	19.0465	50.00
Pg4, MW	21.2110	35.0000	35.0000	30.9689	35.00
Pg5, MW	11.8819	30.0000	30.0000	10	30.00
Pg6, MW	12.0002	40.0000	40.0000	12.0017	40.00
Vg1, pu	1.1000	1.0927	1.1000	1.0162	1.0136
Vg2, pu	1.0370	1.0825	1.04169	1.0099	0.9368
Vg3, pu	1.0647	1.0572	1.08315	1.0264	0.9739
Vg4, pu	1.0544	1.0685	1.08791	1.0491	1.0435
Vg5, pu	0.9634	0.9442	1.0996	1.0977	1.0849
Vg6, pu	1.1000	1.0935	1.1000	1.1000	1.1000
Tap6-9, pu	0.9514	1.0151	1.0173	0.9000	1.0284
Tap6-10, pu	0.9910	0.9562	0.9689	0.9000	0.9443
Tap4-12, pu	0.9919	0.9949	0.9831	0.9000	1.0184
Tap27-28, pu	0.9679	0.9665	0.9704	0.9000	1.0013
QC10	15.9744	17.7849	21.0731	30.000	14.1342
QC24	10.4601	17.5381	11.6769	5.0000	22.1433
Cost	800.1774	944.3457	967.4024	813.487	1388.881
Emission	0.3664	0.2047	0.2071	0.3225	0.4103
Loss	8.9355	3.2031	2.9909	9.8222	15.6692
VSI	0.1321	0.1288	0.1464	0.1265	0.2012
Loadability	0	0	0	0	0.4636

In Table.1, the bold quantities can be constituted as pay-off table, and the corresponding e-constrained values are generated between these values.

B. *Case – 2 (Two objectives)*

To show the performance of the used methodology Cost and Emission objectives are combined together as an optimization problem and the obtained result are tabulated in Table.2. From this table it is observed that, minimum cost (892.0613 $/h) is obtained with the emission of (0.2126 ton/h) and maximum cost (899.5169 $/h) is with the emission of (0.2107 ton/h). It is clear that the generation cost increases as the emission decreases.

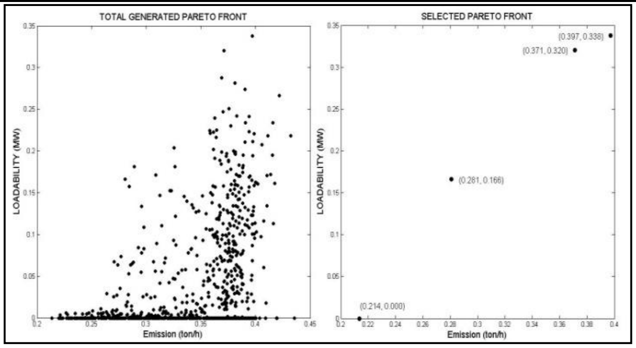
Table.2: Multi-objective result for different weight factors (Cost-Emission)

W1	W2	COST	EMISSION
0.9	0.1	892.0613	0.212559
0.8	0.2	892.0613	0.212559
0.7	0.3	892.0613	0.212559
0.6	0.4	894.3731	0.211671
0.5	0.5	895.0237	0.211486
0.4	0.6	899.5169	0.210677
0.3	0.7	899.5169	0.210677
0.2	0.8	899.5169	0.210677
0.1	0.9	899.5169	0.210677

Table.3: Multi-objective result for different weight factors (Emission - Loadability)

W1	W2	EMISSION	LOADABILITY
0.9	0.1	0.2135385	0
0.8	0.2	0.2135385	0
0.7	0.3	0.2135385	0
0.6	0.4	0.2807102	0.16619
0.5	0.5	0.3709212	0.32012
0.4	0.6	0.3709212	0.32012
0.3	0.7	0.3970462	0.33809
0.2	0.8	0.3970462	0.33809
0.1	0.9	0.3970462	0.33809

Table. 3 reveals that, the minimum loadability of 0.16619 is with the emission of 0.2807 ton/h and maximum loadability of 0.33809 is with the emission of 0.39704 ton/h. It clearly shows that the emission objective has a great impact on loadability. The corresponding Pareto values are shown in Fig.1.



Emission - Loadability

Figure 1. Two dimensional generated Pareto-optimal fronts

C. Case – 3(Three objectives)

In this section, Cost-Emission-Loadability and Emission-Loss-Loadability combinations are explained. Variation of the objective function values for these combinations is given in Table.4 and Table.5.

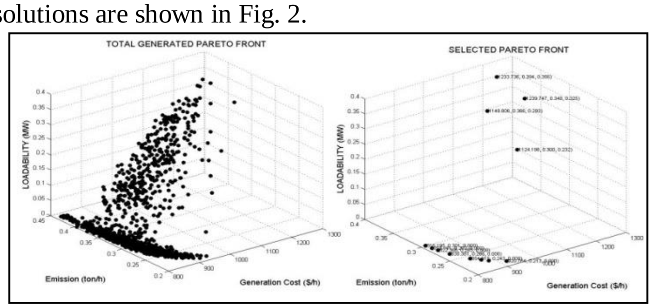
Table.4: Multi-objective result for different weight factors (Cost-Emission-Loadability)

W1	W2	W3	COST	EMISSION	LOADABILITY
0.1	0.1	0.8	1233.736	0.393632	0.35591
0.1	0.8	0.1	920.7645	0.213094	0
0.8	0.1	0.1	816.1951	0.301356	0
0.1	0.4	0.5	1239.747	0.347521	0.32532
0.1	0.5	0.4	1124.198	0.300141	0.23172
0.4	0.1	0.5	1149.806	0.365993	0.29272

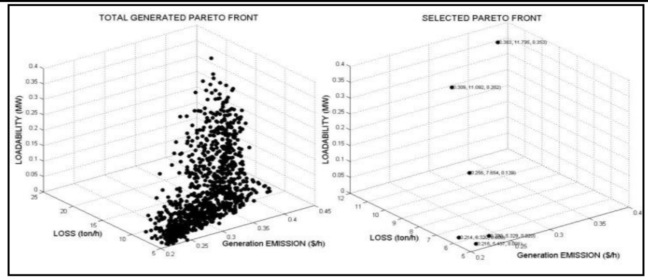
Table.5: Multi-objective result for different weight factors (Emission-Loss-Loadability)

W1	W2	W3	EMISSION	LOSS	LOADABILITY
0.1	0.1	0.8	0.382624	11.79525	0.35334
0.1	0.8	0.1	0.230076	5.328916	0.02001
0.8	0.1	0.1	0.213668	6.319546	0
0.1	0.6	0.3	0.25605	7.653978	0.13913
0.2	0.4	0.4	0.309046	11.09202	0.28237
0.3	0.6	0.1	0.21629	5.457069	0.00093

Table.4 reveals that maximum loadability (0.35591) is with the maximum cost of 1233.736 $/h and maximum emission of 0.3936 ton/h. At minimum cost and minimum emission, there is no chance for getting loadability. It is observed that emission has a great impact on loadability, with little scarifying the emission objective, the loadability can be increased. From table.4, at maximum loadability (0.35334) the losses are 11.795MW, losses are increased by a factor of 1.22 (with respect to its minimized value). At minimized emission there is no chance for getting loadability. Very less loadability (0.00093) is with the emission of 0.21629 ton/h and losses of 5.45069 MW. The corresponding three dimensional Pareto solutions are shown in Fig. 2.



(a) Cost – Emission – Loadability



(b) Emission – Loss – Loadability (LBI)

Figure 2. Three dimensional best Pareto-optimal fronts

D. Case – 4 (Four objectives)

Cost, Loss, VSI and Loadability objectives are considered to formulate multi-objective optimization function. The results are tabulated in Table.6.

Table.6: Multi-objective result for different weight factors (Four objectives)

W1	W2	W3	W4	COST	LOSS	VSI	LBI
0.1	0.1	0.1	0.7	1343.18	15.4059	0.1485	0.42554
0.1	0.1	0.3	0.5	1255.43	14.1844	0.1262	0.37709
0.1	0.1	0.4	0.4	1131.372	11.4403	0.0974	0.23964
0.2	0.2	0.2	0.4	1184.962	13.2902	0.1183	0.32939
0.4	0.1	0.1	0.4	1020.483	12.1603	0.1177	0.19679
0.7	0.1	0.1	0.1	808.5326	9.4108	0.1411	0
0.1	0.7	0.1	0.1	897.7866	6.1689	0.1113	0
0.1	0.1	0.7	0.1	1131.372	11.4403	0.0974	0.23964

From Table.6, minimum cost is 808.5326, minimum loss is 6.16894, minimum VSI is 0.097366 and maximum loadability is 0.42554. The increase in loadability increases the cost, loss, and VSI to greater values. Minimum loadability is 0.19679 with the cost of 1020.483 $/h. Corresponding three dimensional Pareto optimal solutions by keeping one of the objective functions at constant is shown in Fig. 3. This figure shows the confinement of the generated Pareto solutions in the trade-off region.

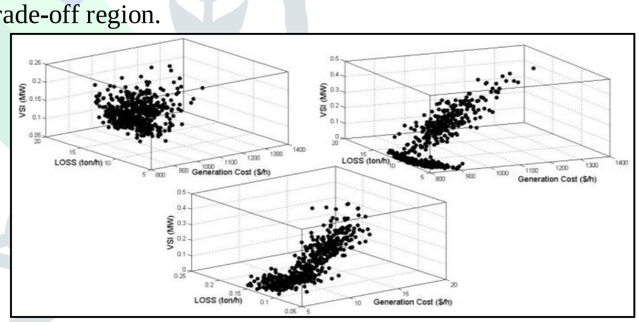


Figure 3. Three dimensional best Pareto-optimal fronts

E. Case – 5 (Five objectives)

In this section, all considered five objectives are combined together to form a multi-objective optimization problem. A total of 126 combinations are tested and the obtained results for some combinations are tabulated in Table.7. This shows the effectiveness of the used algorithm.

Table.7: Multi-objective result for different weight factors (Five objectives)

W1	W2	W3	W4	W5	COST	EMI	LOSS	VSI	LBI
0.1	0.1	0.1	0.1	0.6	1348.17	0.39	16.47	0.19	0.426
0.1	0.1	0.2	0.1	0.5	1191.11	0.37	11.09	0.17	0.313
0.1	0.2	0.1	0.1	0.5	1348.17	0.39	16.47	0.19	0.426
0.2	0.1	0.1	0.1	0.5	1348.17	0.39	16.47	0.19	0.426
0.2	0.1	0.2	0.1	0.4	1191.11	0.37	11.09	0.17	0.313
0.6	0.1	0.1	0.1	0.1	825.67	0.27	8.01	0.12	0
0.5	0.1	0.1	0.2	0.1	816.076	0.30	8.09	0.12	0
0.2	0.4	0.1	0.2	0.1	926.495	0.21	6.47	0.12	0

From Table.7, the stated hypothesis is validated and there is a chance for getting loadability on a given system subjected to the constraints and by scarifying other objectives simultaneously. Maximum loadability of 0.426616 increases the other objectives to greater values. The same value can also be achieved by changing the importance of the objectives.

VI. Conclusion

The used MOECO technique can solve multi-objective optimization problem subjected to given equality and inequality constraints. The obtained result supports that this method can be applied to the objectives namely, cost, emission, loss, VSI and loadability objectives towards its nature. The result confirms that, the requirement of the certain objectives can be met by scarifying other objectives simultaneously. By using this method the formulated multi-objective optimization function has been solved within 20-30 iterations. This method can handle different objectives based on its nature (i.e minimization/maximization of objectives simultaneously). The fuzzy decision making tool to select best Pareto front from the generated Pareto optimal solutions proves its effectiveness in selection of globally best solution. The proposed methodology works independent of nature of the objective functions and can be applied to any type of the objectives.

References

[1] R.B. Squires, Economic dispatch of generation directly from power system voltages and admittances, AIEE Transactions on Power Apparatus and Systems, No.3, 1235–1245, 1961.

[2] J. Carpentier, Contribution e letude do Dispatching Economique, Bulletin Soci-ety Francaise Electriciens pp.431–447, 1962.

[3] Z. Gaing, H.-S. Huang, Real-coded mixed-integer genetic algorithm for con-strained optimal power flow, in: IEEE TENCON Region 10 Conference, pp. 323–326, 2004.

[4] D. Devaraj, B. Yegnanarayana, Genetic-algorithm-based optimal power flow for security enhancement, IEE Proceedings on Gen. Trans. and Dis., vol. 152, No. 6, pp. 899–905, 2005.

[5] D.B. Das, C. Patvardhan, Useful multi-objective hybrid evolutionary approach to optimal power flow, IEE Proceedings on Gen. Trans. and Dis., vol. 150, No. 3, pp. 275–282, 2003.

[6] M.A. Abido, Multiobjective optimal power flow using strength Pareto evolu-tionary algorithm, in: The 39th International Universities Power Engineering Conference, pp. 457–461, 2004.

[7] T.K. Hahn, M.K. Kim, D. Hur, J.K. Park, Y.T. Yoon, Evaluation of available trans-fer capability using fuzzy multi-objective contingency-constrained optimal power flow, Electric Power Systems Research No.78, 873–882, 2008.

[8] X. Liu, J. Li, H. Li, H. Peng, Fuzzy modeling and interior point algorithm of multi-objective OPF with voltage security margin, in: IEEE/PES Transmission and Distribution Conference and Exhibition: Asia and Pacific, pp. 1–6, 2005.

[9] R. Ma, P. Wang, H. Yang, G. Hu, Environmental/economic transaction plan-ning using multiobjective particle swarm optimization and non-stationary multi-stage assignment penalty function, IEEE/PES Trans. and Dist. Conference and Exhibition, Asia, China, pp. 1–6, 2005.

[10] J.G. Vlachogiannis, K.Y. Lee, A comparative study on particle swarm opti-mization for optimal steady-state performance of power systems, IEEE Transactions on Power Systems, Vol.21, No. 4, 1718–1728, 2006.

[11] Z.L. Gaing, Constrained optimal power flow by mixed-integer particle swarm optimization, in: IEEE Power Engineering Society General Meeting, San Francisco, USA, pp. 243–250, 2005.

[12] M. Tripathy, S. Mishra, Bacteria foraging-based solution to optimize both real power loss and voltage stability limit, IEEE Transactions on Power Systems, Vol.22, No.1, pp.240–248, 2007.

[13] J L Cohon., "Multiobjective Programming and Planning", NewYork:Academic, 1978.

[14] A. Lashkar Ara, A. Kazemi, S.A.Nabavi Naiki., "Multiobjective Optimal Location of FACTS Shunt-Series Controllers for Power System Operation Planning", IEEE Transactions on power delivery, Vol.27, No.2, pp.481-490., 2012.

[15] M.R.AlRashidi, M.E.El-Hawary., "Applications of computational intelligence techniques for solving the revived optimal power flow problem", Electric power system research, Vol.79, pp. 694-702, 2009.

[16] George Mavrotas., "Effective implementation of the e-constraint method in multi-objective mathematical programming problems", Applied mathematics and computation, Vol.213, pp.455-465., 2009.

[17] R.E. Steuer, Multiple Criteria Optimization, Theory, Computation and Application, Krieger, Malabar, FL, 1986.

[18] K.M. Miettinen, Nonlinear Multiobjective Optimization, Kluwer Academic Publishers, 1998.

[19] M. Ehrgott, D.M. Ryan, Constructing robust crew schedules with bicirteria optimization, Journal of Multi-Criteria Decision Analysis, Vol.11, pp.139–150, 2002.

[20] M. Laumanns, L. Thiele, E. Zitzler, An efficient, adaptive parameter variation scheme for metaheuristics based on the epsilon-constraint method, European Journal of Operational Research, Vol.169, pp.932–942, 2006.

[21] H.W. Hamacher, C.R. Pedersen, S. Ruzika, Finding representative systems for discrete bicriterion optimization problems, Operations Research Letters, Vol.35, pp.336–344, 2007.

[22] El-Keib. A. A, Ma. H, Hart. J. L., "Economic Dispatch in view of the clean AIR ACT of 1990," IEEE Transactions on Power Systems, Vol. 9, No. 2., 1994, pp. 972-978.

[23] Ya-Chin Chang, Rung-Fang Chang, Tsun-Yu Hsiao, and Chan-Nan Lu., "Transmission System Loadability Enhancement Study by Ordinal Optimization Method", IEEE Transactions on power systems, Vol. 26, No. 1., 2011, pp. 451-459.

[24] M.A.Abido., "Optimal power flow using particle swarm optimization," Electric Power and Energy Systems, Vol. 24., 2002, pp. 563-571.

[25] M Saravanan, S M R Slochanal, P Venkatesh, J P S Abraham., "Application of particle swarm optimization technique for optimal location of FACTS devices considering cost of installation and system loadability," Electrical power systems research, Vol.77, No.3-4, pp. 276-283, 2007.