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Fuzzy Ranking Based Real Coded Genetic Algorithm for Combined Economic Emission Dispatch with Loss Minimization

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Abstract— ***In this paper, fuzzy ranking based real coded genetic algorithm is proposed to deal with multi-objective problem of fuel cost, emission and system loss minimization. Emission substances like NO_X, CO_2, SO_2, power balance constraint and generation capacity constraints are considered here. This tri-objective problem is converted into single objective problem known as Combined Economic Emission Dispatch (CEED) with loss minimization by introducing novel price penalty factor (PPF). Due to the conflicting behavior of the objectives, set of Pareto optimal solutions is obtained instead of getting the single optimal solution. In order to extract the best compromise solution out of the available non-dominated solutions depending upon its highest rank, fuzzy ranking approach is employed. Several optimization runs have been carried out on standard IEEE-30 bus system by identifying three test cases. The results demonstrate the capability of proposed method to generate well distributed Pareto optimal non-dominated solutions of multi-objective problem. The comparison with the reported results confirms its potential in solving other power systems multi-objective optimization problems.***

Index Terms— **Multi-Objective Optimization Problem, Fuzzy Ranking, Pareto Optimal Solutions, Combined Economic Emission Dispatch, Real Coded Genetic Algorithm (RCGA).**

I. INTRODUCTION

Traditionally electric power systems are operated in such a way that the total fuel cost is minimized regardless of the emission produced in the system. However, after the implementation of US clean air act amendments of November 1990 and similar acts in other countries, the concern of the public towards the reduction of pollutants, such as CO, CO2, SO2 and NOX from thermal power generation is increased. In this regard Gent and Lamont have started the early work on minimum emission dispatch [1]. Nowadays, utilities would like to supply the power to its consumers with minimum total emission as well as minimum total fuel cost. Hence, this will generate a large-scale highly constrained non-linear multi-objective optimization problem.

To handle the multi-objective EED problem with conflicting objectives, many approaches and methods have been reported in the previous literature. By using conventional optimization method a summary of environmental dispatch algorithm is presented in [9]. In literature [4, 6-8, 27] different objectives were expressed into a unit function to handle it as a single-objective optimization problem using the linear weighted sum method or the price penalty factor. K.Srikrishna and C.Palanichamy [16] have proposed a method for Combined Emission and Economic Dispatch (CEED) using price penalty factor. Recently price penalty approach is presented for solving Emission, reserve and economic load dispatch (ERELD) problem with non-smooth and non-convex cost functions problem by proposing Bacterial Foraging -Nelder–Mead algorithm method [28].Whereas some papers address the issue as a multi-objective optimization problem [2, 3, 11-15]. Here, both fuel cost and the emission were simultaneously optimized as competing objectives. Over the past decade, the later approach has attracted many researchers' interests due to the new development of multi-objective evolutionary search techniques. Multi-objective evolutionary algorithms like non-dominated sorting genetic algorithm (NSGA) [11], niched Pareto genetic algorithm (NPGA) [12], the strength Pareto evolutionary algorithm (SPEA) [13] and the NSGA-II [17,18] have been introduced to solve the CEED problem.

In addition, some other optimization approaches, such as fuzzy satisfaction maximizing technique [19], and genetic and evolutionary programming based hybrid approaches [12, 20, 21] have been proposed for this problem. In reference [21] a fuzzy based penalty is imposed on the fitness for any constraint violation, while the genetic algorithm is used for searching the optimal solution. Fuzzy set theory is effectively used for finding the best compromise solution out of the pareto-optimal set [12]. A fuzzified multi-objective particle swarm optimization (FMOPSO) algorithm [22], harmony search algorithm [3], a modified neo fuzzy neuron based approach [7], improved Hopfield neural network [23] is also proposed and implemented to solve the Environmental Economic Dispatch (EED) problem with competing and non-commensurable cost and emission.

In this paper the performance of the fuzzy ranking based real coded genetic algorithm is proposed and implemented for solving CEED with loss minimization problem. Here, three cases have been identified and tested on standard power system. Due to the presence of multiple objectives, a single best solution does not exist. Therefore fuzzy based mechanism is incorporated into the algorithm to extract the best compromise solution. The best results obtained from the solution of the CEED problems by adopting this proposed method are compared with the different techniques reported in the literature.

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II. MATHEMATICAL MODEL FOR COMBINED ECONOMIC EMISSION DISPATCH WITH LOSS MINIMIZATION

The Combined Economic Emission Dispatch with loss minimization problem is to minimize simultaneously the three competing objective functions fuel cost, emission and system loss while satisfying all equality and inequality constraints. The mathematical model for the above problem is described as follows:

A. Problem objectives

Economic load dispatch: ELD problem can be formulated as an optimization problem with objective of minimizing the fuel cost of the power system only. The generators cost curves are represented by the quadratic functions and expressed as

$$F_T = \sum_{i=1}^{N} F_i(P_i) = \sum_{i=1}^{N} (a_i P_i^2 + b_i P_i + c_i) \$/h \qquad (1)$$

Where F_i is the fuel cost and a_i, b_i and c_i are the fuel-cost coefficients of the i^{th} unit and P_i is the output of the i^{th} unit. F_T is the total fuel cost of the system. Emission dispatch: ED problem is carried out for the optimization of emission only while satisfying the several equality and inequality constraints. Total emission content of atmospheric pollutants such as sulphur oxides (SOx) and nitrogen oxides (NOX) caused by fossil-fueled thermal generators in (lb/hour) can be represented as

$$E_T = \sum_{i=1}^{N} E_i(P_i) = \sum_{i=1}^{N} 10^{-2} * (\alpha_i + \beta_i P_i + \gamma_i P_i^2) + \xi_i \exp(\lambda_i P_i) \qquad (2)$$

Where $\alpha_i, \beta_i, \gamma_i, \xi_i$ and λ_i are the pollution coefficients of the *ith* generating unit. E_T is the total emission of the system.

B. Objective constraints

Generation capacity constraints: For stable operation, real power output of each generator is restricted by lower and upper limits as follows:

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1,2,\ldots,N \qquad (3)$$

Power balance constraints: The total power generation must cover the total load demand PD and the real power loss in transmission lines Ploss. Hence,

$$\sum_{i=1}^{N} P_i - (P_D + P_L) = 0 \qquad (4)$$

The total transmission network losses PL can be expressed using B-coefficients and unit power output as

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \qquad (5)$$

Where B_{ij}, B_{io} and B_{oo} are the line loss coefficients.

C. The optimization Problem

The multi-objective optimization problem consisting of the fuel cost and emission as competing objectives can be converted into a single objective minimization problem by introducing price penalty factor (PPF). A practical way of determining PPF is discussed by Palanichamy and Srikrishan [16].Therefore this complex multi-objective problem can be expressed as:

$$MinTC = F_T + h * E_T \qquad (6)$$

Where h is the price penalty factor which blends the fuel cost with emission and TC is the total operating cost in \$/hr. If the number of objective function is three as for example when the fuel cost, emission and loss are considered all together than overall objective function can be formulated as follows:

$$MinTC = F_T + (h_1 * E_T) + (h_2 * P_L) \qquad (7)$$

Here h_1 is the price penalty factor for emission defined as the ratio between the maximum fuel cost & maximum emission of corresponding generator whereas penalty factor for loss (h_2) is defined as the ratio between the maximum fuel cost and maximum loss of that corresponding generator. The value of h_1 and h_2 obtained for load P_D =2.834 pu is 5928.7134 \$/lb & 10435.0862 \$/pu respectively using algorithm from reference [16].

III. PROPOSED TECHNIQUES

In this paper real coded genetic algorithm using fuzzy ranking is tested on standard IEEE-30 bus system for obtaining best compromise solution from the set of available Pareto optimal solutions obtained for all identified test cases.

A. Best compromise solution

In multi-objective optimization of the above formulated problem there are more than one evaluation functions to be considered which in turn provides set of non-dominated solution instead of giving single optimal solution. In real applications, due to imprecision of judgments by decision makers a fuzzy membership functions adopted to provide best compromise solution out of the Pareto optimal solutions which satisfies different goals to some extent[21,24]. The membership value '0' indicates incompatibility with the sets, while '1' means full compatibility. In other words, the membership value indicates the degree of satisfaction of the solution for an objective. Here, it is assumed that $\mu(F_i)$ is a strictly monotonic decreasing function defined as:

$$\mu(F_i) = \begin{cases} 1; F_i \le F_i^{\min} \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}}; F_i^{\min} \le F_i \le F_i^{\max} \\ 0; F_i \ge F_i^{\max} \end{cases} \qquad (8)$$

Where $F_i^{\min}$ and $F_i^{\max}$ are the expected minimum and maximum values of i^{th} objective function. The value of the membership function indicates how much (in scale from 0 to 1) a solution is satisfying the i^{th} objective F_i. The best solution can then be selected using fuzzy min-max proposition.

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$$\mu_{bestsolution} = Max\left\{\min\left[\mu(F_j)\right]^k\right\} \tag{9}$$

Where *j* is number of objectives to be minimized and *k* are number of pareto-optimal solutions obtained. First the minimum of membership values of all the objectives (for each solution) is taken implying that all objectives must have achieved higher satisfaction of membership function than this value. Then out of *k* values available for *k* solutions, the best solution is judged based on the maximum value of membership out of these *k* values.

B. Pareto optimality

Pareto Optimality is a measure of efficiency in multi-criteria and multi-objective situations. It is a situation which exists when economic resources and output have been allocated in such a way that no part of a Pareto optimal solution can be improved without making some other part worse. A state X (a set of object parameters) is said to be Pareto optimal, if there is no other state Y dominating the state X with respect to a set of objective functions. A decision vector x is said to strictly dominate another vector y (denoted $x \prec y$) if

$f_i(x) \le f_i(y) \qquad \forall i = 1,.............,n$

And $f_i(x) < f_i(y)$ for at least one i.

Where *n* is the number of objectives to be optimized.

C. Real coded genetic algorithm

Genetic algorithm is an optimization and a search technique based on the principles of genetics and natural selection. It was developed by John Holland in 1975 over the course of 1960's and 1970's and finally it was popularized by his student Goldberg. The binary GA solves many optimization problems that stump traditional techniques, but where variables are continuous each variable requires many bits to represent it. If the number of variables is large, the size of the chromosome is also large. Of course, 1s and 0s are not the only way to represent a variable. When the variables are naturally quantized, the binary GA fits nicely. However, when the variables are continuous, it is more logical to represent them by floating-point numbers. Due to which it requires less space, inherently faster and also reduces the chances of error occurrence.

In this paper real coded (continuous) genetic algorithm is proposed to solve the CEED with loss minimization problem. In this optimization method, the output of each generating unit is represented by a floating point number, instead of binary coding, resulting in absolute precision, hence dependence of accuracy on string length (number of bits) is eliminated. The outputs of all generators are consolidated to form a solution string called chromosome. A population of chromosomes is initially generated randomly. The population size is an important parameter of GA and its selection needs to be done carefully for each problem. Each chromosome in the population represents a possible solution to the problem. A fitness value, derived from the problem's objective function is then evaluated for each solution string in the population. Strings that have better solutions are awarded higher fitness values, ensuring their survival in the coming generations. The GA searches for better solutions by letting the fitter individuals take over the population through a combined stochastic process of selection and recombination. The main three operators that influence the GA performance are selection, crossover and mutation.

Their interaction is highly complex and slight variations in their implementations result in a variety of models. The different models depend on many factors like selection method and mechanism, parent replacement method, crossover and mutation method, serial or parallel implementation, and the type of problem to be solved. The GA model to be used is chosen after a careful analysis of the problem to be solved. The accuracy and computational time of binary GA increases exponentially with problem dimension. But real coded GA does not suffer from these limitations and is a powerful tool for solving real-world engineering problems.

Algorithm can be represented by flow chart shown in Fig.1 [25]:

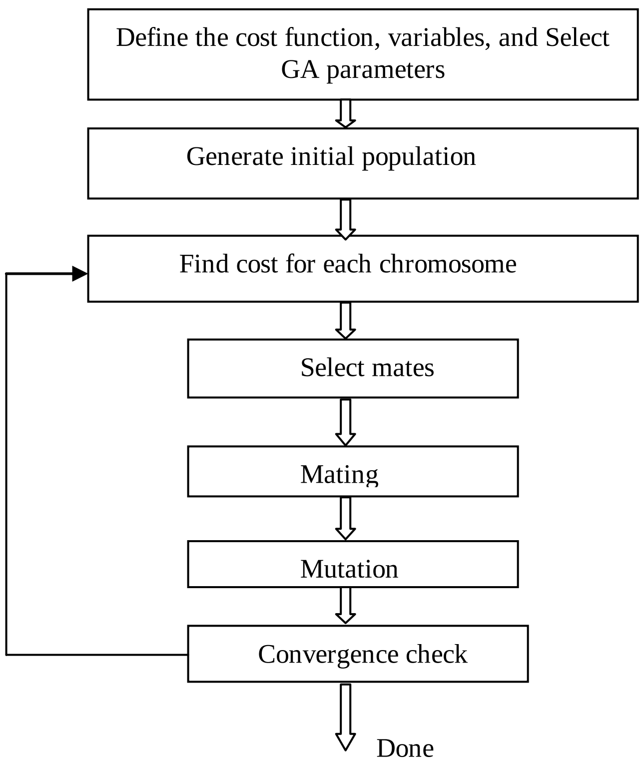

Fig.1. Flow chart of continuous GA

The pseudo-code for the algorithm is given as follows:

i. Set the parameters for the problem
ii. Initialize population within bounds
iii. Evaluate the fitness for individual
iv. **Start** iteration
v. Pair and mate
vi. Perform mating using single point crossover
vii. Mutate the population on random basis
viii. Evaluate the new offspring and mutated chromosomes

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ix. Sort the costs and associated parameters
x. Do statistics for a single non averaging run
xi. **Stop** when criteria is satisfied
xii. Find fuzzy ranking for the function as given below
- If f <= f^{min} then μ=1
- Else if f >= f^{max} then μ=0
- Else μ= (f^{max}- f) / (f^{max}- f^{min})

xiii. Display the optimal generation for the set objectives.

IV. EXPERIMENTS AND RESULTS

To access the potential of the proposed method for solving Combined Economic Emission Dispatch with loss minimization problem IEEE-30 bus with six generating unit is considered. Data for the cost curve, emission coefficients with generation limits of IEEE 30-bus six-generating unit system and the transmission loss coefficients has been adopted from [15] and [26] and shown in Table I, Table II and Table III respectively. The load demand considered is 2.834 p.u with 100 MVA base.

Table I. Cost coefficient and generation limits for six generating unit system

No.	$P_{\min i}$*(pu)*	$P_{\max i}$ *(pu)*	a_i	b_i	c_i
1	0.05	0.50	100	200	10
2	0.05	0.60	120	150	10
3	0.05	1.00	40	180	20
4	0.05	1.20	60	100	10
5	0.05	1.00	40	180	20
6	0.05	0.60	100	150	10

Table II. Emission coefficients and generation limits for six generating unit system

No.	α_i	β_i	γ_i	ξ_i	λ_i
1	4.091	-5.554	6.490	0.0002	2.857
2	2.543	-6.047	5.638	0.0005	3.333
3	4.258	-5.094	4.586	0.00001	8.000
4	5.326	-3.550	3.380	0.002	2.000
5	4.258	-5.094	4.586	0.000001	8.000
6	6.131	-5.555	5.151	0.00001	6.667

Table III.B-coefficients and generation limits for six generating unit system

B_{ij}	0.1382	-0.0299	0.0044	-0.0022	-0.0010	-0.0008
	-0.0299	0.0487	-0.0025	0.0004	0.0016	0.0041
	0.0044	-0.0025	0.0182	-0.0070	-0.0066	-0.0066
	-0.0022	0.0004	-0.0070	0.0137	0.0050	0.0033
	-0.0010	0.0016	-0.0066	0.0050	0.0109	0.0005
	-0.0008	0.0041	-0.0066	0.0033	0.0005	0.0244
B_o	-0.0107	0.0060	-0.0017	0.0009	0.0002	0.0030
B_{oo}	0.00098573					

Fig.2 shows the single line diagram of the standard IEEE-30 bus system with six generating units. The source code were written on MATLAB of version 7.0.1 and implemented on a 256 MB of memory, Pentium IV processor. The optimal parameter selected for running the algorithm is as follows: Mutation rate=0.2, selection rate=0.5, number of variable=6, trials=60, population=300 (case 1), 400(case 2) &500(case 3) and no. of iteration = 250.

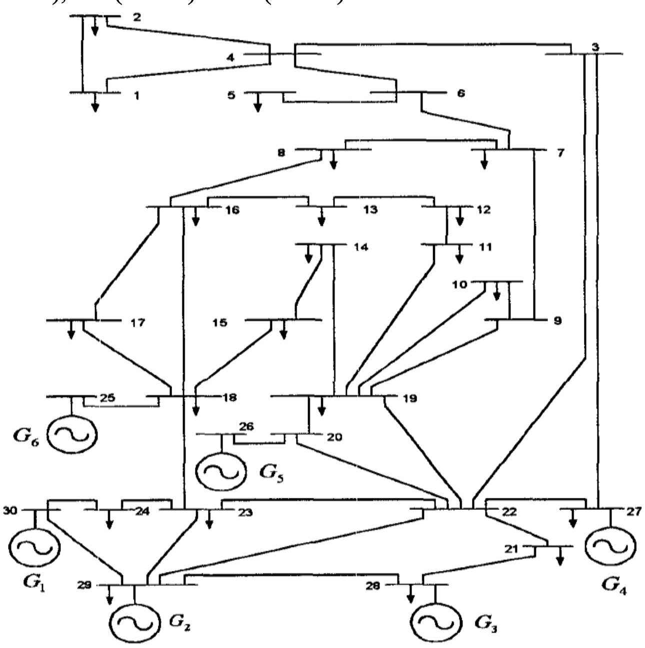

Fig.2 The single-line diagram of IEEE30-bus system

Three test cases have been identified for demonstrating and validating the effectiveness of the proposed method:

Case 1: For the purpose of comparison with the previously Reported results the CEED problem is simulated for a lossless system. Here all above defined constraints are considered.

Case 2: In this case transmission losses P_L is considered for CEED problem with equality and inequality Constraints.

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Case 3: Tri-objective optimization problem with fuel cost, Emission and loss impact objectives are considered here.

The results are obtained by setting parameters for the algorithm and by providing minimum and maximum limits for different objectives to determine fuzzy membership of each objective based on which the best solution depending upon the highest rank can be found out of the available Pareto-optimal solutions. For this initially fuel cost objective, emission objective and system loss objective are optimized individually to explore the extreme points of the Pareto front. This procedure is applied to all identified test cases.

A. Case 1: Combined Economic Emission Dispatch without transmission losses

In this case, no transmission line losses are considered. Hence, bi-objective optimization is performed only by considering the generation capacity and power balance constraints. Here the two competing objectives of fuel cost and emission were simultaneously minimized using eq. (6). The single objective optimization results obtained in Table IV give the two extreme points of the Pareto front. In order to know how competitive the proposed method was, the single objective optimization results was compared with the LP[10], NSGA[11], NPGA[12], SPEA[13] and BB-MOPSO[2].

Table IV.Comparison of best solution for fuel cost and emission with five algorithms on optimizing case 1for a lossless system

		Fuel cost	Emission
Best fuel cost	Proposed method	**599.872**	0.220944
	LP[10]	606.314	0.22330
	NSGA[11]	600.572	0.22282
	NPGA[12]	600.259	0.22116
	SPEA[13]	600.150	0.22151
	BB-MOPSO[2]	600.112	0.2222
Best emission	Proposed method	632.322	**0.193911**
	LP[10]	639.600	0.194227
	NSGA[11]	639.209	0.194356
	NPGA[12]	639.180	0.194327
	SPEA[13]	638.507	0.194210
	BB-MOPSO[2]	638.262	0.194203

Table V.Pareto optimal solutions based on fuzzy ranking for load P_D=2.834 p.u

	Cost($/h)	Emission	μ_1	μ_2	μ_{min}
SOL.1	601.8472	0.2121	0.9457	0.3258	0.3258
SOL.2	602.0295	0.2116	0.9335	0.3462	0.3462
SOL.3	602.3696	0.2098	0.9230	0.4117	0.4117
SOL.4	603.9172	0.2077	0.8754	0.4902	0.4902
SOL.5	**607.8557**	**0.2036**	0.7540	0.6420	**0.6420**

When only cost minimization was considered for a lossless system, the minimum value obtained was 599.872 $/h and when only emission minimization problem was solved the value was 0.193911 lb /h for 2.834 pu load. The maximum values for objective functions were set on the basis of the results. Here, the maximum value computed for cost and emission is 632.322 $/hr and 0.220944 lb/hr respectively. These minimum and maximum values set the limits for finding the membership value of the non-dominated solutions. The five intermediate solutions with their membership value out of the obtained non-dominated solution set using proposed method is shown in Table V for test case 1. The target is now to find the best compromise solution depending upon its highest rank i.e. the solution which minimizes both the objectives simultaneously. The best solution is shown in bold and it has a rank of 0.6420 which means that both the objectives are satisfied at least 64.20%.

Table VI compares our results for the best compromise solution with those results reported in literature, which are obtained by using NSGA [11], NPGA [12], SPEA [13] and BB-MOPSO [2]. As shown in Table IV and Table VI, it is quite evident that the proposed method performs better than the other algorithms for the problem under discussion and yields satisfactory compromise solutions. Here for a lossless system, the best compromise solution obtained is quite satisfactory and has the value of 607.85 $/hr and 0.2036 lb/hr respectively for cost and emission.

Table VI. Best compromise solution of CEED problem for lossless six unit generator system with four different techniques (P_D=2.834 pu)

	Prop. Case1	NSGA[11]	NPGA[12]	SPEA [13]	BB-MOPSO[2]
P1	0.2035	0.2571	0.2696	0.2785	0.2595
P2	0.4027	0.3774	0.3673	0.3764	0.3698
P3	0.4179	0.5381	0.5594	0.5300	0.5351
P4	0.7504	0.6872	0.6496	0.6931	0.6919
P5	0.5978	0.5404	0.5396	0.5406	0.5500
P6	0.4602	0.4337	0.4486	0.4153	0.4277
Fuel cost	**607.85**	610.06	612.12	610.25	609.474
Emission	**0.2036**	0.2006	0.1994	0.2005	0.20083

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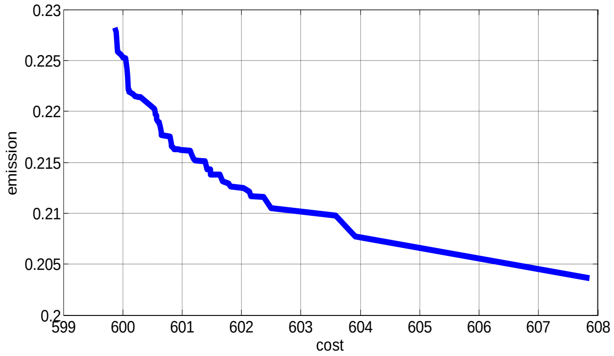

Fig.3: Pareto-front of cost vs. emission for P_D = 2.834 pu (case 1)

Fig. 3 shows the relationship (trade-off curve) of fuel cost and emission objectives of non-dominated solutions obtained by the proposed method. This demonstrates the effectiveness of the proposed method to span over the entire Pareto front.

B. Case 2: Combined Economic Emission Dispatch with transmission losses

In order to validate the constraint handling strategy and to evaluate the performance of our proposed method transmission line losses are considered here. In Table VII, the simulated results for best cost and best emission are presented and compared with NSGA [11], NPGA [12], SPEA [13], BB-MOPSO [2] and MODE [14] to show its effectiveness with other proposed algorithms.

Table VII. Comparison of best solution for fuel cost and emission with five algorithms on optimizing case 2

		Fuel cost	Emission
Best fuel cost	Proposed method	**605.8711**	0.2203
	NSGA[11]	607.790	0.2191
	NPGA[12]	608.06	0.2207
	SPEA[13]	607.86	0.2176
	BB-MOPSO[2]	605.9817	0.2201
	MODE [14]	606.126	0.2195
Best emission	Proposed method	644.5208	**0.1940**
	NSGA[11]	638.98	0.1947
	NPGA[12]	644.23	0.1943
	SPEA[13]	644.77	0.1943
	BB-MOPSO[2]	646.4847	0.1941
	MODE [14]	642.849	0.1942

From the above comparison, it is noticed that the proposed algorithm gives reduction in the fuel cost and emission as compared to the reported ones. This also provides the minimum and maximum value of the objectives for setting the limits. Fuzzy membership values are assigned to each objective using eq. (8). The different solutions obtained can be easily judged based on the merit of their fuzzy membership values.

Table VIII. Pareto optimal solutions based on fuzzy ranking for load P_D=2.834 p.u

	Cost($/h)	Emission	μ_1	μ_2	μ_{min}
SOL.1	630.0739	0.1951	0.3738	0.9612	0.3738
SOL.2	628.3658	0.1956	0.4180	0.9412	0.4180
SOL.3	628.0249	0.1960	0.4268	0.9268	0.4268
SOL.4	621.8039	0.1977	0.5878	0.8600	0.5878
SOL.5	**619.9047**	**0.1999**	0.6369	0.7751	**0.6369**

The Pareto optimal results obtained from the proposed fuzzy ranking based RCGA for demand 2.834 p.u is presented in Table VIII. The results simulated from Table VIII reveals that the best compromise solution of CEED problem is sol.5 with the highest rank of 0.6369. The detailed result of the best compromise solution selected for CEED problem with rank of 0.6369 is shown in Table IX and compared with previously reported results using NSGA [11], NPGA [12], SPEA [13] and MODE [14].Here, the best compromise solution obtained is quite satisfactory and has the value of 619.904 $/hr and 0.1999 lb/hr respectively for cost and emission. The true Pareto front between fuel cost vs. emission for load 2.834 p.u is displayed in Fig.4 while satisfying all the constraints mentioned above. This clearly shows the conflicting behavior of the objectives.

Table IX.Best solutions for compromise solution with four algorithms on optimizing Case 2 (P_D=2.834 pu)

	Prop. method	NSGA[11]	NPGA[12]	SPEA [13]	MODE[14]
P1	0.2793	0.2935	0.2976	0.2752	0.2355
P2	0.3937	0.3645	0.3956	0.3752	0.3489
P3	0.5414	0.5833	0.5673	0.5796	0.5700
P4	0.6975	0.6763	0.6928	0.6770	0.7251
P5	0.4224	0.5383	0.5201	0.5283	0.5535
P6	0.5288	0.4076	0.3904	0.4282	0.4260
Fuel cost	**619.904**	617.80	617.79	617.57	613.27
Emission	**0.1999**	0.2002	0.2004	0.2001	0.2026

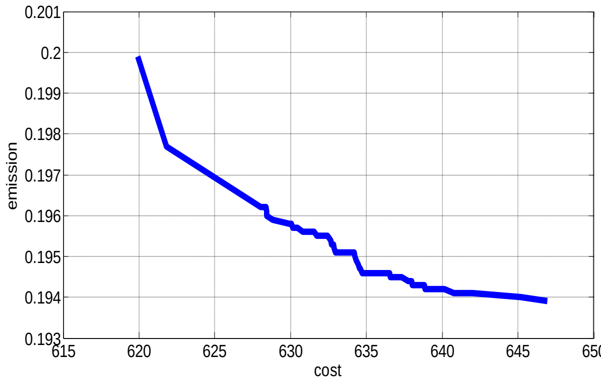

Fig.4: Pareto-front of cost vs. emission for P_D = 2.834 pu (case 2)

C. Case 3: Tri-objective optimization of fuel cost, emission and system loss

Here the relationship between the cost, emission and system loss is demonstrated which in turn increases the complexity level of the system. The comparisons of best solution for cost, emission and losses of IEEE-30 bus system by the proposed method with various methods are provided in Table X. It is clear that the proposed method gives the minimum cost, emission and system loss of 606.4085 $/hr, 0.194131 lb/hr and 0.0194 p.u respectively which is almost identical with cost, emission and loss obtained from MODE

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[14].

Table X.IEEE-30 bus system best cost, emission and system losses for Tri-objective problem (2.834 p.u)

	Prop. method	MODE[14]
Best cost	**606.4085**	606.416
Best emission	**0.194131**	0.1942
Best loss	**0.0194**	0.0175

By applying the limits to the algorithm the membership value of the cost, emission and loss is shown in Table XI. Than, depending upon the merit of the objectives the best compromise solution is obtained using eq. (9).

Table XI.Pareto optimal solutions based on fuzzy ranking for load P_D=2.834 p.u

	Cost	Emission	Loss (pu)	μ_1	μ_2	μ_3	μ_{min}
SOL.1	612.4361	0.2083	0.0205	0.8555	0.5484	0.9321	0.5484
SOL.2	624.3104	0.2030	0.0206	0.5708	0.7160	0.9253	0.5708
SOL.3	616.370	0.2068	0.0199	0.7612	0.5952	0.9681	0.5952
SOL.4	620.599	0.2035	0.0209	0.6598	0.6990	0.9090	0.6598
SOL.5	**614.411**	**0.2044**	**0.0210**	0.8081	0.6717	0.9005	**0.6717**

Here, in Table XI sol.5 is treated as the best compromise solution shown in bold with the highest rank of 0.6717 which means that all the three objectives are satisfied at least 67.17%. In order to compare the best compromise solution with the previously reported best result the detailed result of the selected best compromise solution is given in Table XII.

Table XII.Best solutions for compromise solution with MODE on optimizing Case 3 (P_D=2.834 pu)

	Prop. method	MODE[14]
P1	0.2137	0.2120
P2	0.2919	0.3065
P3	0.7510	0.6887
P4	0.6521	0.6793
P5	0.5617	0.5821
P6	0.3777	0.3869
Fuel cost($/h)	**614.4111**	614.170
Emission (lb/hr)	**0.2044**	0.2043
Loss (p.u)	**0.0210**	0.0220

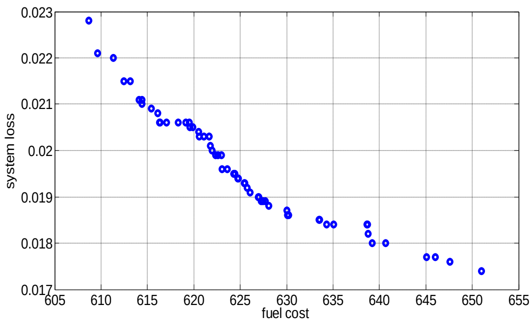

Fig.5: Pareto-front of cost vs. system loss for P_D = 2.834 pu (case 3)

The Pareto front of fuel cost and emission with system losses are shown in Fig.5 and Fig.6 respectively for load 2.834 pu. Whereas Fig.7 shows the Pareto front between system fuel cost vs. emission. It can be observed from theses figures that three objectives are naturally conflicting objectives; the attempt of decreasing fuel cost gives an operating point closer to higher emission and higher system loss and vice-versa. A well distributed Pareto front is obtained for all the test cases.

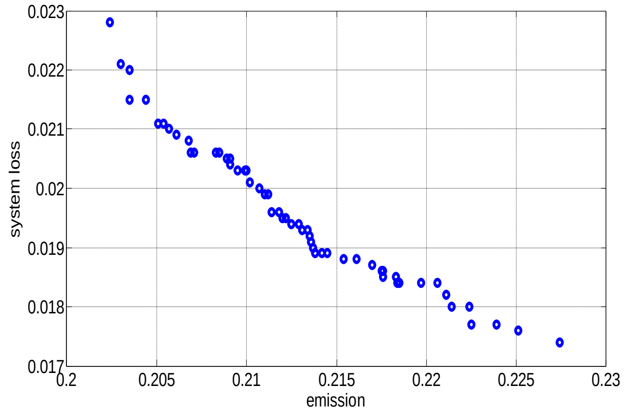

Fig.6: Pareto-front of system loss vs. emission for P_D = 2.834 pu (case 3)

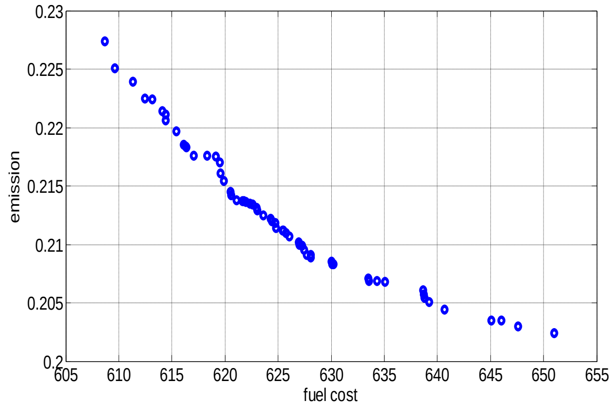

Fig.7: Pareto-front of cost vs. emission for P_D = 2.834 pu (case 3)

From the above discussion it is clear that the results in all cases are almost identical. This demonstrates that the search of the proposed method span over the entire trade-off surface. In addition the close agreement of the results shows clearly the capability of the proposed approach to handle multi-objective problem.

V. CONCLUSION

This paper successfully employed the fuzzy ranking based real coded genetic algorithm on constrained tri-objective problem formulated as single objective problem with competing fuel cost, emission and loss impact objectives. The proposed method has been tested and examined on the standard IEEE-30 bus system with six generating units. Here, three test cases have been considered with varying complexity level. The results are computed by satisfying the constraints of the system. Due to which the proposed approach is found to compute superior results as compared to those reported in literature. A well distributed Pareto front is obtained which gives a wide choice to the operator while deciding the dispatch strategy. The comparison of these obtained results with the previous reported results confirms the effectiveness and the superiority of the proposed method over the other techniques in terms of solution quality. Therefore, this method can be applied to other type of multi-objective problem due to the impressive success for IEEE-30 bus system.

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