Multi-Objective Optimization using NDSPSO with Cost, Emission and Loss Objectives

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Abstract— This paper presents a new multi-objective optimization approach based on non-dominated sorting to solve complex problem subject to the heavy equality and inequality constraints in power system. The proposed approach employs application of non-dominated sorting mechanism based on crowding distance calculation to produce a well distributed Pareto-optimal set of non-dominated solutions. Moreover, fuzzy set theory is employed to extract the best compromise solution over the trade-off curve. Several optimization runs of the proposed approach are carried out on the standard IEEE-30 bus test system. The results demonstrate the capabilities of the proposed approach to generate true and well-distributed Pareto-optimal non-dominated solutions of the multi-objective problem in one single run. Finally, some of the system objectives are improved by sacrificing other objectives. The transmission losses, emission and generation fuel cost objectives are optimized simultaneously using the proposed algorithm.

Keywords— Nondominated Sorting, Particle swarm optimization, Generation Cost, Emission, Losses.

I. Introduction

THE Optimal Power Flow (OPF) is a popularly used method in electrical power system for effective controlled operation and proper planning towards meeting the load growth subjected to meeting various objectives. The chief necessity of the optimization of the power flow is to estimate the proper combination of the controllable parameters like voltage and real power generation at generator buses, tap setting of the transformers in transmission lines, value of compensating capacitors towards minimization of the specific objective functions. A problem with more number of controllable parameters makes the system non-linear and discontinues. So, traditional solution methodologies failed to give an optimized global solution.

The conventional dynamic technique is applied to OPF problem and benders decomposition for effective scheduling in a power system to meet the required demand at minimum production cost [1, 2]. At power stations, various strategies like installation of electrostatic precipitators and gas scrubbers, replacement of fuel-burners, efficient cleaners and shifting towards low emission fuels are the alternatives for low emission dispatch. These options can be made for long-run planning. In [3], a strategy to minimize emission was proposed.

In power system, minimizing of transmission real power losses can be considered as one of the objective functions for the effective reactive power dispatch [4].

The literature concentrated on the application of evolutionary optimization techniques to OPF problems like, linear and non-linear programming [5-7], Newton's method [8], Quadratic Programming [9], Fast Successive Linear Programming algorithm [10], etc. At present, these evolutionary algorithms are promoted to overcome the drawbacks of the traditional optimization techniques, as their inherent capability of processing towards the best result and extensive exploration in search space [11].

The algorithms like Multi-Objective Stochastic Search Techniques (MOSST) [12], Multi-Objective Evolutionary Algorithm (MOEA) [13], Strength Pareto Evolutionary Algorithm (SPEA) [14], Niched Pareto Genetic Algorithms (NPGA) [15] and Nondominated sorting in Genetic Algorithms (NSGA) [16], etc., can be used to solve multi objective optimization problem.

PSO is a stochastic algorithm that can be applied to non-linear optimization problems. PSO has been developed from the simulation of simplified social systems such as bird flocking and fish schooling by Kennedy and Eberhart [17].

The main contribution of this paper is "the application of Nondominated Sorting methodology with Particle Swarm Optimization (NDSPSO)" to organize objectives on a given system subjected to satisfy multiple objectives and to find globally compromised solution using fuzzy decision-making tool.

The proposed methodology is applied to IEEE-30 bus test system. Some of the results of the proposed method were compared with the results of the existing method [5].

II. Problem Statement

Many of the optimization problems discussed in the literature is restricted to either of the certain objectives like Generation Cost, Emission, and Losses etc. But in practice it is necessary to optimize many of the above objectives simultaneously, subjected to equality, inequality, practical and operating constraints. Hence, it is clear that the effectiveness and efficiency of multi-objective algorithm gives best compromised solution subjected to constraints on a system.

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A multi-objective optimization technique NDSPSO is applied to optimize system objectives such as Generation Cost, Emission, and Losses simultaneously subjected to the system constraints.

Aggregating all objectives and constraints, the problem can be formulated mathematically as a constrained nonlinear multi-objective optimization problem as follows:

$$Minimize\ [F(x), E(x), Loss] \quad --(1)$$

Subject to

$$g_i(x) = 0;\ \ \forall\ \ i = 1,2,3, \ldots .J \quad -(2)$$

$$h_k(x) \leq 0;\ \ \forall\ \ k = 1,2,3, \ldots .K \quad -(3)$$

where 'g' and 'h' are the equality and inequality constraints respectively and x is a control vector of variables corresponding to solution. J and K are number of objective functions.

The organization of the paper is given as: Constrained Problem formulation, multi-objective optimization approach with algorithm and corresponding numerical results are given in sections III, IV, and V respectively.

III. Problem Formation

Multi-objective optimization can have two or more objective functions to be optimized at same time. As a result, there is no unique solution to multi-objective optimization problems, but the aim is to find all possible compromised solutions available in search space (called Pareto front set).

A. Generation Fuel Cost

The fuel cost function which satisfies particular operating constraints and practical loading concern can be represented approximately by a simple quadratic function, under the assumption that the incremental cost curves of the generating units are monotonically increasing piecewise linear functions. The fuel cost function of any generator can be mathematically expressed as

$$F(P_{G_i}) = \sum_{i=1}^{N_G} a_i P_{G_i}^2 + b_i P_{G_i} + c_i\ \$/h \quad --(4)$$

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. Emission

While minimizing fuel cost of generating units, may produce high levels of SO_2 and NO_2 emissions [18].

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

$$E(P_{G_i}) = \sum_{i=1}^{N_G} \left(\alpha_i + \beta_i P_{G_i} + \gamma_i P_{G_i}^2 + \xi_i\, exp^{(\lambda_i P_{G_i})}\right) \quad ton/h \quad --(5)$$

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

C. Power System Active Power Losses

In power system to enhance power delivery performance, one of the important issues to be considered is active power loss.

$$Losses\ (L) = \sum_{i=1}^{N_{line}} g_i\left[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)\right] MW \quad --(6)$$

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, $V_j\ and\ \delta_i, \delta_j$ are voltage magnitude and angle of $i^{th}\ and\ j^{th}$ buses.

D. Constraints

Equality constraint

This constraint is typically load flow equations.

- Power balance constraint

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

E. In equality constraints

These constraints represent system operating limits.

- Active and reactive power generation constraint

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

  where $P_{G_i}\ and\ Q_{G_i}$ are the active and reactive power generations of i^{th} generator, $P_{G_i}^{min}$, $P_{G_i}^{max}$and $Q_{G_i}^{min}$, $Q_{G_i}^{max}$ are the corresponding minimum and maximum active and reactive power generation limits of the i^{th} generator.

- Security constraint

$$S_{l_i} \leq S_{l_i}^{max}; \quad i = 1,2,3, \ldots \ldots . . n_l$$

  where S_{l_i} is the line MVA flow and $S_{l_i}^{max}$ is the maximum MVA flow limit of the i^{th} line, n_l is the total number of lines.

- Transformers tap position constraint

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

  where T_i^{min} and T_i^{max} are the minimum and maximum tap positions of the i^{th} transformer, respectively, n_t is the total number of tap positions.

- Bus voltage magnitude constraint

$$V_{i,min} \leq V_i \leq V_{i,max}$$

  where V_i is the i^{th} bus voltage magnitude, $V_{i,min}$ and $V_{i,max}$ are the minimum and maximum voltage magnitude values of the i^{th} bus, respectively.

- Switchable VAr sources constraint

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

  where $Q_{C_i}^{min}$ and $Q_{C_i}^{max}$ are the minimum and maximum values of the reactive power compensated by the i^{th} capacitor and n_c is the number of compensators respectively.

A penalty function [19] is added to the objective function, if any of the controllable parameters violates any of the constraints. The methodology of the penalty handling is considered as in [20]. The penalized objective function can be written as the sum of unpenalized objective function $(f(x))$ plus penalty.

$$F(x) = f(x) + \lambda_p \left(P_{G_1} - P_{G_1}{}^{limit}\right)^2 + \lambda_v \left(\sum_{i=1}^{NL} \left(V_{L_i} - V_{L_i}{}^{limit}\right)^2\right)$$
$$+ \lambda_q \left(\sum_{i=1}^{NG} \left(Q_{G_i} - Q_{G_i}{}^{limit}\right)^2\right) + \lambda_s \left(\sum_{i=1}^{nl} \left(S_{L_i} - S_{L_i}{}^{limit}\right)^2\right)$$

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

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

IV. Multi-Objective Solution Approach

Multi-objective optimization means optimizing multiple objectives of a system simultaneously and systematically. Generally, these objective functions are peculiar and often challenging and inconsistent. Multi-objective optimization with such challenging objectives produces set of optimal solutions, instead of a single optimal solution. The reason for this type of optimality is that, choosing better choice to all objective functions as per the requirement consist many issues. These optimal solutions are known as Pareto front sets.

A general multi-objective optimization problem consists of a number of objectives to be optimized (either minimization and/or maximization) simultaneously and is associated with a number of equality and inequality constraints given in $Eq\ (1), Eq(2)\ and\ Eq(3)$ subject to control vector U consisting of generator bus voltage magnitudes, active power generations, transformer tap settings, and reactive shunt compensators.

$$U = \left[V_{G1}, \ldots, V_{GN_G}, P_{G1}, \ldots, P_{GN_G}, T_1, \ldots, T_{nt}, Q_{c1}, \ldots, Q_{cnc}\right] \quad --(7)$$

where N_G, n_t, n_c are the number of generators, number of regulating transformers, and number of shunt compensators, respectively.

For a multi-objective optimization problem, let any two solutions S_1 and S_2 can have one of two possibilities: one prevails the other or none prevails the other. If S_1 leads the solution S_2, S_1 is called the nondominated solution. The solutions that are nondominated within the search space are expressed as Pareto front and composed as Pareto optimal set.

A. Non Dominated Sorting

Deb [21] proposed a nondominated sorting method to solve multi-objective optimization problems. There is a requirement to find multiple Pareto front sets in a single run. The fundamental reason behind this multi-objective problem formulation is that it is not probable to have a single solution which optimizes all objectives [22].

In order to find the superiority of each solution in a population of size 'N' with respect to other solutions corresponds to other populations, sorting and comparison operations are performed. This needs $C(mN)$ comparisons for each solution, where m is the number of objectives. At first the nondominated front set is found by using comparison operation on all individuals. In order to find the next front, the comparison procedure for the remaining individuals needs to be repeated.

Again new population is generated along with the current population, comparison and sorting procedures are applied to obtain best N individuals from the total individuals where N is the population size. The sorting is based on the crowding distance between the Pareto front sets.

B. Detailed description

1) Population initialization

The population for the control parameters is initialized between the ranges.

2) Nondominated sort

The generated population is ordered based on individual domination with the other individuals. The algorithm is described in [21] is used for sorting Pareto front solutions.

3) Crowding distance

Crowding distance is calculated for the individuals after nondominated sorting procedure is completed. Finally main front sets are selected based on crowding distance of the individuals in the front set.

The fundamental idea behind the calculation of crowding distance is to find the Euclidian distance between each individual in a Pareto front, based on their $'m'$ objectives in the m dimensional solution space. The individuals in the boundary are always selected since they have infinite distance assignment.

C. Particle Swarm Optimization [28]

Particle swarm optimization conducts its search using a population of particles. Each particle in PSO changes its position according to new velocity and the previous positions in the problem space.

Because of the advantages of the PSO, like simple concept and implementation mechanism, handling of control parameters, finding procedure of the global best solution is chosen to implement the defined solution methodology.

In PSO, the particle velocity and the position in $(k+1)^{\text{th}}$ iteration is updated using $Eq's\ (13)\ and\ (14)$

$$V_j^{k+1} = \omega . V_j^k + C_1 . rand1() . \left(P_{best,j} - X_j^k\right) + C_2 . rand2() . \left(G_{best} - X_j^k\right) \quad --(8)$$

$$X_j^{k+1} = X_j^k + V_j^{k+1} \quad --(9)$$

$$\forall \quad j = 1,2,3, \ldots \ldots . . n$$

where k is the iteration count, C_1 and C_2 are acceleration coefficients, $rand1$ and $rand2$ are uniformly distributed random numbers in [0 1]. $P_{best,j}$ is the best position found by the particle j so far, G_{best} is the position among all particles. Here, the second part is a cognitive part and has its own thinking and memory. The third term is the social parameter on which the particle changes its velocity. $'\omega'$ is the inertia weight and can be calculated as follows

$$\omega^{k+1} = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{k_{max}}\ X\ k \quad --(10)$$

Equations $(13)\ and\ (14)$ have three tuning parameters ω, C_1 and C_2 that greatly influence the PSO algorithm performance. The value of 'ω' was proposed linearly with time from a value of 1.4–0.5 [23]. As such global search starts with a large weight value and then decreases with time to favor local search over global search [24]. In this paper, the methodology to find values for the tuning parameters and the procedure of updating dynamic inertia weight is implemented

[5]. Because this provides a balance between global and local explorations, thus it needs less number of iterations to get an optimal solution.

D. Best compromise solution

Upon having the multiple nondominated Pareto front sets, fuzzy decision maker is used to select the best compromised solution. The m^{th} objective function $'F_m'$ is represented by a membership function μ_m defined as in [25]

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

for minimization of objectives where F_m^{min} and $F^{max}_{,}$ are the minimum and maximum value of the m^{th} objective function among all non-dominated solutions, respectively.

For each solution in nondominated front set $'k'$, the normalized membership function μ^k is calculated as

$$\mu^k = max \left\{ \frac{\sum_{i=1}^{N_{obj}} \omega_k \cdot \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{N_{obj}} \omega_k \cdot \mu_i^k} \right\} \quad --(11)$$

where $'M'$ is the number of non-dominated solutions. The best compromised solution is the one corresponds to the value of $'\mu^k'$.

E. The computational flow

The main objective is to find the multi-objective optimized loadability estimation on a system by satisfying the constraints. In NR load flow, the 'Q_{gen}' limits at generator buses are verified and the same bus has been converted into the load bus if any of the minimum/maximum values is violated. The chaotic formula for the inertia weight and the self adaptive method for computing the learning factors beside the proposed algorithm work well for multi-objective optimization problems. So, proper weight should be given to the objectives to get an optimized performance on a system. As a matter of fact, after acquiring the Pareto front solutions, the decision maker needs to choose one best solution according to the requirement. In this study, W_1, W_2, and W_3 are the weights of corresponding objective functions, respectively, and also $\sum_{i=1}^{N_{obj}} W_i = 1$.

F. Setting of the proposed approach

The methodology used in this study was developed and tested on 2.19 GHz PC with 2GB RAM using MATLAB platform. On all optimization runs, the PSO population size and the maximum number of iterations were considered as 100 and 100 respectively.

V. NUMERICAL RESULTS

In this study, the standard IEEE 30-bus, 6-unit test system is considered to investigate the effectiveness of the proposed approach. The system data is taken from [26, 27].

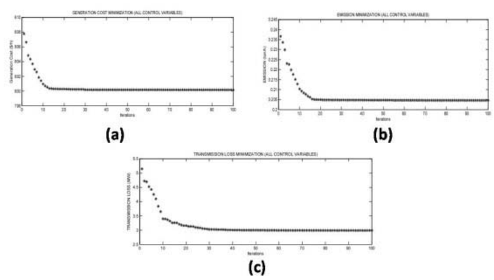
The entire analysis is divided into cases I, II, and III which corresponds to single, two and three objectives optimization problem respectively. The detailed analysis of each case is presented in the following sections. Some of the results of the proposed method are compared with the existing method [5] and are given in Appendix A.

i. Case – I (Single objective)

The result of 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 and losses by 1.9874 (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 and losses by 0.0709. Minimization of losses in the system increases the cost by a factor of 0.2089 and emission by 0.0119. The corresponding convergence patterns are shown in Fig 2.

Table 1. Control variables related to multiple objectives

	Cost, $/h	**Emission, ton/h**	**Loss, MW**
Pg_1, MW	177.22929	64.00868	51.39099
Pg_2, MW	48.550303	67.59438	80.00
Pg_3, MW	21.462934	50.00	50.00
Pg_4, MW	21.211045	35.00	35.00
Pg_5, MW	11.881975	30.00	30.00
Pg_6, MW	12.000032	40.00	40.00
Vg_1, pu	1.1	1.092719	1.1
Vg_2, pu	1.0370108	1.082577	1.041686
Vg_3, pu	1.0646606	1.057189	1.083148
Vg_4, pu	1.0544999	1.068489	1.087906
Vg_5, pu	0.9634969	0.944209	1.099556
Vg_6, pu	1.1	1.093477	1.1
Tap_{6-9}, pu	0.9514214	1.015055	1.017291
Tap_{6-10}, pu	0.9910521	0.9562	0.968865
Tap_{4-12}, pu	0.9919611	0.994948	0.983142
Tap_{27-28}, pu	0.9679805	0.966505	0.970435
Q_{C10}	15.974439	17.78494	21.07306
Q_{C24}	10.460198	17.53809	11.67689
Cost	**800.17747**	944.3457	967.4024
Emission	0.3664768	**0.204683**	0.207122
Loss	8.9355744	3.203066	**2.99099**



(a) Cost minimization, (b) Emission minimization, (c) Loss minimization,
Figure 2. Convergence pattern of the objective functions

ii. Case – II (Two objectives)

In this case, the proposed methodology handles two objectives together as multi-objective optimization problem. There are three possible combinations with three objective functions. For each combination there are nine sets, which are selected based on the distribution of weights between objectives. Due to space limitation, the results of the best compromised over Pareto optimal solutions for Cost-Emission combination is given in Table 2. The corresponding variation of active power generations, voltages, tap positions and Q_C values with respect to sets is shown in Fig 3.

Table 2. Multi-objective optimized result for different sets (weight factors)

W1	**W2**	**COST**	**EMISSION**
0.9	0.1	805.9989	0.311993
0.8	0.2	805.9989	0.311993

0.7	0.3	814.6776	0.279295
0.6	0.4	820.8772	0.265939
0.5	0.5	830.0619	0.251936
0.4	0.6	844.5205	0.23754
0.3	0.7	862.3286	0.225341
0.2	0.8	880.9416	0.217372
0.1	0.9	907.6102	0.211557

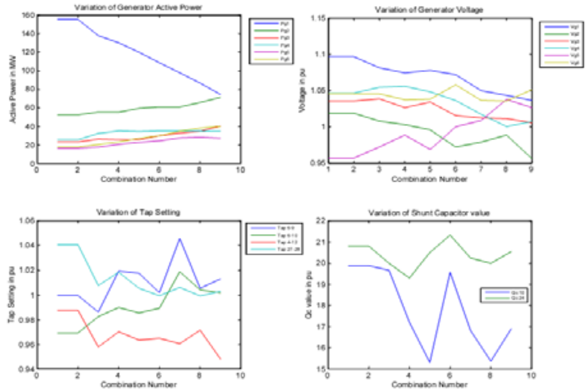


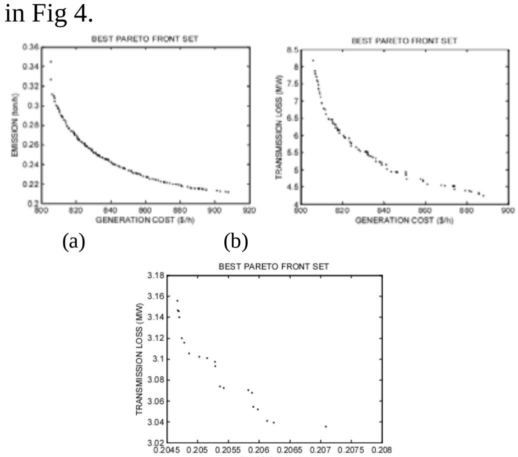
Figure 3. Variation of P_G, V_G, Tap, and Q_C for different Cost-Emission sets

For the remaining combinations, selective analysis is given Table 3.

Table 3. Multi-objective result for different weight factors (Two objectives)

W1	W2	W3	Cost ($/h)	Emission (ton/h)	Loss (MW)
0.8	0.2	0	805.9989	0.3119	-
0.5	0.5	0	830.0619	0.2519	-
0.2	0.8	0	880.9416	0.2174	-
0.8	0	0.2	809.8782	-	6.9513
0.5	0	0.5	824.0478	-	5.6957
0.2	0	0.8	860.8800	-	4.5731
0	0.8	0.2	-	0.2047	3.1200
0	0.5	0.5	-	0.2054	3.0738
0	0.2	0.8	-	0.2062	3.0391

Table 3 reveals that the importance of the objective function gives the suitable minimized value. Highest generation cost (880.9416 $/h) is possible with the emission (0.2174 ton/h). Two dimensional plots for the following combinations are shown in Fig 4.



(a) (b)

(c)

(a) Cost – Emission (b) Cost – Loss (c) Emission – Loss

Figure 4. Two dimensional best Pareto-optimal fronts

iii. Case – III (Three objectives)

Here in this case all the three objectives are considered to form multi-objective optimization problem. With three objectives the possible number of sets is 34 based on weights distribution, here some sample sets are considered and are tabulated in Table 4, which shows the effectiveness of the algorithm.

Table 4. Multi-objective result for different weight factors (Three objectives)

W1	W2	W3	Cost ($/h)	Emission (ton/h)	Loss (MW)
0.8	0.1	0.1	807.0440	0.305555	7.733541
0.1	0.8	0.1	914.1322	0.211742	4.766982
0.1	0.1	0.8	883.9452	0.223555	4.571413
0.4	0.4	0.2	857.5084	0.230174	5.067601
0.4	0.2	0.4	857.5084	0.230174	5.067601
0.2	0.4	0.4	882.7626	0.221819	4.629423
0.3	0.3	0.4	869.4727	0.22509	4.856591

From the Table 4 it is clear that, the maximum cost (914.1322) is possible with the emission (0.2117) and loss (4.7669). The generated Pareto fronts confines to entire trade-off regions; this is because of the effectiveness of the proposed methodology.

The three dimensional Pareto fronts for three objective functions is shown in Fig 5.

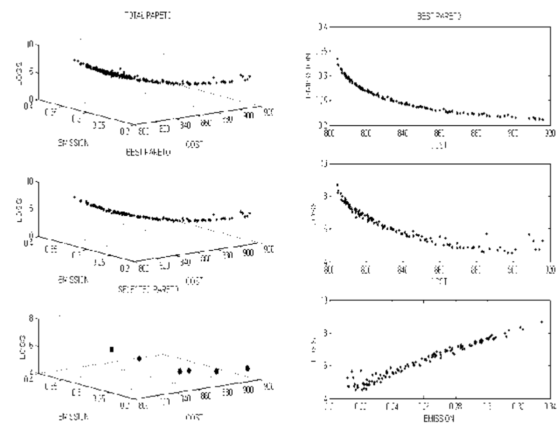


Figure 5. Three dimensional Pareto fronts for Cost-Emission-Loss

VI. Conclusion

The stated hypothesis has been proved and validated with proposed NDSPSO algorithm. The handling of the multiple objectives needs a lot of expertise and estimating simultaneous control actions towards the objective optimization has been validated with the proposed method. The objectives generation cost, emission and loss are optimized subjected to equality, inequality and physical constraints. The proposed evolutionary algorithm named "NDSPSO" shows its capability to handle different objectives based on its nature (i.e minimizing certain objectives). 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 developed code takes around 60-80 seconds for the combinations. Since the proposed methodology uses the calculation of acceleration coefficients and inertia weight based on the nature of the solution and it can be applied to any type of the objectives

Appendix

The results validation of proposed method is compared with the existing method [5] and is tabulated in Table.A1.

From Table.A1, it is observed that, the proposed methodology yields better results.

Table A1. Comparison between Multi-objective results for IPSO & NDSPSO

Weights			Existing IPSO [5]			Proposed NDSPSO		
W1	W2	W3	Cost ($/h)	Emission (ton/h)	Loss (MW)	Cost ($/h)	Emission (ton/h)	Loss (MW)
0.8	0.2	0	823.134	0.2751	-	805.998	0.312	-
0.5	0.5	0	841.052	0.2585	-	830.061	0.252	-
0.2	0.8	0	860.421	0.2383	-	880.941	0.217	-
0.8	0	0.2	839.843	-	8.976	809.878	-	6.951
0.5	0	0.5	850.916	-	7.893	824.047	-	5.696
0.2	0	0.8	869.731	-	6.775	860.880	-	4.573
0	0.8	0.2	-	0.2061	5.213	-	0.205	3.120
0	0.5	0.5	-	0.2063	5.179	-	0.205	3.074
0	0.2	0.8	-	0.2066	5.162	-	0.206	3.039

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