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Multi-objective economic load dispatch using hybrid NSGA-II and PVDE techniques

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ABSTRACT

Over decades, numerous methods have been used to optimize objective functions. Where cost and emissions clash. The improved non-dominated sorting genetic algorithm (NSGA-II) employs elitism to discover the optimum value and speed convergence in multi-objective optimization problems. Population variant differential evolution algorithm alters differential evolution (DE). The main distinction between DE and population variant differential evolution algorithm (PVDE) is population replenishment. NSGA-II and PVDE are combined in the suggested hybrid approach. The hybrid technique solves multi-objective optimization problems efficiently by combining two or more methods. The hybrid technique solves multi-objective optimization problems well. This optimization problem pits cost vs pollution. The hybrid approach exposes half the population to the NSGA-II algorithm and half to the PVDE algorithm. In optimization problems with opposing aims, such as minimizing costs and emissions, a hybrid technique is utilized to find the optimal solution. Elitist diversity-preserving strategies avoid optimization issues becoming converging too soon. A 10-generator IEEE 39 bus test system was validated using this method. The hybrid NSGA-II and PVDE methodology achieves global optimal solutions with more durability, simplicity, and optimization performance than existing methods.

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1. INTRODUCTION

A systematic planning and economic operation of generating units for electric power generation are always important in the electrical industry. In an extensive integrated power system network, the utilization of fossil fuels over a decade demands the optimal operation of thermal units. A little saving related to the operation of a generating system leads to a notable reduction in fuel consumption quantities and cost [1]. In generating systems, the problem associated with economic dispatch is bringing off the minimum operation cost. Over recent years, emphasis on diminishing operating costs has become an issue. Load forecasting, security analysis, unit commitment, and economic load dispatch are vital issues in the modern power system. One of the possible ways is the gentle and efficient operation of generating units economically.

The main objective of the economic load dispatch is the economic operation of thermal units with minimum fuel cost while maintaining the system constraints [2]. Economic load dispatch is related to the online process of the minute-to-minute requirement of load allocation among the connected thermal units with an objective of total cost minimization [3]. Thermal units should generate for reasonable optimization problems. Optimization concerns include premature convergence, keeping to the local optimal value, and convergence rate [4].

In former days, economic load dispatch optimization was a single-objective optimization issue that minimized overall cost [5]. Electricity industries generate electricity and pollute. Many nations have rules to minimize hazardous fumes from power plants and protect the environment. This measure reduces power sector NO_2 by two million tons/year and SO_2 by 10 million tons/year. Therefore, several studies include emission as additional target, creating multi-objective environmental and economic load dispatch [6]–[8].

Navaneetha *et al.* [9] Used a strong linear programming tool to reach global optima for rescheduling power dispatch under overloaded conditions utilizing the part reduction and third simplex techniques. A genetic algorithm (GA), a meta-heuristic related to bio-inspired evolutionary algorithms, was proposed by Xu *et al.* [10]. The authors optimize multi-objectively using this method. In an interconnected system, cost, emission dispatch, transient stability, small perturbation stability, and power exchange conflict. This method is used in three areas. GA efficiently addresses the issue, the authors discovered. Abido [11] recommend population-based evolutionary algorithms like the new strength Pareto evolutionary algorithm. A connectivity-based clustering technique with a diversity mechanism controls the Pareto set without compromising trade-off features to maintain non-dominated solution persistence.

A detailed examination of non-dominated sorting genetic algorithm (NSGA), strength Pareto evolutionary algorithm (SPEA), and niched Pareto genetic algorithms was performed [12]. SPEA predicts non-dominated solutions from the existing population and stores them in a repository to evaluate the cost-emission trade-off curve. SPEA takes longer to optimize. Palanichamy and Babu [13] used a single identical objective function to optimize. This optimization used analytical solution to describe cost and emission characteristics as total generation. The recommended technique reduces computing time in economic, emission, and cost function integration. Agrawal *et al.* [14] created updated repository particles and used fuzzy decision-making to fix stochastic approach defects. To improve the suggested fuzzy clustering with particle swarm algorithm (FCPSO) elite particles of the repository, self-adaptive mutation, and other proven methodologies are used on the IEEE 30 bus six generator system to create a good compromise solution of a diverse Pareto.

Sivasubramani and Swarup [15] introduced a new harmony search method (HSA) to restore Pareto front uniformity. Fast non-dominated sorting and ranking are used to expand HSA on 30 and 118 IEEE bus test systems, resulting in a more diverse Pareto front than NSGA-based methods II. Bayon *et al.* [16] improved the economic emission dispatch issue analytical solution. Niknam and Mojarrad [17] propose a modified adaptive θ-PSO with a new mutation operator to address drawbacks such as stagnant optimal solutions.

Jubril *et al.* [18] used semi-definite programming, a crucial mathematical programme. Cost and transmission losses were two goals in a multi-objective optimization problem. They made them single-objective convex by lowering vector objective to scalar objective. Diversity pertains to nonlinear weighted selection. Multi-area power systems by Pandit *et al.* [19] reduce dynamic crowding distance. This technique optimizes multi-objective system cost, emission, and dependability. Tie line restriction is added by multi-objective multi-area economic dispatch. Fuzzy selection priorities decision-maker significance. El-sobky and Abo-elnaga [20] solved the multi-objective optimization problem with security, power balancing, and min-max power generation restrictions using trust region globalization. Weighting turns multi-objective problems into unitary problems and applies them to 30 bus six generator test network to compare outcomes with previous approaches. Economic and stability levels are competing goals in the multi-objective optimization issue, according to Vempalle and Dhal [21]. Load dynamics on load side composition affect transient stability. Risk-based criteria calculate system transient stability probabilistically. A multi-objective programming paradigm is used to get a suitable Pareto set. The planned one on ten machines 39 bus system stabilizes load variance.

For multi-objective to single-objective conversion, Chopra *et al.* [22] used the cost penalty factor. The nature-inspired grey wolf optimization technique performed well on three test systems and yielded comparable results. Rafi *et al.* [23] created a novel technique for difficult power systems with strong non-linearity. Used population variant differential evolution algorithm (PVDE) to reduce population inactivity. Price penalty factor mono-objectivizes bi-objective.

Vijay *et al.* [24] introduced the multi-objective economic load dispatch issue with valve point loading impact and gearbox losses limitations. Amorim and Rocha [25] developed objective optimization issues to reduce pollution, fuel cost, wind generation, and gearbox power losses within system constraints. NSGA-III addressed several objective optimization issues. The recommended dominance relation method employs reference points. NSGA-III was tested on IEEE 30 to demonstrate its potential. Sakthivel *et al.* [26] established multi-area economic environmental dispatch (MAEED) to reduce fuel cost and pollutant emissions with tie-line, valve point loading, multi-fuel, and power balancing restrictions. MAEED should use multi-objective squirrel search. Elitist depositary mechanism with crowding distance and dominance theory sustains diversity with non-dominant solutions. The issue is tested on 40-, 10-, and 140-unit Korean power grids. Multi-objective squirrel search algorithm (MOSSA) beats existing approaches. For combined economic emission dispatch, Hassan *et al.* [27] proposed chaotic artificial ecosystem-based optimization (CAEO). The CAEO algorithm simulates nicely. Tahir *et al.* [28] Showed combined economic emission dispatch (CEED) without and with renewable energy. The price penalty made CEED one goal. We investigate multi-objective optimization. Flower pollination algorithm (FPA) cuts costs and pollutants. FPA tests 11–15-unit systems with and without renewable energy. FPA surpassed previous literature methods.

Heuristic approaches like GA, neural networks (NN), simulated annealing (SA), particle swarm optimization (PSO), Ant Colony, and artificial bee colony (ABC) and its variants have improved economic and emission dispatch issue analysis and combination of both and produced excellent and acceptable solutions. Power systems are modernizing daily under grid and rule control. Quality of solutions, emission control, convergence, decreased losses, treatment of all limitations, and global optimal solutions for combined emission and economic dispatch must be improved continuously. The literature study suggests that the article will concentrate on novel algorithms and how they might solve combined emission and economic dispatch concerns. This study addresses CEED valve-point impact using NSGA-II and PVDE. The reference Pareto-front is derived using real coded genetic algorithm's (RCGA) weighted sum. The remaining sections are: i) the CEED issue formulation is shown in section 2; ii) in section 3, we discuss how to apply NSGA-II, PVDE, and a hybrid NSGA-II-PVDE to the CEED problem; iii) section 4 presents the simulation results of many test scenarios; and iv) section 5 concludes.

2. PROBLEM FORMULATION

The power business needs well-planned economic generating unit operation. In an interconnected power system with 'n' units, economic load dispatch is linked to scheduling thermal unit active power production to reduce operating costs using nonlinear cost functions. Cost and thermal unit emissions must be reduced in scheduling difficulties for environmental reasons. Thus, the issue is a multi-objective economic load dispatch optimization problem (MOELD) with two competing goals of minimizing cost and emission by fulfilling equality and inequality constraints.

2.1. Mathematical formulation

The objective function and associated constraints of the multi-objective economic load dispatch problem are given by (1).

$$Min \sum_{x=1}^{n} [CF_x(Pg_x) + EF_x(Pg_x)] \tag{1}$$

Where CF_x: represents the cost function of thermal unit 'x'; EF_x: indicates the emission function of thermal unit 'x'; Pg_x: is the real power generation of thermal unit 'x'; x': is a number of thermal units varying from 1 to n. The mathematical expression of a cost function $CF_x(Pg_x)$ represented in quadratic form as (2).

$$CF_x(Pg_x) = a_x + b_x Pg_x + c_x Pg_x^2 \tag{2}$$

Where a_x, b_x, c_x represents the cost coefficients of thermal unit 'x'. The mathematical expression of an emission function $EF_x(Pg_x)$represented in quadratic form as (3).

$$EF_x(Pg_x) = \alpha_x + \beta_x Pg_x + \gamma_x Pg_x^2 \tag{3}$$

Where $\alpha_x, \beta_x, \gamma_x$represents the emission coefficients of thermal unit 'x'. The inequality and equality constraints of the problem are as (4).

$$Pg_x^{min} \le Pg_x \le Pg_x^{max} \tag{4}$$

Where $Pg_x^{min}, Pg_x^{max}$is minimum and maximum real power generation limits of 'x' unit. Equality constraint relates to the sum of total generation and total demand [29]–[31].

$$\sum_{x=1}^{n} Pg_x = P_D \tag{5}$$

Where P_D is the total demand; $Pg_x$is the power generation of thermal unit 'x'; 'n' represents the total number of thermal units

3. METHODOLOGY

Maintenance of power balance is essential between the variation of load demand and power generation from thermal units. Linear programming, nonlinear programming, quadratic programming, the gradient technique, the Newton Raphson method, and the lambda iteration method, were all used to find an answer to the aforementioned optimization issue. Evolutionary algorithms like the non-dominated sorting genetic algorithm-II (NSGA-II) and PVDE are more efficient in obtaining an optimal global solution for the MOELD.

3.1. Non-dominated sorting genetic algorithm – II (NSGA-II)

NSGA-II, an upgraded version of the non-dominated sorting genetic algorithm (NSGA), uses elitism to find the best value and accelerate convergence in multi-objective optimization problems. Figure 1 shows the NSGA-II flowchart for MOELD cost and emission calculations. The NSGA-II implementation phases are:

a) To begin, random populations are created and their fitness values are assessed. These parent populations are chosen by ranking and crowding distance. Each population's rank is decided via non-dominated sorting [32].
b) Crowding distance reveals population proximity to neighbours. Crowding distance is assessed for each population to identify parent populations with the same rank.
c) NSGA-II operations, including binary crossover and polynomial mutation, produce offspring from selected parent populations.
d) Iterations continue until the maximum number is achieved. Get the optimum cost and emission values from the optimization problem.

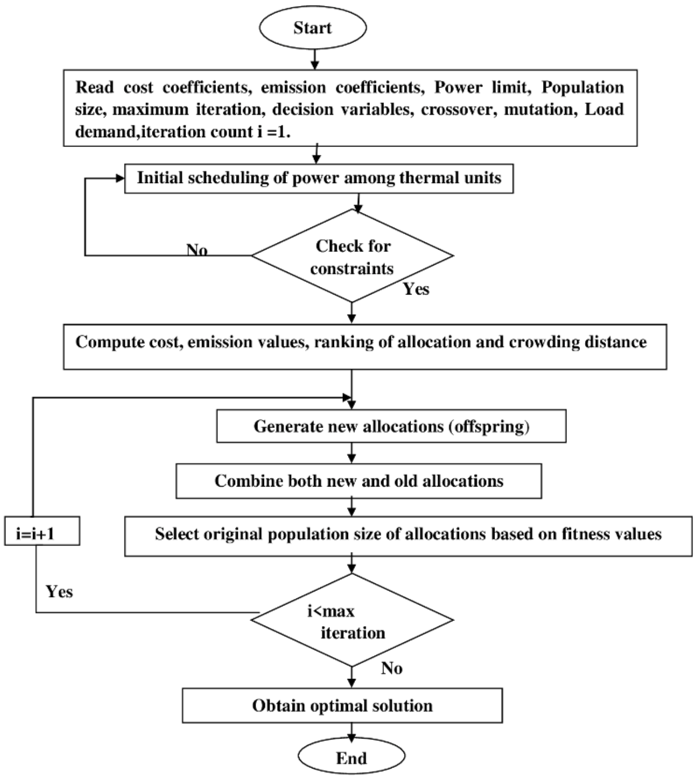

Figure 1. Flowchart for MOELD using NSGA-II

3.2. Population variant differential evolution algorithm (PVDE)

DE-modified PVDE. Population refreshment separates DE/PVDE. The DE population is fixed but regenerated in PVDE using interquartile range. Figure 2 shows the PVDE approach for IEEE 39 bus system MOELD flowchart. PVDE procedures are:

a) Set the number of deciding factors to 1, power limits, scaling factor vector (tsf), crossover probability vector (tcp), and refreshment factor β.
b) From tsf and tcp evaluate maximum, minimum, and median values [23].

c) Initialize the random parent populations which have to satisfy both equality and inequality constraints, show in (3)-(5).
d) For the refreshment of the parent populations, Var_{min} and Var are evaluated.
e) Var_{min} is the vector difference of power limits i.e. maximum and minimum limits multiplied by 0.01.
f) Var is evaluated on parent populations based on the interquartile range (IQR).
g) IQR is defined as the difference between the upper quartile and lower quartile range.
h) If Var is less than Var_{min} new generation limits are evaluated. A new population is generated with the new generation of limits which is termed a refreshed population.
i) Determine the fitness values of refreshed parent populations and find the best population i.e. which is having minimum fitness value.
j) Find scaling factor (SF), and crossover probability (CP) which are useful for the performance of mutation and crossover.
k) Perform mutation, crossover, and selection process to generate offspring population.
l) If the fitness of the offspring population is less than the fitness of the parent population, the offspring population is considered for the next generation. Otherwise, the parent population is considered for the next generation.
m) Update cp and sf as well as the current best population. Process repeats until the iteration count reaches the maximum iteration count.
n) Finally, a set of optimal solutions are obtained called Pareto optimal solutions evaluate an optimal solution.

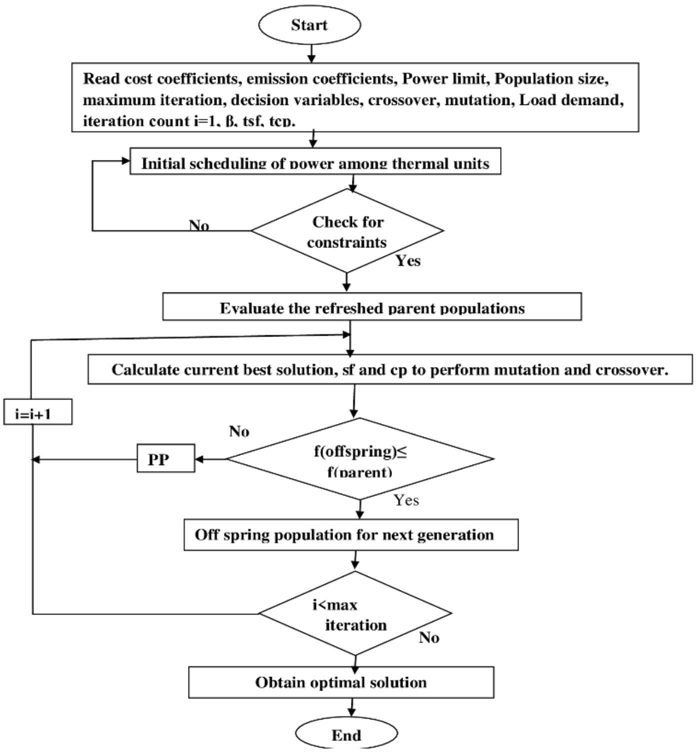

Figure 2. Flowchart for MOELD using PVDE

3.3. Multi-objective optimization problems using hybrid method

Section 2's issue formulation in (1)-(3) must maintain equality and inequality restrictions in (4) and (5). This optimization issue was addressed hybrid. NSGA-II and PVDE are combined in the suggested hybrid approach. The hybrid technique solves multi-objective optimization problems efficiently by combining two or more methods. The hybrid technique solves multi-objective optimization issues well. In this optimization challenge, cost, and emission clash. The hybrid technique executes the NSGA-II algorithm on half the population and the PVDE algorithm on the other [33]. The hybrid technique (NSGA-II and PVDE) implementation plan is shown in Figure 3. Hybrid technique process:

a) Before starting the hybrid approach, the decision variables, goals, emission and cost coefficients, maximum iterations, and system demand are initialised.
b) The output of each generator is represented as a decision variable and presented as Pg= [Pg1, Pg2, Pg3 …] where Pg is the decision vector and Pg1, Pg2, Pg3…….. are the decision variables.
c) Random population is generated, which has to satisfy in (4) and (5).
d) Initial half of the population is considered for NSGA-II and fitness is evaluated for each parent population using (2) and (3).
e) Apply the non-dominated sorting based on the ranking and crowding distance, and the process continues until all ranking fronts are obtained.
f) The corresponding genetic operators i.e. selection, crossover, and mutation are implemented to generate half of the offspring population [33].
g) The remaining parent population includes PVDE. Initially, population is analysed using interquartile range.
h) Appraisal of scaling factor and crossover probability supports the operation during the production of offspring populations.
i) Best population is evaluated from the half-refreshed population. The sequence of mutation, crossover, and selection is carried out to generate half the offspring populations.
j) The two half offspring populations are combined to form the population of original size.
k) The parent population is amalgamated with the offspring population which leads to enhancement of population size, which is twice in number.
l) Based on the best fitness values the initial size of a population is selected and remaining discarded.
m) The newly produced population serves as the parent population for the next iteration, and the iteration process continues until the maximum number of iterations is reached.

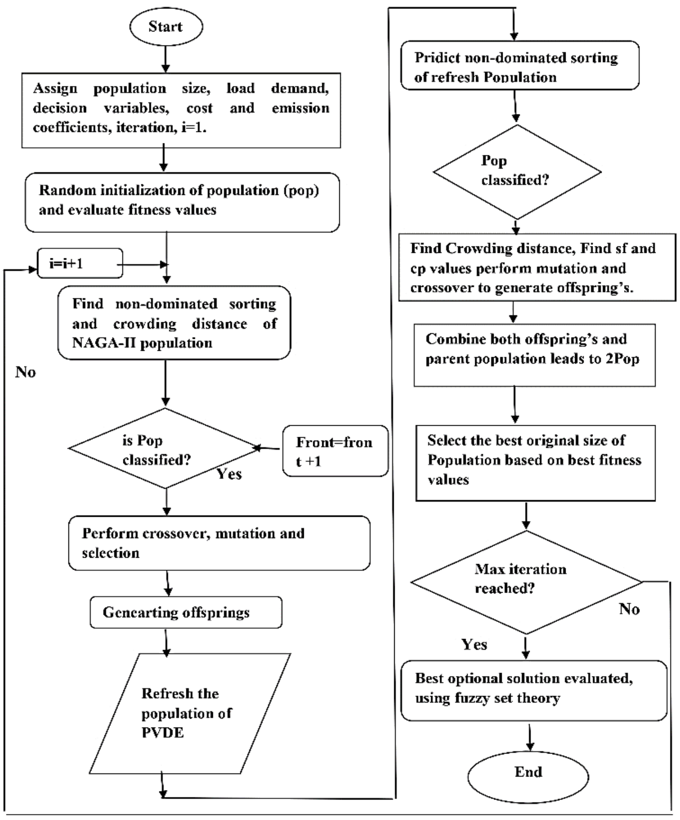

Figure 3. Flowchart of a hybrid method

4. SIMULATION RESULTS

In this we are focusing on the economic load dispatch (ELD) and combined economic and emission dispatch for various test systems including different buses. Standard coefficients would be provided for each system under test. The system considered would be provided with the full loads that need to be generated. The range of power that can be generated with each generator of the system is also provided. These values were fed as input to optimization models of hybrid NSGA-II and PVDE method. This NSGA-II-PVDE is validated IEEE 39 bus test network with ten generators. The results of the entire algorithm provide total cost of the system (fuel cost, emission cost, and combined total cost) and the output (load) needed to be generated from each generator system.

4.1. IEEE 39 bus system using NSGA-II

The single-line diagram of the IEEE 39 bus system is shown in Figure 4 and its parameter values are given in Table 1. Cost and emission values of IEEE 39 bus system in MOELD using NSGA-II for 700 MW, 850 MW, 1000 MW, 1300 MW, and 1500 MW given in Table 2. The Pareto front for maximum load demand of 1500 MW is shown in Figure 5.

Table 1. Parameter values employed to obtain a global optimal solution for IEEE 39 bus system in MOELD using NSGA-II

Parameter	Value	Parameter	Value
Crossover rate	0.8	Population size	80
Mutation rate	0.2	number of iterations	100

Table 2. Cost and emission values of IEEE 39 bus system in MOELD using NSGA-II for 700 MW, 850 MW, 1000 MW, 1300 MW, and 1500 MW

Load(MW)	700	850	1000	1300	1500
P1	400.52	440.46	451.29	444.98	454.96
P2	156	159.32	248.51	436.49	451.96
P3	23.47	85.94	93.56	125.50	129.89
P4	25	25	106.61	95.49	131.11
P5	20	63.24	25	121.40	160.90
P6	10	10	10	10	66.23
P7	10	10	10	10	25.59
P8	10	10	10	10	32.60
P9	25	25	25	25	20.47
P10	20	20	20	20	27.45
Cost (Rs)	14,79,315	16,73,628	18,74,080	22,94,360	26,38,125
Emission (lb)	1,994.99	2,206.74	2,407.15	3,024.34	3,139.86

4.2. IEEE 39 bus system using PVDE

The same initial parameter values are considered in PVDE, which was considered in NSGA-II case (i). Cost and emission values of IEEE 39 bus system in MOELD using PVDE for 700 MW, 850 MW, 1000 MW, 1300 MW, and 1500 MW is given in Table 3. In a comparison of IEEE 39 bus system with NSGA-II, cost value increased and emission values are decreased using PVDE. Figure 6 shows the Pareto front obtained for IEEE 39 bus system for a load of 850 MW using PVDE.

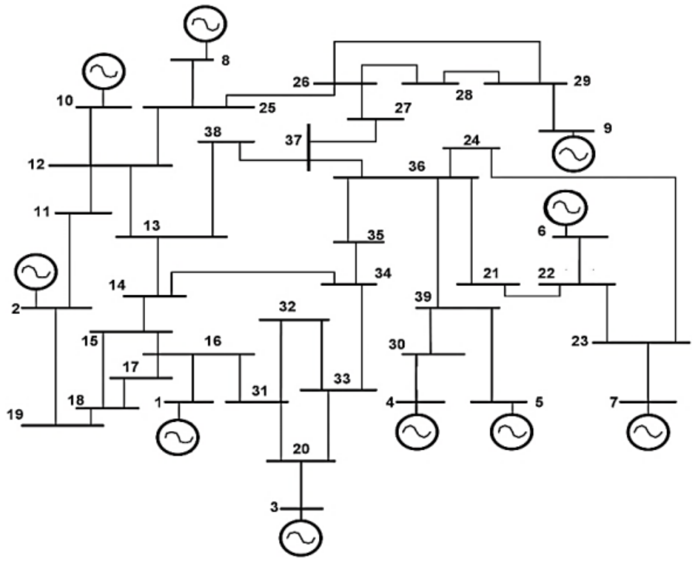

Figure 4. Single line diagram of IEEE 39 bus system

Table 3. Cost and emission values of IEEE 39 bus system in MOELD using PVDE for 700 MW, 850 MW, 1000 MW, 1300 MW, and 1500 MW

Load (MW)	700	850	1000	1300	1500
P1	360.18	360.62	440.24	450.72	458.14
P2	152.79	164.40	283.32	414.98	452.14
P3	40.12	98.77	47.43	131	129.98
P4	46.90	126.20	128.23	128.99	129.99
P5	10	10	10	21.14	54.89
P6	10	10	10	10.35	54.26
P7	10	10	10	10	16.50
P8	25	25	25	82.15	141.34
P9	20	20	20	25.25	28.94
P10	25	25	25	25	34.05
Cost (Rs)	14,80,967	16,77,759	18,77,406	23,01,943	26,58,865
Emission (lb)	1,888.32	2,029.47	2,389.87	2,945.30	3,091.92

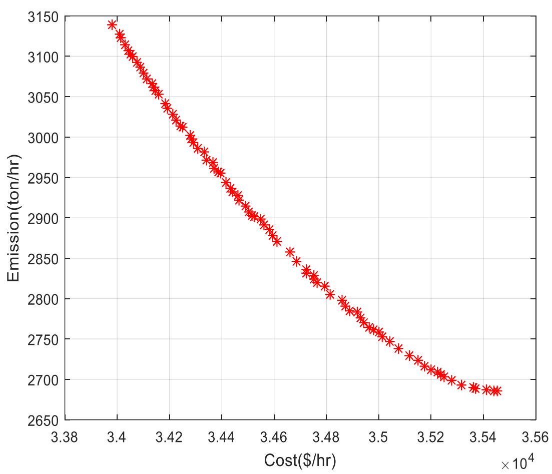

Figure 5. Pareto front of IEEE 39 bus system using NSGA-II

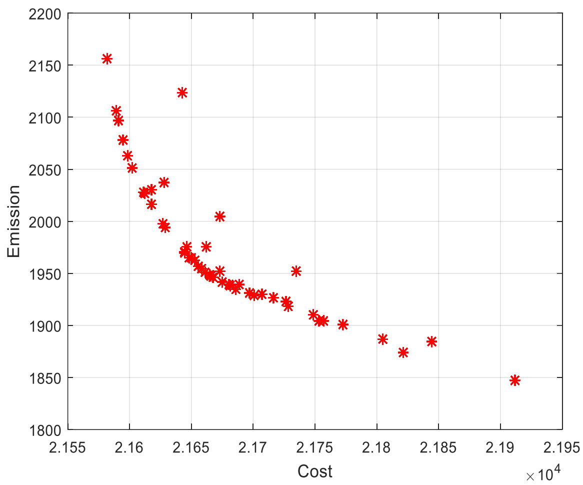

Figure 6. Pareto front of IEEE 39 bus system using PVDE

4.3. MOELD using hybrid method

The parameters used for this hybrid method are as in Table 4, population parameter is considered 80, the number of iterations is 100, crossover value 0.90, and mutation value 0.01. The results obtained from this method for MOELD are given in Table 4, which illustrates the cost and emission values of IEEE 39 bus system in MOELD using hybrid method for 700 MW, 850 MW, 1000 MW, 1300 MW, and 1500 MW. The cost and emission values for each load demand of 24 hours with one hour time horizon are given in Table 4. The optimal value of cost is Rs 26,45,344 and Rs 14,81,924 for loads 1500 MW (highest) 700 MW (lowest) which is illustrated in Table 4. Table 5 shows the comparative analysis of cost and emission values of IEEE 39 bus system in MOELD.

Table 4. Cost and emission values of IEEE 39 in MOELD using HM for 700 MW, 850 MW, 1000 MW, 1300 MW, and 1500 MW

Load(MW)	700	850	1000	1300	1500
P1	410	450.57	445.11	452.64	453.93
P2	150	150	253.75	394.27	442.46
P3	20	57.99	124	128.50	130
P4	20	91.42	77.12	129.99	130
P5	25	25	25	104.49	162
P6	20	20	20	20.5	69.82
P7	25	25	25	25	26.5
P8	10	10	10	24.57	39.43
P9	10	10	10	10	24.87
P10	10	10	10	10	20.96
Cost (Rs)	14,81,924	16,76,787	18,85,833	23,07,059	26,45,344
Emission (lb)	2,009.13	2,206.05	2,435.11	2,901.30	3,109.97

Table 5. Comparative analysis of cost and emission values of IEEE 39 bus system in MOELD

Method	NSGA-II		PVDE		Hybrid method (NSGA-II-PVDE)	
Load (MW)	Cost (Rs)	Emission (lb)	Cost (Rs)	Emission (lb)	Cost (Rs)	Emission (lb)
700	14,79,315	1,994.99	14,80,967	1,888.32	14,81,924	2,009.13
850	16,73,628	2,206.74	16,77,759	2,029.47	16,76,787	2,206.05
1000	18,74,080	2,407.15	18,77,406	2,389.87	18,85,833	2,435.11
1300	22,94,360	3,024.34	23,01,943	2,945.30	23,07,059	2,901.30
1500	26,38,125	3,139.86	26,58,865	3,091.92	26,45,344	3,109.97

5. CONCLUSION

The power sector must design and operate low-emission producing units economically to fulfill demand. MOELD and multi-objective unit commitment (MOUC) are emphasized in power systems to save cost and emission by preserving system limits. Many methods exist for tackling optimization issues with competing goals. We first solve the MOELD with two competing objectives—cost and emission—using NSGA-II and PVDE. Both optimization methods are used to two IEEE 39 bus and 17-unit test systems with 24 load demands in one hour. NSGA-II has cheap cost and PVDE has low emissions, according to simulations. Hybrid approaches tackle multi-objective optimization problems better. Hybrid technique combines NSGA-II and PVDE to find optimum MOELD and MOUC solutions. Results suggest that MOUC objective values are better than MOELD optimization problem. NSGA-II, PVDE, Hybrid, and modified hybrid methods are compared using metrics. Metric analysis shows that the hybrid approach outperforms the modified hybrid method. That indicates the Hybrid technique reduces cost and emissions better than NSGA-II, PVDE, and modified hybrid for all three optimization issues. The NSGA-II-PVDE algorithm also outperformed or equaled other meta-heuristic optimization methods. Formulating any multi-objective function in optimum power flow using HBSA makes it easy to include power system emergent challenges like the environmentally friendly EED without complicating the solution approach.

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