Review of Energy Technologies and Policy Research
2015 Vol. 2, No. 1, pp. 16-28
ISSN(e): 2313-7983
ISSN(p): 2409-2134
DOI: 10.18488/journal.77/2015.2.1/77.1.16.28

ECONOMIC LOAD DISPATCH IN THERMAL POWER PLANT CONSIDERING ADDITIONAL CONSTRAINTS USING CURVE FITTING AND ANN

S.K.Gupta[1]† --- Pankaj Chawala[2]

[1]*Professor and Research scholar at DCR University of Sc. & Technology, Murthal (Sonepat) Haryana, India*

[2]*Research scholar at DCR University of Sc. & Technology, Murthal (Sonepat) Haryana, India*

ABSTRACT

This paper presents a new efficient approach to economic load dispatch (ELD) problem with cost functions using curve fitting, ANN and particle swarm optimization (PSO). Economic load dispatch is one of the most important problems in power system operation. The practical ELD problems may not have fixed cost functions rather it changes with the coal quality, that make the problem of finding the global optimum difficult using any traditional mathematical approach. Therefore, curve fitting technique is used to obtain the coefficients of the cost curve. The same data is used for the training of the artificial neural network. The effectiveness of the algorithm is validated by carrying out extensive test on a power system involving 8 thermal generating units. The variation in calorific values of the coal used in different generators cause the change in coefficients of cost curve. This effect is incorporated using curve fitting, ANN and PSO approaches. The ELD problem is then optimized. The comparison shows the better results.

Keywords: Economic load dispatch, Gross calorific value, Curve fitting technique, Artificial neural network, Efficiency in thermal generating units, Particle swarm optimization.

Contribution/ Originality

This study for economic load dispatch is one of very few studies which have investigated for variation in calorific values of the coal used time to time in thermal power plants. This uses the comparison of conventional, curve fitting, PSO and ANN.

1. INTRODUCTION

The economic load dispatch (ELD) is one of the most important optimization problems in power system operation and planning to derive optimal economy. The main objective of economic load dispatch is to determine the optimal combination of all generating units so as to meet the required load demand at minimum cost while satisfying the various operating constraints like energy balance, max-min generation limits, transmission line constraints, running spare capacity

† Corresponding author

and network security. A station has incremental operating costs for fuel, maintenance cost and fixed cost associated with the station itself that can be quite considerable for a typical thermal and nuclear power plant for example. Things get even more complicated when utilities try to account for transmission line losses and the seasonal changes associated with hydraulic power plants. Conventionally, the cost function for each unit for ELD problem has been approximately represented by a quadratic equation and is solved by using various mathematical techniques like Lambda-iteration method, Lagrange method, Curve Fitting and Artificial Neural Network etc [1-4]. Unfortunately, the cost characteristics of thermal generating units are highly non-linear because of prohibited operating zones, valve point loading and multi fuel insertion etc. Thus, Practical ELD problem is represented as a non linear optimization problem with various equality and inequality constraints, which directly cannot be solved by conventional mathematical techniques. Hence numerous intelligent techniques like Biogeography-Based Optimization (BBO) [5], genetic algorithm (GA) [6], Differential Evolutionary (DE) [7], Evolutionary Programming (EP) [8-10], neural network approaches [11], Tabu Search [12] etc were introduced to solve complex nonlinear ELD problems over past few years.

Recently, Eberhart and Kennedy suggested particle swarm optimization (PSO) based on the analogy of swarm of bird and school of fish [13]. In PSO, each individual makes its decision based on its own experience together with other individual`s experiences. The individual particles are drawn stochastically towards the position of present velocity of each individual, their own previous best performance, and the best previous performance of their neighbor. PSO have been successfully applied to various fields of power system optimization in recent years such as reactive power and voltage control [14], power system stabilizer design [15] and dynamic security border identification [16]. Yoshida, et al. [14] presented a modified PSO to control reactive power and voltage considering voltage security constraint. Since the problem was a mixed-integer nonlinear optimization problem with inequality constraints, they applied the classical penalty method to reflect the constraint- violating variables. In order to utilize the PSO algorithm to solve ELD problem, it is necessary to revise the original PSO to reflect the equality/inequality constraints of the variables in the process of modifying each individual's search. Victoire and Jeyakumar [17] presented a deterministically guided particle swarm optimization (DGPSO) algorithm to solve the dynamic ELD of generating units considering the valve-point effects. Pandian and Thanushkodi [18] presented an Evolutionary Programming (EP) and Efficient Particle Swarm Optimization (EPSO) techniques to solve ELD problems including transmission losses in power system. Efficient Particle Swarm Optimization (EPSO) technique is employed so that optimized results are obtained, and by applying EP, faster convergence is obtained.

In this paper, cost characteristics for different coal quality are obtained by curve fitting method. The same data is used to train the ANN. The generated power, cost, GCV and these values as previous operating point are considered input values of ANN to obtain a, b, c coefficients of cost characteristics for all the generators. The fuel cost curves of generators are represented by quadratic equation of real power generation.

The coefficients a, b, c of each unit are updated automatically depending upon the point of operation used and GCV of coal. It is therefore, expected better result than conventional method where a, b, c coefficients are constant throughout all the range of generation irrespective of coal quality which may actually change time to time. The remaining organization of this paper is as follows. Section II addresses the formulation of economic load dispatch problem, section III describes the curve fitting, ANN and PSO approaches, and section IV describes the results and discussion. Finally, the conclusion is given in section V.

2. FORMULATION OF ELD PROBLEM

The ELD problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying an equality constraint and inequality constraints. The most simplified cost function of each generator can be represented as a quadratic function as given in (2).

$$FC_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \quad Rs/\,Hr \qquad \text{.......(1)}$$

$$FC_t = \sum_{i=1}^{n} FC_i\,(P_{Gi}) \quad Rs/Hr \qquad \text{.......(2)}$$

Where

FC_t is the total fuel cost.

FC_i is the cost function of generator i.

P_{Gi} is electrical output of generator i.

a_i, b_i, c_i are the cost coefficients of generator i.

While minimizing the total generation cost, the total generation should be equal to the total system demand plus the transmission network loss. However, the network loss is not considered in this paper as all the operating units of a power plant are on single bus. This gives the equality constraint

$$P_D = \sum_{i=1}^{n} P_{Gi} \qquad \text{.......(3)}$$

Where P_D is the total power demand.

The maximum active power generation of a source is limited again by thermal consideration and also minimum power generation is limited by the flame instability of a boiler. If the power output of a generator for optimum operation of the system is less than a pre-specified value $\boldsymbol{P_{min}}$, the unit is not put on the bus bar because it is not possible to generate that low value of power from the unit. Hence the generator power P cannot be outside the range stated by the inequality

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \qquad \text{......(4)}$$

WhereP_{Gi}^{min}, P_{Gi}^{max} is the minimum, maximum output of generator number 'i'.

3. ELD USING NEW APPROACHES

A. Overview of Curve Fitting Technique

A curve which is most near to given points is called approximating curve which may be linear or non linear and is called "best fit". It is obtained by Legendre`s principle of least squares in which we minimize the sum of the squares of the deviations of the actual values from their estimated as given by the curve of best fit. According to the above description, the performance steps of this technique are as follows [19]:

1. Data generation, which can be implemented in floating point, since this portion corresponds to sensors that will be independent of the curve fitting device.
2. Off-line computations which can be implemented in floating points with invariant signals.
3. Run- time computation, which must be implemented in fixed point.
4. Data visualization, which must be implemented in floating point.
5. MATLAB`s extensive, device independent plotting capabilities are one of its most powerful features.

B. Artificial Neural Networks

Artificial Neural Network, here referred to as ANN, are an attempt at modeling the processing power of the human brain. Humans are able to adapt to new situations and learn quickly when given the correct context. Computers are relatively slow at performing simple human tasks such as recognizing a lizard in a painting of the jungle. ANN work by simulating the structure of the human brain. At their basic level they consist of a network of neurons connected by synapse.

Neurons are the basic elements of an ANN. Neurons accept inputs from other connections and produce an output by firing their synapse. Neurons typically perform a weighted sum on all of their input connections and then pass it through a transfer function to produce its output. The traditional ANN is a binary network in which a synapse either fires or doesn`t fire. This type of transfer function in which the neurons compares its weighted sum to a threshold and then either emits a 1 or a 0 (fires or doesn`t fire its synapse). While binary networks have their uses, most engineering applications involve the real number system. ANN has thus been adapted to use real numbers.

In this model are used to the six inputs ppg_1, pg_1, GCV_1, GCV_1, $fppg_1$ and fpg_1 i.e. obtain the output values a_1, b_1 and c_1. In this model, one input layer, one hidden layer and output layer has been considered. Total epochs values considered are 300. Learning rate considered is 0.05. Number of neurons in the hidden layer is 1. Back propagation method is used.

C. PSO as ELD Problem

In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. The system is initialized with a population of random solutions and searches for optima by updating generations.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. All the particles are updated by following two "best" values in each iteration. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called P^{best}. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called G^{best}. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called P^{best}. After finding the two best values, the particle updates its velocity and positions with following equation (8) and (9) as

$$V_i^{(u+1)} = w \times V_i^u + C_1 \times rand(\,) \times (P^{best_i} - P_i^u) + C_2 \times rand(\,) \times (G^{best_i} - P_i^u) \quad \text{......(8)}$$

$$P_i^{(u+1)} = P_i^u + V_i^{(u+1)} \quad \text{......(9)}$$

In the above equation,

- The term $rand(\,) \times (P^{best_i} - P_i^u)$ is called particle memory influence
- The term $rand(\,) \times (G^{best_i} - P_i^u)$ is called swarm influence.
- V_i^u is the velocity of i^{th} particle at iteration '*u*'
- C_1 and C_2 are constants which pulls each particle towards p*best* and *gbest* positions.
- w is the inertia weight provides a balance between global and local explorations. It is set according to the following equation,

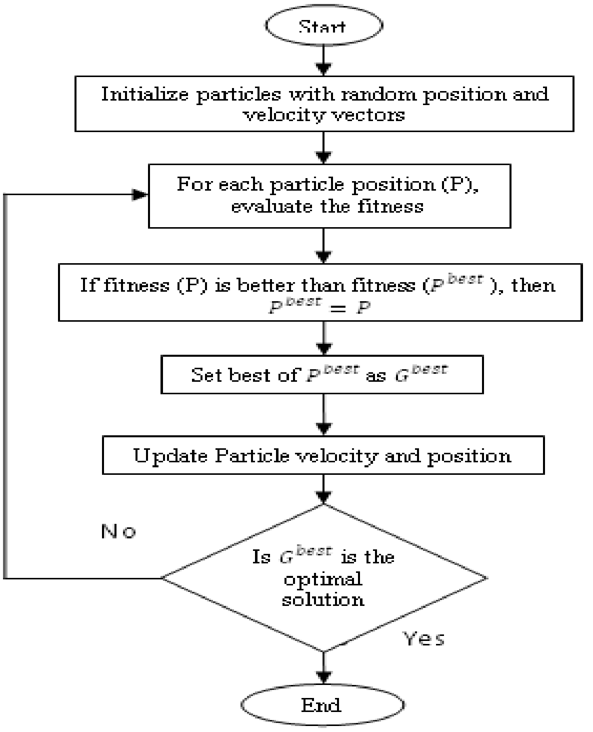

Fig-1. Flow Chart for PSO Algorithm

$$w = w_{max} - \left[\frac{w_{max} - w_{min}}{iter_{max}}\right] \times iter \quad \text{......(10)}$$

Where

w_{max} - maximum value of weighting factor

w_{min} - minimum value of weighting factor

$iter_{max}$ - maximum number of iterations
$iter$ - current number of iteration

When any optimization process is applied to the ELD problem, some constraints are considered. In this work three different constraints are considered. Among them the equality constraint is summation of all the generating power must be equal to the load demand and the inequality constraint is the powers generated must be within the limit of maximum and minimum active power of each unit. The additional constraint is the real time efficiency. The sequential steps of the proposed PSO method are given below.

Step 1) the individuals of the population are randomly initialized according to the limit of each unit including individual dimensions. The velocities of the different particles are also randomly generated keeping the velocity within the maximum and minimum values.

Step 2) each set of solution in the space should satisfy the equality constraints. So equality constraints are checked. If any combination doesn't satisfy the constraints then they are set according to the power balance equation.

Step 3) the evaluation function of each individual P_i is calculated in the population using the evaluation function FC_i (2). The present value is set as the P^{best} value.

Step 4) each P^{best} values are compared with the other P^{best} values in the population. The best evaluation value among the P^{best} is denoted as G^{best}.

Step 5) the member velocity v of each individual Pg is modified according to the velocity update equation (8).

Step 6) the velocity components constraint occurring in the limits from the following conditions are Checked

$$V_i^{min} = -0.5P_i^{min}$$
$$V_i^{max} = +0.5P_i^{max}$$

Step 7) the position of each individual P_i is modified according to the position update equation (9).

Step 8) If the evaluation value of each individual is better than previous P^{best}, the current value is set to be P^{best}. If the best P^{best} is better than G^{best}, the value is set to be G^{best}.

Step 9) If the number of iterations reaches the maximum, then go to step 10.Otherwise, go to step 2.

Step 10) The individual that generates the latest G^{best} is the optimal generation power of each unit with the minimum total generation cost.

4. RESULTS AND DISCUSSION

The proposed methods are used independently to solve case study problem involving 8 generating units. Usually, training of a neural network is a slow intelligence process. So to speed it up optimization is required at every point, i.e., in deciding the neural network architecture, the number and type of training or testing patterns, the learning rate, the error goal etc. The training patterns consist of input-output pairs. The proposed approach is tested on a standard test system. The initial particles are randomly generated within the feasible range. The parameters C_1, C_2 and inertia weight are selected for best convergence characteristic. Here $C_1 = C_2 = 2.0$ The maximum value of w is chosen 0.9 and minimum value is chosen 0.4. The velocity limits are selected as $V_i^{max} = +0.5P_i^{max}$ and the minimum velocity is selected as $V_i^{min} = -0.5P_i^{min}$. There are 10 no of particles selected in the population.

This test case comprises of 8 generating units with quadratic cost functions given in appendixes. The outputs of generating units and aggregate fuel cost comparison for 800 MW and 850 MW are shown in Table-1 and 2. Comparison for load dispatch using Curve Fitting and ANN for different set of data is shown in Fig.2 and Fig.3. The transmission loss is assumed to be zero.

Table-1. Comparison of Fuel Costs for 8-Generator System with P_D = 800MW

	Unit1 (MW)	Unit2 (MW)	Unit3 (MW)	Unit4 (MW)	Unit 5 (MW)	Unit6 (MW)	Unit7 (MW)	Unit8 (MW)	Fuel cost (in Rs/Hr)
Efficiency	42.3	51.4	60.0	52.5	61.9	50.8	61.7	58.6	
Normal Loading	102	83	80	82	195	210	258	258	
ELD Conventional method	60	50	50	50	121.4	138.5	165	165	7651.6
Load Dispatch using Curve fitting GCV3374	60	50	50	50	121.4	138.5	165	165	7651.6
Load Dispatch using Curve fitting GCV 3400	60	50	50	50	121.5	138.5	165	165	7618.8
Load Dispatch using Curve fitting GCV3450	60	50	50	50	121.5	138.4	165	165	7583.1
Load Dispatch using Curve fitting GCV3470	60	50	50	50	121.4	138.5	165	165	7547.2
Load Dispatch using Curve fitting GCV3500	60	50	50	50	121.5	138.4	165	165	7510.1
Load Dispatch using Curve fitting GCV3524	60	50	50	50	121.4	138.5	165	165	7465.9
ANN with GCV3374	60	50	50	50	126.9	133.0	165	165	7599.8
ANN with GCV 3400	60	50	50	50	127	133	165	165	7585.9
ANN with GCV3450	60	50	50	50	126	133	165	165	7597.08
ANN with GCV3470	60	50	50	50	126	133	165	165	7225.08

ANN with GCV3500	60	50	50	50	125	134	165	165	6928.79
ANN with GCV3550	60	50	50	50	126	133	165	165	6911.45
PSO Usingη	69.18	50	50	50	115.76	120.83	165	165	7065.25

Table-2. Comparison of Fuel Costs for 8-Generator System with P_D = 850MW

	Unit1 (MW)	**Unit2 (MW)**	**Unit3 (MW)**	**Unit4 (MW)**	**Unit5 (MW)**	**Unit6 (MW)**	**Unit7 (MW)**	**Unit8 (MW)**	**Fuel cost (in Rs/Hr)**
Efficiency	42.3	51.4	60.0	52.5	61.9	50.8	61.7	58.6	
Normal Loading	102	83	80	82	195	210	258	258	
ELD Conventional	60	50	50	50	144.9	163.4	166.6	165	8715.56
ELD using Curve fitting GCV3526	60	50	50	50	144.9	163.4	166.6	165	8715.56
ELD using Curve fitting GCV3540	60	50	50	50	144.8	163.4	166.6	165	8685.47
ELD using Curve fittingwith GCV 3570	60	50	50	50	144.9	163.1	166.6	165	8648.02
ELD using Curve fitting GCV4100	60	50	50	50	144.8	163.2	166.8	165	8612.16
ELD using Curve fitting GCV4120	60	50	50	50	144.9	163.2	166.7	165	8576.26
ELD using Curve fitting GCV4150	60	50	50	50	145.0	163.2	166.7	165	8531.31
ANN with GCV3526	60	50	50	50	151.2	158.7	165	165	8531.3
ANN with GCV3540	60	50	50	50	150.6	159.3	165	165	8616.9
ANN with GCV3570	60	50	50	50	149.6	160.3	165	165	8623.0
ANN with GCV4100	60	50	50	50	147.3	160.2	167.4	165	8244.0
ANN with GCV4120	60	50	50	50	146.0	161.4	167.4	165	7937.3
ANN with GCV4150	60	50	50	50	147.3	166.2	166.2	165	7892.2
PSO Usingη	73.3	53	51.2	52.4	123.5	130.9	165.7	165.7	8235.8

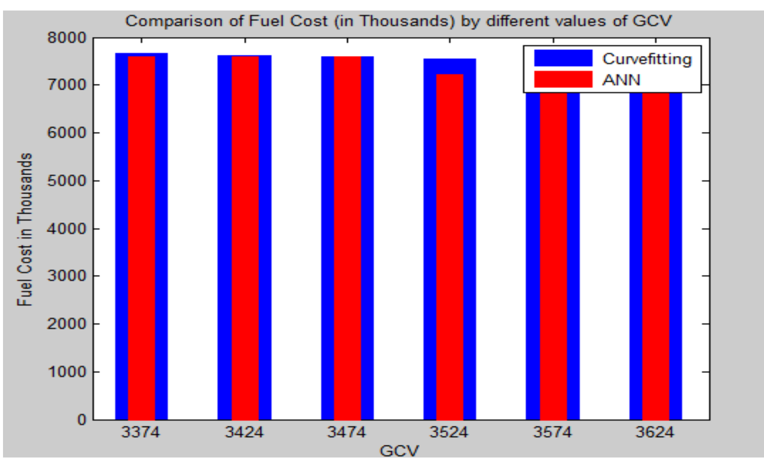

Fig-2. Comparison of Total Fuel Cost (in Thousands) obtained by applying curve fitting and ANN against step wise increase in different values of GCVs

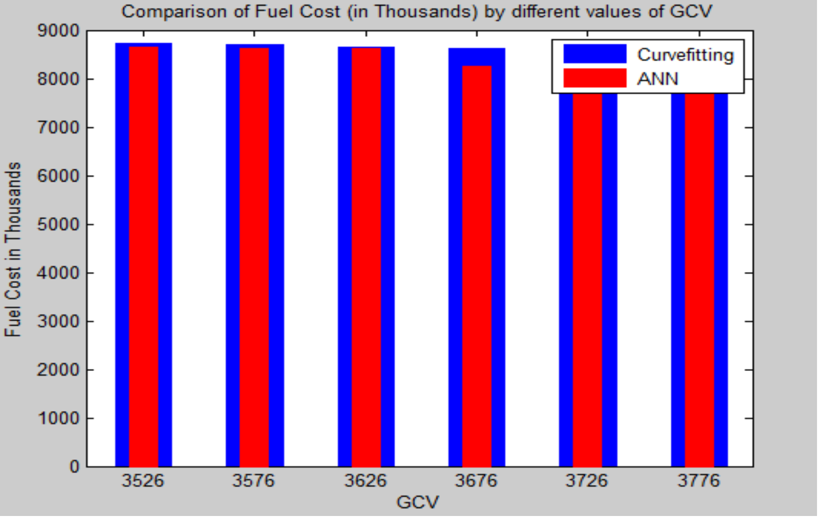

Fig-3. Comparison of Total Fuel Cost (in Thousands) obtained by applying curve fitting and ANN against step wise increase in different values of GCVs

5. CONCLUSION

This paper presents a new approach of considering efficiency (Turbine, Boiler and Generator), GCV value of coal as an inequality constraint to solve the economical load dispatch problem in thermal power plants. A comparison analysis has been made on a test systems comprises 8 generating units for different load demands. Since quality of coal changes time to time, the program incorporates the change in GCV of coal. In curve fitting method, we are able to obtain a, b, c coefficients of cost characteristics from experimental data. This program may not give it best results for new value of GCV. The program using ANN has been trained to obtain a, b, c coefficients of cost characteristics from operating point's (pg) current value of cost, GCV and previous operating point. Thus ANN based computer programs developed is most robust and works dynamically and gives better results in compare to the conventional method as well as curve fitting approach.

APPENDIX

Table-3. Input Parameters of Various Operating Units

	Normal Loading (MW)	Max limit (MW)	Min limit (MW)	Tripping limit (MW)	a	b	C
Unit1	102	110	60	35	0.3167	-10.9	102.8
Unit2	83	105	50	35	0.3463	-7.57	100.6
Unit3	80	85	50	60	0.6362	-23.5	104.6
Unit4	82	82	50	60	0.5263	-16.2	109.6
Unit5	195	216	110	30	0.0884	-2.34	63.7
Unit6	210	216	100	45	0.0839	-4.14	77.77
Unit7	258	266	165	80	0.0864	-5.49	98.7
Unit8	258	266	165	75	0.0953	-6.38	58.44

Table-4. Total efficiency for various operating units

Unit No.	η_t	η_b	η_g	η_{total}
Unit1	77.26	68.81	79.73	42.39 (Min)
Unit2	82.99	69.09	89.80	51.49
Unit3	82.84	80.10	90.56	60.09
Unit4	83.15	74.53	84.83	52.57
Unit5	83.67	79.31	93.34	61.94 (Max)
Unit6	74.61	72.04	94.65	50.87
Unit7	87.56	75.82	92.99	61.73
Unit8	76.61	80.29	95.30	58.62

Table-5. Cost of generator at the different GCVs

Ppg1	Pg1	GCV1	Fppg1	Fpg1
63	66	3374	670.56	760.30
63	66	3400	670.56	760.30
63	66	3450	670.56	760.30
63	66	3470	670.56	760.30
63	66	3500	670.56	760.30
63	66	3550	670.56	760.30

Ppg2	Pg2	GCV2	Fppg2	Fpg2
53	56	3526	671.29	761.78
53	56	3540	671.29	761.78
53	56	3570	671.29	761.78
53	56	4100	671.29	761.78
53	56	4120	671.29	761.78
53	56	4150	671.29	761.78

Ppg3	Pg3	GCV3	Fppg3	Fpg3
53	56	3572	645.13	782.60
53	56	3580	645.13	782.60
53	56	3588	645.13	782.60
53	56	3599	645.13	782.60
53	56	4200	645.13	782.60
53	56	4210	645.13	782.60

Ppg4	Pg4	GCV4	Fppg4	Fpg4
53	56	3728	732.03	855.68
53	56	3740	732.03	855.68
53	56	3760	732.03	855.68
53	56	3800	732.03	855.68
53	56	3860	732.03	855.68
53	56	3900	732.03	855.68

Ppg5	Pg5	GCV5	Fppg5	Fpg5
191	194	3779	2841.6	2936.7
191	194	3790	2841.6	2936.7
191	194	3810	2841.6	2936.7
				Continue
191	194	3850	2841.6	2936.7
191	194	3890	2841.6	2936.7
191	194	4050	2841.6	2936.7

Ppg6	Pg6	GCV6	Fppg6	Fpg6
181	184	3955	2000.8	2078.8
181	184	4000	2000.8	2078.8
181	184	4050	2000.8	2078.8
181	184	4100	2000.8	2078.8
181	184	4160	2000.8	2078.8
181	184	4200	1996.6	2073.8

Ppg7	Pg7	GCV7	Fppg7	Fpg7
168	171	3426	1613.4	1684.7
168	171	3450	1613.4	1684.7
168	171	3490	1613.4	1684.7
168	171	4200	1613.4	1684.7
168	171	4250	1613.4	1684.7
168	171	4280	1575.5	1610.4
Ppg8	**Pg8**	**GCV8**	**Fppg8**	**Fpg8**
168	171	3600	1674.6	1752.3
168	171	3650	1674.6	1752.3
168	171	3700	1674.6	1752.3
168	171	3750	1674.6	1752.3
168	171	3800	1674.6	1752.3
168	171	3850	1645.9	1720.5

NOMENCLATURE

AGC Automatic Generation Control

a Quadratic fuel coefficient

b Linear fuel coefficient

c Minimum fuel used during no load

$CIPMS$ Computer Integrated Plant Management System

$Effic$ Efficiency of generating units

$C1$ and $C2$ Acceleration Constants

DE Differential Evolution

ELD Economic Load Dispatch

FC Fuel Cost (in Rupees)

G^{best} Best of P^{best} called as Global best

$Effictot$ Total efficiency of generating units

$Efficmin$ Manimum value of efficiency

IC	Incremental Cost
$Iter_{max}$	Maximum number of iteration
$iter$	Current number of iteration
Li	Gross Penalty Factor for operating unit
$L_i^{Turbine\ Effic}$	Penalty Factor associated with turbine efficiency
$L_i^{Boiler\ Effic}$	Penalty Factor associated with boiler efficiency
$L_i^{Generator\ Effic}$	Penalty Factor associated with generator efficiency
L_i^{Effic}	Penalty Factor associated with efficiency
MATLAB	Matrix Laboratory
MW	Mega-Watt
ANN	Artificial Neural Network
PSO	Particle Swarm Optimization
η	Efficiency
GCV	Gross Calorific Value
W	Inertia Weighting factor
W_{MAX}	Maximum value of weighting factor
W_{MIN}	Minimum value of weighting factor
λ	Incremental Fuel Cost of the plant
Pgi	Power generated by generator no. "i"
GCVi	Gross Calorific Value of Coal in generator no"i"
Fpgi	Cost offered by generator no. "i" in ₹ per hour
Ppgi	Previous Power generated by generator no. "i"
Fppgi	Previous Cost offered by generator no. "i" in ₹ per hour

REFERENCES

[1] P. Aravindhababu and K. R. Nayar, "Economic dispatch based on optimal lambda using radial basis function network," *Elect. Power Energy Syst.*, vol. 24, pp. 551–556, 2002.

[2] H. H. Happ, "Optimal power dispatch – a comprehensive survey," *IEEE Transection on Power Apparatus and Systems*, vol. 96, 1977.

[3] R. Ramanathan, "Fast economic dispatch based on the penalty factors from Newton's method," *IEEE Transection on Power Apparatus and Systems*, vol. PAS-104, pp. 1624-1629, 1985.

[4] E. H. Chowdhury and R. Saifur, "A review of recent advances in economic dispatch," *IEEE Transactions on Power System*, vol. 5, p. 1248, 1990.

[5] B. Aniruddha, I. Member, and K. C. Pranab, "Biogeography-based optimization for different economic load dispatch problems," *IEEE Transactions on Power Systems*, vol. 25, p. 542 548, 2010.

[6] T. Yalcinoz and H. Altun, "Environmentally constrained economic dispatch via a genetic algorithm with arithmetic crossover," presented at the IEEE 6th Africon Conference in Africa 2002, 2002.

[7] S. C. Leandro dos and C. M. Viviana, "Combining of chaotic differential evolution and quadratic programming for economic dispatch optimization with valve-point effect," *IEEE Transactions on Power Systems*, vol. 21, p. 989, 2006.

[8] S. Nidul, R. Chakrabarti, and P. K. Chattopadhyay, "Evolutionary programming techniques for economic load dispatch," *IEEE Transactions on Evolutionary Computation*, vol. 7, p. 83, 2003.

[9] Y. M. Park, J. R. Won, and J. B. Park, "A new approach to economic load dispatch based on improved evolutionary programming," *Eng. Intell. Syst. Elect. Eng. Commun.*, vol. 6, pp. 103–110, 1998.

[10] H. T. Yang, P. C. Yang, and C. L. Huang, "Evolutionary programming based economic dispatch for units with nonsmooth fuel cost functions," *IEEE Trans. Power Syst.*, vol. 11, pp. 112–118, 1996.

[11] J. H. Park, Y. S. Kim, I. K. Eom, and K. Y. Lee, "Economic load dispatch for piecewise quadratic cost function using hopfield neural network," *IEEE Trans. Power Syst.*, vol. 8, pp. 1030–1038, 1993.

[12] K. Senthil and K. Manikandan, "Economic thermal power dispatch with emission constraint and valve point effect loading using improved tabu search algorithm," *International Journal of Computer Applications (0975 – 8887)*, vol. 3, pp. 0975–8887, 2010.

[13] R. C. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in *Proceedings of the 6th International Symposium on Micro Machine and Human Science*, Nagoya, Japan, 1995, pp. 39-43.

[14] H. Yoshida, K. Kawata, Y. Fukuyama, S. Takayama, and Y. Nakanishi, "A particle swarm optimization for reactive power and voltage control considering voltage security assessment," *IEEE Trans. Power Syst.*, vol. 15, pp. 1232–1239, 2000.

[15] M. Clerc and J. Kennedy, "The particle swarm-explosion, stability, and convergence in a multidimensional complex space," *IEEE Trans. Evol. Comput.*, vol. 6, pp. 58–73, 2002.

[16] I. N. Kassabalidis, M. A. El-Sharkawi, R. J. Marks, L. S. Moulin, and A. P. A. Da Silva, "Dynamic security border identification using enhanced particle swarm optimization," *IEEE Trans. Power Syst.*, vol. 17, pp. 723–729, 2002.

[17] T. A. A. Victoire and A. E. Jeyakumar, "A modified hybrid EP-SQP approach for dynamic dispatch with valve-point effect," *Int. J. Elect. Power Energy Syst.*, vol. 27, pp. 594–601, 2005.

[18] S. M. V. Pandian and K. Thanushkodi, "Solving economic load dispatch problem considering transmission losses by a hybrid EP-EPSO algorithm for solving both smooth and non-smooth cost function," *International Journal of Computer and Electrical Engineering*, vol. 2, pp. 1793-8163, 2010.

[19] G. D. Pradeep, *A text book on computer oriented statistical methods*: Jeevansons, Publications, 2010.