Economic Load Dispatch in Thermal Power Plant Considering Additional Constraints Using Curve Fitting and ANN

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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 have cost functions with equality and inequality constraints that make the problem of finding the global optimum difficult using any traditional mathematical approach. Therefore, curve fitting technique is used for generating training data for 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 curve fitting, ANN and PSO approaches are used as it is easy to implement and there are few parameters to adjust with high computational efficiency and high accuracy.

Keywords: Economic Load Dispatch, Gross Calorific Value, Curve Fitting Technique, Artificial Neural Network, Efficiency in Thermal Generating Units, Particle Swarm Optimization.

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 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]. 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. Victorie 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.

In this paper, cost characteristics for different coal quality are obtained by curve fitting method. The data, thus generation using curve fitting, are 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 coefficients a, b, c of each unit are updated automatically depending upon the point of operation used GCV of coal. It is therefore, expected better result than conventional method where a, b, c coefficients are constant through at all the range of generation irrespective of coal quality which may change time to time.

2. FORMULATION OF ELD PROBLEM

A. Classical 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 equation (2).

$$\boldsymbol{FC_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \; Rs/\,Hr} \qquad \ldots\ldots \qquad (1)$$

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

Where, $\boldsymbol{FC_t}$ is the total fuel cost.
$\boldsymbol{FC_i}$ is the cost function of generator i.
$\boldsymbol{P_{Gi}}$ is electrical output of generator i.
$\boldsymbol{a_i, b_i, c_i}$ are the cost coefficients of generator i.
This gives the equality and inequality constraints.

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

Where, $\boldsymbol{P_D}$ is the total power demand.

$$\boldsymbol{P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}} \qquad \ldots\ldots \qquad (4)$$

Where, $\boldsymbol{P_{Gi}^{min}, P_{Gi}^{max}}$ is the minimum, maximum output of generator i.
ELD problem with efficiency as an additional inequality constraint

It is estimated that, if a whole generating Unit worked as running smoothly, then the whole units to calculate the turbine, boiler and generator efficiency. In a thermal power Plant, efficiencies are calculated every day from the bunkers of respective operating Units and are tested for various contents (like hot water, GCV values of coal, moisture contents etc). Suppose on a particular day, the EFFIC is as under

$$\boldsymbol{Effic_{total} = [Effic_1\ Effic_2\ Effic_3\ \ldots\ldots\ldots\ Effic_n]}$$

Now

$$\boldsymbol{L_i^{EFFIC} = \frac{EFFICto_i}{EFFIC_{min}}} \qquad .. \qquad (5)$$

Where

$$\boldsymbol{L_i = L_i^{Turbine} \times L_i^{Boiler} \times L_i^{Generator}} \qquad .. \qquad (6)$$

The generation from each unit obtained by applying PSO will be modified by multiplying the individual penalty factors with respective generating unit as given in eq. (6)

$$\boldsymbol{P_{Gi}^{new} = P_{Gi} \times L_i} \qquad \ldots\ldots \qquad (7)$$

For a particular amount of load demand, after considering the effect of penalty factors, it is sometimes possible that the generation from any (or more than one) unit violate the maximum or minimum limits. In that case, it is recommended that the additional amount (after settling the maximum or minimum limits) will be proportionally distributed among the remaining units.

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 [20]:

B. Artificial Neural Networks

Artificial Neural Network, here referred to as ANN, is 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. 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.

4. IMPLEMENTATION OF PSO AS ELD PROBLEM

A. Overview Of PSO

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. In each iteration, all the particles are updated by following two "best" values. 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

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

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

In the above equation,

- The term $\boldsymbol{rand}(\,) \times \left(\boldsymbol{P}^{\boldsymbol{best}_i} - \boldsymbol{P}_i^{\boldsymbol{u}}\right)$ is called particle memory influence
- The term $\boldsymbol{rand}(\,) \times \left(\boldsymbol{G}^{\boldsymbol{best}_i} - \boldsymbol{P}_i^{\boldsymbol{u}}\right)$ is called swarm influence.
- $\boldsymbol{V}_i^{\boldsymbol{u}}$ is the velocity of $\boldsymbol{i}^{\boldsymbol{th}}$ particle at iteration 'u'
- $\boldsymbol{C_1}$ and $\boldsymbol{C_2}$ are constants which pulls each particle towards p*best* and gbest positions.
- $\boldsymbol{w}$ is the inertia weight provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. It is set according to the following equation,

$$\boldsymbol{w} = \boldsymbol{w_{max}} - \left[\frac{\boldsymbol{w_{max}} - \boldsymbol{w_{min}}}{\boldsymbol{iter_{max}}}\right] \times \boldsymbol{iter} \qquad \ldots\ldots \qquad (10)$$

Where, $\boldsymbol{w_{max}}$ - maximum value of weighting factor

$\boldsymbol{w_{min}}$ - minimum value of weighting factor

$\boldsymbol{iter_{max}}$ - maximum number of iterations

$\boldsymbol{iter}$ - current number of iteration

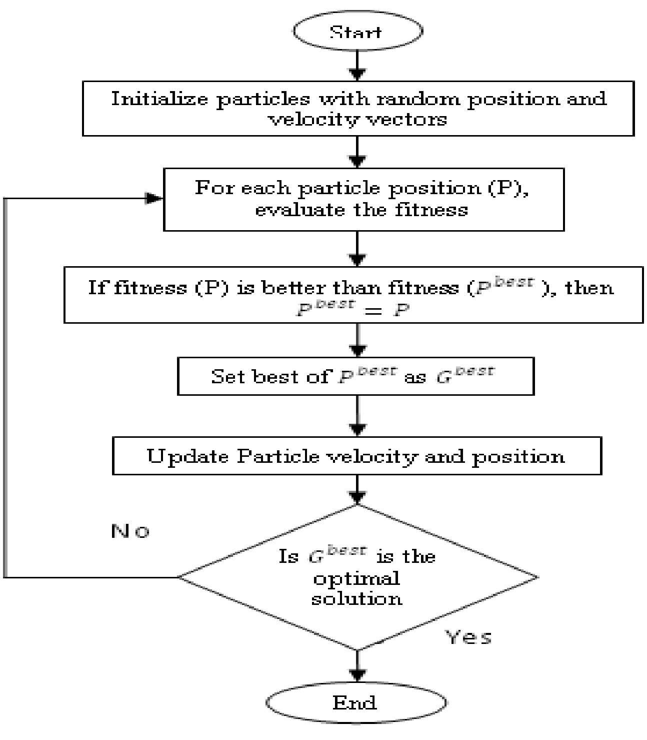

Fig.1 Flow Chart for PSO Algorithm.

The sequential steps of the proposed PSO are described in the flow chart.

5. RESULTS AND DISCUSSION

The proposed method is used to solve case study involving 8 generating units. The proposed approach is tested on a standard test system. The initial particles are randomly generated within the feasible range. The parameters $\boldsymbol{C_1}, \boldsymbol{C_2}$ and inertia weight are selected for best convergence characteristic. Here $\boldsymbol{C_1}$ = $\boldsymbol{C_2}$ = 2.0 The maximum value of w is chosen 0.9 and minimum value is chosen 0.4. The velocity limits are selected as $\boldsymbol{V_i^{max}} = +\boldsymbol{0.5P_i^{max}}$ and the minimum velocity is selected as $\boldsymbol{V_i^{min}} = -\boldsymbol{0.5P_i^{min}}$. 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 for 800 MW and 850 MW are shown in Table III, IV and V appendixes. Comparison for load dispatch using Curve Fitting and ANN are shown in Fig.2 and Fig.3. The transmission loss is assumed to be zero.

TABLE1 COMPARISON OF COSTS 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)
GCV	3374	3526	3572	3728	3779	3955	3426	3600	
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	
Load Dispatch using Proportionate method	64.3	52.3	50.4	51.7	123.0	132.4	162.7	162.7	7737.08
Load Dispatch using □	60	50	50	50	132.3	127.6	165	165	7672.21
ELD	60	50	50	50	121.4	138.5	165	165	7651.6
Load Dispatch using Curve fitting	60	50	50	50	121.4	138.5	165	165	7651.6
Load Dispatch using Curve fitting	60	50	50	50	121.5	138.5	165	165	7618.8
Load Dispatch using Curve fitting	60	50	50	50	121.5	138.4	165	165	7583.1
Load Dispatch using Curve	60	50	50	50	121.4	138.5	165	165	7547.2

fitting									
Load Dispatch using Curve fitting	60	50	50	50	121.5	138.4	165	165	7510.1
Load Dispatch using Curve fitting	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 Using□	69.18	50	50	50	115.76	120.83	165	165	7065.25

TABLE2 COMPARISON OF COSTS 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)
GCV	3374	3526	3572	3728	3779	3955	3426	3600	
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	
Load Dispatch using Proportionate method	61.4	55.6	53.6	54.9	130.7	140.7	172.9	172.9	9033.51
Load Dispatch using □	60	50	50	50	153.7	146.1	175.1	165	8753.22
ELD	60	50	50	50	144.9	163.4	166.6	165	8715.56
Load Dispatch using Curve fitting	60	50	50	50	144.9	163.4	166.6	165	8715.56
Load Dispatch using Curve fitting	60	50	50	50	144.8	163.4	166.6	165	8685.47
Load Dispatch using Curve fitting	60	50	50	50	144.9	163.1	166.6	165	8648.02

Load Dispatch using Curve fitting	60	50	50	50	144.8	163.2	166.8	165	8612.16
Load Dispatch using Curve fitting	60	50	50	50	144.9	163.2	166.7	165	8576.26
Load Dispatch using Curve fitting	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 Using□	73.3	53	51.2	52.4	123.5	130.9	165.7	165.7	8235.8

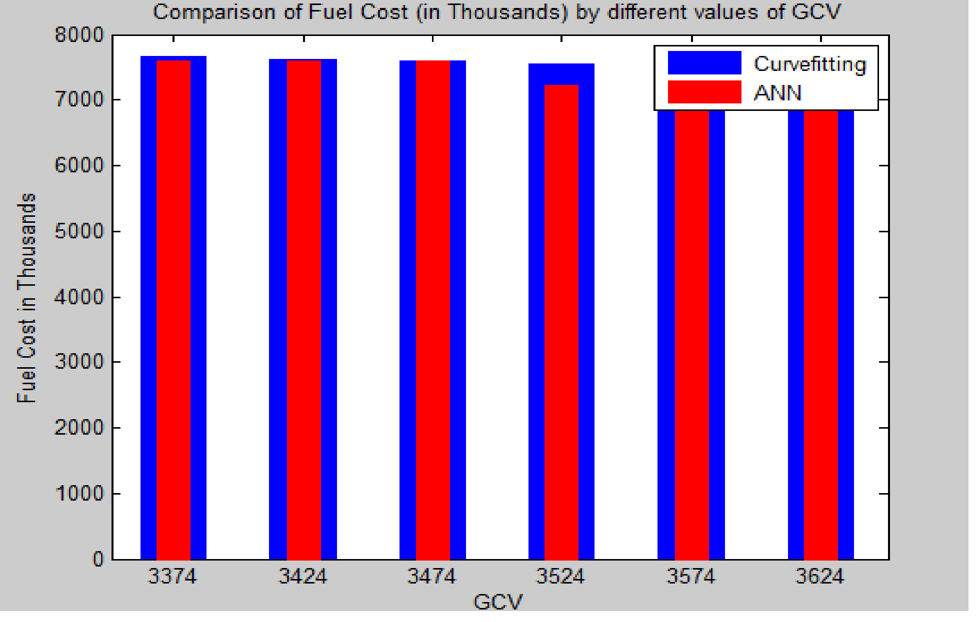

Fig.2 Comparison of Total Fuel Cost (in Thousands) obtained by applying curve fitting and ANN against step wise increase in different values of GCVs

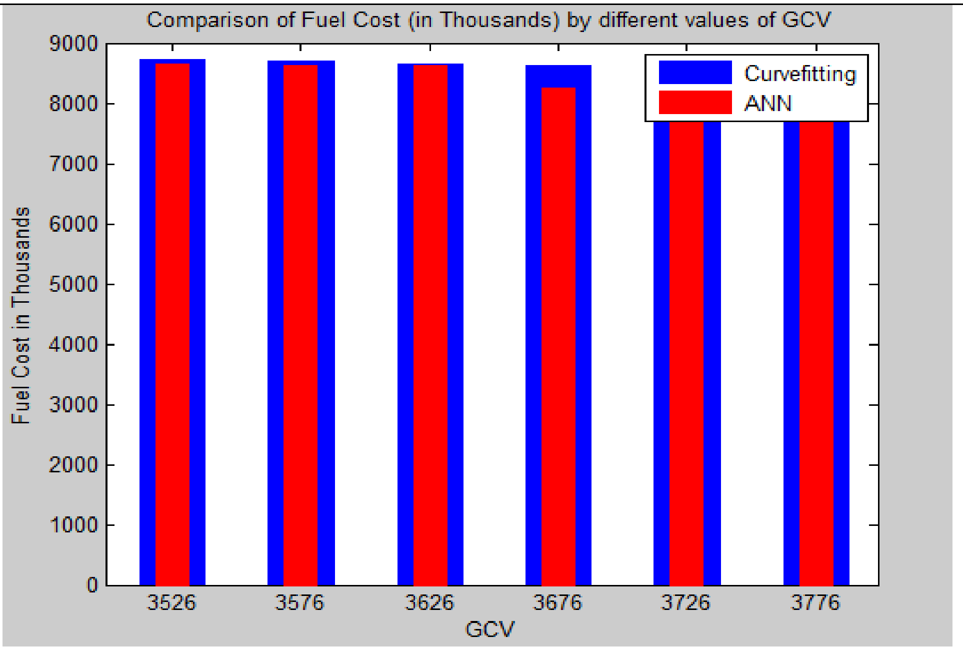

Fig.3 Comparison of Total Fuel Cost (in Thousands) obtained by applying curve fitting and ANN against step wise increase in different values of GCVs

6. 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. The efficiency of individual operating units is formulated as Penalty Factors (L_i) of respective units. These penalty factors are utilized to economically distribute the total power demand (P_D) among individual operating units in order to achieve minimum fuel cost. A comparison analysis has been done on different test systems comprises 8 generating units for different load demands. In some of the cases, by taking efficiency as an operating constraint, the total fuel cost may get increased by a small amount but this small increase in fuel cost is justified as at the same time the generation from various operating units are improved (i.e. if efficiency of any unit is poor, contribution from that unit is decreased accordingly and vice-versa). Since quality of coal is not constant, it changes time to time. The programs has been written for ELD which incorporate the change in GCV of coal. In curve fitting method, we are able to obtain a, b, c coefficients of coal characteristics from earlier 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 general and works dynamically.

APPENDIX

TABLE3 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

TABLE4 Total efficiency for various operating units

Unit No.	□t	□b	□g	□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

TABLE5 Cost of generator output at the different values of GCVs

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

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

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

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

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

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

Ppg7	Pg7	GCV7	GCV7	Fppg7	Fpg7
168	171	3426	3426	1613.4	1684.7
168	171	3450	3450	1613.4	1684.7
168	171	3490	3490	1613.4	1684.7
168	171	4200	4200	1613.4	1684.7
168	171	4250	4250	1613.4	1684.7
168	171	4280	4280	1575.5	1610.4

Ppg8	Pg8	GCV8	GCV8	Fppg8	Fpg8
168	171	3600	3600	1674.6	1752.3
168	171	3650	3650	1674.6	1752.3
168	171	3700	3700	1674.6	1752.3
168	171	3750	3750	1674.6	1752.3
168	171	3800	3800	1674.6	1752.3
168	171	3850	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

 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

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