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 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
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).

\[ FC_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \quad Rs/ Hr \quad (1) \]

Where

- $FC_i$ 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

\[ P_D = \sum_{i=1}^{n} P_{Gi} \quad (3) \]

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 $P_{min}$, 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

\[ P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad (4) \]

Where $P_{Gi}^{min}$, $P_{Gi}^{max}$ 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

$$V_i^{(u+1)} = w \times V_i^u + C_1 \times rand() \times (P^{best}_i - P_i^u) + C_2 \times rand() \times (G^{best} - P_i^u)$$ 

...(8)

$$P_i^{(u+1)} = P_i^u + V_i^{(u+1)}$$ 

...(9)

In the above equation,

- The term $rand() \times (P^{best}_i - P_i^u)$ is called particle memory influence.
- The term $rand() \times (G^{best} - P_i^u)$ 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 $g^{best}$ positions.
- $w$ is the inertia weight provides a balance between global and local explorations. It is set according to the following equation,

$$w = w_{max} - \left[ \frac{w_{max} - w_{min}}{iter_{max}} \right] \times iter$$  

...(10)

Where

- $w_{max}$ - maximum value of weighting factor
- $w_{min}$ - minimum value of weighting factor

Fig-1. Flow Chart for PSO Algorithm
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 $P_g$ is modified according to the velocity update equation (8).

Step 6) the position of each individual is modified according to the position update equation (9).

Step 7) 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 8) 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 $V_i^{\text{max}} = +0.5P_i^{\text{max}}$ and the minimum velocity is selected as $V_i^{\text{min}} = -0.5P_i^{\text{min}}$. 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 $P_D = 800\text{MW}$**

| Efficiency  | Unit1 (MW) | Unit2 (MW) | Unit3 (MW) | Unit4 (MW) | Unit5 (MW) | Unit6 (MW) | Unit7 (MW) | Unit8 (MW) | Fuel cost (in Rs/Hr) |
|-------------|------------|------------|------------|------------|------------|------------|------------|------------|---------------------|
| Normal Loading | 42.3       | 51.4       | 60.0       | 52.5       | 61.9       | 50.8       | 61.7       | 58.6       |                     |
| ELD         | 102        | 83         | 80         | 82         | 195        | 210        | 258        | 258        |                     |
| 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 GCV3400 | 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         | 126.9      | 133.0      | 165        | 165        | 7599.8              |
| ANN with GCV3374 | 60         | 50         | 50         | 50         | 127        | 133        | 165        | 165        | 7585.9              |
| ANN with GCV3400 | 60         | 50         | 50         | 50         | 126        | 133        | 165        | 165        | 7597.08             |
| ANN with GCV3450 | 60         | 50         | 50         | 50         | 126        | 133        | 165        | 165        | 7225.08             |

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Table-2. Comparison of Fuel Costs for 8-Generator System with $P_D = 850\text{MW}$

| Efficiency | Normal Loading | ELD Conventional | ELD using Curve fitting GCV3526 | ELD using Curve fitting GCV3540 | ELD using Curve fitting with GCV 3570 | ELD using Curve fitting GCV4100 | ELD using Curve fitting GCV4120 | ELD using Curve fitting GCV4150 | ANN with GCV3526 | ANN with GCV3540 | ANN with GCV3570 | ANN with GCV4100 | ANN with GCV4120 | ANN with GCV4150 | PSO Using |  |
|------------|---------------|------------------|-------------------------------|--------------------------------|--------------------------------------|--------------------------------|-------------------------------|-------------------------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|------------|----------|
| 42.3       | 51.4          | 60.0             | 52.5                          | 61.9                          | 50.8                                 | 61.7                          | 58.6                          | 69.18             | 50            | 50            | 115.76        | 120.83        | 165           | 165           | 7065.25    |           |  |
| 102        | 83            | 80               | 82                            | 195                           | 210                                  | 258                          | 258                          | 6928.79            |                |               |                |                |                |                |            |          |  |
| 60         | 50            | 50               | 50                            | 144.9                         | 163.4                                 | 166.6                         | 165                          | 8715.56            |                |               |                |                |                |                |            |          |  |
| 60         | 50            | 50               | 50                            | 144.8                         | 163.4                                 | 166.6                         | 165                          | 8685.47            |                |               |                |                |                |                |            |          |  |
| 60         | 50            | 50               | 50                            | 144.9                         | 163.1                                 | 166.6                         | 165                          | 8648.02            |                |               |                |                |                |                |            |          |  |
| 60         | 50            | 50               | 50                            | 144.8                         | 163.2                                 | 166.8                         | 165                          | 8612.16            |                |               |                |                |                |                |            |          |  |
| 60         | 50            | 50               | 50                            | 144.9                         | 163.2                                 | 166.7                         | 165                          | 8576.26            |                |               |                |                |                |                |            |          |  |
| 60         | 50            | 50               | 50                            | 145.0                         | 163.2                                 | 166.7                         | 165                          | 8531.31            |                |               |                |                |                |                |            |          |  |
| 60         | 50            | 50               | 50                            | 151.2                         | 158.7                                 | 165                           | 165                          | 8531.3             |                |               |                |                |                |                |            |          |  |
| 60         | 50            | 50               | 50                            | 150.6                         | 159.3                                 | 165                           | 165                          | 8616.9             |                |               |                |                |                |                |            |          |  |
| 60         | 50            | 50               | 50                            | 149.6                         | 160.3                                 | 165                           | 165                          | 8623.0             |                |               |                |                |                |                |            |          |  |
| 60         | 50            | 50               | 50                            | 147.3                         | 160.2                                 | 167.4                         | 165                          | 8244.0             |                |               |                |                |                |                |            |          |  |
| 60         | 50            | 50               | 50                            | 146.0                         | 161.4                                 | 167.4                         | 165                          | 7937.3             |                |               |                |                |                |                |            |          |  |
| 60         | 50            | 50               | 50                            | 147.3                         | 166.2                                 | 166.2                         | 165                          | 7892.2             |                |               |                |                |                |                |            |          |  |
| 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
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

| Unit | 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. | η₁ | η₂ | η₃ | η_total |
|----------|----|----|----|---------|
| Unit 1   | 77.26 | 68.81 | 79.73 | 42.39 (Min) |
| Unit 2   | 82.99 | 69.09 | 89.80 | 51.49 |
| Unit 3   | 82.84 | 80.10 | 90.56 | 60.09 |
| Unit 4   | 83.15 | 74.53 | 84.83 | 52.57 |
| Unit 5   | 83.67 | 79.31 | 93.34 | 61.94 (Max) |
| Unit 6   | 74.61 | 72.04 | 94.65 | 50.87 |
| Unit 7   | 87.56 | 75.82 | 92.99 | 61.73 |
| Unit 8   | 76.61 | 80.29 | 95.30 | 58.62 |

Table 5. Cost of generator at the different GCVs

| PPG1 | PG1 | GCV1 | FPG1 | 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 | FPG2 | 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  | 4150 | 671.29 | 761.78 |

| PPG3 | PG3 | GCV3 | FPG3 | FPG3 |
|------|-----|------|------|------|
| 53   | 56  | 3572 | 645.15 | 782.60 |
| 53   | 56  | 3580 | 645.15 | 782.60 |
| 53   | 56  | 3588 | 645.15 | 782.60 |
| 53   | 56  | 3599 | 645.15 | 782.60 |
| 53   | 56  | 4200 | 645.15 | 782.60 |
| 53   | 56  | 4210 | 645.15 | 782.60 |

| PPG4 | PG4 | GCV4 | FPG4 | 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 |
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| 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

| 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
- **Eff ic**: Efficiency of generating units
- **C1 and C2**: Acceleration Constants
- **DE**: Differential Evolution
- **ELD**: Economic Load Dispatch
- **FC**: Fuel Cost (in Rupees)
- **G\text{best}**: Best of P\text{best} called as Global best
- **Eff ic\text{tot}**: Total efficiency of generating units
- **Eff ic\text{min}**: Minimum value of efficiency

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Incremental Cost

Maximum number of iteration

Current number of iteration

Gross Penalty Factor for operating unit

Penalty Factor associated with turbine efficiency

Penalty Factor associated with boiler efficiency

Penalty Factor associated with generator efficiency

Penalty Factor associated with efficiency

Matrix Laboratory

Mega-Watt

Artificial Neural Network

Particle Swarm Optimization

Efficiency

Gross Calorific Value

Inertia Weighting factor

Maximum value of weighting factor

Minimum value of weighting factor

Incremental Fuel Cost of the plant

Power generated by generator no. “i”

Gross Calorific Value of Coal in generator no “i”

Cost offered by generator no. “i” in ₹ per hour

Previous Power generated by generator no. “i”

Previous Cost offered by generator no. “i” in ₹ per hour

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