Combined Economic and Emission Dispatch by ANN with backprop algorithm using variant learning rate & momentum coefficient

B. Kar, *Member*, *IEEE,* K. K. Mandal, *Member*, *IEEE,* D. Pal, *Member*, *IEEE*
and N. Chakraborty, *Member, IEEE*

***Abstract*-A Multi-layered Feed-forward Artificial Neural Network (ANN) trained by Back-propagation algorithm is used to solve the problem of Combined Economic and Emission Dispatch in this paper. The system of generation associates thermal generators and emission involves oxides of nitrogen only. Equality constraints on power balance as well as inequality constraints on generation capacity limits of the generators and transmission loss are also considered. The idea is to minimize total fuel cost of the system and control emission. The problem is first optimized by Lagrange Multiplier technique and the result is used to train the ANN wherein tuning parameters η & α are altered to check their effect on convergence rate. The trained ANN is then used to generate test data. It is found that the convergence characteristic of the algorithm is excellent and the results achieved by the proposed method are quite accurate and faster in comparison to the conventional method.**

***Index Terms-* Artificial Neural network, Back-propagation Algorithm, Combined Economic and Emission Dispatch, Economic Load Dispatch**

I. INTRODUCTION

Normally electric power plants are operated on the basis of least fuel cost strategies without considering the pollutants produced. Fossil-fired plants use coal, oil, gas or thereof as the primary energy source, and produce atmospheric emissions whose nature and quantity depend on the fuel type and its quality. Coal produces particulate matters such as ash and gaseous pollutants such as carbon oxides CO & CO_2, sulphur oxides SOx and oxides of nitrogen NOx. The contributions of the electric energy industry to environmental pollution raise questions concerning environmental protection. Several Governmental rules are coming up for the production of power at minimum pollution levels. Different methods are available for reducing emissions such as switching to fuels with low emission potential, installing post-combustion cleaning system e.g. electrostatic precipitators and re-allocation of loads to generators with low emission coefficients. The third method involves less capital display & requires only minor modification of dispatching programs to include emissions. The approach of considering emission in Combined Economic and Emission Dispatch (CEED) is to include the reduction of emission as an objective. Since the ideas of minimum cost and minimum emission dispatch are conflicting to each other, therefore the problem of choosing the least cost generation schedule with environmental objectives becomes much more complicated.

In recent years modern heuristic techniques like Artificial Neural Network, Evolutionary programming, Simulated Annealing (SA), Genetic Algorithms (GA) and Fuzzy Logic have been used in several complex optimization problems in Power System research.

ANNs are mathematical tools originally inspired by the way human brain processes information. The different parameters of the neural network are estimated through learning or training. Once the network is trained properly for a given range of inputs and outputs, then results for other inputs within that range can be obtained from the trained ANN without going into further iterative techniques. This characteristic makes them suitable for solving larger practical problems quickly and accurately. Economic Load Dispatch problem has been solved by a Hopfield neural network approach by different groups of researchers [1]-[2]. ANN technology has been utilized by N. Chakraborty et al to achieve Economic Generation Scheduling with Transmission loss [3]. An earlier attempt on solving Minimum Emission Dispatch problem was taken up by M.R. Gent and J.W. Lamont [4] that stressed on methods of minimizing emission. In recent times economic & emission dispatch problems stressing on methods of minimizing cost subject to emission constraints are also solved by different heuristic techniques. To name a few, P.S. Kulkarni et al [5] have used improved Back-propagation, S. Bhaskar et al [6] used Hybrid GA while Y. Demirel et al used Hopfield Neural Network for solving these problems [7]. Y. H. Song et al applied Fuzzy Logic Controlled Genetic Algorithms on Environmental/Economic Dispatch problems [8] & M. A. Abido dealt Environmental/Economic Power Dispatch using Multi-objective Evolutionary Algorithms [9].

In this paper an ANN methodology has been applied to a

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B. Kar is with the Power Engg. Dept.of Jadavpur University, Kolkata, India (e-mail: barnali_kar@yahoo.com).

K. K Mandol is with the Power Engg. Dept.of Jadavpur University, Kolkata, India (e-mail: kkm567@yahoo.co.in).

D. Pal is with the Elec. Engg. Dept., Central Calcutta Polytechnic, West Bengal General Services, India (e-mail: debasiscol@hotmail.com).

N. Chakraborty is with the Power Engg. Dept. of Jadavpur University, Kolkata, India (e-mail: chakraborty_niladri@hotmail.com).

simple problem of CEED where the quantity of emission of NO_x is minimized by proper sharing of load between the available generating units. A simple power system consisting of six generators supplying power to a common grid has been considered for this study. The ANN has been trained by a Back-propagation algorithm (BP) and the training set of input-output data is generated through classical Lagrange Multiplier method of solution. This conventional method is implemented by a software program written in Matlab. The BP algorithm has provisions for varying learning rate parameter, η and momentum coefficient, α where optimum values of these parameters are studied for obtaining better convergence. The effects of using various normalization rules on input-output training data sets and varying ANN parameters like, number of hidden layers, number of nodes in the hidden layers etc. on the convergence characteristics are also studied at length to ascertain maximum training accuracy. A Matlab program is developed for the implementation of the proposed ANN. It is found that the algorithm convergences accurately and it is obvious that once the training part is over, using the proposed ANN method test data generation will be much more time effective for a realistic system.

II. PROBLEM FORMULATION

The problem of an Economic Dispatch is to find the real power generation for each generating unit such that the objective function i.e. total production cost as defined by (1) is minimum [10]-[11],

$$\varphi_t = \sum_{i=1}^{n} F_i \qquad (Rs/h) \tag{1}$$

where ϕ_t is the total augmented cost function, F_i is the total fuel cost in the system (Rs/h), n is the number of thermal units & i = 1,…,n. The objective of emission control is to be included in the above expression by adding the emission cost and the emission cost is blended with the normal fuel cost by multiplying it with the rate coefficient, h (Rs/kg). Thus the total operating cost of the system is the cost of fuel plus the implied cost of emission as expressed by (2):

$$\varphi_t = \sum_{i=1}^{n} F_i + h \sum_{i=1}^{n} E_i \qquad (Rs/h) \tag{2}$$

where E_i is the total emission of NO_x in the system (kg/h).
Thus a multi-objective problem of CEED is converted to a single objective optimization problem by introducing 'h' and total cost Φ_t needs to be minimized subject to the constraints on power generation capacities (3) & active power balance (4):

$$P_{i,min} \le P_i \le P_{i,max} \tag{3}$$

$$\sum_{i=1}^{n} P_i = P_D + P_L \tag{4}$$

where P_i is power generated by ith unit, $P_{i,\ max}$ & $P_{i,\ min}$ are maximum and minimum power outputs of it, as found in appendix. P_D is power demand & P_L is total transmission loss.

Now for controlling a balance between economic cost and emission level of the pollutant, equation (2) may be modified as (5) where w_1 and w_2 are the two weight factors.

$$\varphi_t = w_1 \sum_{i=1}^{n} F_i + hw_2 \sum_{i=1}^{n} E_i \tag{5}$$

Thus different emission conditions may occur by varying w_1 & w_2 : i) $w_1 = 1$, $w_2 = 0$ for pure economic dispatch.
ii) $w_1 = 0.8$, $w_2 = 0.2$ for CEED
iii) $w_1 = 0.5$, $w_2 = 0.5$ for CEED with lesser emission.
iv) $w_1 = 0$, $w_2 = 1$ for pure emission dispatch

Again considering quadratic fuel cost curves for the thermal generating plants and similar emission curves we get the following expression,

$$\varphi_t = w_1 \sum_{i=1}^{n}\left(a_i P_i^2 + b_i P_i + c_i\right) + hw_2 \sum_{i=1}^{n}\left(d_i P_i^2 + e_i P_i + f_i\right) \tag{6}$$

where a_i, b_i, c_i are fuel cost coefficients & d_i, e_i, f_i are emission coefficients of ith unit respectively. The above coefficients are generally obtained by curve fitting whose values were obtained from Bhaskar et al [6] for this study. For getting the optimal conditions for CEED, equation (6) is optimized by Lagrange Multiplier technique considering constraints (3) & (4) and taking the derivative of the Lagrange function we get the co-ordination equation as:

$$2(w_1 a_i + hw_2 d_i)P_i + (w_1 b_i + hw_2 e_i) + \lambda \frac{\partial P_L}{\partial P_i} = \lambda \tag{7}$$

where λ is the Lagrange multiplier and P_L is calculated by (8):

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} (P_i B_{ij} P_j) \tag{8}$$

where P_i & P_j is the active power generations of i^{th} & j^{th} plants respectively and B_{ij} is the loss co-efficient whose values considered for this study can be found in appendix.

The value of rate coefficient, h is found out by a practical method as discussed by Kulkarni et al [5]. It is needed to obtain h-value of each generator at its maximum output as (9)

$$\frac{F_i(P_{i,max})/(P_{i,max})}{E_i(P_{i,max})/(P_{i,max})} = h_i \qquad (i = 1,...,n) \qquad (Rs/kg) \tag{9}$$

h_i (i =1, ...,n) in then arranged in ascending order, the maximum capacity of each unit, $P_{i,\ max}$ one at a time, starting from the smallest h_i unit, until,

$$\sum_{i=1}^{n} P_{i,max} \ge P_D \tag{10}$$

At this stage, h_i associated with the last unit in the process is the value of h for the given load. Once the value of h is fixed, equation (7) is solved along with the load balance equation by λ - iteration method to find out n number of active power outputs.

III. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) can be seen as highly parallel dynamical systems consisting of multiple simple units that can perform transformations by means of their state response to their input information [12]. Foremost amongst the various models for supervised classification tasks is the multi-layer perceptron (MLP) or multi-layer feed-forward neural network. These are general-purpose, flexible, nonlinear models consisting of a number of units organized into multiple layers. Every processing node in one particular layer is usually connected to every node in the layer above and below. The connections carry weights that encapsulate the behaviour of the network and are adjusted during training. The operation of the network consists of two stages, the forward pass and the backward pass or back-propagation. In the forward pass an input pattern vector is presented to the network and the output of the input layer nodes is precisely the components of the input pattern. For successive layers the input to each node is then the sum of the scalar products of the incoming vector components with their respective weights. A sigmoid neural model is considered in this case where the activation function of each node may be given by (11):

$$f(x) = \frac{1}{1 + exp^{(-x)}} \tag{11}$$

where x = $input_j$. The non-linear sigmoidal function is chosen as because neuron transfer functions are compressive and it resembles this property. Its derivative is continuous & simple to determine from the value of the input signal and its output is always positive.

A. Back-propagation algorithm

The MLP network is normally trained by supervised learning using the iterative BP. This is a gradient descent optimization procedure. In the learning phase a set of input patterns, called the training set, are presented at the input layer as feature vectors, together with their corresponding desired output pattern. Beginning with small random weights, for each input pattern the network is required to adjust the weights attached to the connections so that the difference between the network's output and the desired output for that input pattern is decreased. The mean square error, E between the network's output and the desired output for all input patterns P is given by (12):

$$E = \frac{1}{2P} \sum_p \sum_k \left(d_k - out_k \right)^2 \tag{12}$$

Based on this difference the error terms or ∂ terms for each node in the output layer are computed. The weights between the output layer and the layer below (hidden layer) are then adjusted by the generalized delta rule given by (13):

$$w_{kj}(t+1) = \eta (d_k \; out_k) + \alpha \, w_{kj}(t) \tag{13}$$

where $w_{kj}(t + 1)$ and $w_{kj}(t)$ are the weights connecting nodes k and j at iteration (t+1) and t respectively, η is the learning rate parameter and α is the momentum co-efficient between the two successive layers. Then the ∂ terms for the hidden layer nodes are calculated and the weights connecting the hidden layer with the layer below (another hidden layer or the input layer) are updated. This procedure is repeated until the last layer of weights has been adjusted. The ∂ term in (13) is the rate of change of error with respect to the input to node *k*, and is given by:

$$\partial_k = (d_k - out_k) \, f'(input_k) \tag{14}$$

for nodes in the output layer,

$$\partial_j = f'(input_k) \sum_k \partial_k w_{kj} \tag{15}$$

for nodes in the hidden layers, where d_k is the desired output for a node k. The threshold of a node/neuron is assumed as a modifiable connection weight between that neuron and a fictitious neuron in the previous layer that always has an output value of unity. The training set is presented iteratively to the network until a stable set of weights is achieved and the error function is reduced to an acceptable level. Both η and α can be varied in the algorithm using (13) for faster convergence.

IV. SOLUTION AND DISCUSSION ON RESULTS

The particular problem of CEED considered here consists of six inter-connecting generating units P_1, P_2, P_3, P_4, P_5 and P_6 required to share a total load P_D & total transmission loss P_L in the system economically and environmentally w. r. t the emission of NO_x. The problem has been first solved by conventional Lagrange Multiplier technique that is implemented by a Matlab program. In this case the proportion of emission cost and economic cost are controlled in the total cost structure by two weights w_1 and w_2 where $(w_1 + w_2) = 1.0$. Fig.1 shows the variation of w_2 (associated with the emission part) from 0 to 1 and its effect on fuel cost. It is obvious that as we increase w_2 (or decrease the value of w_1), quantity of emission of the pollutant is reduced to a great extent but at the same time cost of fuel is shooting up. To keep a balance between the two aspects, value of w_2 is chosen as 0.5 for further study. Next a set of the results as shown in Table I, is obtained by this conventional method for training the proposed neural network using BP with variant η and α where all generations are in Megawatt. The output data set for training is thus emission constrained. The ANN architecture proposed here consists of only one input parameter, system load demand P_D while six generator outputs P_1 to P_6 and total transmission loss, P_L are treated as seven output parameters. Both the input and output data sets are normalized since it has been found to have significant effects on learning accuracy and on convergence [6]. Standard normalization by Maximum (Max), Maximum-Minimum (Max-Min) and Mean & Standard

Deviation (M &S.D) rules are tried out in this case. The optimization technique followed here is based on training and test data accuracy for fixed number of iterations which is measured by the root mean square error (RMSE) value. The results of normalization on the above data set are given in Table II.

Using conventional learning algorithm for an ANN with one hidden layer having six nodes and choosing η = 0.8 and α = 0.9, the best normalization scheme is found to be by mean & standard deviation and maximum methods for the input & output training data sets respectively. The corresponding RMSE is 0.0057 for 10000 iterations.

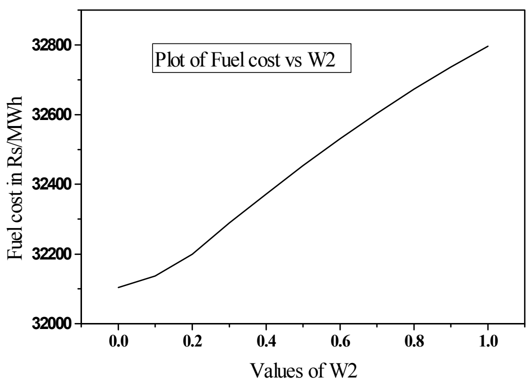

Fig. 1. Fuel cost as a function of W_2 coefficient

TABLE I
TRAINING DATA SET FOR THE ANN

P_D	P_1	P_2	P_3	P_4	P_5	P_6	P_L (%)
450	24.3220	16.1374	80.5476	81.4307	130.0000	125.0000	1.654
500	33.2868	26.8715	89.9276	90.4990	135.5645	132.7837	1.787
550	40.4125	35.4319	97.4055	97.7209	146.2139	143.5136	1.947
600	47.7130	44.2851	104.8770	104.9221	156.7143	154.1298	2.107
650	54.9070	52.9637	112.4122	112.1889	167.4006	164.8834	2.271
700	62.1192	61.6906	119.9870	119.4870	178 1187	175.6631	2.437
750	69.3430	70.4586	127.5951	126.8102	188.8590	186.4593	2.604
800	76.5853	79.2762	135.2438	134.1653	199.6315	197.2820	2.774
850	83.8447	88.1423	142.9323	141.5513	210.4345	208.1293	2.945
900	92.3427	98.4066	150.2081	148.5717	220.3319	218.1497	3.112
950	99.7516	107.4618	157.9220	155.9783	231.1310	228.9741	3.286
1000	107.1771	116.5671	165.6762	163.4162	241.9604	239.8226	3.461
1050	114.6157	125.7183	173.4674	170.8820	252.8148	250.6899	3.637

TABLE II
EFFECT OF DIFFERENT NORMALIZATION SCHEMES ON RMSE FOR FIXED η AND α

Sl. No.	Input data optimization	Output data optimization	RMSE
1.	Max.	Max	0.0184
2.	Max	Max-in	0.0598
3.	Max	Mean & S.D	0.0598
4.	Max-Min	Max-Min	0.0205
5.	Max-Min	Max	0.0086
6.	Max-Min	Mean & S.D	0.0205
7.	Mean & S.D.	Max.	0.0057
8.	Mean & S.D.	Max-Min	0.0099
9.	Mean & S.D.	Mean & S.D	0.0101

Studies have been carried out for the effects of varying α & η on the convergence rate. Since α gives a momentum to each change in weights, it has a significant role in deciding the speed of learning. As α is varied upwards from 0.5 to 0.9 keeping η constant at 0.2 for all layers of the ANN, RMSE is found to decrease and the most suitable value of α is 0.9 [Table III]. The choice of η is a tricky task in BP algorithm. Since it decides the size of the weight adjustments made at each iteration, it can influence the rate of convergence. The range of η that will produce rapid training depends on the number and type of input pattern [13]. η has to be chosen as high as possible to allow fast learning without leading to oscillations. In this case, as η is increased from 0.2 to 0.8 keeping α constant at 0.9 [Table IV], most suitable value of η is found to be 0.8.

TABLE III
EFFECT OF VARYING α

α Values	RMSE
0.5	0.0126
0.6	0.0117
0.7	0.0110
0.8	0.0106
0.9	0.0081

TABLE IV
EFFECT OF VARYING η

η Values	RMSE
0.2	0.0081
0.3	0.0075
0.4	0.0074
0.5	0.0070
0.6	0.0067
0.7	0.0066
0.8	0.0057
0.9	0.0070

The most suitable ANN structure as regards number of hidden layers and number of nodes or neurons in them is found out & different parameters for BP for the problem are also determined to find a minimum RMSE. Table V gives the RMSE values corresponding to particular number of nodes in the hidden layer for 10,000 iterations freezing other parameters to their optimum values. It is found from the data that there is a gradual decrease in RMSE from 0.0182 to 0.0057 as we increase the number of nodes but after that RMSE is again increasing with increased nodes. Thus on the basis of minimum training error, we select 6 nodes in the single hidden layer. Next keeping six nodes for the first hidden layer and combining it with different number of nodes for the second hidden layer convergence is studied w. r. t. RMSE. It is found that an error of minimum 0.0055 can be achieved with two hidden layers having 6 & 14 nodes in them. This particular combination is selected for further study.

TABLE V
EFFECT OF CHANGING NO. OF NODES IN HIDDEN LAYER

No. of nodes in hidden layer	RMSE
2	0.0182
3	0.0096
4	0.0085
5	0.0065
6	0.0057
7	0.0059
8	0.0064
9	0.0062

Thus the number of hidden layers and number of nodes in them are not constant factors but are problem dependant. However training time increases with complexities in the ANN structure e.g. time for single hidden layer with 6 nodes is 5.5 seconds (approximately) whereas for the two layer [6;14] combination it is about 8.8 seconds (approx.) on a Pentium 4, 400 MHz. machine involving 10,000 iterations. Therefore it should be decided accordingly.

The conventional learning rates for the connection weights between input layer (i) and first hidden layer (j) η_{ij} ,between two hidden layers η_{jk} and that between second hidden layer (k) and output layer (l) η_{kl} are now varied to study its effect on the convergence criteria. Table VI shows these variations where the best choice of η is [0.8; 0.8; 0.8] i.e. same between all the layers at α=0.9. A similar investigation is carried out for the variations in α for the connection weights between the different layers. Table VII shows these results where η is kept at [0.8; 0.8; 0.8] in different layers.

TABLE VI
EFFECT OF VARYING η IN DIFFERENT LAYERS WITH α CONSTANT

η_{ij}	η_{jk}	η_{kl}	RMSE
0.8	0.8	0.7	0.0057
0.8	0.8	0.8	0.0055
0.8	0.8	0.9	0.0068
0.8	0.7	0.8	0.0059
0.8	0.9	0.8	0.0074
0.7	0.8	0.8	0.0057
0.9	0.8	0.8	0.0056

TABLE VII
EFFECT OF CHANGING α IN DIFFERENT LAYERS WITH η CONSTANT

α_{ij}	α_{jk}	α_{kl}	RMSE
0.9	0.9	0.7	0.0075
0.9	0.9	0.8	0.0075
0.9	0.9	0.9	0.0055
0.9	0.7	0.9	0.0050
0.9	0.8	0.9	0.0060
0.7	0.7	0.9	0.0076
0.8	0.7	0.9	0.0066

Thus it is found that small variations in the values of learning rate parameter in different layers of the ANN around the best values as obtained earlier do not achieve any further significant improvement on the convergence rate in this particular case. But the variations in momentum coefficient values yield better results as can be seen from Table VII where the RMSE has been reduced to 0.0050 for same 10000 iterations with α in different layers as [0.9; 0.7; 0.9]. Therefore for this case study the best choice of η & α in different layers of the selected ANN is [0.8; 0.8; 0.8] & [0.9; 0.7; 0.9] respectively.

Table VIII shows the convergence characteristics of the studied algorithm within particular NIT values along with the time needed for computation. It is obvious that as we increase NIT, time increases and we get improved results. The proposed ANN is trained with the optimum parameters as obtained earlier for 10000 NIT and is developed by a Matlab program. Test data for four different power demand values (in MW) are obtained by the proposed ANN method.

TABLE VIII
EFFECT OF VARYING NIT ON RMSE & TIME

NIT	RMSE	Time(sec)
1000	0.0136	0.8910
2000	0.0122	1.7650
4000	0.0099	3.5470
6000	0.0079	5.2660
8000	0.0058	7.0160
10000	0.0050	8.8280

Table IX gives corresponding values of emission in Kg/h and fuel cost in Rs/h. These data are compared with the data obtained by the conventional method. It is found that data found by the proposed ANN method within the training range is in close proximity with that given by conventional method (deviations are within an acceptable range of 1.0%) and in case of data outside the training range but within the total generation capacity limits (i.e. for 400 & 1250 MW), the error is more and for the data shown it is within 2.5%. In case of conventional method, the speed of computation depends on the initialization of λ and the time to get final results corresponding to final λ is appreciable and it is found that once the training is over, the ANN method is almost 10-12 times faster than the conventional one.

TABLE IX
COMPARISON OF RESULTS YIELDED BY THE TWO METHODS

P_D	ANN method		Conventional method	
	Emission	Fuel cost	Emission	Fuel cost
400	209.0288	2.3066e+04	208.2600	2.2977e+04
525	279.0273	2.8698e+04	280.9066	2.8807e+04
675	415.5358	3.6330e+04	413.2790	3.6224e+04
825	588.0177	4.4099e+04	589.7110	4.4152e+04
975	812.7573	5.2741e+04	810.1580	5.2670e+04
1250	1333.0000	6.8091e+04	1363.000	6.8751e+04

V. CONCLUSION

An approach of using ANN methodology with back propagation training algorithm having variable tuning parameters is studied in this paper to solve a simple problem on Combined Emission and Economic Load Dispatch. Computational results reveal that the convergence characteristics of the algorithm are quite remarkable and these are further improved by varying learning rate and momentum coefficient. In the conventional method, assessing the proper value of λ is rather difficult and this leads to an increased processing time to yield the ultimate results. In case of ANN a suitable data set is needed for training and the time of training is appreciable but thereafter test data generation is much faster. Therefore for a realistic system of CEED consisting of more number of generating units, this ANN method is supposed to be comparatively more time effective and quite accurate though this part of the verification will be taken up as a future work.

VI. APPENDIX

Generating capacity limits (MW):

GENERATOR	P_1	P_2	P_3	P_4	P_5	P_6
P_{MIN}	10	10	35	35	130	125
P_{MAX}	125	150	225	210	325	315

Loss coefficients, B_{ij}:

$$\begin{bmatrix} 1.40 & 0.17 & 0.15 & 0.19 & 0.26 & 0.22 \\ 0.17 & 0.60 & 0.13 & 0.16 & 0.15 & 0.20 \\ 0.15 & 0.13 & 0.65 & 0.17 & 0.24 & 0.19 \\ 0.19 & 0.16 & 0.17 & 0.71 & 0.30 & 0.25 \\ 0.26 & 0.15 & 0.24 & 0.30 & 0.69 & 0.32 \\ 0.22 & 0.20 & 0.19 & 0.25 & 0.32 & 0.85 \end{bmatrix} \times 10^{-4} \text{ per MW}$$

VII. ACKNOWLEDGEMENTS

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IX. BIOGRAPHIES

Barnali Kar graduated in Electrical Engg. from Regional Engineering College, Durgapur, West Bengal, India in 1981. She received her Masters degree in Electrical Engg. from Jadavpur University, Kolkata in 1991. Her employment experience includes Mining and Allied Mach -inery Corporation, Durgapur and Bengal Engineering College, Howrah.

She is presently working as a Research Fellow in the Dept of Power Engg. in Jadavpur University, Kolkata, India. Her special field of interest is application of soft computing methods in power system economics & optimization.

K. K. Mandal received the B.E Degree in Electrical Engineering from Jadavpur University, Kolkata, India in 1986 and M.E Degree from Allahabad University, Allahabad, India in 1995. His employment experience includes Indian Telephone Industries, Regional Engineering College, Durgapur, India.

He is presently working as a Reader in the Department of Power Engineering, Jadavpur University, Kolkata, India. His present research interest includes Power Economics, Deregulated Electricity Industry and Power Electronics.

Debasish Pal received his Bachelor of Electrical Engineering degree from Jadavpur University, Kolkata in 1986. Currently he has been teaching at Central Calcutta Polytechnics under West Bengal General services in the field of measurement and control, power system for more than 15 years. His research interests include stochastic application and economic operation of power system planning.

Niladri Chakraborty received his Bachelor of Electrical Engineering in 1986 and Masters of Electrical Engineering in 1989 from Jadavpur University, Kolkata. He was awarded with the D.I.C from Imperial College, London, U.K. and Ph.D Degree from University of London in 1999.

Presently he is a professor in the Dept. of Power Engineering, Jadavpur University, Kolkata. His fields of research interest includes Power Economics, Applied Superconductivity and Environmental Measurements and analysis.