Application of Multi-Layered Perceptron Neural network (MLPNN) to Combined Economic and Emission Dispatch

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***Abstract*— This paper presents a multi-layered perceptron neural network (MLPNN) method to solve the combined economic and emission dispatch (CEED) problem. The harmful ecological effects caused by the emission of particulate and gaseous pollutants like sulfur dioxide (SO_2) and oxides of nitrogen (NOx) can be reduced by adequate distribution of load between the plants of a power system. However, this leads to a noticeable increase in the operating cost of the plants. This paper presents the (MLPNN) method applied for the successful operation of the power system subject to economical and environmental constraints. The proposed MLP NN method is tested for a three plant thermal power system and the results are compared with the solutions obtained from the classical lambda iterative technique and simple genetic algorithm (SGA) refined genetic algorithm (RGA) method.**

***Index Terms*— Economic dispatch, Emission dispatch, the multi-layered perceptron neural network.**

I. INTRODUCTION

The combined economic and emission dispatch (CEED) problem is to determine the optimal combination of power outputs for all generating units which minimize the total fuel cost while satisfying load demand and operational constraints [1-2]. CEED problem is a multiobjective mathematical programming problem which is concerned with the attempt to improve each objective simultaneously satisfying the standard load constraints and fuel constraints. The objective functions are made up of sum of linear or piecewise linear functions, each of which is a function of one or more variables from only one time step. Some constraints are made up of variables drawn from one time step whereas others span two or more time steps.

Currently neural networks have become the popular tool for solving optimization problem involving complex objective function and have been applied to many areas of power system engineering such as security assessment, load forecasting, and economic dispatch. In [3-5] have presented method for economic load dispatch for units with a Hopfield Modeling Framework. In this paper, we have applied MLPNN approaches to CEED problem and compare our result with other methods like the classical lambda, and genetic algorithms.

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II. THE PROBLEM FORMULATION

The classic economic dispatch problem aims to supply the required quantity of power at the lowest possible cost [6]. The dispatch problem can be stated mathematically as follows:
To minimize the total fuel cost at thermal plants:

$$F = MIN \sum_{i=1}^{n} \left(a_i + b_i P_i + c_i P_i^2 \right) \tag{1}$$

Subject to the equality real power balance constraints:

$$\sum_{i=1}^{n} P_i - P^D - P^L = 0 \text{ , } P^L = \sum_{i=1}^{n} B_i P_i^2 \tag{2}$$

The inequality constraint of limits on the generator outputs is:

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

Where a_i, b_i and c_i are the cost coefficients of the i-th generator and n is the number of generators committed to the operating system. P_i is the power output of the i-th generator, P^D is the load demand and P^L represents the transmission losses. However there is a large financial beneficial from the classical dispatch strategy described above, it tends to produce high SO_2 and NO_x emissions. An alternative dispatch strategy to satisfy the environmental requirement is to minimize operation cost under environmental constraints. Emission control can be included in conventional economic dispatch by adding the environmental cost to the normal dispatch. The emissions need to be converted as an environmental cost and added to the generation cost. The objective function then becomes:

$$Minimize C = W_0 F + W_1 E_S + W_2 E_N \tag{4}$$

Where ES is the SO_2 emission function, EN is the NO_x emission function. W_0, W_1 and W_2 are cost, SO_2 emission and NO_x emission weights respectively.

In this paper, like fuel cost curves, the SO_2 and the NOx curves can be expressed as follows:

$$E_s = \sum_{i=1}^{n} (d_i + e_i P_i + f_i P_i^2) \qquad (5)$$

$$E_n = \sum_{i=1}^{n} (g_i + h_i P_i + k_i P_i^2) \qquad (6)$$

Where d_i , e_i , f_i , g_i , h_i and k_i are parameters estimated on the basis of unit emissions test results.

In this model, when emission weights are equal to zero, the objective function becomes a classical economic dispatch problem. In this economic dispatch option, units are to minimize the total system production costs. When cost weight is set to zero, the problem becomes emission minimization. In this case, units are to minimize the amount of emissions. When weights are not zero in the objective function, the problem becomes minimizing the fuel cost plus emission at the same time.

III. OVERVIEW OF THE MULTILAYER NEURAL NETWORK

According to [7], the term multi-layered perceptron (MLP) is used for the neural networks with a structure of input layer, one or more hidden layers and an output layer. Each of the layers consists of inter-connected assembly of simple processing elements called neurons. These processing elements are organized in a layered fashion. Each neuron in a layer is connected to the neuron in the subsequent layer and so on. The interconnections between layers are called weights. Despite of their simplified structure, neural networks have ability to mimic human characteristics of problem solving via learning and generalization. MLP can be used to model non-linear systems due to their ability to learn the system behavior under inspection from samples. For a successful application of MLP neural networks, one should determine internal parameters, such as initial weights and network structure, to meet required performance criteria.

In engineering neural network models, this is one of the main problems, as an inadequate network would be unable to learn. The problem of finding a suitable architecture and the corresponding weights of the network, however, is a very complex task and main difficulties arise from the fact that the theory does not provide instruments to choice optimal values for these parameters. This, in turn, results in the need to train an MLPNN multiple times, effectively using different initializations and architectures. Consequently, the practitioner is involved in a process that requires more development time as well as experience and intuition.

Furthermore, this approach does not guarantee the optimality of the obtained parameters for a given problem. The common practice in the literature is to determine the number of neurons in the hidden layers by experience and some rule of thumb. Therefore, there could be more than one topology for an MLP to model a process successfully.

However, the performance criteria of a MLP NN could be achieved by modifying the training data distribution. After a successful learning phase, a MLP neural network will have an ability to generalize for the unseen data. During the training phase the weights are optimized in order to minimize a predefined error function. MLP neural networks are trained using the back propagation (BP) algorithm which is a gradient based supervised learning method. According to the algorithm, a mean squared error between the predicted and target values for the given input parameters is propagated backward to adjust the interconnection between neurons in order to minimize the pre-defined error. In this structure each neuron in a layer is mapping the sum-of-weighted input into an activation level that is determined by an activation function. The most commonly used activation functions are the sigmoid, the tangent hyperbolic, and the linear activation function. If a sigmoid function is used, the output of the kth neuron, Ok, in nth layer is determined by the following equation:

$$O_k = \frac{1}{1+\exp(-net_k)} \ , net_k = \sum_j W_{jk} O_j \qquad (7)$$

And Oj is the output of a neuron in the previous layer and Wjk is weight between neurons (jth neuron in a layer and kth neuron in subsequent layer). In this structure the adjustable network parameters are optimized based on the BP algorithm as follows:

$$W_{jk}^{new} = W_{jk} + \Delta W_{jk} \qquad (8)$$

Where ΔW_{jk} is weight update for the connection W_{jk}.

The weight update is calculated as follows:

$$\Delta W_{jk} = -\eta (\frac{\partial E}{\partial W_{jk}}) \qquad (9)$$

Where η is learning rate which is chosen between 0 and 1 and E is the error (the cost function) defined as:

$$E = \frac{1}{2} \sum_k (t_k - O_k)^2 \qquad (10)$$

Where t_k is the target for the kth neuron in the output layer. Notice that O_i and tk pair constitutes the input and output parameters in the training data set.

IV. IMPLEMENTATION OF MLP NN IN CEED PROBLEM

To solve the constrained economic dispatch problem using the MLP Neural Network, a training set should be constructed by combining the input and target pattern as pairs, i.e. (Oi and tk). Input patterns Oi's are consist of total power load sum (P_i) in (2) and the corresponding target patterns consist of the unit powers constraints Pi and the total cost in (1) . An additional set of the target parameters is applicable as target patterns in the case of environmental economic dispatch problem, such as environmental constraints NOx, and SO_2. The number of neuron in the input layer of MLPNN in 3 units ED problem is determined by the total load. The number of the neuron in the output layer of MLP is set by the power generated by 3 units, the total operation cost, power losses and pollutants of NO_x Therefore, a MLP NN with a structure of 1–6–6–6 is chosen to solve the 3 units CEED problem. The MLPNN algorithm is coded in MATLAB using Neural Network Toolbox with an adaptive gradient descent BP algorithm. The learning rate is chosen as 0.01 and %5 increment is allowed. The maximum allowed iteration is set to 1000. For 3 units CEED problem, training and test data pairs are produced by using genetic algorithm (GA) and implemented in MATLAB [8-10]. As it is known that neural learning is sensitive to the initial weight settings, a fixed initial weight set should be used to fairly evaluate the performance of MLP neural network. If the initial weights are randomized at each training session, different final weights will be achieved and accordingly the obtained solution will be different.

V. SIMULATION RESULT

For simulate our result, we consider a system with three plants. Our simulation is performed in MATLAB neural network toolbox. all components of the data presented to network (except the total load for input) were normalized with following equations :

$$x' = \frac{x - \bar{x}}{Std_x} \quad , x_{norm} = \frac{1}{1+\exp(-x')} \tag{11}$$

Where x is the value of the component that must normalize, $\bar{x}$ and Std_x are , respectively , the mean and standard deviation of the same component. x_{norm} is the component value after normalization. Our input for network is total load and our output is P_1, P_2, P_3, P_{loss}, $NO_{x\text{ -emission}}$ and $T_{t\text{-otal.}}$ That

P_i = power who generate in pant i.Where (i=1, 2, 3)

P_{loss} = total losses for system.

$NO_{x\text{ -emission}}$ = total weight of NO_x for every hour.

$T_{t\text{-otal}}$ = total cost for system work.

We design a network who have a one input neuron (total load) and sex output neurons for (P_1 , P_2 P_3 , P_{loss} , $NO_{x\text{ -emission}}$ and $T_{t\text{-otal}}$). Hidden layers consist of two layers with sex neuron in every layer. Our transfer function of hidden layers is 'tansig', 'purelin' for output layer. Our back propagation error method is 'train'. Training parameters are: Epoch = 50, Learning rate = .05, Max number of iteration =1000, Error tolerance=1e-10

The system tested consists of three thermal units. The parameters of this system and result of simulation are given in Table (1,2).

Table 1: The parameters of tested system

Unit *I*	*a_i* *(\$/h)*	*b_i* *(\$/MWh)*	*c_i* *(\$/MW^{2}h)*	*d_i* *(\$/h)*	*e_i* *(\$/MWh)*	*f_i* *(\$/MW^{2}h)*	*P_{imin}* *(MW)*	P_{imax} (MW)
1	1243.5311	38.30553	0.03546	40.26690	□0.54551	0.00683	35	210
2	1658.56960	36.32782	0.02111	42.89553	□0.51160	0.00461	130	325
3	1356.65920	38.27041	0.01799	42.89553	□0.51160	0.00461	125	315

Table 2: Comparison of test results obtained from conventional method, SGA and RGA, MLP NN

No	*Power Demand, MW*	*Method*	*P_1, MW*	*P_2, MW*	*P_3, MW*	*P_L, MW*	*NO_x Emission, Kg/h*	*Total Cost, Rs/h*
1	400	Conventional	102.66	153.87	151.13	7.41	201.5	29922
		SGA	99.47	147.26	161.08	7.69	201.35	29820
		RGA	99.52	165.11	142.32	7.39	201.21	29812
		MLP NN	**99.03**	**158.44**	**135.12**	**7.45**	**201.19**	**29818**
2	500	Conventional	120.00	192.81	190.08	11.88	312.00	39458
		SGA	127.54	200.58	183.43	11.80	311.89	39441
		RGA	127.52	193.50	190.62	11.70	311.33	39433
		MLP NN	**126.98**	**198.88**	**185.89**	**11.75**	**309.80**	**39400**
3	700	Conventional	182.62	271.27	269.47	23.37	652.55	66690
		SGA	190.11	274.71	258.21	23.29	652.04	66659
		RGA	187.21	273.56	262.35	23.28	651.60	66631
		MLP NN	**180.28**	**290.48**	**252.17**	**22.93**	**649.28**	**66640**

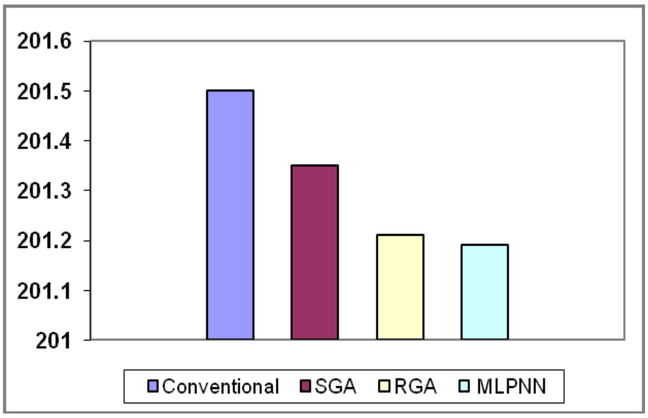

Figure 4: Comparison of NO_x emission obtained from various methods for power demands of 400MW

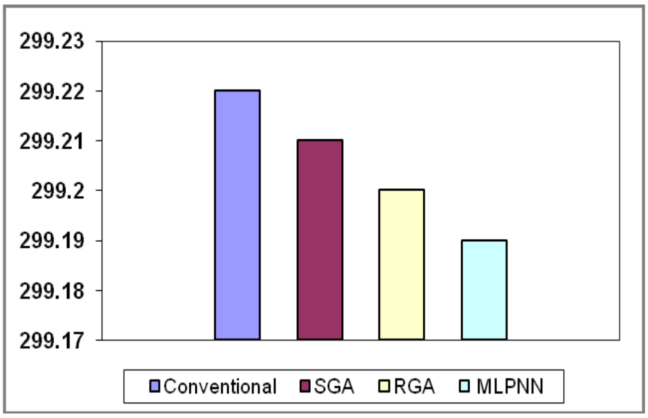

Figure 1: Comparison of total cost obtained from various methods for power demands of 400MW

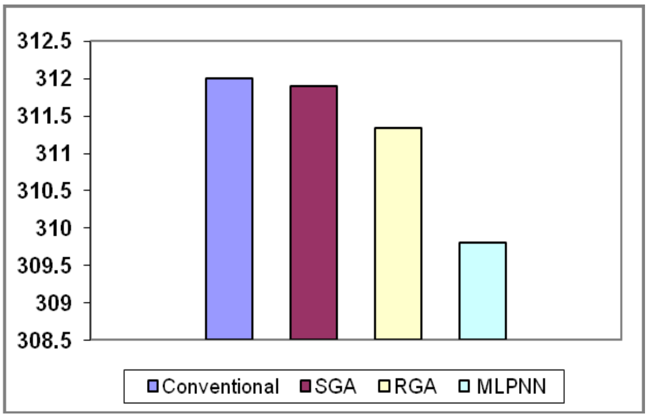

Figure 5: Comparison of NO_X emission obtained from various methods for power demands of 500MW

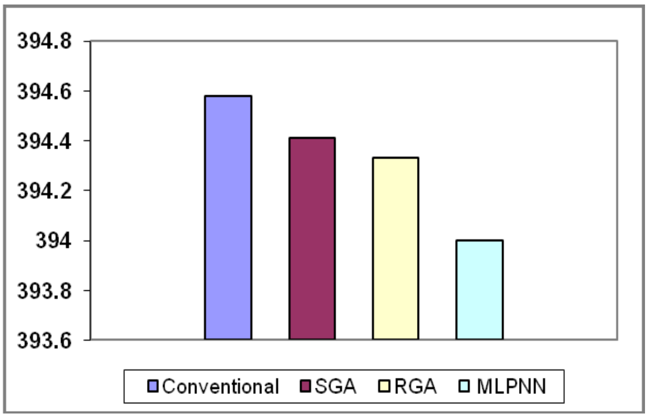

Figure 2: Comparison of total cost obtained from various methods for power demands of 500MW

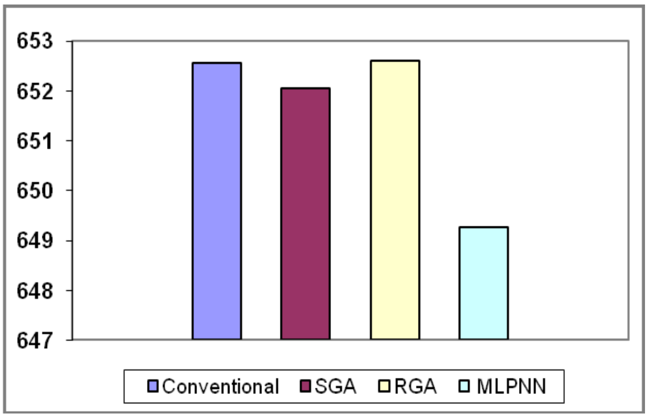

Figure 6: Comparison of NO_X emission obtained from various methods for power demands of 700MW

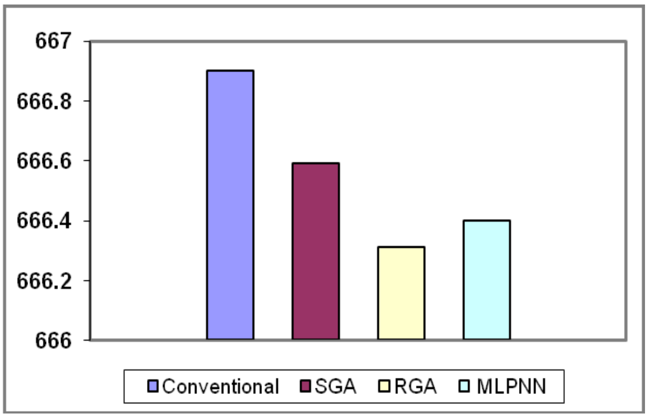

Figure 3: Comparison of total cost obtained from various methods for power demands of 700MW

VI. CONCLUSION

In this paper, solution to the economic dispatch problem as a constrained optimization problem has been obtained using MLPNN. The MLP method has advantage of being a quick method compared to the iterative optimization methods such as GA. once a MLPNN is trained, it provides solutions in a cycle. According to table response of net is acceptable and in some case, better from other approaches such conventional and SGA and RGA method.

We propose, using of combined method of genetic and neural network for better response for CEED. Three methods (conventional, SGA, RGA [10]) are came in following table for comparison

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