An Artificial Neural Network Method For Optimal Generation Dispatch With Multiple Fuel Options

S.K. Dash
Department of Electrical Engineering, Gandhi Institute for Technological Advancement,Badaraghunathpur,Madanpur, Bhubaneswar,752054, Orissa, India
Email: Saroj_dash2006@rediffmail.com

***Abstract* – This paper presents an artificial neural network method to solve the optimal generation dispatch problem with multiple fuel options. Traditionally, in the optimal generation dispatch problem, the cost function for each generator is approximately represented by a single quadratic function. However, it is more realistic to represent the generation cost function for fossil fired plants as a segmented piecewise quadratic functions, as in the case of valve point loading. Some generation units especially, those units which are supplied with multiple fuel sources (gas and oil) are faced with the problem of determining which is the most economical fuel to burn. The proposed method has applications to fossil fired generating units capable of burning gas and oil, etc., as well as other problems which result in multiple intersecting cost curves for a particular unit. An advantage of this method is the capability to optimize over a greater variety of operating conditions. The simulation results show that the solution method is practical and valid for real time operation.**

Index Terms— Optimal generation dispatch, Multiple fuel options, Hybrid cost function, Radial basis function network, Hopfield neural network.

I. INTRODUCTION

Traditionally in economic load dispatch problem, the cost function for each generating unit has been approximately represented by single quadratic function [1]. It is more realistic, however, if the cost curve of each generating fossil-fired unit can be represented as a segmented piece-wise quadratic functions [2], as in the case of valve point loading. For piece-wise quadratic cost function, the generating units are supplied with multiple fuel sources such as (1) gases or gases with different heat content, (2) coal or different heat content of coal and (3) oil or different heat content of oil. Thus, the cost function of any fossil-fired unit can be partitioned into different segments for multiple fuels. Each segment for multi-fuel cost function is being associated with different types of fuel. For this reason any or single unit for multi-fuel option can be burnt with at least two types of fuels. Some generation units especially, those units which are supplied with multiple fuel sources (gas/ oil/ coal, etc.) are faced with the problem of determining which is the most economical fuel to burn. As fossil fuel costs increase, it becomes even more important to have a good model for the production cost of each generator. In this work, the piece-wise quadratic function is used to represent multi-fuel which is available to each generating unit. For any given unit with multiple cost curves, these curves can be superimposed as shown in Fig.1. The resulting cost function is known as "hybrid cost" function [3]. The hybrid cost function is known as piece-wise cost function also. The hybrid incremental cost function can be obtained from hybrid cost function which is indicated in the Fig.1. The economic load dispatch for multiple-fuel generation schedule of any unit is done in such a way that the fuel cost is at minimum level, i.e., burning of fuel of each unit is done economically. Therefore, an efficient method which is to be used to obtain the generation schedule of each unit for such type of ELD problem is needed to be developed. There has been a growing interest in neural network models with massively parallel structures, which mimic to resemble the human brain [4]. Owing to the powerful capabilities of neural networks such as learning, optimization and fault-tolerance, neural networks have been applied to the various fields of complex, non-linear and large-scale power systems [5-7]. Novak [8] has described the various fields of power system where the Radial basis neural network can be applied successfully. J.Park and I.W.Sandberg [9] have described the radial basis function networks as universal tool for function

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approximation. The most promising advantage of this network over back propagation neural network is its auto-configuring architecture. Besides, the training time for a practical sized problem in case of Radial basis function network is significantly less as compared to that of the back-propagation network. On the other hand, the Hopfield neural network [10-11] has been applied to various fields since Hopfield proposed the model in 1982. In the problem of optimization, the Hopfield neural network has a well demonstrated capability of finding solutions to difficult optimization problems. The TSM (traveling salesman problem)[12], typical problems of NP (nondeterministic polynomial)-complete class, A/D conversion, linear programming and job-shopping schedule are good examples [13-14] which the Hopfield network provides with solutions. In the field of power systems, the Hopfield network has been applied to unit commitment [15], and economic load dispatch problems [16-18]. This paper particularly presents a new method to solve the problem of optimal generation dispatch with multiple fuel options using a Radial basis function neural network along with a heuristic rule based search algorithm and a Hopfield neural network. The simulation results show that the solution method is practical and valid for real-time operation. An advantage of the proposed method is its capability to optimize over a greater variety of operating conditions. The proposed ANN method has applications to fossil fueled generation units capable of burning coal, gas, and/or oil as well as other problems which result in multiple intersecting cost curves for a particular generating unit.

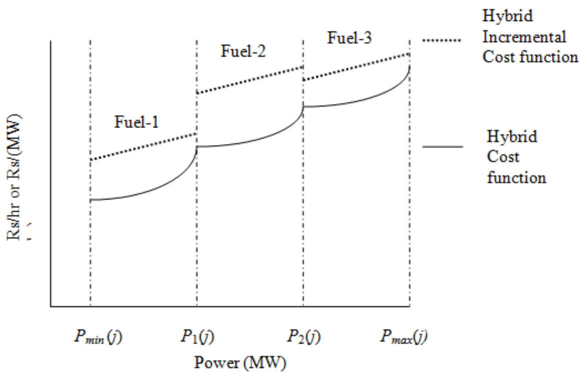

Figure 1: Multiple cost curves

II. PROBLEM FORMULATION

The modern power system experiences that the cost functions of fossil-fuel fired generating units are found to be piece-wise quadratic functions. The piece-wise quadratic cost functions are generally equipped with either the provision of multi-fuels or oil/ gases with different heat contents. In general, these lead to hybrid cost functions and hybrid incremental cost (IC) functions as given below [18]. The notations of the following hybrid cost functions and hybrid incremental cost functions are:

Pmin is the minimum power generation limit of jth unit with fuel (1).

P1 is the maximum power generation limit of jth unit with fuel (1).

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Pn-1 is the minimum power generation limit with fuel (n), and Pmax is the maximum power generation limit of jth unit with fuel (n). Subscript j indicates generating unit number and subscript k indicates type of fuel. ajk, bjk and cjk are cost curve coefficients of jth generating unit with fuel (k). Cost (Pj) is the hybrid cost function and IC(Pj) is the hybrid incremental cost function of jth generating unit.

$$Cost(P_j) = \begin{cases} a_{j1} + b_{j1} \times P_{j1} + c_{j1} \times P_{j1}^2 \\ P_{min} \le P_{j1} \le P_1, \; for\ fuel\ (1) \\ a_{j2} + b_{j2} \times P_{j2} + c_{j2} \times P_{j2}^2 \\ P_1 \le P_{j2} \le P_2, \; for\ fuel\ (2) \\ . \\ . \\ . \\ a_{jk} + b_{jk} \times P_{jk} + c_{jk} \times P_{jk}^2 \\ P_{k-1} \le P_{jk} \le P_k, \; for\ fuel\ (k) \\ . \\ . \\ . \\ a_{jn} + b_{jn} \times P_{jn} + c_{jn} \times P_{jn}^2 \\ P_{n-1} \le P_{jn} \le P_{max}, \; for\ fuel\ (n) \end{cases} \tag{1}$$

$$IC(P_j) = \begin{cases} b_{j1} + 2c_{j1} \times P_{j1} \; for\ fuel (1) \\ b_{j2} + 2c_{j2} \times P_{j2} \; for\ fuel\ (2) \\ . \\ . \\ . \\ b_{jk} + 2c_{jk} \times P_{jk} \; for\ fuel (k) \\ . \\ . \\ . \\ b_{jn} + 2c_{jn} \times P_{jn} \; for\ fuel\ (n) \end{cases} \tag{2}$$

The load balance equation of above power system without transmission loss can be written as:

$$(\sum_{j=1}^{m} P_{jk}) - P_D = 0 \tag{3}$$

for $k = 1, 2, \dots, n$, and $j = 1, 2, \dots, m$,

III. NUMERICAL COMPUTATIONAL ALGORITHM

The following steps are required for developing an algorithm to solve the economic load dispatch problem with multiple fuel options.

Step-1. Read the values of hybrid cost coefficients ajk, bjk and cjk of each unit along with their maximum and minimum generating capacity corresponding to each fuel and also total load demand (PD), where j denotes unit number and k denotes type of fuel option.

Step-2. Initially assume fuel-1 option for all units, i.e., k =1.Step-3. Compute jk and jk using equation (5), i.e.,

11=1 and 11= 0

2k= c1k/c2k and 2k= (b1k-b2k)/2c2k
3k= c1k/c3k and 3k= (b1k-b3k)/2c3k
: :
: :
: :
mk= c1k/cmk and mk= (b1k-bmk)/2cmk

Step-4. Compute the generation of unit-1 using equation (11), i.e.,
and also compute generation of other units in terms of P1k using equation (8), i.e.,
.

Step-5. Check generation of each unit Pjk to remain within its operating limits, i.e. and

If generation of all units are within their operating limits of corresponding fuel options then go to Step-6. Otherwise, for each unit whose inequality is violated, find out the new fuel option k, so that the inequality is satisfied and then aj1, bj1 and cj1 are replaced by ajk, bjk and cjk, respectively and then repeat the Steps 3 to 5.

Step-6. Print the fuel option and generation schedule of each unit.

IV. ANN BASED METHOD

The basic block diagram of the proposed ANN method to solve the optimal generation dispatch problem with multiple fuel options has been shown in Fig. 2. Initially, the proposed numerical technique is applied to find out the economic fuel option for each unit corresponding to a particular load demand. The dotted box shows this for generation of training patterns for the Radial basis function ANN. Once this ANN is trained, then for a given load demand, a preliminary economic fuel option for each generating unit is obtained. In fact the fuel options are integer values like 1, 2 or 3, etc. But, in the preliminary economic fuel option results, we may get fractional values like 1.008, 0.987, etc. Therefore, a simple heuristic rule based algorithm is developed to reach a correct economic fuel option, i.e., an integer value for each output. After obtaining the economic fuel option for each generating unit corresponding to a given load demand, the optimal generation dispatch result is obtained by a Hopfield neural network which satisfies the operational constraints. As shown in Fig. 3, the design procedure of the proposed ANN technique consisting of Radial basis function ANN, Hopfield ANN methods along with a heuristic rule based search algorithm for optimal generation dispatch solutions with multiple fuel options involves five major steps, viz. training set creation, training, testing of Radial basis function ANN, heuristic search and Hopfield ANN. In the proposed ANN technique, the economic fuel options are obtained by proposed numerical technique. For determination of economic fuel option for each generating unit, neural network of supervised learning is needed. This is because, the economic fuel option for each generating unit (outputs) for each total system load demand (input) in the training set are required to be known in advance by some suitable method. A radial basis function ANN called as RBANN is employed in the present work for training and testing due to its auto configuring architecture and faster learning ability. In the training process, the RBANN is presented with a series of pattern pairs; each pair consists of an input pattern and a target output pattern. The training pattern 'p' is described by:

t(p) = {(input (p)), (output (p))}
= {(PD (p)), (F1(p) , F2 (p) , ... , FNG (p))} (16)

Here, Fj(p) indicates the fuel option of jth generating unit corresponding to pth training pattern. The sum of the squared errors (SSE) between the actual and the desired (target) outputs over the entire training sets is used as the measure to find out the convergence of the network. The RBANN used is trained by the orthogonal least squares learning algorithm. Training is continued until the given error-goal in terms of SSE is reached. Once the RBANN is trained, there after only the Steps 3 and 4 are used to obtain the economical fuel option for each generating unit for any given load PD. In the Step-3 only a preliminary (non-integer) economical fuel options may be obtained. Therefore, a heuristic rule based search algorithm is developed in the Step-4 to reach a correct (integer) economical fuel option for each unit. Once the economical fuel options are found out, then the optimal generation dispatch is merely an ELD problem which is solved by a Hopfield neural network in final step (Step-5).

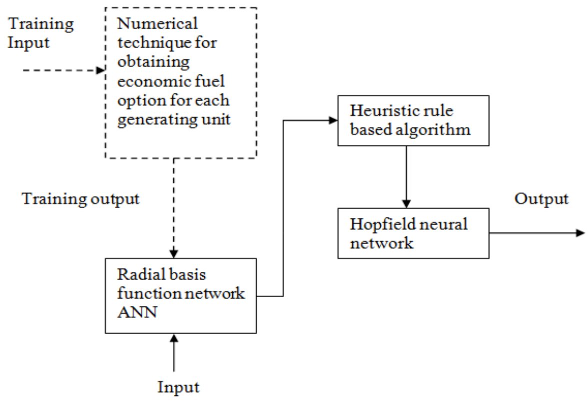

Figure 2: Block diagram of proposed ANN technique for optimal generation dispatch with multiple fuel options

A. Heuristic rule based search algorithm for determination of final economical fuel options

In this work the following heuristic rules are applied to transform the preliminary fuel option results (non-integer values) into integer values.

$$\text{Rule-1}: F_j = k \quad \text{if, } k \le F_j < k+0.5 \quad \text{for } j = 1, 2, \ldots, m \quad \text{and} \quad k = 1, 2, \ldots, n \tag{14}$$

$$\text{Rule-2}: F_j = k+1 \quad \text{if, } k+0.5 \le F_j \le k+1 \quad \text{for } j = 1, 2, \ldots, m \quad \text{and} \quad k = 1, 2, \ldots, n \tag{15}$$

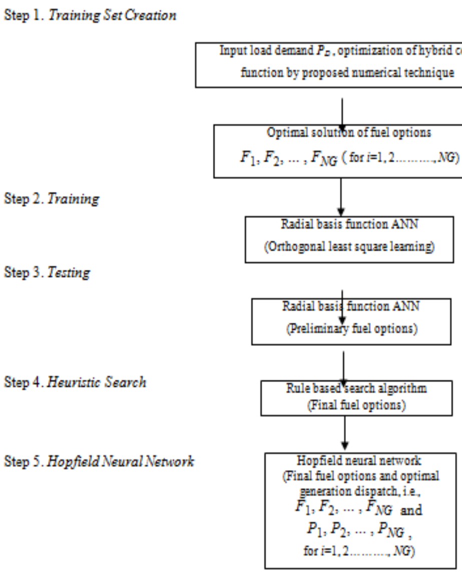

Figure 3: Design procedure of the proposed ANN technique for optimal generation dispatch problem with multiple fuel options

V. HOPFIELD NEURAL NETWORK

Hopfield neural network model is a single layer recursive neural network, where the output of each neuron is connected to the input of every other neuron. There is an external input to the each neuron. In a Hopfield network all connective weight values are calculated initially from system data. Then as patterns or input values are applied, the network goes through a series of iterations until it stabilizes on a final output. Thus, the values of neuron inputs and the outputs change with time and form a dynamic system. It is important to ensure that the system will converge to a stable solution. This requires finding a bounded function (a Lyapunov or energy function) of the state variables such that all state changes result in a decrease in energy. There are two types of Hopfield neuron model. The original model of Hopfield neural network used a binary neuron model. The continuous and deterministic model of the Hopfield neural network [19] is based on continuous variables and responses but retains all of the significant behaviors of the original model and hence, used in the present work. The output variable Vi for neuron i has the range and the input-output function is a continuous and monotonically increasing function of the input Ui to neuron i. The typical input-output function gi (Ui) is a sigmoidal function.

The dynamics of the neuron is defined by

$$dU_i/dt = \sum_j T_{ij} V_j + I_i$$

where,

$V_i = g_i(U_i)$: the output value of the neuron i

$g_i(U_i) = 1/(1+\exp(-U_i/u_0)$

g_i : the input-output function of the neuron i

u_0 : a coefficient that determines the shape of the sigmoidal function.

The energy function of the continuous Hopfield network is similarly defined as

$$E = -1/2 \sum_i \sum_j T_{ij} V_i V_j - \sum_i I_i V_i \tag{17}$$

and its time derivative is given by

$$dE/dt = -1/2 \sum_i \sum_j T_{ij} [V_j (dV_i/dt) + V_i (dV_j/dt)] - \sum_i I_i (dV_i/dt) \tag{18}$$

$$= -1/2 \sum_i (dV_i/dt) [\sum_j (T_{ij} V_j + T_{ji} V_j) + 2 I_i]$$

$$= -1/2 \sum_i (dV_i/dt)(2 \sum_j T_{ij} V_j + 2 I_i)$$

$$= -\sum_i (dV_i/dt)(\sum_j T_{ij} V_j + I_i)$$

$$= -\sum_i (dV_i/dt)(dU_i/dt)$$

$$= -\sum_i g_i'(U_i)(dU_i/dt)^2$$

From this, it can be seen that dE/dt is always less than zero because gi is a monotonic increasing function. Therefore, the network solution moves in the same direction as the decrease in energy. The solution seeks out a minimum of E and comes to a stop at such point.*C.*

A. The Economic Load Dispatch Problem

The ELD problem is to find the optimal combination of power generation which minimizes the total fuel cost while satisfying the total required demand. In this dissertation work, the cost function is as follows:

$$C = \sum_i (a_i + b_i P_i + c_i P_i^2).$$

where,

C: total cost

ai, bi, ci: cost coefficients of generator i

Pi: the generated power of generated i

In minimizing total fuel cost, the following constraints should be satisfied.

a) Power balance:

$$PD + L = \sum_i P_i \tag{20}$$

where,
PD: total load
L: transmission loss.

The transmission loss can be represented as

$$L = \left[\sum_{i=1}^{NG} \left(D_i P_i^2 \right) \right] \qquad (21)$$

where,
NG: number of generators
Di: transmission loss coefficients

b) Maximum and Minimum limits of Power:

The generator power of each generator should be laid between maximum and minimum limit. That is,

$$P_i^{\min} \leq P_i \leq P_i^{\max} \qquad (22)$$

where,

$P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum real power output of ith unit, respectively.

B. Mapping of the ELD into the Hopfield Neural Network

In order to solve the ELD problem, the following energy function is defined by combining the objective function with the constraint as defined by Eqn. (19) and Eqn. (20), respectively.

$$E = A(P_D + L - \sum_i P_i)^2/2 + B\sum_i (a_i + b_i P_i + c_i P_i^2)/2 \qquad (23)$$

where, $A(\geq 0)$ and $B(\geq 0)$ are weighting factors.

The synaptic strength and the external input are obtained by mapping the above energy function into the Hopfield energy function as described by Eqn. (23) into the Hopfield energy function, Eqn.(17). First by assuming that the loss L is constant, the Eqn. (23) is expanded and compared to Eqn. (17) in which Vi and Vj correspond to Pi and Pj, respectively:

$$E = A[(P_D+L)^2 - 2(P_D+L)(\sum_i P_i) + (\sum_i P_i)^2]/2 + B\sum_i (a_i + b_i P_i + c_i P_i^2)/2$$

$$= A(P_D+L)^2/2 - \sum_i [A(P_D+L) + Bb_i/2]P_i$$

$$+ \sum_i \sum_i (A + Bc_i) P_i P_i/2 + \sum_{i \neq j} \sum A P_i P_j/2 + B\sum_i a_i/2. \qquad (24)$$

Thus, by comparing Eqn. (17) with Eqn. (24), the synaptic strength and external input of neuron i in the Hopfield network are given by

Tii = -A-Bci

Tij = -A (25)

Ii = A(PD +L)-Bbi/2.

The differential synchronous transition model [18] used in the computation for this Hopfield neural network is as follows:

$$U_i(k) - U_i(k-1) = \sum_j T_{ij} V_j(k) + I_i$$

$$V_i(k+1) = g_i[U_i(k)]. \qquad (26)$$

Accordingly, the output value Pi can be obtained by this Hopfield neural network and the transmission loss can be calculated by the loss formula as described in Eqn. (21). Again the calculated loss is assumed as a constant value and thereafter the above process is repeated. In representing a large value with the neural network, the binary number representation requires a large number of neurons which is a clear-cut disadvantage. Therefore, in this work a modified sigmoidal function as suggested in Reference-18 is used, which is given below as:

$$V_i = g_i(U_i) = (P_i^{\max} - P_i^{\min})(1/(1+\exp(-U_i/u_0))) + P_i^{\min} \qquad (27)$$

VI. SYSTEM STUDIES

In this section a neural network procedure comprising of a radial basis function network along with a heuristic rule based search algorithm and a Hopfield neural network has been proposed to solve the economic load dispatch problem with multiple fuel options. The test system consisting of four generating units with unit-1 supplied with two types of fuels and other remaining units supplied with three types of fuels, has been considered for the performance evaluation of the proposed algorithm. The hybrid cost coefficients, i.e., the cost curve coefficients of each unit corresponding to different types of fuel are given in Table 1. The minimum and maximum generation capacity of each unit corresponding to each type of fuel options are summarized in Table 2.

Table 1 *The hybrid cost coefficients*

Unit No.	Fuel-1			Fuel-2			Fuel-3		
	a_{jk}	b_{jk}	c_{jk}	a_{jk}	b_{jk}	c_{jk}	a_{jk}	b_{jk}	c_{jk}
1.	26.970	-0.39750	0.002176	21.130	-0.30590	0.00186100	-	-	-
2.	118.400	-1.26900	0.004194	1.865	-0.03988	0.00113800	13.650	-0.19800	0.0016200
3.	39.790	-0.31160	0.001457	-59.140	0.48640	0.00001176	-2.876	0.03389	0.0008035
4.	1.983	-0.03114	0.001049	52.850	-0.63480	0.00275800	266.800	-2.33800	0.0059350

Table 2 *Generation limits (MW) of units corresponding to different fuel options*

Unit No.	Fuel-1		Fuel-2		Fuel-3	
	P_{min} (MW)	P_1 (MW)	P_1 (MW)	P_2 (MW)	P_2 (MW)	P_{max} (MW)
1.	100	196	196	250	-	-
2.	157	230	50	114	114	157
3.	200	332	388	500	332	388
4.	99	138	138	200	200	265

For determination of economic fuel option of each thermal unit, neural networks of supervised learning are needed. This is because, the optimal fuel option of the thermal units (outputs) for each total system load demand (input) in the training set are required to be known in advance by some suitable method. A radial basis function ANN called as RBANN is employed in the present work for training and testing due to its auto configuring architecture and faster learning ability. The proposed numerical technique as described earlier has been applied to create the necessary training set. A radial basis function ANN model, namely RBANN is designed for the purpose. There is only 1 input node (load demand) for the model. The optimal fuel options of the thermal units in the system, i.e., ,..., are the output nodes. Therefore, there are 4 output nodes for the RBANN. The number of neurons in the single hidden layer is equal to the number of iterations required for training and is set adaptively for RBANN. It is not unusual to get good performance on training data followed by much worse performance on test data. This can be guarded against by ensuring that the training data are uniformly distributed. Two different cases were computed by the proposed ANN technique, i.e., (1) Optimal generation dispatch with multiple fuel options without considering losses and (2) Optimal generation dispatch with multiple fuel options considering losses. For both the test cases, to train the networks PD was varied in the range 850 MW to 950 MW in steps of 5 MW. Therefore, 21 different training patterns were generated covering the system load from 850 MW to 950 MW for each test case. Two different radial basis function networks namely, the RBANN1 for test case 1 and RBANN2 for test case 2 were trained with their corresponding 21 patterns to reach the error-goal (convergence target) which was SSE = 0.001. Two different neural networks are used as the outputs i.e., the optimal fuel options for same load demand PD for loss inclusion case and without loss case may be different. However, their architecture remains same. RBANN1 and RBANN2 required 19 and 20 iterations (epoch), respectively, in reaching the convergence target. To achieve the best performance on the test data and good generalization an appropriate value of spread factor (SF) is set. Computations were carried out for different values of SF to find the best value of SF. For a given set of test patterns the percentage mean absolute error (% MAE) is recorded for each value of SF. Then the value of SF corresponding to the minimum of the % MAE is taken as the best value of SF. Accordingly, the best SF is found to be 5 for both RBANN1 and RBANN2. For the performance evaluation of the RBANN, 4 different load levels other than those in training sets but within 850 MW to 950 MW are considered. These test cases were generated by proposed numerical technique. The test cases were computed by the RBANN1, which was trained earlier taking the best value of SF i.e., 5. The final optimal fuel options obtained from the RBANN1 along with heuristic rule based search algorithm was compared with those obtained from proposed numerical method and the comparison is shown in Table 3. From this table it is observed that the optimal fuel options obtained from RBANN1 along with heuristic rule-based search algorithm matches to that of the proposed numerical method. Similarly, Table 4 shows the comparison of final optimal fuel options obtained from the RBANN2 along with heuristic rule based search algorithm and those obtained from proposed numerical method. The RBANN2 results matches to that of the proposed numerical method.

A. Simulation of Hopfield Neural Network

After obtaining the economic fuel option for each generating unit corresponding to a given load demand, the optimal generation dispatch result is obtained by a Hopfield neural network which satisfies the operational constraints. During simulation, it was found that the assumed initial solutions did not affect the results for different cases since they are convex problems.

Table 3 Comparison of optimal fuel options obtained from RBANN1 along with heuristic rule based search algorithm and proposed numerical method.

Load	Generator No.	Fuel options from RBANN1	Fuel options from Heuristic rule based search algorithm	Fuel options from proposed numerical method
902	1	2.1314	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3
912	1	2.0281	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3
922	1	1.9957	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3
932	1	2.0041	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3

Table 4 *Comparison of optimal fuel options obtained from RBANN2 along with heuristic rule based search algorithm and proposed numerical method*

Load	Generator No.	Fuel options from RBANN2	Fuel options from Heuristic rule based search algorithm	Fuel options from proposed numerical method
902	1	2.0066	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3
912	1	2.0014	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3
922	1	1.9992	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3
932	1	1.9953	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3

B. Determination of weighting factors

Determination of weighting factors in case of Hopfield neural network is very crucial in achieving the optimal generation schedules. A is the penalty factor to the constraint of the total load demand and B is the penalty factor to the constraint of the objective function. It was observed that when A was bigger than 0.5 regardless of B values, the network oscillated. Usually, when there is self-feedback (Tii 0), the solutions can be in oscillation as reported in Reference-. Through simple trial and error method, it was found that A = 0.5 and B = 0.06 were appropriate values. The inequality constraints of maximum-minimum limits are dealt by the sigmoidal function variation as shown in Eqn.(27). The results of different case studies are shown in Table 5 and Table 6, respectively, for without loss and loss inclusion cases and compared with those of proposed numerical technique. The results of the Hopfield network method shows small error in power balance (the mismatch power is 0.8001 MW in without loss case and 0.9141 MW in loss inclusion case). When this error is converted into the fuel cost of a power plant with the highest cost function, the total cost increase is extremely small compared with the total cost of numerical method. The convergence characteristics for both the cases have been observed and shown in Figs. 4 (a) and (b). In second case, where the transmission loss is considered, the Hopfield neural network method also shows good results.

Table 5. Comparison of optimal generation dispatch results obtained from Hopfield Neural Network and Proposed Numerical Method without considering loss

Load in MW	Proposed Numerical Method	Hopfield Neural Network Method	Power Mismatch in MW
902	Gen.1 (MW) : 202.3490 Gen.2 (MW) : 204.5093 Gen.3 (MW) : 260.4127 Gen.4 (MW) : 234.7291 Total Power (MW): 902.0001 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 172.0293	Gen.1 (MW) : 202.3325 Gen.2 (MW) : 204.5021 Gen.3 (MW) : 260.3917 Gen.4 (MW) : 234.7237 Total Power (MW): 901.9500 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 172.0070	0.0501
912	Gen.1 (MW) : 205.6459 Gen.2 (MW) : 205.9714 Gen.3 (MW) : 264.6222 Gen.4 (MW) : 235.7606 Total Power (MW): 912.0001 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 176.5631	Gen.1 (MW) : 205.5451 Gen.2 (MW) : 205.9273 Gen.3 (MW) : 264.4962 Gen.4 (MW) : 235.7314 Total Power (MW): 911.7000 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 176.4253	0.3001
922	Gen.1 (MW) : 208.9405 Gen.2 (MW) : 207.4331 Gen.3 (MW) : 268.8315 Gen.4 (MW) : 236.7948 Total Power (MW): 921.9999 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 181.2195	Gen.1 (MW) : 208.8745 Gen.2 (MW) : 207.4032 Gen.3 (MW) : 268.7474 Gen.4 (MW) : 236.7749 Total Power (MW): 921.8000 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) :181.1252	0.1999
932	Gen.1 (MW) : 212.2360 Gen.2 (MW) : 208.8946 Gen.3 (MW) : 273.0401 Gen.4 (MW) : 237.8294 Total Power (MW): 932.0001 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 185.9986	Gen.1 (MW) : 211.9715 Gen.2 (MW) : 208.7774 Gen.3 (MW) : 272.7052 Gen.4 (MW) : 237.7459 Total Power (MW): 931.2000 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) :185.6118	0.8001

Table 6 Comparison of optimal generation dispatch results obtained from Hopfield Neural Network and Proposed Numerical Method considering loss

Load in MW	Proposed Numerical Method	Hopfield Neural Network Method	Power Mismatch In MW
902	Gen.1 (MW) : 213.7862 Gen.2 (MW) : 208.1258 Gen.3 (MW) : 266.3219 Gen.4 (MW) : 235.8940 Total Loss (MW) : 22.1278 Total Power (MW): 924.1279 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 182.2831	Gen.1 (MW) : 213.7144 Gen.2 (MW) : 208.0945 Gen.3 (MW) : 266.2377 Gen.4 (MW) : 235.8722 Total Loss (MW) : 22.1188 Total Power (MW): 923.9188 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 182.1839	0.2091
912	Gen.1 (MW) : 217.3946 Gen.2 (MW) : 209.6812 Gen.3 (MW) : 270.5507 Gen.4 (MW) : 236.9535 Total Loss (MW) : 22.5806 Total Power (MW): 934.5800 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 187.3134	Gen.1 (MW) : 217.2501 Gen.2 (MW) : 209.6194 Gen.3 (MW) : 270.3817 Gen.4 (MW) : 236.9111 Total Loss (MW) : 22.5623 Total Power (MW): 934.1623 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 187.1096	0.4177
922	Gen.1 (MW) : 221.0075 Gen.2 (MW) : 211.2398 Gen.3 (MW) : 274.7773 Gen.4 (MW) : 238.0147 Total Loss (MW) : 23.0393 Total Power (MW): 945.0393 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 192.4810	Gen.1 (MW) : 220.9353 Gen.2 (MW) : 211.2084 Gen.3 (MW) : 274.6929 Gen.4 (MW) : 237.9934 Total Loss (MW) : 23.0301 Total Power (MW): 944.8301 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 192.0626	0.2092
932	Gen.1 (MW) : 224.6252 Gen.2 (MW) : 212.7993 Gen.3 (MW) : 279.0025 Gen.4 (MW) : 239.0770 Total Loss (MW) : 23.5040 Total Power (MW): 956.1040 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 197.7862	Gen.1 (MW) : 224.5166 Gen.2 (MW) : 212.7526 Gen.3 (MW) : 278.8757 Gen.4 (MW) : 239.0451 Total Loss (MW) : 23.4899 Total Power (MW): 955.1899 $(P_1+P_2+P_3+P_4)$ Total Cost (Rs/hr) : 197.6250	0.9141

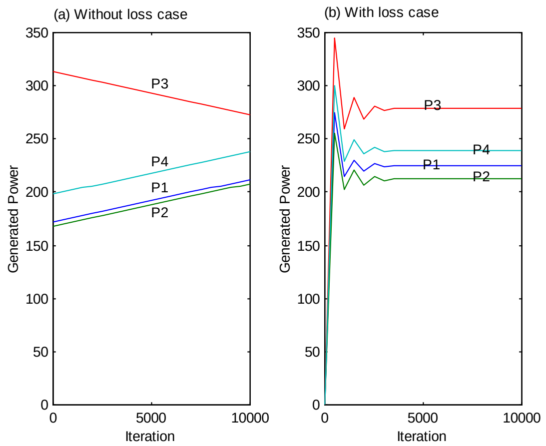

Figure 4: Convergence characteristics of Hopfield neural network

VII. CONCLUSION

This paper presents an ANN method consisting of Radial basis function ANN, Hopfield ANN methods along with a heuristic rule based search algorithm for optimal generation dispatch solutions with multiple fuel options. Initially, a numerical technique as proposed in this paper is applied to find out the economic fuel option for each unit corresponding to a particular load demand which is used for generation of training patterns for the Radial basis function ANN. Once this ANN is trained, then for a given load demand, a preliminary economic fuel option for each generating unit is obtained. In fact the fuel options are integer values like 1, 2 or 3, etc. But, in the preliminary economic fuel option results, we may get fractional values like 1.008, 0.987, etc. Therefore, a simple heuristic rule based algorithm is developed to reach a correct economic fuel option, i.e., an integer value for each output. After obtaining the economic fuel option for each generating unit corresponding to a given load demand, the optimal generation dispatch result is obtained by a Hopfield neural network which satisfies the operational constraints. The simulation results show that the solution method is practical and valid for real-time operation. An advantage of the proposed method is its capability to optimize over a greater variety of operating conditions. The proposed ANN method has applications to fossil fueled generation units capable of burning coal, gas, and/or oil as well as other problems which result in multiple intersecting cost curves for a particular generating unit. This neural network method has the special advantage of solving the ELD problem without calculating incremental fuel costs and incremental losses required by conventional numerical methods. The proposed ANN technique for solving optimal generation dispatch problem with multiple fuel options was implemented in MATLAB language which was run on a 2.4 GHz Pentium-IV machine. The average computation time for each load demand in case of ANN method was found to be about 40 second while the average computation time of the proposed numerical technique is about 1 minute. This indicates that there is not much difference in computation time. But, when implemented in hardware, the proposed neutral network technique can achieve much faster real time response than the proposed numerical technique. Therefore, the proposed ANN based technique promises to have a good merit in its applications.

VIII. REFERENCES

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