VALIDATION OF NEURAL NETWORK IN TRANSMISSION LOSS ALLOCATION USING ORTHOGONAL PROJECTION TECHNIQUE

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Abstract- A new transmission loss allocation tool based on artificial neural network has been developed and presented in this paper. The proposed artificial neural network computes loss allocation much faster than other methods. A relatively short execution time of the proposed method makes it a suitable candidate for being a part of a real time decision making process. Most independent system variables can be used as inputs to this neural network which in turn makes the loss allocation procedure responsive to practical situations. Moreover, transmission line status (available or failed) was included in neural network inputs to make the proposed network capable of allocating loss even during the failure of a transmission line. The proposed neural networks were utilized to allocate losses in two types of energy transactions: bilateral contracts and power pool operation. Circuit Theory and Orthogonal Projection loss allocation methods were utilized to develop training and testing patterns. The 6-bus reliability network was utilized to conduct studies and illustrate numerical examples for bilateral transactions. Techniques were developed to expedite the training of the neural networks and to improve the accuracy of results.

Keywords – Transmission Loss, Loss Allocation, ANN, Orthogonal Projection concept, Loss function decompositiyion

I. INTRODUCTION

Transmission loss in electric power system is a natural phenomenon. Electric power has to be moved from generation place to the consumer's place through some wires for consumption. All wires have some resistance, which consume some power. The power consumed in this way is referred to as "loss". Most of this loss is attributable to the heating of the power lines by the electrical current flowing through them. The loss (i^2R) is then lost to the surrounding of the power lines. Transmission loss represents about 5% to 10% of total generation, a quantity worth millions of dollar per year. In Alberta alone . total transmission loss costs about million dollars per year. In a traditional power system total transmission loss is optimized while keeping the running cost at the minimum. In a deregulated power system, due to competition in the generation sector, transmission loss has to be allocated to individual generators.

In a deregulated power system transmission loss has to allocated to individual supplier, generators and contracts . Loss allocation does not affect generation levels or power flows,however it does modify the distribution of revenues and payments at the network buses among suppliers and consumers. In a deregulated power system, every supplier has to supply the power they want to sell plus the transmission loss corresponding to that transaction. Therefore, system operator has to allocate losses to every individual generation and load. Depending on the contract, a supplier may supply the contracted load and the corresponding loss or supply the load and pay for the loss. In later case, the loss may be supplied by a contracted generator or ISO may buy the power to meet the loss from a spot market. Depending upon who will supply the loss, the allocation will vary to some extent.

Transmission loss allocation became a contentious issue as it corresponds to a huge amount of money. Transmission loss is a highly non-linear function of these factors. The main problem associated with loss allocation is the fact that transmission loss is a non-separable entity. Any attempt to separate it is further complicated by its non-linear nature. The challenge facing by a typical power pool and an ISO is how to allocate the transmission loss and what should be the criterion for charging other utilities. Utilities in general, look for locational signal, consistency, simplicity, accuracy and predictability in a loss allocation method. It is an extremely hard task to accommodate all these considerations in a complex phenomenon like transmission loss allocation. In a deregulated environment, the economic and market related factors are as important as technical factors. Although no ideal or standard loss allocation method exists, some methods have been reported in literature [2, 5-14]. But all these methods require time consuming and complex mathematical computation and therefore limited acceptance by the industry.

H.H.Happ introduced some methods for calculating cost of power wheeling [5]. Conejo et al [6] have discussed the Pro Rata (PR) procedure, a technique used in Mainland Spain for allocation of transmission loss, where losses are globally assigned to generators and consumers, and then a proportional allocation rule is used. The loss allocated to a generator or consumer is proportional to its level of energy generation PR procedure ignores the network and, therefore, is not consistent with solved power flow. Conejo et al [6] have also discussed two other methods called 'Marginal Procedure' and 'Proportional Sharing'. In 'Marginal Procedure', losses are assigned to generators and consumers through so-called incremental transmission loss co-efficient (ITL). Conejo et al [7] proposed a loss allocation method called "Z-bus allocation". It is based on the exact network equations as defined by the complex impedance matrix and the complex nodal injections. Strbac et al [8] have proposed a transmission loss allocation method by tracing the generator and load contributions to line flows. This method traces the contributions of each generator and of each load to the line flows instead of marginal contributions. Since the allocation method had been proposed on the basis of maximum flows in the lines, it does not reflect the actual load condition. Bialek et al [9] had proposed another method of loss allocation in which power flows in the lines are traced and a proportional sharing principle is used. Cheng et al [10] addressed different challenges associated with bilateral contracts in a deregulated power system network. The authors described modeling of bilateral contracts using a transaction matrix. A two-dimensional matrix that includes power generators and load demands is termed as a transaction matrix. Anderson and Yang [11] proposed a structure to determine the use of transmission system. Instead of proportional sharing, a power flow comparison is used to determine the use of transmission line. Power flow comparison method uses load flow study to find a generator's contribution by superimposing the generator on the base load. The difference obtained from the two load flows are attributed to generator's account. This method goes in sequence for each generator to calculate its effect on load flow studies. Loss allocation depends on the sequence of generator used. Results vary widely for different sequences. F and and David [12] discussed power dispatch issue in a power network structure dominated by bilateral and multilateral transmission contracts. A frame work of price-based operation under deregulated structure was developed and a solution to optimal transmission dispatch is proposed. This paper particularly concentrates on dispatch curtail challenges with bilateral and multilateral contracts in a power system.

II. METHODOLOGY

The orthogonal projection concept could be applied to determine the shares of each current injection on the branch currents. Taking the total branch current I_r as the reference vector, decompose all the branch current contributions due to current injections into two components, one vertical to I_r, the other parallel to I_r , as shown in Fig. As doing work, analogously, only the components in the direction of I_r take shares of I_r. While for the components vertical to I_r , their addition equals to zero and they take no shares.

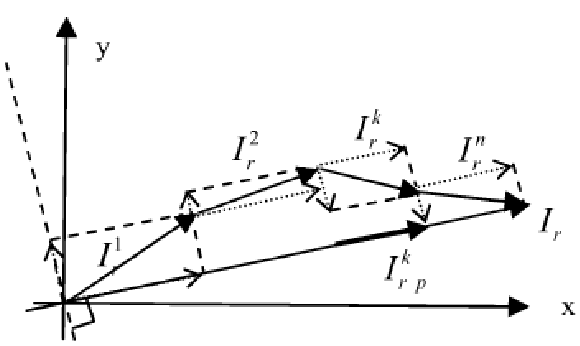

Fig.1 Orthogonal decomposition of the branch current contributions due to individual current injections.

The components in the direction of the total branch current accord with the concept of orthogonal projection exactly. Let $I_{r\,p}^k$ denote the orthogonal projection vector of I_r^k in the direction of I_r, which is defined to be the current projection component of branch r produced by the current injection at bus k , and it is calculated as

$$\begin{aligned} I_{r\,p}^k &= \frac{I_r^k \cdot I_r}{|I_r|} e^{j\varphi_r} \\ &= |I_r^k| \cos\left(\varphi_r^k - \varphi_r\right) e^{j\varphi_r}. \end{aligned} \tag{1}$$

The current projection components satisfy:

$$\sum_{k=1}^{n} I_{r\,p}^k = I_r. \tag{2}$$

Then the share of the current injection at bus k on total branch current will be:

$$\begin{aligned} \frac{I_{r\,p}^k}{I_r} &= \frac{|I_r^k| \cos\left(\varphi_r^k - \varphi_r\right) e^{j\varphi_r}}{|I_r| e^{j\varphi_r}} \\ &= \frac{|I_r^k| \cos\left(\varphi_r^k - \varphi_r\right)}{|I_r|}. \end{aligned} \tag{3}$$

From above it can be seen that the share is a real number. And the share would keep stable when the voltage reference bus changes since it is relative to the difference of the two phase angles, φ_r^k and φ_r, which is independent on the choice of the voltage reference bus.

By using the current projection component, $I_{r\,p}^k$, the contribution of current injection at bus k to the power flow at the sending bus of branch r($S_{r\,fp}^k$) can be calculated as

$$\begin{aligned} S_{r\,f\,p}^k &= V_{r\,f} I_{r\,p}^{k*} \\ &= |V_{r\,f}|\,|I_r^k| \cos\left(\varphi_r^k - \varphi_r\right) e^{j(\theta_{r\,f} - \varphi_r)} \end{aligned} \tag{4}$$

Where $\theta_{r\,f}$ is voltage angle of the sending bus of branch r. While the total power flow at the sending bus of branch r(S_{rf}) equals to:

$$\begin{aligned} S_{r\,f} &= V_{r\,f} I_r^* \\ &= |V_{r\,f}||I_r| e^{j(\theta_{r\,f} - \varphi_r)}. \end{aligned} \tag{5}$$

Then the share of current injection at bus k on the power flow at the sending bus of branch r is calculated as

$$\frac{S_{r\,f\,p}^k}{S_{r\,f}} = \frac{|I_r^k| \cos\left(\varphi_r^k - \varphi_r\right)}{|I_r|}. \tag{6}$$

Comparing (6) and (3), it can be seen that the share of current injection at bus k on the power flow through branch r equals the ratio of its current projection component to the total branch current. Similar results can be obtained for the power flow decomposition at the receiving bus. Moreover, for the power flow contribution taking the sending bus for example, which is calculated as

$$S_{rf}^{k'} = V_{rf} I_r^{k*} \tag{7}$$

After obtaining the contributions of current injection at bus k on the power flows at the sending and receiving bus of branch r, its allocated loss of branchr(L_r^k) is accordingly given by the following formula:

$$L_r^k = S_{rfp}^k - S_{\mathrm{rt}p}^k. \tag{8}$$

The sum of L_r^k satisfies

$$\sum_{k=1}^{n} L_r^k = L_r. \tag{9}$$

Focusing on the active losses, the active loss allocation for current injection at bus k($P_{\mathrm{loss}\,r}{}^k$) is expressed as

$$P_{\mathrm{loss}_r}{}^k = \left|I_r^k\right| \left|I_r\right| \cos\left(\varphi_r^k - \varphi_r\right) r_r. \tag{10}$$

From (10) it can be seen that the allocated active loss portions are only relative to the branch resistance but not to the branch reactance, which ensures the validity of loss allocation. According to the orthogonal projection concept, (21) could be explained as the orthogonal projection vector of I_r^k in the direction of $r_r I_r$, where $r_r I_r$ means the voltage drop across the branch resistance.

The equivalence for power injections needs be considered when using the circuit-based methods. Two equivalence modes have been proposed in previous research. One of the equivalence modes converts all power injections including generators and loads into current injections, as expressed in (1). Here, we call it CC equivalence mode. The other mode, called CE equivalence mode here, distinguishes generators and loads by net power injections and calculates their shares separately. Take the calculation for generators for example. A bus is considered to be a generator if its net real power injection is nonnegative; otherwise it is classified as a load. Then convert the generators into current injections and the loads into equivalent admittances as

$$\begin{aligned} I_k &= (S_k/V_k)^*, \quad \text{if} PG_k - PD_k \geq 0 \\ y_{d,k} &= -(S_k^*/V_k^2), \text{ if } PG_k - PD_k < 0. \end{aligned} \tag{11}$$

Integrate the equivalent load admittances into the original bus admittance matrix, and invert the new bus admittance matrix to get the bus impedance matrix including the equivalent load admittances as

$$\begin{aligned} Y_d &= Y + \mathrm{diag}(y_d) \\ Z_d &= Y_d^{-1} \end{aligned} \tag{12}$$

where $y_d = [y_{d,1} \cdots y_{d,k} \cdots y_{d,n}]^T$.

By using this concept, the current projection component is defined to determine the share of a generator or load on the currents through a branch. Then the power flow through each branches decomposed, and subsequently branch loss allocation is obtained. By the combination of the circuit theories and the concept of orthogonal projection, the method gives intuitively clear explanation of the obtained branch loss allocation. When using the circuit-based methods, the first step is the equivalence for power injections. In other method one of the equivalence modes converts all generators and loads into current injections. But this equivalence mode fails when the bus admittance matrix is singular due to no shunt elements. Thus another equivalence mode is proposed. In that method loads (generators) are converted into equivalent admittances when generators (loads) are converted into current injections

III Case Study

A small hypothetical system has been considered in this section for the purpose of numerical examples related to the allocation of transmission loss. The hypothetical system consists of six buses with two generators, four loads . Figure 2 shows the diagram of the example system. Generators 1and 2 are connected to Bus 1 and Bus 2 respectively. Loads are connected to Bus 3, Bus 4, Bus 5 and Bus 6.. The details of loads are shown in Table 1 and the generation capacity of each generator is shown in Table 2.

Load at Bus	Real Load pu	Reactive load pu
3	0.8500	0.4000
4	0.4000	0.2000
5	0.2000	0.1000
6	0.2000	0.1000

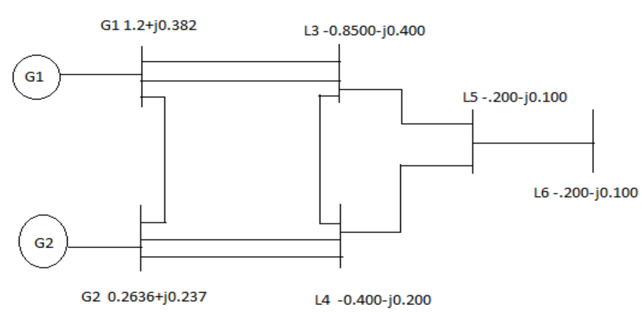

Fig 2: Six bus test system with four load

Table 2: Generation Capacity of the system

Generator at Bus	Active Power pu	Reactive Power pu
1	1.2000	0.3820
2	0.2636	0.2370

Table 3 Line Data

From Bus	To Bus	R(ohm)	X(ohm)
1	3	0.034200	0.18000
2	4	0.114000	0.60000
1	2	0.091200	0.48000
3	4	0.22800	0.12000
3	5	0.22800	0.12000
1	3	0.034200	0.18000
2	4	0.114000	0.60000
4	5	0.022800	0.12000
5	6	0.000000	0.12000

Table 4 Load Flow Solution for the System

Bus No.	P(pu)	Q(pu)	V(pu)	Θ(rad)
1	1.2000	0.3820	1.050	0.101
2	0.2636	0.2370	1.050	0.000
3	0.8500	0.4000	1.002	0.025
4	0.4000	0.2000	0.996	-0.001
5	0.2000	0.1000	0.988	-0.001
6	0.2000	0.1000	0.978	-0.015

Table 5 Branch Power Flow Decomposition for Generator

Line	G1	G2
1-3	0.98467+j0.39260 0.96539+j0.30223	0.14356+j0.05724 0.14075+j0.04406
2-4	0.17065+j0.08438 0.16195+j0.07988	0.15751+j0.07788 0.14948+j0.07373
2-1	-0.06223+j0.07204 -0.06918+j0.06539	-0.00233+j0.00270 -0.00259+j0.00245
3-4	0.16496+j0.01726 0.16437+j0.01289	-0.02473+j0.00259 -0.02188+j0.00193
3-5	0.22147+j0.06387 0.21994+j0.05728	0.02203+j0.00635 0.02188+j0.00570
1-3	0.98467+j0.39260 0.96539+j0.30223	0.14356+j0.05724 0.14075+j0.04406
2-4	0.17065+j0.08438 0.16195+j0.07988	0.15751+j0.07788 0.14948+j0.07373
4-5	0.05464+j0.02759 0.05420+j0.0273	0.04941+j0.02495 0.04901+j0.02475
5-6	0.13714+j0.04535 0.13637+j0.04299	0.03583+j0.01185 0.03563+j0.01123

IV Proposed Neural Network

Many types of neural networks had been developed so far for various purposes. Some of these neural networks have been described in Chapter 3. All artificial neural networks are based on the concept of neurons, connections and transfer functions, and there is a similarity between the different structures or architectures or neural networks. There is no limitation for their applications but some of them showed better performance in specific applications. Basically, most applications of neural networks fall into five categories: prediction/ estimation, classification, data association, data conceptualization and data filtering. Feedforward and Self-organizing Back Propagation networks are suitable for estimation or prediction, Learning Vector Quantization and Probabilistic Neural networks for classification, Hopfield and Boltzmann Machine for data association, Self-organizing Map for data conceptualization and Recurring networks for data filtering [27]. Feed Forward Multilayer Neural networks are the most popular among all types of networks due to their effectiveness and ease of learning using back propagation algorithm. One of the significant advantages of a feed forward multilayer neural network is its ability to provide solutions for highly non-linear systems and also for systems with ill-defined problems. Transmission loss is a non-linear function of system parameters and states. Due to this non-linearity a multilayer feed forward neural network structure has been utilized in this research. A multilayer feed forward neural network has been developed for loss allocation for the bilateral contracts. Inputs and outputs of the network were selected carefully so that the proposed network represents all possible practical situations in a power system network. Most independent system variables have been used as inputs to this neural network which in turn makes the loss allocation process responsive to practical situations. There are four outputs of the network which are real loss and reactive loss for contracts A and B. The inputs and outputs of the network are described in Table 6.

Table 6 Input & Output Neurons

Layer	Neurons	Description
Input	I1 I2-I8	Real Generation of Bus1 Load on Buses
Output	I9-I26	Losses on all Buses

To find the most suitable architecture for loss allocation, number of hidden layers and number of neurons in the hidden layers have to be optimized. For a single hidden layer, the number of hidden neurons was varied from 10 to 55 and convergence characteristics and performance for various test patterns were observed.To speed up learning, some measures were taken which have been described in the following section. After adapting all speed enhancement techniques, the number of hidden layers and the number of neurons were selected based on convergence criteria and performance. The most significant property of an artificial neural network is that it can learn from experience and becomes knowledgeable about the environment. Among all the learning algorithms, back propagation learning, more precisely described as the steepest gradient descent learning using back propagation of error is widely used in the learning of ANNs. The advantage of this algorithm is its simplicity of calculation for updating weights and thresholds. Hence, in this research back propagation algorithm has been utilized to train the proposed ANN. It is a supervised learning algorithm which requires an external teacher which generates the desired output for the ANN. The Circuit theory and Orthogonal Projection has been used as a teacher to generate an output vector corresponding to an input vector, and these two vectors together termed as 'training patterns' have been used by the back propagation algorithm to train the proposed ANN. The input vector and the number of training patterns have been carefully selected so that they represent almost all possible states of the environment. In classical pattern recognition, the number of training patterns should be 3-5 times higher than the number of features (inputs) used [27]. According to Lippmann [28], this number should be at least several times larger than the ratio of the number of synaptic weights in the network to the number of outputs. According to the first suggestion, minimum number of training patterns required for an effective training of the network is 270 (54 x 5) using the upper bound. Referring to the second suggestion, this number would be greater than the previous one. With 54 inputs, 29 hidden neurons and 4 outputs, training patterns should be few times larger than 797.5 {(54*55+55*4)/4}. If we consider a multiplication of 3 times, the number becomes 2392. Although the higher the training samples the better knowledge and performance of the network, the performance of the network will tend to saturate as the number is increased beyond certain value and at the same time it will take more time to learn. However, we have selected 2600 training patterns, a number greater than both suggestions so that the trained ANN can give better performance with the test patterns.

In the previous section we observed that proper initialization of synaptic weights and the thresholds, adapting different learning rate for each weight direction, adapting thresholds and the use of dual activation functions in output layer increased the convergence speed in the back propagation learning. With all these learning enhancement techniques, different neural network architectures were studied for the purpose of transmission loss allocation in the test system. It was found that increasing the number of neurons beyond 45, neither improves convergence characteristics nor gives better performance with the test patterns. Similarly, the optimum number of neurons with two hidden layers was obtained.

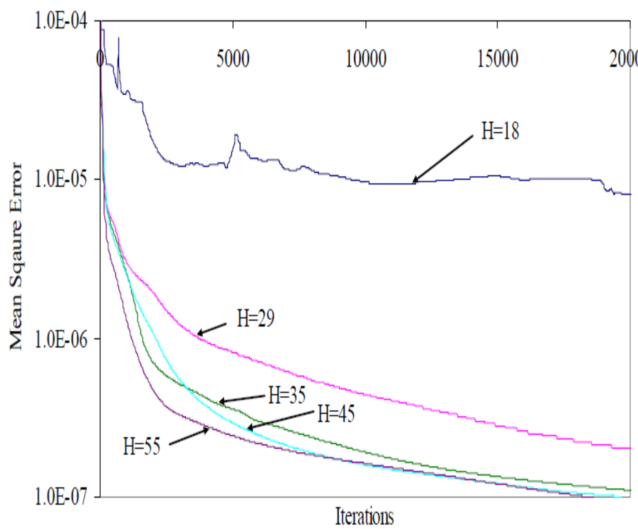

Fig. 2: Convergence characteristics for different numbers of hidden neurons in a single hidden layer feed forward network

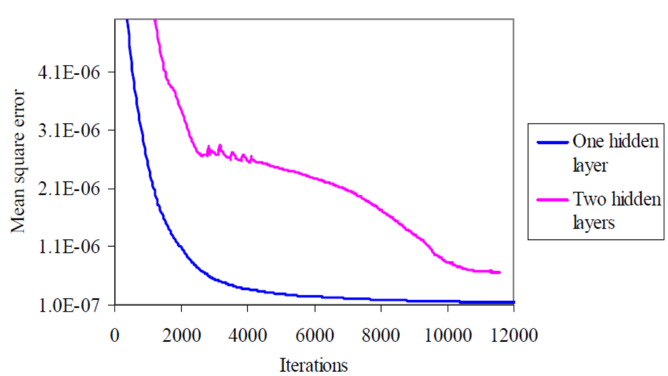

Fig.3: Convergence characteristics of proposed neural networks with one and two hidden layers

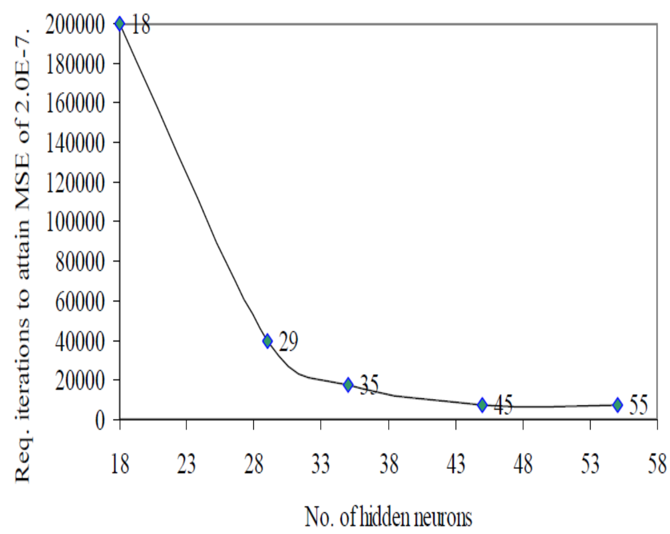

Fig. 4: The required number of iterations to attain a particular accuracy level for MSE $=1.2\times10^{-7}$.

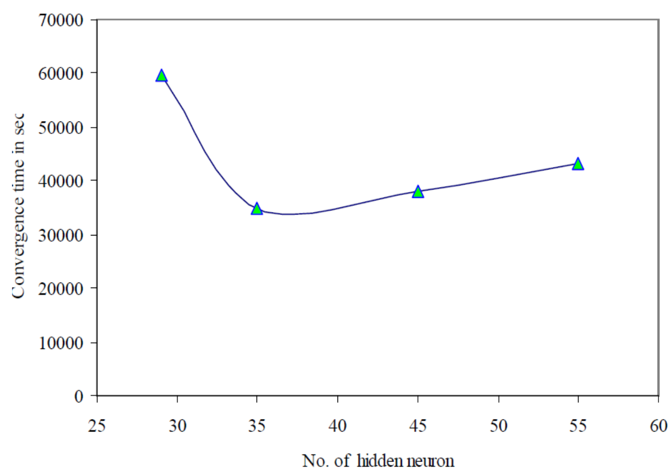

Fig.5: The time required to attain same accuracy level

Among all network architectures considered, it was observed that the network with a single hidden-layer with 45 hidden neurons provided the best result in terms of speed of convergence and accuracy.

V Result

The proposed network was trained in 8000 iterations. Amplitudes of activation functions were 0.1116 and 0.5115 for real and reactive loss allocations respectively. A value of 0.61 was used for 'b' for both the activation functions. Learning rate (η) was chosen to be 0.85, momentum factor α was 0.48, step size γ for adaptive learning was 0.85. Mean square error (MSE) was used to check convergence accuracy. A value of 5.0E-08 was chosen for MSE to determine convergence of training. The trained network was tested with 838 test patterns. Test patterns were derived by varying all 9 inputs to simulate Losses. Results obtained from the ANN and Orthogonal Projection show that ANN can allocate losses with good accuracy.

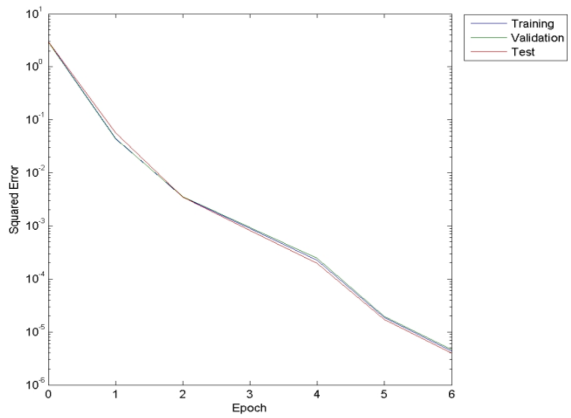

Fig 6 Testing, Training and Validation of Cluster 1.

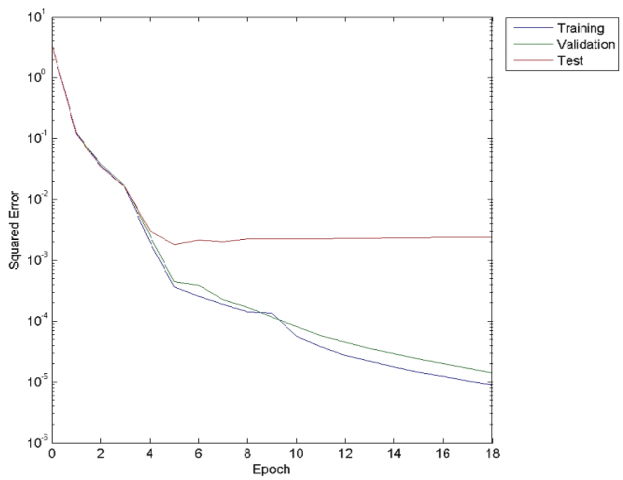

Fig 7Testing, Training and Validation of Cluster 2.

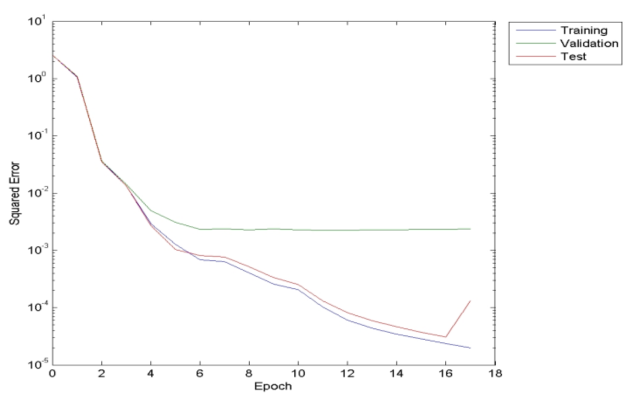

Fig 8 Testing, Training and Validation of Cluster 3

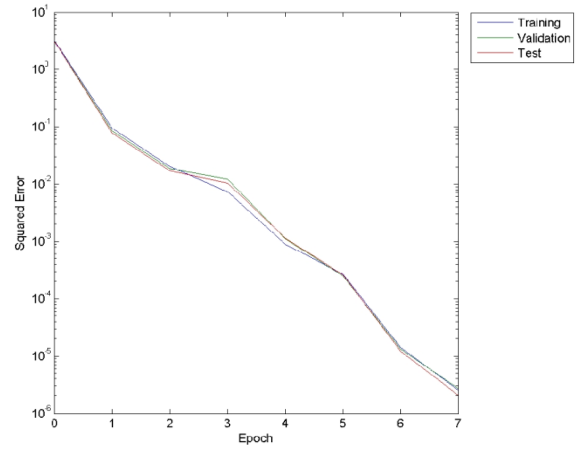

Fig 9 Testing, Training and Validation of Cluster 4

VI Conclusions

A new transmission loss allocation tool based on artificial neural networks has been developed. The proposed artificial neural networks can simulate transmission loss allocation determined by Circuit Theory and Orthogonal Projection and techniques. For loss allocations to bilateral contracts, the Circuit Theory and Orthogonal Projection was used as a teacher to train the proposed neural network. The developed ANN was tested with the 6-bus reliability test system with 4 Load bus. Results obtained from the Circuit Theory and Orthogonal Projection and the proposed ANN was compared for various loading conditions. It was found that the proposed ANN can allocate transmission loss to Load with good accuracy. The ANN was designed to handle loss allocation even under single transmission contingency provided the contingency does not threaten voltage stability during the bilateral transaction. The proposed ANN can be trained with little difficulty for large power system network. The trained ANN can provide solution in a quick manner. The proposed ANN can yield negative loss allocation to reward generators or loads that cause counter flow in the network. Although the Circuit Theory and Orthogonal Projection was utilized to generate training data, any other method of loss allocation can be utilized for that purpose.

A major disadvantage of a neural network is that it is depended on the architecture of a power system network. Its configuration would change whenever a transmission line becomes unavailable due to maintenance or line failure. As a consequence, the ANN has to be retrained. To avoid retraining, an ANN was developed to handle the unavailability of a transmission line. To accomplish this objective, we can add transmission line status (available /unavailable) to the input vector of the neural network. With the inclusion of line status, the developed ANN was able to allocate losses to all parties accurately even during a transmission line outage. Unlike other inputs e.g. loads, generations, bus voltages which are directly used in p.u., each line was given a binary status, '0' if available and '1' if failed. Inclusion of line status in the input vector, however, created another problem. The number of inputs related to line status could be very high in a large system. This could increase the training time tremendously. Extensive loss allocation studies proved that only a few transmission line outages had significant impact on loss allocation. A selection criterion for line status input was developed to identify these lines and to keep the size of the neural network manageable. The status of a line was selected as input if its failure had significant impact on loss allocation but did not threaten system voltage stability nor made the bilateral transaction impossible. Only single level contingency was considered as the probability of two line failures at the same time is negligible. The proposed ANN was developed and tested with the 6-bus Reliability Test System. The results showed that the developed ANN can allocate real and reactive parts of transmission loss with good accuracy. The training and testing patterns were obtained using the Circuit Theory and Orthogonal Projection method. The results obtained from the developed ANN were in good agreement with those obtained using the Circuit Theory and Orthogonal Projection. Therefore, an ANN can be used to simulate the loss allocations obtained using the Circuit Theory and Orthogonal Projection. The ANN provides results in fast and convenient manner with less mathematical complexity.

In a pool operation, the principle of transmission loss allocation is different than that of bilateral contracts. One of the main objectives of a pool operation is to minimize the operating cost. When the price of energy is set by market clearing price i.e. every suppliers get same price for per unit of energy they supply, the load scheduling is done in such a way that transmission loss is minimized. In a pool operation, transmission loss can be allocated to generators or to both the generators and consumers.

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