# Chapter 3

# Available Transfer Capability Calculation using Artificial Neural Network

## 3.1 Introduction

The congestion management in Power system has been identified as an integral part of modern power system, but its real time implementation is still a challenging task to power system engineers. Outage of a transmission unit (line or transformer) or a generator may lead to over loading of other healthy lines and cause sudden change in power flow of transmission line and thus force the system to enter the emergency state. The transmission line capability has been fixed at the time of erection of transmission line. Hence, Available Transfer capability calculation has been recognized as key factor for congestion management.

Artificial Neural Networks (ANN) is largely used due to their ability to mimic natural intelligence. ANN have been used in a broad range of applications. These include pattern classification, function approximation, optimization, prediction, and automatic control. ANN can achieve high computational speed by employing a massive number of simple processing elements arranged in parallel with high degree of connectivity called neurons which operate concurrently. There are large number of neural network paradigms [71]. Most of the Artificial Neural Networks perform essentially the function of vector or functional mapping. The ANN models accept a set of inputs (an input vector) and produce a corresponding set of outputs (an output vector). Neural networks have also been applied to various fields of engineering including electrical power systems. Vankayala and Rao [72] carried out a survey of various artificial neural networks and their applications to power systems. Majority of the works in the power systems have used feed forward networks based on back propagation algorithm (BPA).

The feed forward network based on back propagation algorithm (BPA) has been used in all the work of power system. Many methods [73] has been used in electrical power system. The ANN has been also used to compute Nodal Congestion Price [74] in spot electrical market. To alleviate Congestion, the accurate load forecasting [75] has been carried out with the help of ANN in restructured electrical power network.

ANN has been extended in the present work to compute ATC for secure and stable operation of power system and its effectiveness has been demonstrated on the IEEE 30 bus system. The system consisting of total 41 lines has been evaluated for a given IEEE 30 bus system. The objective of the study is to determine ATC calculation as fast as possible. For calculation of ATC, a back propagation feed forward algorithm has been used for secure and stable operation of power system.

## 3.2 Artificial Neural Network Based Available Transfer Capability computation

Due to the stressed operation of the power system networks today,the computation of Available Transfer Capability (ATC) has become one of the major concerns. The fast calculation of Available Transfer Capability (ATC) has been recognized as a key factor in real time operation of restructured power system for congestion management. The load flow has been run for all the the traded transactions to calculate ATC in deregulated environment. Hence, it will take more time to calculate ATC.

For the specific loading condition , the generation at different generator bus has been taken as inputs to the neural network and ATC is the output of the neural network. The data has been collected from Tournament Selection Based Genetic Algorithm to train the ANN with feed forward back propagation method as explained in next subsection.

### 3.2.1 Back Propagation Algorithm

For many year, there was no theoretical sound algorithm for the training of multilayer ANN. The Back Propagation Algorithm (BPA) has been identified as a systematic method for the training of multilayer ANN. BPA has been build on high mathematical foundation and good application potential.

The key idea of the method is to find a suitably enhanced representation of the input data. The inputs has been used for training along with the actual input data as shown in Fig:3.1.

This section describes an overview of Artificial Neural Networks (ANN), the ANN architecture with the MultiLayer Feed Forward (MLFF) network based on conventional back propagation algorithm [76]for training the neural network.

The biological neuronal network consists of numerous (trillion numbers) interconnections among the neurons. The collective actions in the network in which all the neurons has been interconnected give power to neurons. In a human brain, around 10 billion neurons are performing jointly with $10^{14}$ interconnections. An ANN has been created from the interconnection of several unit neurons or nodes. The neuron arrangement is capricious. It depends upon following factors:

- The Nature of Application.
- Motivation from the real biological structure.

The multilayer perceptron has been discussed in this presented work. The basic arrangement of ANN has been shown in Fig.3.1. There are three layers in the ANN structure i.e input layer, hidden and an output layer. These layers has been described as under:

- **Input layer**

  The input to the neural network is equal to the number of neurons. This layer consists of a passive nodes i.e.do not take part in the genuine signal alteration, but only transmits the signal to the following layer.

- **Hidden layer**

  It has a random number of layers with a capricious number of neurons. The node in this layer has been act as an active node, i.e. taking part in the signal modification.

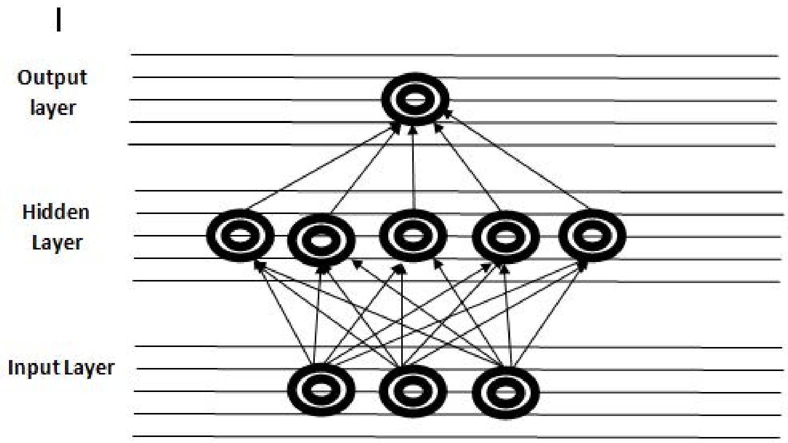


Figure 3.1: Fundamental structure of ANN

- **Output layer**

  For the perceptron in input layer, linear transfer function has been used. For the perceptron in hidden and output layer, sigmoidal function has been used. The input and output mapping has been shown by Fig:3.1. The output of the neural network is equal to the number of neurons in the output layer. The node in this layer has been active in nature.

The main theme of training the network is to produce the needed set of outputs. The output-input set has been assigned as vectors. At the training stage, each input vector has been paired with a target vector showing the desired output. This pair has been identify as a training pair. Normally, the number of training pair trained a network. This set of training pairs has been recognized as training sets.

As inputs has been passed from the input layer to the first hidden layer, the input gets increased by interconnection weights. The inputs get summed and processed by a nonlinear function like sigmoidal or hyperbolic tangent in the hidden layer. The data gets multiplied by weights before final one-time process within the output layer to create final neural network output after leaving the hidden layer.

The back propagation techniques [76] used to develop MATLAB algorithm as represented by mathematical formula.

### 3.2.2 Training of Neural network

For the mathematical modeling, following points to be considered.

1. Normalize the inputs and outputs variables with respect to their maximum value. The neural networks work superior between inputs and outputs range of $[0 - 1]$. For the each training pair,$l$ inputs are given by $I_I$ and $n$ input to $O_O$ in normalized form.

2. The number of hidden neurons (m) is within $l < m < 2 \cdot l$

3. $v$ stands for weight of nerves connecting between input and hidden neurons.

4. $w$ symbolize for weight of nerves connecting between hidden to output neurons.

5. Initialization of weight with random small number between $[0 - 1]$. The slop parameter $\lambda$ and threshold can be assumed 1 and 0 respectively.

6. Initialize weights $V^0 = W^0 =$ Random values and $\Delta V = \Delta W = 0$.

7. The pattern to the input layer is $[l_i]$. By using the linear activation function, the output of the input layer is given by Eq.3.1

$$[O]_I = [I]_I \tag{3.1}$$

8. The inputs to the hidden $[I_H]$ layers has been calculated by multiplying equivalent weights of synapses as

$$[I]_H = [V]^T \cdot [O]_I \tag{3.2}$$

9. The output using the sigmoidal function can be evaluated after hidden layer unit evaluated.

$$[O]_H = (1/(1 + e^{-I_{Hi}})) \tag{3.3}$$

   Work out the inputs to output layer by multiplying matching weights of synapses as

$$[I]_O = [W]^T \cdot [O]_H \tag{3.4}$$

10. the output layer units evaluated the output with the help of sigmoidal function for each output of $j_{th}$ neuron has been given by Eq. 3.5.

$$(O)_O = [1/(1 + e^{-I_{Oj}})] \tag{3.5}$$

11. The evaluation of error($ER^P$), divergence among the network output and desired output for the $i_{th}$ training set is given by 3.6

$$ER^p = \frac{\sqrt{\sum (T_j - O_{O_j})^2}}{n} \tag{3.6}$$

Where $T_j$ and $O_j$ are the target output and predicted output.

12. Change in weight $[\Delta W]$ has been comupted from Equation:3.7

$$[\Delta W]^(t + 1) = \alpha \cdot [\Delta W]^t + \eta_l [O]_H \cdot (d) \tag{3.7}$$

$\alpha =$ momentum coefficient. $[0.5 - 0.9]$

$\eta_l =$ learning rate.

The calculate (d) has been carried out by Eq. 3.8 for output of output of $k^{th}$ neuron

$$(d) = (T_k - O_{O_k}) \cdot (O_{O_k}) \cdot (1 - O_{O_k}) \tag{3.8}$$

Change in weight $\delta V$ has been determined by Eq. 3.9

$$[\Delta V]^{(t+1)} = \alpha [\Delta V]^t + \eta_l \cdot [O]_I \cdot (d)^* \tag{3.9}$$

13. Find $e$

$$e = [W] \cdot [d]^T \tag{3.10}$$

14. Compute $d^*$

$$d^* = e_i \cdot (O_{H_i})(1 - O_{H_i}) \tag{3.11}$$

15. Weights $[V]$ and $[W]$ are adjusted for the next iteration as presented by Eq. 3.12 and 3.12

$$[V]^{(t+1)} = [V]^t + [\Delta V]^{(t+1)} \tag{3.12}$$

$$[W]^{(t+1)} = [W]^t + [\Delta W]^{(t+1)} \tag{3.13}$$

16. Calculate error rate from 3.14

$$\text{Error rate} = \frac{\sum ER^p}{nset} \tag{3.14}$$

where, $nset = 20$ is number of observations

Repeat steps 7 to 20 until the convergence in the error rate is less than the tolerance value.

### 3.2.3 Implementation of Back Propagation for Available Transfer Capability Prediction

The artificial neural network based on the Back Propagation Algorithm (BPA) model have been developed for prediction of Available Transfer Capability (ATC) for the specific loading condition served by varying generator output. The present study was limited to only IEEE 30 bus system. Hence, the BPA model was trained and tested to predict ATC with generation at different generator bus for a specific loading condition. Original inputs to the BPA are the real power injections at generator bus to serve a load and compute optimized value ATC. The configuration parameters used in ANN architecture has been shown in Table:3.1. Figure 3.2 shows a block diagram of the ANN for ATC prediction listing the original inputs and output variables for a IEEE 30 bus system.

## 3.3 System Studies and Results

Once the training was complete, the ANN was tested with novel patterns not included in the training set. During training, the learning rate $\eta_l$ and and momentum $\alpha$ were taken as 0.6 and 0.9 respectively. The predicted ATC values were compared with their exact values obtained from Tournament selection based Genetic algorithm (TSBGA) method. The ATC prediction for a specific loading condition with generation variation are described below for the IEEE 30 bus system.

**IEEE 30 Bus System**

For IEEE-30 bus system the ANN was trained for 50 training patterns corresponding to different generation conditions for a specific load. After training, the ANN model was tested for 20 novel test patterns. These test patterns were not included in the training

Table 3.1: Configuration Parameters for ANN

| Sr.no | Parameter | Value |
|---|---|---|
| 1 | Activation function | Sigmoid |
| 2 | Learning rule | Back propagation |
| 3 | Initial weights | Random using MATLAB rand function |
| 4 | Number of layers | 03 |
| 5 | Number of input neurons | 05 |
| 6 | Number of neurons in hidden layer | 05 |
| 7 | Number of neurons in output layer | 01 |
| 8 | Momentum coefficient,$\alpha$ | 0.9 |
| 9 | Learning rate, $\eta_l$ | 0.6 |
| 10 | Number of training set(nset) | 50 |

patterns. During testing, the absolute average error, the absolute maximum error and absolute minimum error, and in the values of predicted voltages were found to be 0.545 %, 0.944 % and 0.100 % respectively.The values of Predicted ATC and Calculated ATC with different generations at generator nodes for a specific load 10 MW,15 MW and 22 MW at bus number 3, 10 and 25 respectively has been given in Table3.2 using neural network.

To assess the performance of neural network, the Mean Absolute Percentage Error (MAPE) formula has been used. The expression for MAPE is shown by Equation:3.15. The MAPE for the IEEE 30 bus test system is given by table: 3.3

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \cdot \frac{(ATC_{actuali} - ATC_{predicted_i})}{(ATC_{actual_i})} \tag{3.15}$$

The final weights has been used for final result output. After training, ANN will predicts the value of ATC for specific loading condition served by different generator. The final comparison has been presented by Fig. 3.3. The graphical presentations has been shown in Fig. 3.3.

Table 3.2: Comparison between Actual and Predicted value for ANN for IEEE 30 bus system

| **Sr.no** | MW Generation | | | | | **Actual** value of ATC | **Predicted** value of ATC | **Absolute** Percentage Error |
|---|---|---|---|---|---|---|---|---|
| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | | | |
| 1 | 43.01 | 1.91 | 39.54 | 32.99 | 42.62 | 84.25 | 84.85 | 0.71 |
| 2 | 43.01 | 1.66 | 39.98 | 34.26 | 41.06 | 83.09 | 83.81 | 0.86 |
| 3 | 43.01 | 1.66 | 39.98 | 34.26 | 41.06 | 83.09 | 83.81 | 0.86 |
| 4 | 42.23 | 1.86 | 39.88 | 32.94 | 43.50 | 85.14 | 85.31 | 0.20 |
| 5 | 39.88 | 1.66 | 39.98 | 34.26 | 40.66 | 84.30 | 84.38 | 0.10 |
| 6 | 39.88 | 1.66 | 39.98 | 34.26 | 40.66 | 84.30 | 84.38 | 0.10 |
| 7 | 39.98 | 1.71 | 39.98 | 34.26 | 41.06 | 84.39 | 84.55 | 0.19 |
| 8 | 39.88 | 1.66 | 39.98 | 33.48 | 41.94 | 85.50 | 85.25 | 0.30 |
| 9 | 39.88 | 1.66 | 39.88 | 33.48 | 41.84 | 85.69 | 85.21 | 0.56 |
| 10 | 39.88 | 1.66 | 39.88 | 33.48 | 41.84 | 85.69 | 85.21 | 0.56 |
| 11 | 39.93 | 1.66 | 39.88 | 33.48 | 41.84 | 85.66 | 85.20 | 0.53 |
| 12 | 39.93 | 1.66 | 39.88 | 33.48 | 41.84 | 85.66 | 85.20 | 0.53 |
| 13 | 43.06 | 1.66 | 39.49 | 34.26 | 41.84 | 84.95 | 84.18 | 0.91 |
| 14 | 43.06 | 1.66 | 39.49 | 33.48 | 41.06 | 83.42 | 84.21 | 0.94 |
| 15 | 46.38 | 1.66 | 39.88 | 33.48 | 43.40 | 84.97 | 84.70 | 0.32 |
| 16 | 46.38 | 1.66 | 39.88 | 33.48 | 43.40 | 84.97 | 84.70 | 0.32 |
| 17 | 44.62 | 1.66 | 39.98 | 33.48 | 43.40 | 85.22 | 85.02 | 0.23 |
| 18 | 43.26 | 0.10 | 39.98 | 33.48 | 41.06 | 85.87 | 85.11 | 0.88 |
| 19 | 43.60 | 0.34 | 39.98 | 31.52 | 42.82 | 88.43 | 89.20 | 0.87 |
| 20 | 43.35 | 0.34 | 39.98 | 31.87 | 42.86 | 89.89 | 89.08 | 0.90 |
| | | | | | | | Mean Absolute Percentage Error | 0.545 |

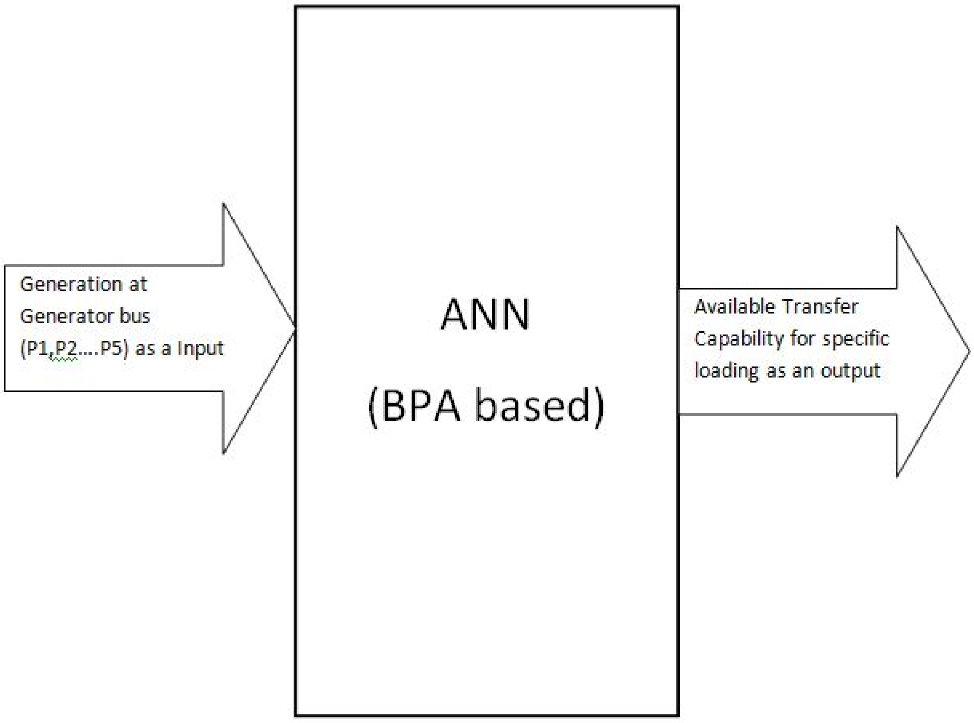


Figure 3.2: Block diagram of ANN based ATC Prediction

Table 3.3: Error in Prediction of ATC using ANN for IEEE 30 Bus system

| Test system | Percentage Error | | |
|---|---|---|---|
| | MAPE | Max. Error | Min. Error |
| IEEE 30 bus test System | 0.545 | 0.944 | 0.100 |

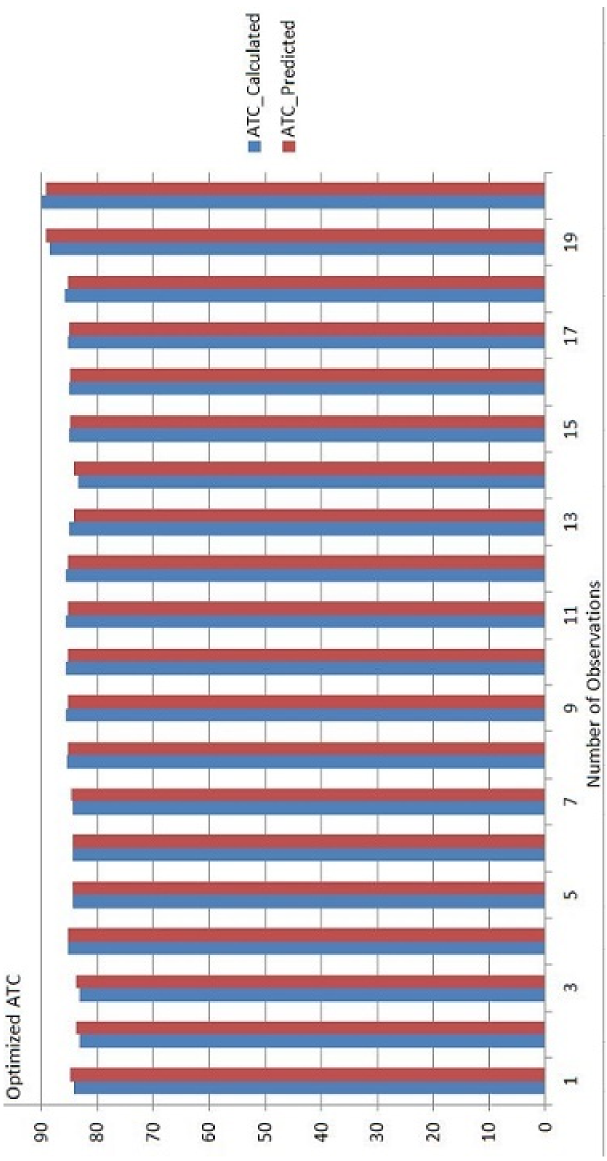


Figure 3.3: Bar chart comparison of Actual and Predicted value of ATC for IEEE 30 Bus system

## 3.4 Conclusion

The Artificial Neural Network using generalized back propagation has been designed to predict ATC. As shown in Table 3.3 the Mean Absolute Percentage error,maximum percentage error and min percentage error are 0.545 %, 0.944 % and 0.100 % respectively for IEEE 30 bus system. The model developed is sufficiently accurate and used for on line prediction of ATC.