Multi-output On-Line ATC Estimation in Deregulated Power System Using ANN

R. Prathiba, B. Balasingh Moses, Durairaj Devaraj, and M. Karuppasamypandiyan

Abstract. Fast and accurate evaluation of the Available Transfer Capability (ATC) is essential for the efficient use of networks in a deregulated power system. This paper proposes multi output Feed Forward neural network for on line estimation of ATC. Back Propagation Algorithm is used to train the Feed Forward neural network. The data sets for developing Artificial Neural Network (ANN) models are generated using Repeated Power Flow (RPF) algorithm. The effectiveness of the proposed ANN models are tested on IEEE 24 bus Reliability Test System (RTS). The results of ANN model is compared with RPF results. From the results, it is observed that the ANN model developed is suitable for fast on line estimation of ATC.

Keywords: Artificial Neural Network, Available Transfer Capability, Bilateral transaction, Repeated Power Flow.

1 Introduction

Transition of electric industry from its vertically integrated structure to horizontal structure poses many problems to power system engineers and researchers [1].In the environment of open transmission access, US Federal Energy Regulatory Commission (FERC) requires that Available Transfer Capability (ATC) information be made available on a publicly accessible Open Access Same Time Information System (OASIS) [2]. Methods based on DC load flows [3] are faster

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than the AC load flow [4], since no iterations are involved. Complexity in computation is also less as the number of data to be used is less. The DC-Power Transfer Distribution Factors (DC-PTDF) [5] are easy to calculate and can give quick estimate of ATC. But the ATC values calculated using them are not very accurate as DC power flow neglect reactive power effects. AC-PTDFs for transfer capability calculation is investigated in [6].AC-PTDFs are based on derivatives around the given operating point and may lead to unacceptable results when used at different operating points to calculate ATC. Also, neither DC nor AC PTDFs based method considers generator limits and bus voltage limits when used to determine ATC. The continuation power flow(CPF)based methods[7] perform full-scale ac load flow solution, and is accurate but due to the complexity involved in the computation it is difficult to be implemented for large systems. The optimal power flow and RPF based methods [8-9] determine ATC formulating an optimization problem in order to maximize the power transmission between specific generator and load subject to satisfying power balance equations and system operating limits. The conventional methods are not applicable for fast estimation of ATC. Neural Network for Estimation of ATC between two areas was developed using ACPTDF [10].MLP Neural network was designed with Quick Prop algorithm to train the network for IEEE 30 bus system and was useful for reliability assessment [11]. A novel MLP with input feature selection and Levenberg-Marquardt algorithm was designed for both bilateral and multilateral transactions in [12] for single and multi-output ATC and the performance is compared with Optimal power flow.

A new model employing multi-output artificial neural networks to calculate transfer capability is developed in this paper. Based on the power flow formulation for calculating real power transfer capability and with the strong generalizing ability of the neural networks, the new model can calculate ATC quickly for a given power system status. This paper is organized as follows. Section 2 provides the methodology for computation of ATC. In section 3 proposed method for ATC estimation and training algorithm to formulate the input-output data set for the ANN is discussed. Section 4 discusses the review of ANN and BPA algoritham. Simulation results are discussed in Section 5. The outcome of the proposed method is concluded in section 6.

2 Computation of ATC

The objective is to estimate the Available Transfer Capability (ATC) for a bilateral contract by increasing the generation at a seller bus/buses and at the same time increasing the same amount of load at the buyer bus/buses, until the power system reaches system limits

Mathematically, each bilateral transaction, between a seller at bus-i and power purchaser at bus-j, satisfies the following power balance relationship.

$$P_{gi} - P_{dj} = 0 \tag{2.1}$$

Where, P_{gi} and P_{dj} are the real power generation at bus-i and real power consumption at bus-j.

ATC for a bilateral contract can be calculated by increasing the generation at a contracted seller bus/buses and at the same time increasing the same amount of load at the contracted buyer bus/buses, until the power system reaches system limits.

$$\text{ATC value is given by} \quad \text{ATC} = \text{TTC} - \text{ETC} \tag{2.2}$$

Where,

TTC-Total Transfer Capability

ETC - base case transfer

Provided TRM and CBM are assumed to be zero for the sake of simplicity.

Subject to the following operating conditions.

$$P_i - \sum_{j=\in N} V_i V_j Y_{ij} \cos(\theta_{ij} + \delta_j - \delta_i) = 0 \tag{2.3}$$

$$Q_i - \sum_{j=\in N} V_i V_j Y_{ij} \sin(\theta_{ij} + \delta_j - \delta_i) = 0 \tag{2.4}$$

$$V_{min} \leq V \leq V_{max} \tag{2.5}$$

$$S_{ijmin} \leq S_{ij} \leq S_{ijmax} \tag{2.6}$$

Where
N- Set of all buses
P_i, Q_i - Real and reactive power at the ith bus
Y_{ij}, δ_i - Bus matrix elements
V_i, δ_i - Magnitude and angle of ith bus

The testing and training data generation for ANN is done using RPF.

3 Proposed Approach for ATC Estimation

The ATC for real time application by ANN approach is proposed. The objective is to estimate the ATC for bilateral transactions under different loading conditions. The real and reactive power for different loading condition is given as the input for NN and the output of NN is the ATC value in MW for different transaction. The schematic diagram of learning stage of neural network is shown in Figure 1. Neural network approach for any application has three stages: Normalization of inputs, training and testing stages. While training the network, the input and output are first normalized between 0 and 1. The input variables after normalization are presented to the neural network for training.

After training, the networks are evaluated through a different set of input– output data. Once the training and testing of the network is over, then the network will be ready for on-line application.

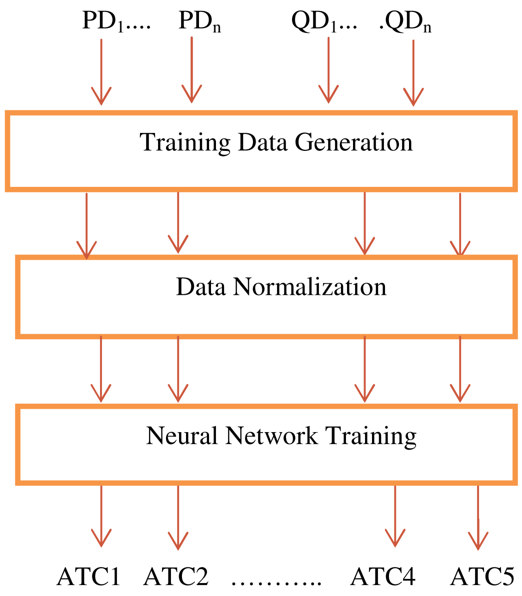

Fig. 1 Schematic diagram of NN learning stage

The various steps involved in the development of multi output ANN – based ATC estimation model are

3.1 Training Set Generation

*F*or generating the training set, a large number of load patterns were generated by perturbing the loads randomly (70 % to 130%) at all the buses. The transaction depends on various factors such as load level, generation level, line status, generator status etc., the frequently changing parameter is the load and so it is taken as input to the ANN. The training set generation is done in off-line mode .The dimension of inputs used in this model is 34x250, where both real and reactive powers are taken with 250 varying load conditions. In the proposed model the ANN will estimate the ATC values for different transactions.

3.2 Normalization of the Data

Normalization of the data is an important aspect for training of the neural network. Without normalization, the higher valued input variables may tend to suppress the influence of smaller ones. To overcome this problem, neural networks are trained with normalized input data. The value of input variables is scaled between some suitable values (0 and 1 in the present case) for each load pattern. In case of output variables, if the value varies over a wide range, the neural network is not able to map it correctly. The remedy is to scale the output between some suitable range (0 and 1 in the present case).

$$x_n = \frac{(x - x_{\min})}{(x_{\max} - x_{\min})} + startingvalue \tag{3.1}$$

Where x_n is the normalized value, and, x_{min}, x_{max} are the minimum and maximum values of the variable x.

3.3 Training and Testing of Neural Network

The neural network used for ATC estimation consists of three layers. The input layer has neurons equal to the number of inputs selected and output layer has six neuron. The activation functions used in the hidden layer neurons have tangent hyperbolic function and the output neurons have linear activation function. The number of hidden units depends on the input units. Best number of hidden unit is determined by training several networks and estimating the generalization error. Large networks require longer training time. Trial and error procedure is followed to select the suitable number of neurons in the hidden layer. The generated variables after normalization are given as input to the neural network for training. After training, the networks are evaluated through a different set of input–output data. Now the developed multi-output ANN can estimate ATC values for different operating conditions.

4 Review of Artificial Neural Network

An ANN is defined [13,14] as a data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons).This architecture is inspired by the structure of the cerebral cortex of the brain.

A structure of multi-layer feed forward network is shown in figure 2.

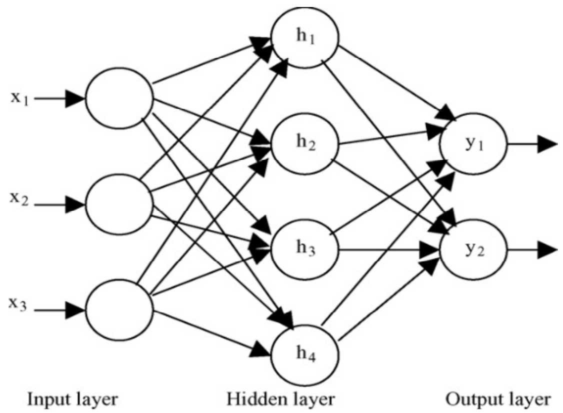

Fig. 2 Artificial Neural Network Structure

The ANN used here consists of three layers, the input vector, hidden layer and output vector. A network is trained so that application of a set of inputs produces the desired (or at least consistent) set of outputs. Each such input (or output) set is referred to as a vector. Training is accomplished by sequentially applying input vectors, while adjusting network weights according to a predetermined procedure. During training, the network weight gradually converts to values such that each input vector produces the desired output vector.

To reduce the computational effort by the conventional method, Back-Propagation Algorithm (BPA) based on Feed forward Neural Network has been utilized to compute the ATC. During the training phase, the training data is fed into the input layer. The data is propagated to the hidden layer and then to the output layer. This is called the forward pass of the Back Propagation Algorithm. In the forward pass, each node in hidden layer gets input from all the nodes of input layer, which are multiplied with appropriate weights and then summed. The output of the hidden node is the non- linear transformation of the resulting sum. Similarly each node in output layer gets input from all the nodes of hidden layer, which are multiplied with appropriate weights and then summed. The output of this node is the non-linear transformation of the resulting sum.

This is mathematically represented as,

$$out_i = f(net_i) = f\left[\sum_{j=1}^{n} w_{ij} out_j + b_i\right] \tag{4.1}$$

Where out_i is the output of the i_{th} neuron in the layer under consideration. out_j is the output of the j_{th} neuron in the preceding layer. w_{ij} are the connection weights between the i_{th} neuron and the j_{th} inputs and b_i is a constant called bias.

The output values of the output layer are compared with the target output values. The target output values are those that we attempt to teach our network. The error between actual output values and target output values are calculated and propagated back toward hidden layer. This is called the backward pass of the back propagation algorithm. The error is used to update the connection strengths between nodes, i.e. weight matrices between input-hidden layers and hidden-output layers are updated.

Mathematically it is written as,

$$W_{ij}(k+1) = W_{ij} + \Delta W_{ij} \tag{4.2}$$

Where W_{ij} is the weight from hidden unit i to output unit j at time k and ΔW_{ij} is the weight adjustment.

During the testing phase, no learning takes place i.e., weight matrices are not changed. Each test vector is fed into the input layer. The feed forward of the testing data is similar to the feed forward of the training data.

5 Simulation Results

This section presents the details of the simulation study carried out on IEEE 24-bus Reliability Test System [15,16] for ATC estimation using the proposed approach. For this system ANN model was developed to estimate the ATC for different bilateral transactions. Neural network toolbox in MATLAB was used to develop the ANN models. The details of the ANN models developed are presented here

5.1 ATC Assessment in IEEE RTS 24 Bus System

IEEE RTS 24 bus system consists of 11 generator buses, 13 load buses and 38 transmission lines. For generating training data for the ANN, the loads at the load buses are varied randomly between 70% to 130% of base load. Based on the algorithm presented in section 3, a total of 250 input-output pairs were generated with 150 for training and 100 for testing. The real and reactive power loads at all load buses are given as input of the neural network and respective ATC values are the output.

The parameters of the network used here are given below:

No. of input – 34
No. of output – 6
No. of hidden neurons – 10
Mean Square Error – $7.730\text{x}10^{-5}$
The network took 44.38sec to reach the error goal.

Table 1 shows training and testing performance of the network for bilateral transaction between 23-3 under normal operating condition. The ATC value obtained at 115% loading condition is 75.95MW.The mean square error is$6.116\text{x}10^{5.}$ The time taken by the network is 1.546s. No. of hidden nodes used are 10 Nos.

Table 1 Training and Testing performance of the Network

Test case	Transaction type	No of Hidden Nodes	Training time(Sec)	Testing Error (mse)
1	23-3	10	1.5756	$6.116\text{x}10^{-5}$

Table 2 shows ATC values for bilateral transaction (23-3), generated by the ANN for different loading condition. In transaction 23-3, bus 23 is source bus and bus 3 is sink bus. ATC obtained from RPF, ANN and the percentage of error in estimating ATC are also given here.

Table 2 ATC values estimated for bilateral transaction (23-3)

% Loading condition	ATC(MW)		% Error
	ANN	RPF	
80.82	159.83	159.00	0.005
86.95	148.39	147.30	0.742
90.95	139.93	139.00	0.006
96.85	126.34	126.00	0.271
100.59	116.92	117.15	0.213
105.2	104.61	105.50	0.84
115.37	75.91	77.20	1.67
119.0	65.31	66.00	0.01
126.07	42.97	42.75	0.51

Table 3 Comparison of RPF and ANN output

Set of Transactions	No of Hidden Nodes	Training time (Sec)	Testing Error (mse)
23-3,21-6,22-5,23-15,18-5	10	44.38	$7.73X10^{-5}$

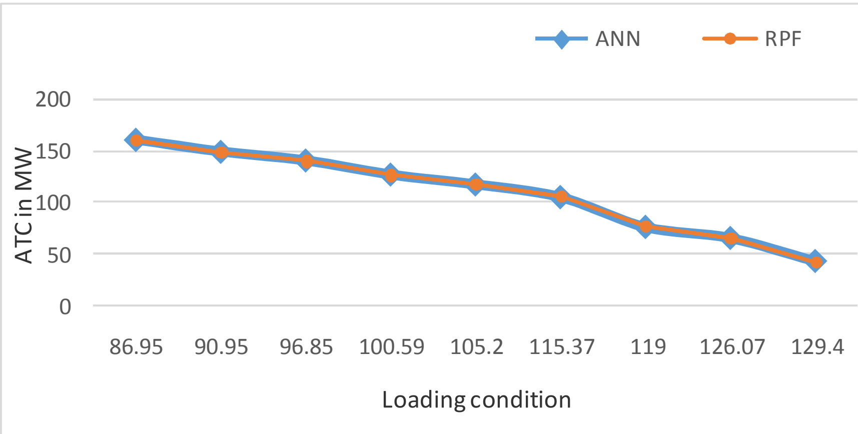

Fig. 3 Comparison of ATC values of RPF with ANN

Table 3 shows training and testing performance of the multi output network for a set of bilateral transaction between 23-3, 21-6, 22-5, 23-15, 18-5 under normal operating condition. The mean square error for the developed model is7.73×10^{-5}. The time taken by the RPF is approximately between 30 to 60 minutes depends on different bilateral transaction and for the developed ANN network it is 44.38s thus validating the objective of on line estimation of ATC.

The Fig 3 shows the ANN estimate accurately in comparison with RPF hence, the proposed ANN is computationally efficient and hence it is suitable for on-line estimation of ATC in real time applications for a set of bilateral transaction.

Table 4 Multi-Output ATC Values for set of Transactions

% Loading condition	Transaction	ATC(MW)		%Error
		ANN	RPF	
80.82	23-3	159.1055	159.0000	0.0663
	21-6	159.6060	159.8500	0.1526
	22-5	220.5404	220.2500	0.1318
	23-15	983.2275	978.4000	0.4934
	22-9	217.7627	218.7500	0.4513
	18-5	212.3887	211.9500	0.2069
86.95	23-3	147.2438	147.3000	0.03815
	21-6	145.7208	145.6000	0.0829
	22-5	243.5330	244.1500	0.2527
	23-15	942.2427	943.2000	0.1014
	22-9	271.7608	268.8500	1.0826
	18-5	147.2438	147.3000	0.0381
90.95	23-3	138.8436	139.0000	0.1125
	21-6	136.0366	136.2000	0.1199
	22-5	237.5142	237.2500	0.1113
	23-15	923.8467	919.8500	0.4344
	22-9	296.9590	301.8000	1.6040
	18-5	237.8198	237.1500	0.2824
100.59	23-3	117.2028	117.1500	0.0450
	21-6	113.8265	113.7500	0.0672
	22-5	218.1531	218.2000	0.02149
	23-15	860.3805	863.8000	0.3958
	22-9	281.5755	279.5000	0.7425
	18-5	217.9468	218.1500	0.0931

Table 4 (*continued*)

105.2	23-3	105.5046	105.500	0.0043
	21-6	102.9265	102.900	0.0257
	22-5	207.6826	207.6500	0.0156
	23-15	832.9591	836.4500	0.4173
	22-9	259.5942	259.1000	0.1903
	18-5	207.4827	207.6500	0.0805
115.37	23-3	77.2100	77.2000	0.0129
	21-6	78.8982	78.9500	0.0656
	22-5	181.0146	181.0500	0.0195
	23-15	781.8435	775.4500	0.8244
	22-9	203.4577	204.3500	0.4366
	18-5	181.1349	181.1000	0.0192

The Table 4 shows Multi-output ATC values for six sets of bilateral transaction obtained using ANN and RPF for different loading condition. The percentage error between ANN output and RPF is calculated and presented in Table 4.

6 Conclusion

In a real time operation of deregulated power system, the ISO has to estimate ATC values for many possible proposed transactions. As the ANN can estimate ATC value for more than one proposed transactions simultaneously, the ISO can evaluate many transactions in short time. This enhances the performance of ISO. This paper has presented an ANN-based multi-output ATC estimation method for on-line applications.Simulation was carried out on the IEEE 24-RTS bus system. Results shows that the ANN model with BPA based approach provides estimation of Multi-output ATC for set of transactions under different loading conditions. Hence for large scale practical power systems the proposed ANN model can estimate ATC in lesser computation time with reasonably good accuracy. This makes the ANN model suitable for real time applications.

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