Multiple Output Radial Basis Function Neural Network with Reduced Input Features for On-line Estimation of Available Transfer Capability

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Abstract: In the deregulated power system, the Independent System Operator (ISO) has to update the value of Available Transfer Capability (ATC) on Open Access Same Time Information System (OASIS) for the secure bilateral/multilateral transaction planning. The off-line methods for calculating ATC requires large computation time and or not suitable for on-line estimation, hence the on-line updating of ATC requires an accurate method with lesser computation time. In this paper, Radial Basis Function Neural Network (RBFNN) with input feature reduction has been proposed for on-line ATC estimation for both bilateral and multilateral transactions under normal condition. Multiple and Multi Neural Network is developed and their performance is analyzed. The training data for Neural Network is generated using Repeated Power Flow (RPF) Algorithm. One of the challenges in the development of Neural Network in the power system is the selection of suitable input variables because a power system contains thousands of variables. For this purpose, a straight forward and quick procedure called the Sequential Feature Selection (SFS) is used to extract the most influenced variables, as features from a large set of variables. Simulation work is performed on standard IEEE 24 bus Reliability Test System (RTS) and IEEE 118 bus system. The feasibility of implementation of the proposed Neural Network for on-line ATC evaluation is discussed. The result of the proposed model is compared with the conventional RPF and developed BPA models. Test result shows the effectiveness of the Neural Network approach for on-line estimation of ATC.

Keywords: Available Transfer Capability Deregulated Environment, Radial Basis Function, Repeated Power Flow and Sequential Feature Selection.

1. INTRODUCTION

In a competitive electricity market, generation companies and distribution utilities are engaged by bilateral/multilateral transactions. Accurate estimation of ATC plays a crucial role in deregulated environment. The ATC of a system is the maximum amount of power that can be transferred between source and sink without violating the voltage and line limit (NERC, 1996) Mathematically ATC is defined as Total Transfer Capability (TTC) minus sum of the Transmission Reliability Margin (TRM), Existing Transmission Commitments (ETC) and capacity benefit margin (CBM) Valuated ATC are posted in an open access same time information system (FERC, 1996) after reporting to the Independent system operator.

Different methods for calculating ATC are proposed in the literature. DC load flow method (Christe et al., 2000) are bit faster than their ac counterparts but model only real power flow in the lines rather than MVA, and assume the network to be loss free. .Multiple ATCs (Hamound, 2000) are computed between more than one pair of locations using PROCOSE which uses dc model. (Yan et al., 2002) proposes transfer based security constrained OPF with probabilistic method to incorporate TRM in ATC calculation. Power transfer distribution factor method (PTDF) is used by many electric utilities for determination of ATC (Kumar et al., 2004*).* (Ejebe et al., 1998) used corrector and predictor method for ATC calculation. It is accurate, but its calculations are complex and time consuming. The RPF (Khaburi et al., 2010*)* due to the repeated solving of power flow, after meeting the constraints is time consuming and not suitable for on line application. The OPF (Joo et al., 2004*)* method determine ATC by 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. Hence the optimal power flow methods are time consuming.

Several methods have been made to speed up and improve the accuracy of calculation of ATC. (Khairuddin et al., 2004) proposed a fuzzy logic, which requires three inputs irrespective of system size for the determination of ATC. The ANN (Luo et al., 2000) requires a large input vector so that the training and testing time required is more. Input feature selection (Jain et al., 2007) method is incorporated for static

ATC with contingency effect in MLP and found to be efficient. (Rao et al., 2008) proposes an MLP with BPA using ACPTDF for the determination of ATC, and the transaction is carried between two areas in IEEE 30 bus system and the results are encouraging. An Adaptive Neural network (Sefriti et al., 2012) for tuning of parameters in neural networks in combination with Fuzzy is proposed and the method if incorporated for power systems leads to handling of large amount of data's for ATC calculation. Support Vector machine (Vaithilingam, 2013) is implemented to find ATC and the time taken for training is found to be independent of the size of the system. A non-holonomic Adaptive neural network for capability calculations is proposed by (Francisco G et al., 2014). Methods reported in literature can estimate single output ATC for different operating conditions, and multiple outputs ATC (Prathiba et al., 2014*)* without reduction in inputs.

This paper proposes RBF network for on-line estimation of ATC with reduced input features. Sequential Forward selection (SFS) method is adopted for selecting an optimal feature set. The time taken by RBFN for training is less and the distance based activation function used in the hidden nodes gives the ability to detect the outliers during the estimation. In addition with the reduced input features, performance of the network is higher with smaller computational effort. The effectiveness of the neural networks is tested on IEEE 24 Reliability Test System (RTS) and IEEE 118 bus system. The results are compared with RPF and developed BPN networks.

This paper is organized as follows: Section 2 provides computation of ATC. In Section 3 proposed method for ATC estimation is briefed. The training algorithm and the methodology to formulate the input-output data set for the ANN is discussed in Section 4. The proposed methodology is implemented in Section 5and case study is given in Section 6 to demonstrate the effectiveness of the presented method. Finally, a conclusion is made in Section 7.

2. COMPUTATION OF ATC

The objective is to estimate the Available Transfer Capability (ATC) for a Bilateral/Multilateral contract by increasing the generation at 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:

$$P_{Gi} - P_{Dj} = 0 \tag{1}$$

Where,P_{Gi} and P_{Dj} are the real power generation at bus-i and real power consumption at bus-j. The bilateral transaction concept can be generalized to multilateral case, where the seller may inject power at several nodes and the buyer can draw loads at same or several nodes. A transaction power balance of injection of power and drawing of power should be satisfied.

Mathematically, each multilateral transaction, between a seller at bus-i and power purchaser at bus-j, satisfies the following power balance relationship and is expressed as

$$\sum_i P_{Gj}^k - \sum_j P_{Di}^k \quad = 0\,, k \quad 1,2,\ldots\ldots.t_k \tag{2}$$

Where,P_{Gj}^k and P_{Di}^k stand for the power injections into the source bus-i and power taken out at the sink bus-j, and $t_k$is the total number of multilateral transactions

ATC is calculated as

$$ATC_i = P_{Di} - P_{Di}^0 \quad , \ \forall_i \ \in t_k \tag{3}$$

The above equation is used for bilateral transactions and equation 4 is used for multilateral transaction calculations

$$ATC_i \quad = \sum_i P_{Di}^k - \sum_j P_{Di}^{k0} \quad , \ k \quad 1,2,\ldots\ldots.t_k \tag{4}$$

Where, P_{Di}^k is the maximum transfer load at the ithbus,$P_{Di}^{k0}$is the base case load and t_k is the total number of transactions. Provided TRM and CBM are assumed to be zero for the sake of simplicity.

Satisfying the following operating conditions

$$P_i - \sum_{j=\in N} V_i V_j Y_{ij} \cos\left(\theta_{ij} + \delta_j - \delta_i\right) = 0 \tag{5}$$

$$Q_i - \sum_{j=\in N} V_i V_j Y_{ij} \sin\left(\theta_{ij} + \delta_j - \delta_i\right) \ = 0 \tag{6}$$

$$V_{min} \le V \le V_{max} \tag{7}$$

$$S_{ijmin} \le S_{ij} \le S_{ijmax} \tag{8}$$

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

Repeated power flow approach for bilateral transaction starts from a base case, and repeatedly solves the power flow equations each time increasing the power transfer by a large increment until an operation limit is reached, here it is thermal and voltage limit. The power transfer is then decreased one step after that it is increased by smaller steps until operation limit is reached. This is done to find accurately the value of ATC. The maximum possible increase in demand which causes no operating limit violation is the ATC.

To calculate ATC for Multilateral transaction which involves more than one seller and one buyer follows the same procedure. Here, power is injected at different buses and taken out at some other buses simultaneously, such that the sum of all generations are equal to all loads in the transaction.

The advantage of this approach is its simple implementation and the ease to take security constraints into consideration. The above method of calculating ATC takes more time for computation and it is not suitable for on-line ATC computation. In this paper, this method is adopted to generate the training and test data for the feature selected RBFNN, approach which is suitable for on-line applications.

3. PROPOSED APPROACH FOR ATC ESTIMATION

The ATC for real time application by Radial Basis Function Neural network approach is proposed. The objective is to estimate the ATC for bilateral/multilateral 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 Fig.1. Neural network approach for any application has three stages: feature selection of inputs, training and testing stages. During the training stage the network is trained using the set of selected randomly generated data sets by using feature selection which extracts the most influence load data's for determination of ATC. This extraction method reduces the dimensionality of inputs to ANN thus substantiating the use of ANN for on line application. 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. Review of Radial Basis Function (RBF) is given in the section IV and the development of the same for the present application is given in section V.

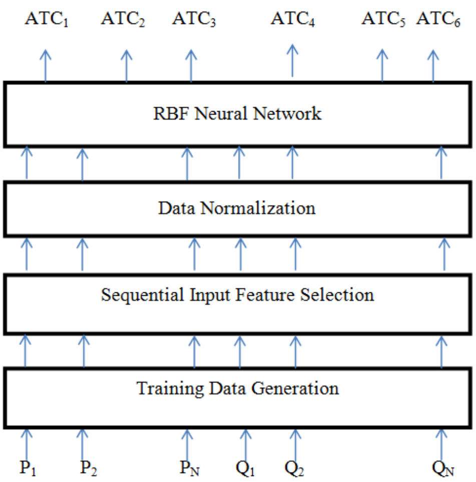

Fig. 1. Schematic diagram of NN learning stage.

4. REVIEW OF RADIAL BASIS FUNCTION (RBF) NEURAL NETWORK

A feed–forward networks (Laurence V. Fauzett., 1993) RBF employs supervised learning algorithm for training. The activation function used for the hidden units is selected from a class of function called basis function. Properties of RBF's such as localization, approximation, interpolation made them attractive in many applications.

RBFN has only one nonlinear hidden layer and linear output layer. During training, all of the input variables are fed to hidden layer directly without any weight and only the weights between hidden and output layers have to be modified using error signal. BPA model requires weight updation in all three layers (Sefriti et al., 2012).Thus RBFN requires less training time in comparison to BPA model (Devaraj et al., 2002). The diagram of RBFN used in the present work is shown in Fig. 2. The RBF network is a three layer feed forward network. The transfer function of hidden nodes is same as that of multivariate Gaussian density function (Francisco et al., 2014).

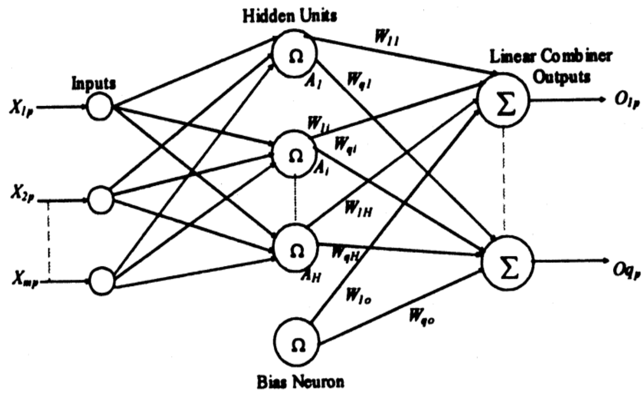

Fig. 2. RBF Neural Network Multiple output Structure.

The output of the jth unit $\emptyset_j(x)$ in the hidden layer is given by the mathematical expression as

$$\emptyset_j(x) = exp\left[-\frac{\|x-u_j\|}{2\sigma_j^2}\right]^2 \qquad (9)$$

Where x is the input vector, u_j, σ_j are the centre and spread of the corresponding Guassian function.||| denotes the Euclidean distance between x and u_j. The connections between the hidden units and the output units are weighted sums. The output value y_k of the k^{th} node is given by,

$$y_k = \sum_{j=1}^{h} W_{kj}\emptyset_j(x) + W_{ko} \qquad (10)$$

The parameters of the RBF units are determined in three steps of the training activity (Devaraj et al., 2011).First, unit centres u_j are determined by the K-means clustering algorithm. Then the widths are determined by a heuristic approach that ensures the smoothness and continuity of the fitted function. The width of any hidden node is taken as the maximum Euclidean distance between the identified centres. Finally, weights connecting the RBF units and the output units are calculated using multiple regression techniques using a least-squares objective function. The normalized input and output data are used for training of the RBF neural network. Radial Basis Function Network (RBFN), which has nonlinear mapping capability, has become increasingly popular in recent years due to its structural implicitly and training efficiency. The potential advantage of Radial Basis

Function Network (RBFN) is its ability to augment new training data without the need for retraining.

5. DEVELOPMENT OF RBFN FOR ATC ESTIMATION

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

5.1 Training Set Generation

For 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 NN. The training set generation is done in off-line mode (Ajit kumar Singh et al., 2013).The dimension of inputs used in IEEE 24-RTS is 250x34, where both real and reactive powers are taken with 250 varying load bilateral/multilateral transactions.

5.2 Input features selection

When electric power is transmitted from one location to another, the entire transmission network responds to that transaction. Flow of power in the transmission lines and bus voltages depend on the network topology, real and reactive power of the load bus, other transactions on the network etc. The ATC of any transmission interface would, therefore, become a function of all these variables. In this paper the input selected for training the neural network were real and reactive loads at all the buses. All the real and reactive loads may not have larger impact on the calculation of ATC, but only few of them will have. Hence the features having greater influential on the calculation of ATC were identified by using Sequential feature selection.

5.3 Sequential Feature selection Technique

Feature selection, a form of dimensionality reduction, is a process of selecting a small optimal set of attributes called features, which will give more useful information for classification. Engineering judgments can also be used for selecting the variables, but the probability of important variables getting rejected is more. Feature selection methods are grouped into two categories namely filter and wrapper method.

In filter method, features are scored and ranked based on certain statistical criteria and the features with the highest ranking values are selected. Frequently used filter methods include t-test, chi-square test, Wilcoxon Mann-Whitney test, Mutual information, Pearson correlation coefficients and Principal component analysis. Filter methods are fast but lack robustness against interactions among features and feature redundancy (Gheyas, 2010).

In wrapper approach, feature selection is wrapped in a learning algorithm. The learning algorithm is applied to subsets of features and tested on a hold-out set and prediction accuracy is used to determine the feature set quality. Generally, the wrapper method is more effective than the filter method because it is a problem-specific method and has better generalization ability. Wrapper methods are broadly classified into two categories based on the search strategy: (i) greedy and (ii) randomized/stochastic. Greedy wrapper method has less computation time than stochastic wrapper method (Kalyani et al., 2011).

Sequential Feature Selection is a greedy wrapper method, which adds or removes from a candidate subset based on evaluation of criterion. Sequential Backward Selection (SBS) and SFS are the two commonly used sequential feature selection methods. SBS method starts with the set of all features and progressively eliminates the least promising ones until no further increase in objective function is reached. SBS stops if the performance of learning algorithms drops.Moreover, in the case of problems dealing with high-dimensional data, SBS finds difficulties in identifying effect of variables on target and also becomes highly time consuming (Gheyas et al., 2010).

5.4 Sequential Forward selection Technique

SFS starts with an empty feature set and iteratively selects one feature at a time, starting with the most promising feature, and evaluating the criterion function based on a 10-fold cross validation. Criterion function is an evaluation function used to test the quality of feature subset. The criterion function used in the present work is loss measure that is calculation of MSE in cross validation of each candidate feature subset. This process is continuous until no further decrease in criterion function is obtained by adding more features (Kalyani et al., 2011).

5.5 SFS Algorithm

Step 1 : Start with an empty set $Z_0 = \{0\}$.

Step 2 : Set the feature count K=1.

Step 3 : Select the best pattern attribute X* giving minimum error rate, i.e.

$$X^* = min_{x \notin Z_k} [J(Z_{k-1} + X^*)] \tag{11}$$

Step 4 : Set $Z_K = Z_{k-1} + X^*$; $k = k + 1$.

Step 5 : Move to step 2 until there is no further decrease in the criterion function J.

5.6 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 eight neurons. The first stage of RBF network learning is the identification of the cluster centres through K-means clustering algorithm which uses Euclidean distance as a measure of dissimilarity. 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. Trial and error procedure is followed to select the suitable number of neurons in the hidden layer.

Twenty iterations of the clustering algorithm followed by liner regression are performed to estimate the parameters of the network. The selected 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. Separate networks dedicated for each normal and contingency state are developed using the data set. Now the developed models of RBFN can estimate ATC values for different operating conditions.

6. RESULTS AND DISCUSSION

The proposed RBFN-based unified approach was applied to IEEE24-RTS, and IEEE-118 bus system (Power System test case, 1993) for on-line estimation of ATC under normal state. Different types of transactions involving both bilateral and multilateral contracts have been considered. Bus voltage limits, line flow limits and generators real and reactive power limits have been considered for determination of the static ATC. The ATC is calculated in terms of real power transfer only. For determination of ATC, both real and reactive power loads at selected sink bus have been increased. The reactive power is increased as a percentage of real power increase. The outcome of the trained network is compared with BPNN and the performance by the conventional Repeated Power Flow algorithm. For the test system, totally four different Neural Network Models have been developed for determining Static ATC under different operating conditions. For each test system, 150 data are used for training and 100 data sets are used for testing. The NN models are developed using the MATLAB toolbox. The ATC estimation is carried out on Intel (R) Core (TM) i5-3317U CPU 1.70 $GH_{Z.}$ Processor.

The developed neural network models are,

Case 1 : Multiple Neural Networks with and without Input Reduction

Case 2 : Multiple-Output Neural Network with and without and Input Reduction

The details and performance of the Individual and Unified Neural Network models developed for the RBFN and BPNN test systems are presented here.

6.1 Static 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. There are 6 frequently occurring transactions including 5 bilateral and one multilateral transaction which have been considered for ATC determination. Transaction T1 is between seller bus 23 and buyer bus-3. Multilateral transaction T6 is between seller buses 23 and 15 and buyer buses 10 and 3. The seller buses 23 and 15 share the increase in load of buyer buses in the ratio of 0.6 and 0.4 respectively. The details of different transaction are given in table 1.

Table 1. Transaction details

Transaction	Source bus (Transaction share)	Sink bus (Transaction share)
T1	23(1.0)	3(1, 0)
T2	21(1.0)	6(1, 0)
T3	22(1.0)	5(1, 0)
T4	23(1.0)	15(1, 0)
T5	22(1, 0)	9(1, 0)
T6	23, 10 (0.6, 0.4)	15, 3 (0.6, 0.4)

Case 1 : Multiple Neural Networks with and without Input Reduction

In this case individual networks dedicated for each transaction have been developed to determine the ATC. The real and reactive power load at all the buses is taken as input and respective ATC is taken as output for neural network. Six neural networks are developed and trained with RBFN, and their performance is compared with BPN. A total of 34 variables were used as input to the BPN and RBFN based neural network. The input layer of BPN contained 34 neurons and the output layer consists of one neuron for all the six transactions. The optimum numbers of neurons in the hidden layer were found to be 10 for all the transactions. Thus the structure of BPN used is (34-10-1). The network was trained with 150 data sets and tested with 100 data sets. The average absolute error is 0.119 and the training time is 23.63 secs.

To demonstrate the effectiveness of the proposed RBFN model it has been trained and tested with the same pattern as BPN has been trained. Six different RBFNs were designed for estimating ATC values for the six transactions considered. The optimum sizes of these six RBFN were found to be (34-25-1),(34-75-1),(34-50-1),(34-50-1),(34-48-1),(34-70-1) with the vigilance parameters equal to 0.415 ,0.461,0.32,0.32,0.31,0.512 for the six transactions. The number of hidden units for RBFN network is calculated by Euclidean distance based clustering. The normalized input and output data are used for training of the RBF neural network. During training of the RBF network, care has been taken to avoid network memorization or over training. The optimal learning is achieved at the global minimum of testing error. It was observed that the training in this case was faster and also its performance was better as compared to the BPA model. The training of RBF neural network requires less computation time as compared to the BPA model, since only the second layer weights have to be calculated using error signal.The network was trained with 150 datas and tested with 100 data sets. The average absolute error is $1.0837\text{x}10^{-4}$ and the training time is 14.718 secs.

The performance of these two neural networks was compared with the conventional RPF method, for different loadings which is given in Table 4 for only one transaction. It can be seen that the ATC value computed by RBFN closely matches with that computed by the RPF method. The RBFN network has been found to compute he ATC values for all the transactions and different loading conditions almost instantaneously. Results from Table 2 reveals that the propose RBFN network estimates ATC values more accurately, apart from that the RBFN exhibits better generalization performance than the BPN network in most of the cases

Table 2. Performance of MNN without SFS

Transaction	Training Time (Secs)		Testing Error (MSE)	
	BPN	RBF	BPN	RBF
T1	1.575	1.010	$6.7x10^{-3}$	$9.17x10^{-5}$
T2	3.901	3.276	$7.5x10^{-3}$	$1.22x10^{-4}$
T3	3.931	2.496	$7.6x10^{-2}$	$1.45x10^{-4}$
T4	5.600	2.449	$3.1x10^{-2}$	$7.83x10^{-4}$
T5	4.882	2.808	$1.0x10^{-2}$	$1.93x10^{-4}$
T6	3.743	2.932	$8.0x10^{-3}$	$8.89x10^{-5}$

The parameters and performance of single output network for transaction 23-3 at normal operating condition is compared with (Prathiba et al., 2014*)* and presented in Table 3.

Table 3. Comparison of Single output Neural Network Without SFS for transaction 23-3

Type of Network	No.of basis Function	Training Time (secs)	Testing Error (MSE)
RBFN	25	1.010	$9.17x10^{-5}$
BPN(Prathiba *etal*., 2014)	10	1.5756	$6.7x10^{-3}$

The Table 3 compares the training and testing performance of the individual network model for bilateral transaction 23-3 under normal operating condition. Total number of input variables for the transaction is 34, which includes the real and reactive power load at all the buses and the respective ATC is taken as output for neural network. The BPA network needs ten hidden layers. The mean squared error is $6.7x10^{-3}$.The time taken by the networks (Prathiba et al., 2014) is 1.5756secs.The developed RBFN network needs 1.010 secs and the mean square error is $9.17x10^{-5}$. Thus the RBFN exhibits better generalization performance than the BPN network in this case.

Table 4. Comparison of Single output Neural Network Without SFS for Transaction 23-3for loading

Loading Condition %	ATC in MW		
	BPA (Prathiba *etal.,2014)*	RBFN	RPF
80.82	160.33	158.43	159.00
86.95	148.39	147.23	147.30
90.95	140.93	138.98	139.00
96.85	126.34	126.06	126.00
100.59	116.92	117.04	117.15

Table 4 shows the static ATC for transaction 23-3 for different operating condition obtained using Neural network and it is compared with the conventional RPF and BPN. The percentage error for 100.59% loading with developed RBFN network is found to be 0.0938 as compared to 0.213 with BPA (Prathiba et al.,2014*)* and thus validates the uniqueness of the developed model. Similarly the estimation of ATC and the error calculated for all the transactions are found to be accurate and time taken for training the network is also comparatively less with the already developed models thus validating the objective of on line estimation of ATC using RBFN. While RBFN network exhibit the same properties as back propagation networks such as generalization ability and robustness, they also have additional advantage of fast learning and ability to detect outliers during estimation.

A large number of input features increases complexity of the neural network as well as its training time. Sequential forward selection was used to identify the optimal features set. A total of 34 in numbers of real and reactive power load are used as input to the network. The extracted variables and the percentage of dimensionality reduction vary for Individual developed model depending upon the transaction and are listed in Table 5.

Table 5. Input Selection for Multiple Neural Networks

Transaction	Selected Features(Loads at buses)
23-3	P_L = 1,3,4,7,8,9,10,11,12,15
	Q_L = 18,19,20,21,22,23,29,30
21-6	P_L = 1,3,4,5,6,7,9,10,11,12,13,15,17
	Q_L = 18,19,21,22,23,24,25,27,29,30,32
22-5	P_L = 1,3,4,5,6,7,9,10,11,12,13,14,15,17
	Q_L = 18,19,20,21,22,23,24,26,27,29,30
23-15	P_L = 3,4,5,6,7,,9,10,11,12,13,14,15,17
	Q_L = 18,19,20,21,22,23,24,26,27,29,30
23-10,15-3	P_L = 1,3,4,7,8,9,10,11,12,15
	Q_L = 18,19,21,22,23,29,30

Total number of input variables for all the transaction is 34. The percentage of dimensionality reduction using SFS technique is presented in Table 6.Dimensionality reduction is given by the ratio of number of optimal selected features to the total number of input variables.

Table 6. Dimensionality Reduction using SFS

Transaction	Features Selected	% Reduction
T1	18	52.94
T2	23	67.76
T3	27	79.41
T4	24	70.58
T5	30	88.23
T6	17	50.0

These reduced data’s after normalization along with the output are used to train the network. Ten iterations of the clustering algorithm followed by linear regression are performed to estimate the parameters of the network. As the value of basis function is not known in advance, a trial and error procedure is followed to select the optimum number. After training, the networks are tested with the test data set to assess the generalization capability of the developed network. Table 7 compares the performance of the proposed RBF network-based approach with the commonly used BPN network. The networks are trained with back propagation algorithm to reach the same error level achieved by RBF networks during the training. After training the networks are tested with the test data. From this table, it is observed that RBF networks take 14.679 secs time for training, but they require more number of hidden nodes as compared to BPN networks, where the training time is 20.532secs. Apart from that the RBF networks exhibits better generalization performance than the BPN network in most of the cases and the average error for RBFN is 4.32×10^{-4} and for BPN the error is 0.0106.

Table 7. Performance of MNN with SFS

Transaction	Training Time (Secs)		Testing Error (MSE)	
	BPN	RBF	BPN	RBF
T1	2.428	2.433	5.8×10^{-3}	1.49×10^{-4}
T2	2.901	2.106	7.3×10^{-3}	6.69×10^{-4}
T3	2.516	2.215	8.7×10^{-3}	7.26×10^{-4}
T4	5.491	2.589	2.9×10^{-2}	9.65×10^{-4}
T5	4.274	2.792	1.1×10^{-2}	8.18×10^{-5}
T6	2.923	2.542	6.4×10^{-4}	1.16×10^{-5}

The estimated ATC with feature reduction for all the six models are presented in Table 8. From the Table it can be observed that RBFN, with features selected using SFS technique, provides accurate results. The comparison of normalized ATC obtained for the various testing patterns using RBF and BPN is made and the results are as shown in the Figures 3 and 4 for the transactions TI and T6. It is inferred that RBF results are very much closer to the actual results than the BPN results.

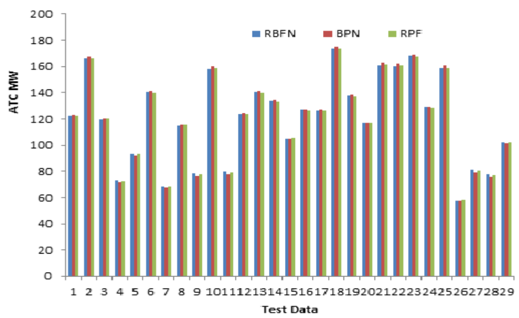

Fig. 3. Comparison of patterns of NN with SFS for T1.

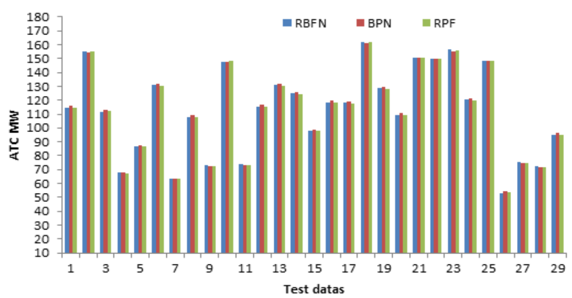

Fig. 4. Comparison of patterns of NN with SFS for T6.

Table 8. ATC for Multiple Neural Networks with SFS

Load %	ATC with RBFN MW	ATC with BPN MW	ATC with RPF MW	Limiting Factor From RPF
Bilateral Transaction T1				
105.32	105.153	105.035	105.200	V_3
115.37	77.764	76.629	77.200	
126.37	41.112	44.257	41.700	
Bilateral Transaction T2				
91.72	135.015	133.657	134.500	V_{10}
116.9	75.296	74.878	75.300	
128.66	47.438	47.438	47.35	
Bilateral Transaction T3				
98.04	223.446	224.488	223.60	V_5
111.79	191.752	190.892	191.00	
115.37	181.848	180.971	181.050	
Bilateral Transaction T4				
90.62	921.862	922.989	922.000	V_{24}
114.27	782.527	786.848	782.100	
123.05	728.005	727.983	728.250	
Bilateral Transaction T5				
94.24	303.856	300.272	303.150	V_9
102.41	271.742	273.881	271.750	
126.07	129.550	129.317	130.100	
Multilateral Transaction T6				
79.59	150.432	150.426	150.450	V_3
96.58	118.472	119.877	118.100	
118.62	62.646	62.412	62.450	

The absolute errors of RBFN and BPN testing patterns results is compared and as shown in figures 5 and 6 for transactions T1 and T6 respectively. From the figures it is observed that the RBF is providing ATC with more reasonable accuracy for the transactions.

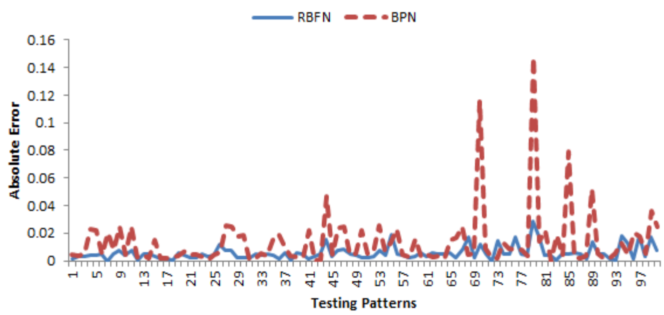

Fig. 5. Errors in ATC estimation for T1 with SFS.

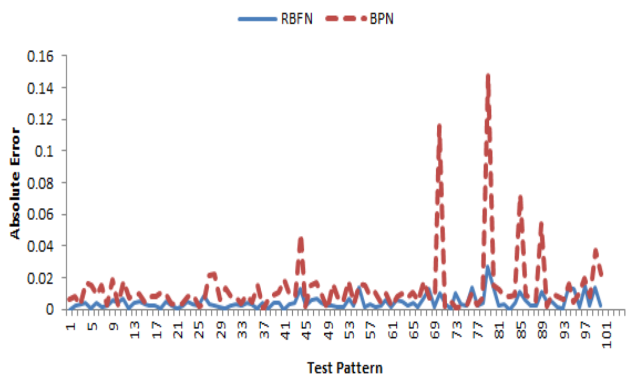

Fig. 6. Errors in ATC estimation for T6 with SFS.

Case 2 : Multiple-Output Neural Network with and without input reduction:

Case 2 presents the performance of multiple-output neural network with and without input reduction. Each transaction contains different selected inputs by SFS technique. So selecting inputs for multiple-output network is challenging. In this work, trial and error method is used to select inputs from six transactions selected inputs based on minimum training error. The finally selected inputs for multi-output network is real and reactive power load at buses are 16 in number and are P_{L1}, P_{L3}, P_{L4}, P_{L7}, P_{L8}, P_{L9},P_{L10}, P_{L11}, P_{L12}, P_{L15}, Q_{L18}, Q_{L21}, Q_{L22}, Q_{L23}, Q_{L29}, Q_{L30}.The Multiple outputs estimated ATC with and without feature reduction are presented in Table 9 for different loading conditions. The feature selection technique used here provides accurate results. This may be attributed to the fact that this technique identifies the best optimal feature set. SFS method uses a simple criterion function called error rate and iteratively selects the optimal features. Once the optimal features are identified the dimension of data matrix is reduced with respect to the input features. These features are fed as input to the developed model. The performance of the multiple-output RBF network-based with and without reduced features with the commonly used BPN network is compared in Table 10 and 11.The networks are trained with back propagation algorithm to reach the same error level achieved by RBF networks during the training. After training the networks are tested with the test data. From these tables, it is observed that RBF networks take less time for training, but they require more number of hidden nodes as compared to BPN networks. Apart from that the RBF exhibits better generalization performance than the BPN network in most of the cases.

Table 9. Multiple Outputs ATC with and without SFS

% Load	RBFN (MW)		BPN(MW)	
	Without SFS	With SFS	Without SFS	With SFS
81.15	158.46	158.40	157.66	157.90
90.62	139.73	139.76	139.71	139.76
96.58	126.74	126.64	126.74	126.64
101.23	115.44	115.54	115.44	115.12
109.77	93.44	92.75	92.12	92.71
114.84	78.67	78.78	78.32	78.84
119.03	66.07	66.00	64.21	63.87
126.07	42.61	42.76	43.21	43.24

Table 10. Performance of MNN without SFS (34-10-6)

Training Time (Secs)		Testing Error (MSE)	
BPN	RBFN	BPN	RBFN
6.318	3.385	1.39×10^{-4}	9.235×10^{-5}

Table 11. Performance of MNN with SFS (16-10-6)

Training Time (Secs)		Testing Error (MSE)	
BPN	RBFN	BPA	RBFN
5.9	2.04	1.26×10^{-4}	7.39810^{-5}

The number of input features for the reduced multiple output neural networks are reduced to 47% of the original inputs, and hence the developed Unified Network is capable of estimating ATC accurately. Table 12 shows training time and generalization capability of various RBFN models developed.

Table 12. Performance of Unified and Individual NN

Network	Variants	
	Time (secs)	Error %
RBFN Individual Model		
Without SFS	14.679	1.0837×10^{-4}
With SFS	8.7	4.32×10^{-4}
RBFN Unified Model		
Without SFS	3.3852	9.235×10^{-5}
With SFS	2.045	7.396×10^{-5}
BPN Individual Model		
Without SFS	23.63	0.119
With SFS	19.12	0.0106
BPN Unified Model		
Without SFS	6.318	1.39×10^{-4}
With SFS	5.990	1.26x10-4

It is found that the generalization capability of proposed RBFN unified model can estimate ATC for more than one operating condition without compromising the accuracy. This reduces the computation time in real folds. In a real time operation of deregulated power system, the ISO has to estimate ATC values for many possible proposed transactions. The process of estimating ATC value for all the proposed transactions will be cumbersome and time consuming. As the RBFN unified model can estimates ATC value for more than one proposed transactions in a single shot the ISO can evaluate many transactions in short time and accurately. Further the computation time is lesser than the other AI based methods. Hence this method is best suited for ATC estimation.

6.2 Static ATC assessment in IEEE 118-Bus Test System

The IEEE 118-bus test system is used to demonstrate the feasibility of the proposed model for normal case. It has 54 generator buses and 186 transmission lines. All other data are the same as the standard IEEE 118-bus data (Power System Test Case Archieve, 1993**)**. Changing the load and generations randomly between 70% to 110% of their base values respectively, and 250 load scenarios were generated. For each of the load scenarios, ATC, for this system, has been determined for five bilateral transactions and a multilateral transaction. The Transaction details are given in Table 13. Multilateral transaction T6 is between seller buses 5 and 6 and buyer buses 40 and 60. The seller buses 72 and 80 share the increase in load of buyer buses in the ratio of 0.6 and 0.4 respectively. The ATC between any transmission interfaces is a function of network topology, generation dispatch and customer demand level. It is mostly affected by the real and reactive power loads. Hence, the real and reactive power loads at all the PV and PQ buses (total 189 in number) were used as the data set for input features selection to the neural network. A large number of input features increases complexity of the network as well as its training time. Hence, SFS technique was used to identify the important variables.

Table 13. Transaction details

Transaction	Source bus (Transaction share)	Sink bus (Transaction share)
T1	32(1.0)	75(1, 0)
T2	12(1.0)	60(1, 0)
T3	24(1.0)	40(1, 0)
T4	65(1.0)	100(1, 0)
T5	46(1, 0)	80(1, 0)
T6	5,6 (0.6, 0.4)	40,60 (0.6, 0.4)

Case 1: Multiple Neural Networks with and without Input Dimensionality Reduction

In this case separate networks dedicated for each transaction have been developed to determine the ATC. The real and reactive power load at all the buses is taken as input and respective ATC is taken as output for neural network. Six neural networks are developed and trained with RBFN, and their performance is compared with BPNN.

Table 14 compares the performance of the proposed RBF network-based approach without reduced features with the commonly used BPN network. The networks are trained with back propagation algorithm to reach the same error level achieved by RBF networks during the training. After training the networks are tested with the test data. From this table, it is observed that the total training time required by RBFN is 26.09 secs whereas BPN took 71.75 secs for complete training. The average error of RBF model is 9.068×10^{-4}. The BPN networks requires ten number of hidden nodes for all the transactions ,but the number of basic functions required by the RBFN is more depending upon the transactions. Apart from that the RBF networks exhibits better generalization performance than the BPN network in most of the cases.

Table 14. Performance of Multi NN without SFS

Transaction	Training Time (Secs)		Testing Error (MSE)	
	BPN	RBF	BPN	RBF
T1	14.10	3.82	8.4×10^{-5}	3.61×10^{-4}
T2	3.38	3.66	7.9×10^{-5}	5.31×10^{-5}
T3	16.72	4.54	2.83×10^{-4}	4.1×10^{-5}
T4	17.06	5.91	2.07×10^{-4}	4.7×10^{-3}
T5	16.98	4.75	2.6×10^{-4}	1.6×10^{-4}
T6	3.51	3.41	7.60×10^{-5}	4.89×10^{-5}

A large number of input features increases complexity of the neural network as well as its training time. Hence it is essential to select optimum number of inputs, which are able to clearly define the input-output mapping.

Sequential forward selection was used to identify important variables by calculating the relevance of the variables to the target output. A total of 189 in numbers of real and reactive power load are used as input to the network. These reduced data's after normalization along with the output are used to train the network. Total number of input variables for all the transaction is 189. Dimensionality reduction is given by the ratio of number of optimal selected features to the total number of input variables. The extracted variables and the percentage of dimensionality reduction vary depending upon the transaction and are listed in Table 15.

Fifteen iterations of the clustering algorithm followed by linear regression are performed to estimate the parameters of the network. As the value of basis function is not known in advance, a trial and error procedure is followed to select the optimum number. After training, the networks are tested with the test data set to assess the generalization capability of the developed network. The estimated ATC with feature reduction for all the six models are presented in Table 16. From the Table it can be observed that RBFNN, with features selected using SFS technique, provides accurate results, in comparison with the conventional RPF method.

Table 15. Dimensionality Reduction with SFS

Transaction	Features Selected	% Reduction
T1	48	25.39
T2	31	16.4
T3	37	19.57
T4	53	28.04
T5	48	25.39
T6	31	16.4

Table16. ATC for Multiple RBFNN with SFS

Load %	ATC with RBFN MW	ATC with BPA MW	ATC with RPF MW	Limiting Factor From RPF
Bilateral Transaction T1				V_{118}
84.0	168.5	168.61	169.05	
107.3	143.27	141.93	143.15	
Bilateral Transaction T2				V_{38}
84.0	212.74	216.07	212.75	
102.69	173.90	176.33	173.9	
Bilateral Transaction T3				
87.22	112.58	112.11	112.6	
90.39	107.44	106.89	107.45	V_{38}
Bilateral Transaction T4				
93.4	519.12	518.72	519.6	
107.3	293.59	291.43	294.85	T_{119}
Bilateral Transaction T5				
76.89	507.47	508.51	506.8	T_{63}
97.86	506.39	498.443	503.7	
Multilateral Transaction T6				V_{38}
77.43	215.61	217.703	215.65	
108.02	158.26	160.85	158.5	

Table 17 compares the performance of the proposed RBF network-based approach with the commonly used BPN network. The networks are trained with back propagation algorithm to reach the same error level achieved by RBF networks during the training. After training the networks are tested with the test data. From this table, it is observed that RBF networks take 22.2886 secs time for training, but they require more number of hidden nodes as compared to BPN networks, where the training time is 43.6437 secs. Apart from that the RBF networks exhibits better generalization performance than the BPN network in most of the cases

Table 17. Performance of Multi NN with SFS

Transaction	Training Time (Secs)		Testing Error (MSE)	
	BPA	RBF	BPA	RBF
T1	6.26	4.52	$8.11\text{x}10^{-5}$	$3.15\ \text{x}10^{-5}$
T2	2.43	2.12	$8.63\text{x}10^{-3}$	$3.51\text{x}10^{-9}$
T3	11.3	5.24	$1.44\text{x}10^{-4}$	$1.73\text{x}10^{-6}$
T4	11.3	4.68	$2.07\text{x}10^{-4}$	$3.83\text{x}10^{-5}$
T5	10.18	4.50	$2.41\text{x}10^{-4}$	$2.27\text{x}10^{-5}$
T6	1.99	1.21	$8.9\text{x}10^{-3}$	$3.92\text{x}10^{-7}$

The comparison of normalized ATC obtained for the various testing patterns using RBF and BPN is made and the results are as shown in the Figures 7and 8 for the transactions T2 and T6. It is inferred that RBF results are very much closer to the actual results than the BPN results

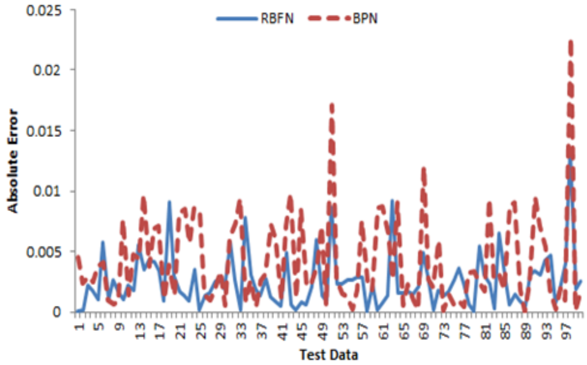

Fig. 7. Errors in ATC estimation for T1 with SFS.

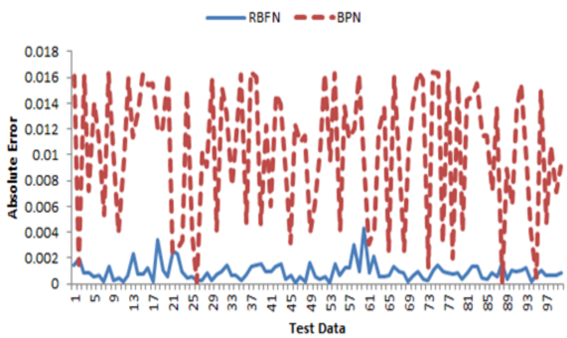

Fig. 8. Errors in ATC estimation for T6 with SFS.

Case 2: Multiple -Output Neural Network with and without input reduction

Case 2 presents the performance of multiple-output neural network with and without input reduction. Each transaction contains different selected inputs by SFS technique. So selecting inputs for multiple-output network is challenging. In this work, trial and error method is used to select inputs from six transactions based on minimum training error. The finally selected inputs for multi-output network are real and reactive power load at buses are 22 in number and they are P_{L8}, P_{L11}, P_{L16}, P_{L19}, P_{L22}, P_{L24}, P_{L26}, P_{L31}, P_{L32}, P_{L36}, P_{L41}, P_{L48}, P_{L49}, P_{L51}, P_{L59}, P_{L70}, P_{L71}, P_{L97}, Q_{L121}, Q_{L125}, Q_{L142}, Q_{L155}. Dimensionality reduction of 8.4%is done. The Multiple outputs estimated ATC with and without feature reduction for different loading conditions are presented in Table 16.

Table 18. ATC for Multiple Networks with SFS for T6

% Load	ATC with RBFN (MW)		ATC with BPN (MW)	
	Without SFS	With SFS	Without SFS	With SFS
79.55	182.292	182.280	181.92	181.62
93.79	149.826	149.810	148.34	148.32
102.97	228.148	227.713	228.05	227.62
107.3	109.581	109.491	108.91	108.58

Table 19 and 20 compares the performance of the multiple-output RBF network-based with and without reduced features with the commonly used BPN network.

Table 19. Performance of Multiple outputs Neural Networks with all features (189-10-6)

Training Time (Secs)		Testing Error (MSE)	
BPN	RBFN	BPN	RBFN
17.8	6.879	$1.85\text{x}10^{-4}$	$3.609\text{x}10^{-5}$

Table 20. Performance of Multiple outputs Neural Network with SFS (17-10-6)

Training Time (Secs)		Testing Error (MSE)	
BPN	RBFN	BPN	RBFN
10.358	2.204	$1.16\text{x}10^{-4}$	9.17810^{-5}

The number of input features for the reduced multiple output neural networks are reduced to half in number, and hence the unified Network is capable of estimating ATC accurately.

Table 20 Performance of Unified and Individual NN

Network	Variants	
	Time (secs)	Error %
RBFN Multiple Networks Model		
Without SFS	26.09	$9.068\text{x}10^{-4}$
With SFS	18.77	$4.32\text{x}10^{-4}$
RBFN Multi- Output Model		
Without SFS	6.879	$3.609\text{x}10^{-5}$
With SFS	2.204	9.17810^{-5}
BPN Multiple Networks Model		
Without SFS	71.75	$1.66\text{x}10^{-4}$
With SFS	40.47	$1.972\text{x}10^{-4}$
BPN Multi- Output Model		
Without SFS	17.8	$1.85\text{x}10^{-4}$
With SFS	10.358	$1.16\text{x}10^{-4}$

The values calculated with SFS and without SFS are same with minimum error. The performance of the RBFN network is superior to the BPN network in terms of testing and training time and thus validates the accurate on-line estimation of ATC. Table 20 compares the training time and generalization capability of various RBFN models developed

It is found that the generalization capability of proposed RBFN multiple output model can estimate ATC for more than one operating condition without compromising the accuracy. This reduces the computation time in real folds. In a real time operation of deregulated power system, the ISO has to estimate ATC values for many possible proposed transactions. The number of input features for the reduced multiple output neural networks are reduced to ninety percent, and hence the multiple outputs Network is capable of estimating ATC accurately.Figure19 shows training time and generalization capability of various RBFN models developed.

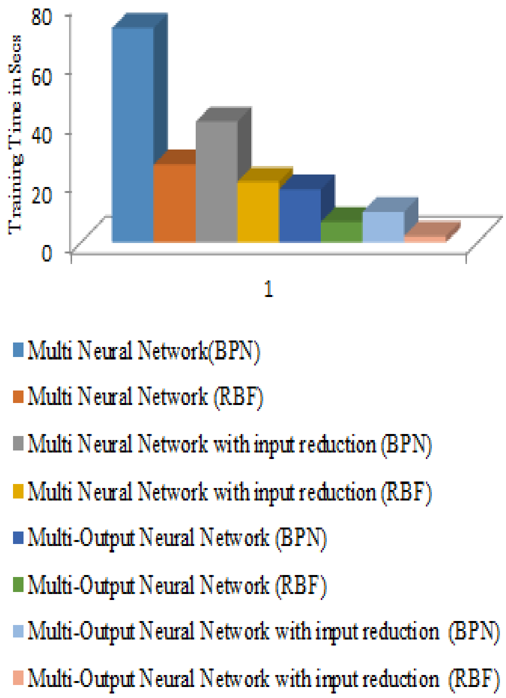

Fig. 9. Comparison of developed Networks with and without SFS

The process of estimating ATC value for all the proposed transactions will be cumbersome and time consuming. As the RBFN unified model can estimates ATC value for more than one proposed transactions in a single shot the ISO can evaluate many transactions in short time and accurately. Further the computation time is lesser than the other AI based methods. Hence this method is best suited for ATC estimation.

7. CONCLUSION

In a real time operation of deregulated power system, the ISO has to estimate ATC values for many possible proposed transactions and for different operating conditions. The evaluation of ATC, by most of the conventional methods, requires large computation time. To overcome this, an approach based on Reduced input Radial basis function Neural Network(RBFNN) Unified Model has been proposed to determine the static ATC under wide range of variations. The reduced features for unified and individual models have been selected using Sequential Feature Selection technique and the performance of the developed Unified and Individual Models for NN are compared. Simulation results on the 24-RTS bus system and IEEE 118 Bus system reveal the following.

- The RBFN trained Unified Model with features selected using Sequential Forward Selection outperformed as compared to that Individual model.
- The proposed RBFN trained Unified model is able to determine ATC value as accurately as obtained through the conventional RPF method.
- The proposed RBFN Unified model is much faster as compared to other developed models and conventional methods and is found to be suitable to estimate ATC values for more than one proposed transactions and for different operating conditions in short time simultaneously. This enhances the performance of ISO. The Unified RBFN model can estimate ATC with good accuracy and with reasonable time. This makes the RBFN model suitable for real time applications.

REFERENCES

Amit Kumar Singh Barjeev and Vishal Kumar,(2013), “Application of Neural Network based Control Strategies to Binary Distillation Column”, *Journal of Control Engineering and Applied Informatics*,Vol.,15, No.,4,pp 47-57.

Christie R.D, Wollenberg B.F and Wangstien. I,(2000) “Transmission management in the Deregulated Environment”, *Proc. IEEE*, Vol.,88, No.2, pp.170–95.

Devaraj. D, Yegnanrayana.B, and Ramar.K, (2002) “Radial basis function Networks for fast contingency ranking”, *Electrical Power Energy Systems*, Vol.,2, pp.387–39.

Devaraj. D, and Preetha Roselyn. J, (2011), “On-line voltage stability assessment using Radial basis function network model with reduced input features”, *Electrical Power Energy Systems*, Vol .,3, pp.1550–1555.

Ejebe.G.C, WaighJ.G., Frame J.G, Wang,X and Tinney (1998), “Available Transfer Capability Calculations”, *IEEE transaction on Power systems*, Vol.(13), pp.1521-1527.

Gheyas and Smith.L, (2010) “Feature subset selection in large dimensionality domains”, *Pattern Recog.*, Vol.,43, No. 1, pp. 5–13.

Hamoud.G, (2000) “Assessment of Available Transfer capability of transmission systems”, *IEEE Transactions on Power Systems*, Vol., 15, pp. 27-32.

Jain.T, Singh S.N, and Srivastava.S.C, (2007), “A Neural Network based method for fast ATC Estimation in Electricity Markets”, *IEEE Transactions on Power Systems*, Vol. (15), No 2, pp.546-570.

Joo.K and Liu C.C, (2004) “Optimization techniques for Available Transfer capability and market calculations”, *IMA Journal of Management Mathematics*, Vol. (15), pp. 321-327.

Kalyani S and Shanthi Swarup K,(2011), “Classification And assessment of Power System Security Using Multiclass SVM”, *IEEE Transaction on systems, Man ,Cybernetics-*Vol.41,No.5,pp 753-758.

Khaburi M.A, Haghifam M.R, (2010), “A Probabilistic modeling based approach for Total Transfer Capability enhancement using FACTS devices", *Electrical Power and Energy Systems*, Vol. no.32, pp.12–16.

Khairuddin.AB,. Ahmed. SS,. Mustafa. MW, Zin. AAM,. Ahmad. H, (2004), "A novel method for ATC computations in a large scale power systems", *IEEE Transactions on Power Systems*, Vol.19.,No.2, pp. 1150-8.

Kumar.S, Srivastava.C, Singh S, N, (2004),"ATC transmission capability determination in a competitive electricity market using AC distribution factors", *Electric Power Components & Systems*, Vol. 32, No.9, pp. 927-939.

LaurenceV.Fauzett, (1993), "Fundamentals of Neural Networks", Pearson Publishers.

Luo. X, Patton.A.D, and Singh.C, (2000) "Real Power Transfer Capability Calculations using Multi-Layer Feed–Forward Neural Networks"*IEEE Transactions on Power Systems,* Vol.,15,.No 2,pp.903-908.

North American Electricity Reliability Council (NERC) (1996), Available Transfer Capability definitions and determination. Open Access Same-Time Information System and Standards of Conduct, (1996), OrderNo.889, Final Rule, FERC.

Prathiba.R, Balasingh Moses.B, Devaraj.D, and Karuppasamy Pandian (2014), "Multi-output On-Line ATC Estimation in Deregulated Power System Using ANN", *Advances in Intelligent system and computing,* Vol. No.,320.pp.215-226.

Rao.N, Kumar K.K,. Amarnath.J, and. Kamakshaiah. S, (2008), "Computation of Available Transfer Capability Using Neural Network", *Int. Conference on condition Monitoring and Diagnosis*, Beijing, China, pp.21-24

Sefriti.S, Boumhidi.J, Naoual.R, Boumhidi.I, (2012), "Adaptive Neural Network Sliding Mode Control For Electrically-Driven Robot Manipulators", J*ournal of Control Engineering and Applied Informatics*, Vol.,14, No.,4, pp. 27-32.

Vaithilingam.C, and Kumudini Devi R.P (2013), "Available transfer capability estimation using SVM, *Electric Power Energy System*, Vol., 47, pp.387–93.

Yan Ou, and.Chanan Singh, (2002), "Assessment of Available Transfer Capability and Margins", *IEEE transaction on Power systems*, Vol.,17, No., 2. pp.463-68.

Zimmerman RD, Gan D. MatPower:A MATLAB Power System simulation Package 3.0,PSERC; September 2004.

University of Washington Electrical Engineering, Power Systems Test Case Archive, 1993, Available from: http://www.ee.washington.edu/research/pstca.