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COMPUTATION OF AVAILABLE TRANSFER CAPABILITY INCORPORATING EFFECT OF REACTIVE POWER AND LOSSES USING COMPLEX NEURAL NETWORK

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ABSTRACT

Transfer capability refers to the ability of a transmission network to transfer electric power reliably from an area of supply to an area of demand by way of all transmission lines (or paths) between two areas under a given operating condition. Available transfer capability (ATC) is, in fact, an estimate of the near-future transmission network's capability of additional power transfer over the existing committed usage. As such, there are several uncertainties associated with the parameters and forecasting quantities used in the ATC evaluation. In this paper the aspects of ATC limited by the voltage collapse point is considered, the main aim of this paper is to provide a fast and efficient method to compute the voltage stability constrained ATC using complex valued neural network (CVNN). The proposed CVNN deals with complex value data with complex number weights and complex value neuron activation functions. The results have been presented and analyzed in this paper.

Keywords: total transfer capability, ATC, complex valued neural network, complex back propagation algorithm.

INTRODUCTION

Transfer capability is the measure of the ability of interconnected electric systems to reliably move or transfer power from one area to another over all transmission lines (or paths) between those areas under specified system conditions. The units of transfer capability are in terms of electric power, generally expressed in megawatts (MW). In this context, "area" may be an individual electric system, power pool, control area, sub region, or a portion of any of these. Transfer capability is also directional in nature. Available Transfer Capability (ATC) is a measure of the transfer capability remaining in the physical transmission network for further commercial activity over and above already committed uses. Transfer capabilities are highly dependent on generation, customer demand and transmission system conditions assumed during the period considered. Where as capacity usually refers to the thermal limit or rating of a particular transmission element or component. The ability of a single transmission line to transfer electric power, when operated as part of the interconnected network, is a function of the physical relationship of that line to the other elements of the transmission network. The task of evaluation of ATC is very complex and the speed and accuracy requirements for the on line ATC evaluation make the task even harder.
One of the most common approaches for transfer capability calculations is the continuation power flow (CPF) [1, 2]. The amount of the transfer is a scalar parameter which can be varied in the model. CPF is a general method for finding the maximum value of a scalar parameter in a linear function of changes in injections at a set of buses in a power flow problem. In principle, CPF increases the loading factor in discrete steps and solves the resulting power flow problem at each step. CPF yields solutions at a voltage collapse points. However, since CPF ignores the optimal distribution of the generation and the loading together with the system reactive power, it can give conservative transfer capability results.

The practical computations of transfer capability are evolving. The computations presently being implemented are usually oversimplified and in many cases do not take sufficient account of effects such as interactions between power transfers, loop flows, non-linearities, operating policies and most importantly voltage collapse blackouts. The goal of the methods described here is to improve the accuracy and realism of transfer capability computations.

Transfer capabilities can be estimated with simple power system models such as the DC load flow approximation. A DC model may be preferable to an AC model particularly in circumstances where the extra data for an AC model is unavailable or very uncertain, such as the case of very long time frame analysis.
The DC approximation is preferred for these reasons:

- Fast computation - no iteration.
- Thermal limits, MW limits are considered.
- Network topology handled with simple and linear methods.
- Good approximation over large range of conditions. Minimum data is required.

But DC approximation is poor for these reasons:
- It cannot identify voltage limits
- It is not accurate when VAR flow and when voltage deviations are considerable.
- Over use of linear superposition increases errors.

In this proposed method the limitations on power system performance that we consider are transmission line flow limits, voltage magnitudes and voltage collapse by implementing a complex valued neural network. The input to the network is diagonal elements of the complex bus admittance matrix and the complex loads in an area which are assumed to be fluctuating in nature. An additional feature of the network is incorporating the line losses in evaluation of ATC. All these limits can only be handled in an AC load flow power system model. Computed ATC values with and without contingency are compared with the Full AC method.

COMPLEX VALUED NEURAL NETWORKS

In recent years, complex-valued neural networks have widened the scope of application in optoelectronics, imaging, remote sensing, and artificial neural information processing. The generalization of real valued algorithms cannot be simply done as complex valued algorithm. The complex back propagation algorithm can be applied to multilayered neural networks whose weights, threshold values, inputs and outputs all are complex numbers. Complex version of back propagation (CVBP) algorithm made its first appearance when Widrow, Mc Cool and Ball [3] announced their complex least mean squares (LMS) algorithm. Kim and Guest [4] published a complex valued learning algorithm for signal processing application. Georgiou and Koutsougeras [5] published another version of CVBP incorporating a different activation function and have shown if real valued algorithms be simply done as complex valued algorithm then singularities and other such unpleasant phenomena may arise. Hirose [6] studied the dynamics of CVNN which was later applied to the problem of reconstructing vectors lying on the unit circle. Benvenuoto and Piazza [5] published a different version of CVBP by using different activation function. Wang [6] proposed a complex valued recurrent neural network to solve the complex valued linear equations. An extensive study of CVBP was reported by Nitta [7]. The average learning speed of complex BP algorithm is faster than that of real BP algorithm. The standard deviation of the learning speed of complex BP is smaller than that of the real BP. Hence the complex valued neural network and the related algorithm are natural for learning of complex valued patterns. Werbos and Titus [8] and then Gill and Wright [9] discussed the different consequences of changing error functions in an optimization scheme. L. Chan *et al.* [10] published applications of complex artificial neural networks to load flow analysis.

STRUCTURE OF COMPLEX VALUED NEURAL NETWORKS

A three layered neural network is shown in Figure-1. In a complex valued neural network shown in Figure-2 all the inputs, outputs, weights, and biases are complex values. To overcome the scaling problem split sigmoidal activation function is used for training the network.

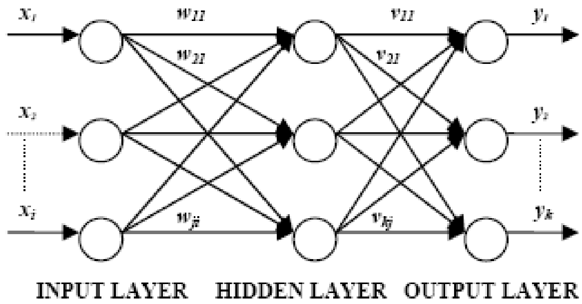

Figure-1. Three layered neural network.

In this complex valued neural network:

L number of input layer neurons
M number of hidden layer neurons
N number of output layer neurons
xi output value of input neuron i (input)
zj output of hidden layer neuron j
ok output of the output neuron k
wji complex weights between input layer neuron i and hidden layer neuron j
vkj complex weight between hidden layer neuron j and output layer neuron k
θj threshold / bias of hidden layer neurons
γk threshold / bias of output layer neurons

The network is trained with a given set of input and output data to learn a functional relationship between input and output. We have used complex BP learning rule which has been obtained by using a steepest descent method for multilayered complex valued neural network given by Nitta [7]. The weights are initiated to some random values. The outputs are obtained for these random input values. The error between actual output and the desired output is calculated. This error is back propagated and the weights are updated. Then for these new values of weights, outputs are once again calculated. These actual calculated outputs are once again compared with the target outputs and the error is calculate, which is again back propagated and the weights are once again updated. This iterative process is continued till the error becomes less then the minimum defined.

Internal potential of hidden neuron j:

$$u_j = \sum_{i=1}^{I}(w_{ji}x_i) + \theta_j = \mathrm{Re}[u_j] + i\,\mathrm{Im}[u_j]$$

Output of hidden neuron j:

$$z_j = \phi(u_j) = \frac{1}{1+e^{-\mathrm{Re}[u_j]}} + i\frac{1}{1+e^{-\mathrm{Im}[u_j]}} = \mathrm{Re}[z_j] + i\,\mathrm{Im}[z_j]$$

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Internal potential of output neuron k:

$$s_k = \sum_{j=1}^{m} (v_{kj} z_j) + \gamma_k = \mathrm{Re}[s_k] + i\,\mathrm{Im}[s_k]$$

Output of output neuron k:

$$o_k = \phi(s_k) = \frac{1}{1+e^{-\mathrm{Re}[s_k]}} + i\frac{1}{1+e^{-\mathrm{Im}[s_k]}} = \mathrm{Re}[y_k] + i\,\mathrm{Im}[y_k]$$

Error

$$e_k = o_k - d_k$$

With the help of this error e_k using different complex error functions the error E is obtained. Then we derive the gradient of E with respect to both the real and imaginary part of the complex weights.

$$\nabla_{w_{ji}} E = \frac{\partial E}{\partial \mathrm{Re}[w_{ji}]} + i\frac{\partial E}{\partial \mathrm{Im}[w_{ji}]}$$

During training the network cost function E is minimized by recursively altering the weight coefficient based on gradient descent algorithm, given by

$$w_{ji}(p+1) = w_{ji}(p) + \Delta w_{ji}(p) = w_{ji}(p) - \eta \nabla_{w_{ji}} E_p \big|_{w_{ji}=w_{ji}(p)}$$

Where 'p' is the number of iterations and 'η' is the learning rate constant.

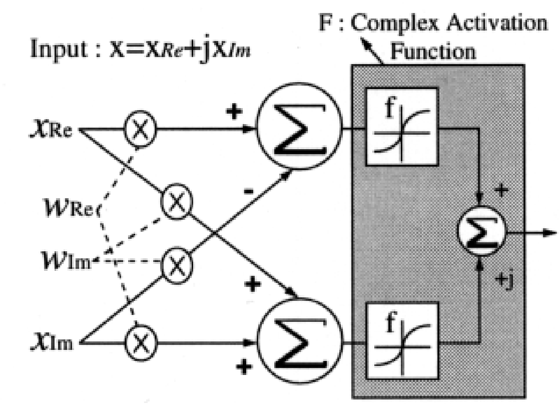

Figure-2. Complex valued neural network.

THE PROPOSED APPROACH

The following assumptions are made while calculating the ATC.

a) The base case power flow of the system is feasible and corresponds to a stable operating point;
b) The load and generation patterns vary very slowly; and
c) TTC calculation is in the steady state analysis domain.

Repeated power flow (RPF) method is used for obtaining the training patterns and the following choices are made in the calculation.

- Establish a secure, solved base case.
- Specify a transfer including source and sink assumptions.
- Identify the branch flows influencing the ATC of selected branch appreciably.
- Identify the line outages having significant influence on the above said branch power flows.
- Generate numerous training data sets involving above said power flows and line outages.
- The transfer margin is the difference between the transfer at the base case and the limiting case.

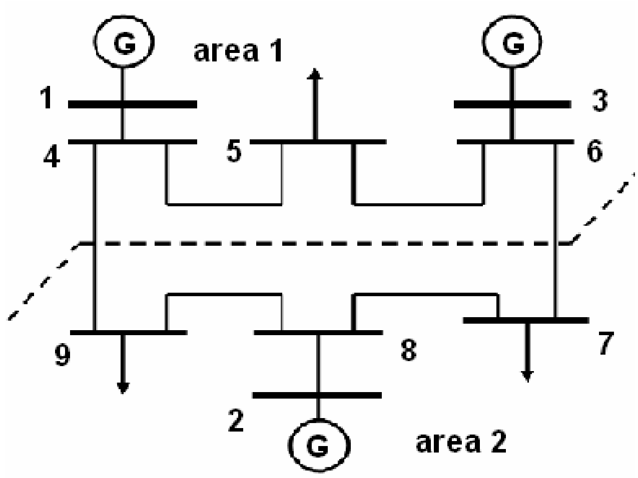

Figure-3. Nine bus system.

For generating training patterns for computing ATC a 9 bus 9 line system is considered as shown in Figure-3. The calculation of ATC is done by using the Newton Raphson load flow solution to compute the power flow of each transfer case. This method is less prone to divergence with ill-conditioned problems. And also the number of iterations required is independent of the system size. The loads at bus number 7 and 9 are increased simultaneously and the transfers from area 1 to area 2 are obtained. The total transfer capability is the sum of transfers through the interconnecting lines i.e. line joining buses 4 and 9, buses 6 and 7. The available transfer capability is given by

ATC = TTC – base case transfer

Satisfying the following system operating conditions

$$Pi - \sum_{j\varepsilon N} V_i V_j Y_{ij} Cos(\theta_{ij} + \delta_j - \delta_i) = 0$$

$$Qi - \sum_{j\varepsilon N} V_i V_j Y_{ij} Sin(\theta_{ij} + \delta_j - \delta_i) = 0$$

$$P_{g\,\min} \le P_g \le P_{g\,\max}$$

$$Q_{g\,\min} \le Q_g \le Q_{g\,\max}$$

$$V_{i,\min} \le V_i \le V_{i,\max}$$

Typical P-V curves are shown in Figures 4 and 5. The variations in ATC with respect to the changes in load

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of area 1 with and without contingency are shown in Figures 4 and 5.

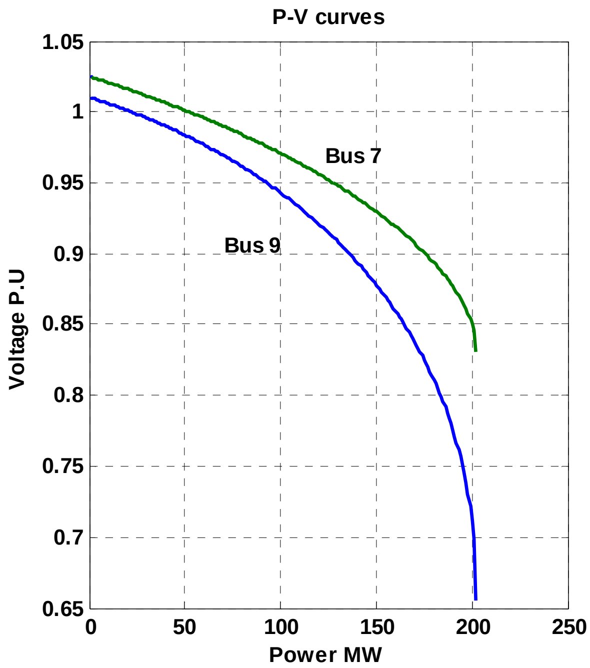

Figure-4. P-V curves of area 2 without contingency.

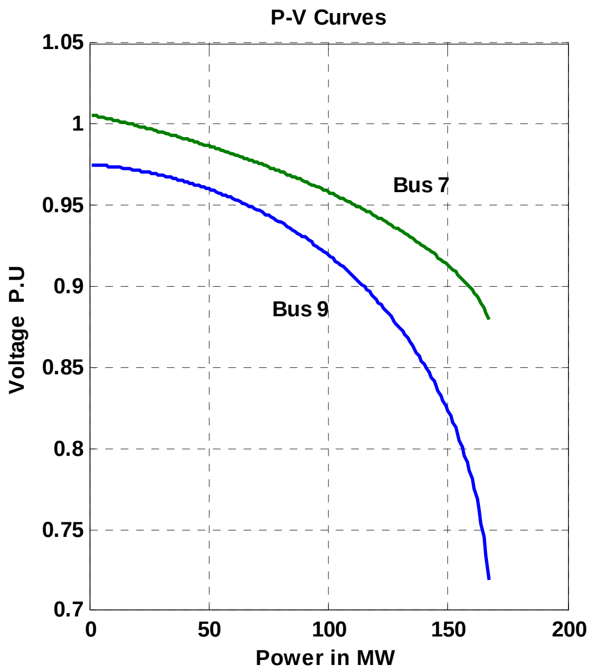

Figure-5. P-V curves of area 2 with contingency.

The effect of interactions between power transfers is taken in to account by varying the load in area 1. The variation of ATC is shown in Figures 6 and 7.

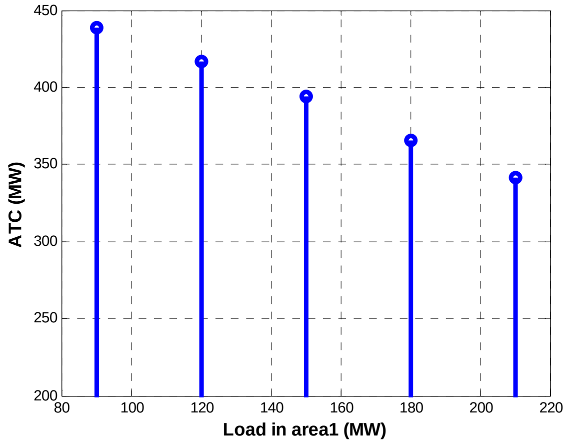

Figure-6. ATC without contingency.

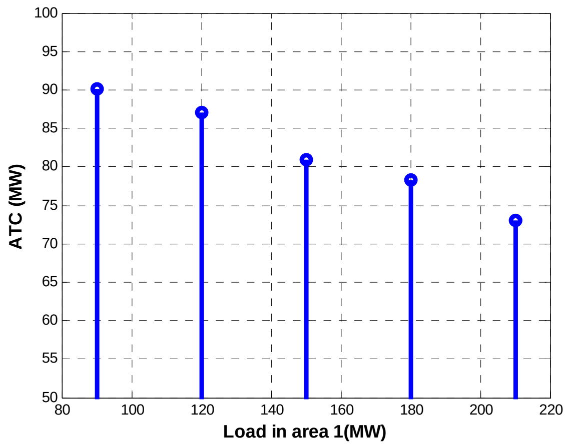

Figure-7. ATC with contingency (line 4-9 outage).

Large number of training patterns is obtained with and without contingency. This method is proposed for better prediction how a realistic power system will react over a wide range of operating conditions. The variation of error with respect to number of iterations is shown in Figure-8.

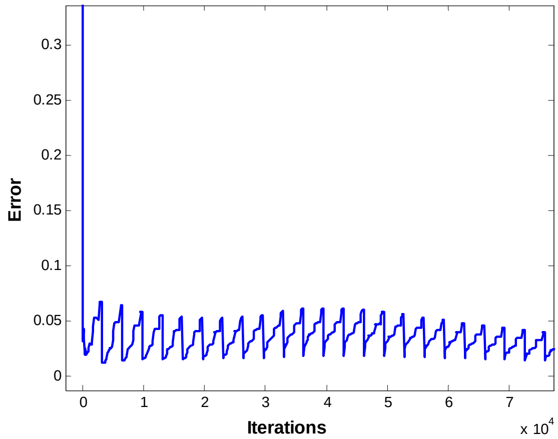

Figure-8. Error.

RESULTS AND DISCUSSIONS

For the purpose of verifying the validity and correctness of the proposed method a 9 bus system is selected to compute the real and reactive power transfer from one area to another area. The system consisting of 9 buses is divided in to two areas. The complex load levels used to create data for training the proposed neural network in area 1 are varied from 100% to 250% of base case values using different line outages. The available transfer capability (ATC) in MW and the reactive power transfers in MVAR at different test cases are computed. The comparison between the proposed CVNN method and the repeated power flow (RPF) methods are shown in Tables 1 to 4.

Table-1. Power transfer and ATC without contingency.

Load in area 1	**RPF**	**CVNN**	**ATC** (MW)
90+30j	438+j276	441+j282	441
120+j40	416+j245	418+j244	418
150+j50	393+j221	385+j224	385
180+j60	365+j190	359+j180	359
210+j70	340+j175	332+j168	332

Table-2. Power transfer and ATC with Line 5-6 outage.

Load in area 1	**RPF**	**CVNN**	**ATC** (MW)
90+30j	357+j214	351+j211	351
120+j40	344+j203	338+j210	338
150+j50	323+j77	318+j95	318
180+j60	287+j130	284+j133	284
210+j70	210+j40	204+j42	204

Table-3. Power transfer and ATC with Line 6-7 outage.

Load in area 1	**RPF**	**CVNN**	**ATC** (MW)
90+30j	298+j192	290+j186	290
120+j40	293+j185	284+j182	284
150+j50	290+j186	281+j179	281
180+j60	282+j175	276+j172	276
210+j70	244+j260	239+j256	239

Table-4. Power transfer and ATC with Line 9-4 outage.

Load in area 1	**RPF**	**CVNN**	**ATC** (MW)
90+30j	90+j34	92+j35	92
120+j40	86+j38	86+j33	86
150+j50	80+j16	81+j20	81
180+j60	78+j20	76+j22	76
210+j70	73+j25	75+j21	75

CONCLUSIONS

This paper introduces the application of complex valued neural network for ATC computations with and without contingencies. To evaluate the performance a numerical example of 9 bus test system is presented. The objective function is load increase on specific source and sink nodes. The voltage limits of the buses and the line losses are well considered in this method. The simulation results show that the proposed method is very effective in determining the ATC.

The main conclusions of the paper are:

- The proposed CVNN method is effective in calculating the ATC between different areas subject to system operating limits;
- Even though this method is proposed for computation of ATC with constant load power factor, it can be used at different power factors; and
- The application of proposed method can also be extended to determine the variations in ATC with respect to reactive power incorporating FACTS devices.

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