Available transfer capability (ATC) determination using intelligent techniques

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Available Transfer Capability (ATC) Determination Using Intelligent Techniques

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***Abstract*--In this paper ATC has been computed for real time applications using three different intelligent techniques viz., i) Back Propagation Algorithm (BPA) ii) Radial Basis Function (RBF) Neural network and iii) Adaptive Neuro Fuzzy Inference System (ANFIS). The ATC is to be made available on Open Access Same time Information System (OASIS), which is accessible to seller and buyer. The Independent System Operator (ISO) updates the ATC in real time. The three different methods are tested on IEEE 24-bus Reliability Test System (RTS) and compared with the conventional full AC Load Flow method for the base case, different transactions and line outage cases.**

***Index Terms* -- Intelligent Techniques, ATC, Power System Deregulation, Real-Time Applications.**

I. INTRODUCTION

THE Available Transfer Capability (ATC) of a transmission network is the unutilized transfer capabilities of a transmission network for the transfer of power for further commercial activity, over and above already committed usage. Power transactions between a specific seller bus/area and a buyer bus/area can be committed only when sufficient ATC is available. Thus such transfer capability can be used for reserving transmission services, scheduling firm and non-firm transactions and for arranging emergency transfers between seller bus/area and buyer bus/areas of an interconnected power system network. The information about the ATC is to be continuously updated in real-time and made available to the market participants through the Internet-based system such as Open Access Same time Information System (OASIS). Every transaction between seller and buyer is communicated to Independent System Operator (ISO) and on the basis of ATC, ISO evaluates the transaction. Thus the ATC must be computed fast and accurately.

A number of methods have been reported to date in literature for ATC determination. The dc load-flow-based methods [2]-[5] are a bit faster than their ac counterparts but model only real power flow (in megawatts) in the lines rather than MVA, and assume the network to be loss free. The methods based on power transfer /outage distribution factors [6]–[8] can cater to only the scenarios that are too close to the base case from which the factors are derived.

The artificial neural network (ANN) method [9] requires a large input vector so that it has to oversimplify determination of ATC by limiting it to a special case of power transfer to a single area from all of the remaining areas. So this method is unable to track down the bus-to-bus transactions, which is the true spirit of deregulation. The Adaptive Neuro Fuzzy method [14] has a limitation with the loading index as all the line outage cases are considered for two categories leading to inaccurate ATC values in most of the line outage cases.

In this paper to overcome the above limitations, to reduce the computational burden and to execute ATC in real time different Artificial Intelligence (AI) techniques viz., Back Propagation Algorithm (BPA), Radial Basis Function (RBF) Neural Network and Adaptive Neuro Fuzzy Inference System (ANFIS) have been utilized and compared with the AC Load flow based ATC. These are tested on standard IEEE 24-bus Reliability Test System (RTS) for base case, different transactions and line outage cases.

II. PROBLEM FORMULATION

The ATC problem for real-time application has been attempted in two different ways i) Neural Network approach and ii) Adaptive Neuro Fuzzy approach. For a given source–sink pair, tracing the least “indirect path” using line impedance data identifies the neighboring bus. The one having the least impedance among all the possible indirect paths is chosen. If there are a number of buses on the chosen indirect path between a source and a sink then the bus immediately after the source is labeled as the neighboring bus. To overcome the limitations of the index [14] a new universal index (γ) has been proposed to represent a given operating condition of a power system taking into account demands at all the buses except the sink and neighboring bus.

The index (γ) is defined as

$$\gamma = \frac{\sum_{i=1, i \neq Ns, Nn}^{N} P_{di}}{A_{\max}} \qquad (1)$$

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Where P_{di} is demand (MW) at bus i, N is the total number of buses, N_s and N_n are sink and neighboring bus and A_{max} is the thermal loadability (MVA) of the line having the highest limit in the system.

Input Variables

ATC between a given pair of source-sink buses in a large system is determined using only three inputs. These are sink bus injection (P_s), the neighboring bus injection (P_n) and the loading index (γ) for the base case and few other binary inputs or a category Index to represent the outages. The sink and neighboring bus injections are the differences between respective local generation and demand in MW.

A. Neural Network approach

Apart from three inputs the sink bus injection (P_s), the neighboring bus injection (P_n), the loading index (γ), various outages and normal operating conditions are considered by categorizing those by taking few other binary inputs that represents for each outage condition. For example, two input binary variables can represent four conditions.

0 0 – normal operating condition
0 1 – outage of line 1
1 0 – outage of line 2
1 1 – outage of line 3

Similarly to represent NL number of line outages we need only maximum of $\log_2(NL+1)$ inputs. Moreover by considering only critical line outages the number of inputs are further decreased.

B. Adaptive Neuro Fuzzy approach

In this approach only one input i.e., Category Index (C) is used to represent various outages and normal operating condition. Thus total inputs considered here are the sink bus injection (P_s), the neighboring bus injection (P_n), the loading index (γ) and the Category Index (C). For the above example, the value of C can be given as follows

C=1 for normal operating condition

C=2 for outage of Line 1

C=3 for outage of Line 2

C=4 for outage of Line 3

III. Artificial Intelligent (AI) models

A. Back Propagation Algorithm (BPA)

A schematic diagram of the topology of BPA is given in Fig. 1. This network consists of a set of 'n' input neurons, 'm' output neurons and one or more hidden layers of k intermediate neurons. Data flows into the network through the input layer, passes through the hidden layers and finally flows out of the network through output layer. The network thus has a simple interpretation as a form of input-output model, with network weights as free parameters. Such networks can model functions of almost any arbitrary complexity, with the number of layer and number of neurons in each layer, determining the function complexity.

In Fig1. The input signal X_i (i=1,……n) are multiplied by the weights W_{ij}; then operated on by the activation function f(x) to produce the b_j of the hidden layer. Similar operations can be made on outputs of the network. Here

$$b_j = f\left(\sum_{i=1}^{n} X_i W_{ij}\right) \tag{2}$$

Where 'f ' is a transfer function of activation function, which can take the form of non-linear function. For the non linear sigmoid function

$$f(x) = (1+e^{-x})^{-1} \tag{3}$$

Training is a procedure used to minimize the difference between outputs of Multi-layer Perceptron (MLP) and the desired values by adjusting the weights of the network. Sets of input vectors are presented to the network until training is completed. Once the network is trained the new input data presented to the network to determine the appropriate output.

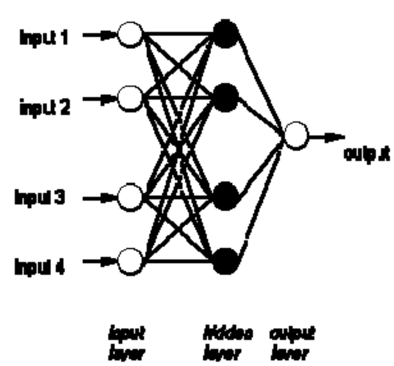

Fig. 1. Topology of a three layered MLP.

B. Radial Basis Function (RBF) Neural Network

A potential advantage of Radial Basis Function Network (RBFN) is its ability to augment new training data without the need for retraining. 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. Thus, it requires less training time in comparison to BPA model.

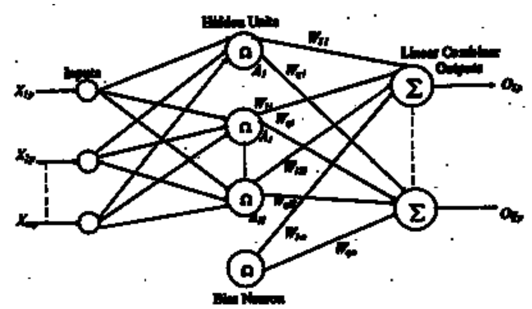

Fig. 2. Radial basis function network model.

The RBFN is shown in Fig. 2. The RBF network hidden layer has non-linear Gaussian function, which is defined by a center position and a width parameter. The width of the RBF unit controls the rate of decrease of function. The output of the i^{th} unit $a_i(x_p)$ in the hidden layer is given by

$$a_i(X_p) = \exp\left(-\sum_{j=1}^{r} \frac{\left| x_{jp} - \overline{x}_{ji} \right|^2}{\psi_i^2} \right) \tag{4}$$

Where $\overline{x}_{ji}$ is centre of ith RBF unit for input variable j, Ψi is width of i^{th} RBF unit, x_{jp} is j^{th} variable of input pattern p and r is dimension of input vector.

The connection between the hidden units and the output units are weighted sums.The output value O_{qp} of the q^{th} output node for p^{th} incoming pattern is given as

$$O_{qp} = \sum_{i=1}^{H} w_{qi}\, a_i(X_p) + w_{qo} \tag{5}$$

Where w_{qi} is weight between i^{th} RBF unit and q^{th} output node, w_{qo} is biasing term at qth output node and H is number of hidden layer (RBF) nodes.

The parameters of the RBF units are determined in three steps of the training activity. First, the unit centers are determined by some form of clustering algorithm. Then the widths are determined by a nearest neighbor method. Finally, weights connecting the RBF units and the output units are calculated using delta rule.

C. Adaptive Neuro Fuzzy Inference System (ANFIS)

The fuzzy logic has two main advantages. The way fuzzy logic tackles the dimensionality of a problem is computationally more efficient than that by other artificial intelligence (AI) techniques (such as ANN, expert system, etc.). Another advantage is that fuzzy logic can capture uncertainties inherent in an incomplete or reduced set of data. It is noteworthy that rigorous mathematics intensive conventional methods have none of these two advantages.

1. Fuzzification of Inputs

Each of the inputs is converted from a single crisp value into a maximum of two fuzzy values using the widely used triangular functions that may overlap with one another as shown in Fig. 3. The x -axis in Fig. 3 represents the crisp values of i^{th} input (I_i) while the y-axis shows "membership grade" (μ_i) that may vary from 0.0 to 1.0. Each triangle has a fuzzy attribute that can be coded by a linguistic variable (e.g., "low") or a number implying level of fuzziness (e.g., 1). However, for the sake of mathematical representation, a number is used. The total number of such attributes or triangles for i^{th} input is denoted by m_i. The x coordinates of three vertices of each triangle are, respectively, a_{ij}, c_{ij} and b_{ij} when j=1, 2,…m_i.

Equation (6) shows crisp (I_i) to fuzzy (I_i^f) conversion for i^{th} input.

$$\begin{aligned} I_i^f &= \{1\}, \quad I_i \le c_{i1} \\ I_i^f &= \{m_i\}, \quad I_i > c_{im_i} \\ I_i^f &= \{(1,2),(2,3)\ldots(m_i-1,m_i)\}, \; c_{i1} < I_i \le c_{im_i} \end{aligned} \tag{6}$$

Where i=1, 2, 3, 4 (i.e., for ATC determination), I_1, I_2, I_3 and I_4 are, respectively, P_s, P_n, γ and C. The membership grade (μ_i) corresponding to each fuzzy value of a given crisp input can be obtained using (7)

$$\begin{aligned} (\mu_i)_j &= \frac{I_i - a_{ij}}{c_{ij} - a_{ij}}; \quad a_{ij} \le I_i \le c_{ij}, \quad j \in I_i^f \\ (\mu_i)_j &= \frac{I_i - b_{ij}}{b_{ij} - c_{ij}}; \quad c_{ij} \le I_i \le b_{ij}, \; j \in I_i^f \end{aligned} \tag{7}$$

Where j implies the numbers picked up by the i^{th} input's fuzzy value (I_i^f) as in (6).

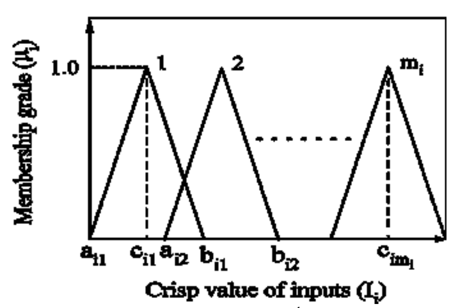

Fig. 3. Triangular membership function for i^{th} input.

2. Inference on ATC

The rule-base relating ATC to the inputs for a large system is developed using Sugeno fuzzy model. A set of first-order polynomial equations is used to infer a crisp value of ATC from crisp values of four inputs.

It should be noted that a given set of crisp values for the four inputs will not fire all of the $\prod_{i=1}^{4} m_i$ rules rather q number of rules when $1 \le q \ge 2^4$ (i.e., one to sixteen rules). This is because, as shown in (6), each input's crisp value has a maximum of two fuzzy values. The required overall crisp value ATC is obtained as in (8) that uses weighted average of the individual crisp outputs from each of the fired rules, that is

ATC_o

$$ATC' = \frac{\sum_{o\in q}(\mu_o ATC_o)}{\sum_{o\in q}\mu_o} \tag{8}$$

Where"o" implies each of the fired q rules, and μ_o is as in (9)

$$\mu_o = \prod_{i=1}^{4}\mu_i \tag{9}$$

Where μ_1, μ_2, μ_3, μ_4 are the membership grades calculated using (7) respectively, for the three input fuzzy values (i.e., I_1^f,I_2^f ,I_3^f andI_4^f).

IV. SIMULATION RESULTS

The IEEE 24-bus RTS has been used to compare the performance of proposed methods with that of full AC load flow-based ATC determination. The test system's line parameters and thermal loading limits (MVA) are given in [10].

The pair of buses 23 (source) and 16 (sink) is considered for illustrating the determination of ATC. The path 23-13-11-14-16 has been identified as the one having the least impedance among all of the indirect paths that connect 16 to 23. This has led to selection of bus 13 as the neighbor to this source–sink.

Generation of Patterns

The Training and Testing patterns are generated using load-flow-based by treating bus 23 as slack, 16 and 13 both as PV (i.e., bus with specified real power and voltage) buses. The other bus types were retained as what those should be in a normal load flow. The load at sink bus (no. 16) was incremented in steps of 10 MW to repeat the load flow until thermal limit is exceeded in any line of the test system. The maximum possible increment achieved above base-case load at the sink bus was the ATC for the corresponding case.

Training

Training sets provided to the neural network are representative of the whole state space of concern so that the trained system has the ability of generalization. Training patterns for the IEEE-24bus system are composed of: Load levels of 50%, 75%, and 100% of base case while all lines in operation with different Sink bus injection. Single Line outage at 50%, 75%, and 100% of base load with different Sink bus injection. There are 180 training patterns in total covering the base case and three line outage cases.

Testing

The trained neural network and ANFIS was tested using 60 patterns, which are composed of 30 load variation cases and 30 line outage cases with different sink bus injections. None of this case was used in the training of the neural network.

A. Back Propagation Algorithm

1. Input Layer

The input layer consists of five neurons to give inputs Sink bus injection (P_s), Neighboring bus injection (P_n) and Loading Index (γ) and 2 binary inputs are selected to represent four cases as below.

0 0 – for Base case
0 1 – for outage of Line number 7
1 0 – for outage of Line number 18
1 1 – for outage of Line number 37

2. Output Layer

The output layer has only one neuron whose output is the Available Transfer Capability from bus 23 to bus 16.

3. Hidden Layer

The neural network with one hidden layer with 9 neurons has been considered by hit and trial, which has provided minimum error.

Fig 4 shows graphically the BPA based ATC as compared to exact values of ATC as determined from AC load flow based calculation [12].

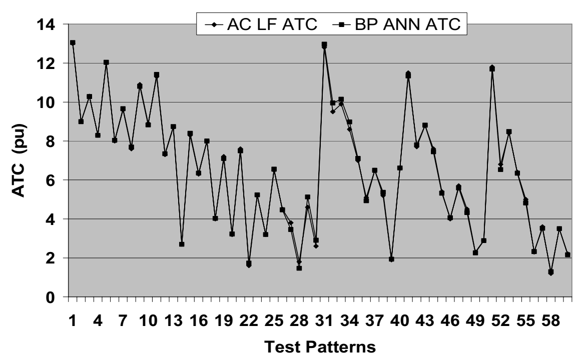

Fig. 4. Comparison of BPA Neural Network ATC and AC LF based ATC.

B. Radial Basis Function Neural Network

To demonstrate the effectiveness of the proposed RBFN model, it has been trained and tested with the same patterns as BPA has been trained. The RBFN model used here has same 5 neurons in the input layer, 1 neuron in the output layer as utilized for BPA. The number of hidden neurons selected as 75 with Gaussian density function.

Euclidean distance-based clustering [13] technique has been employed in this paper to select the number of hidden (RBF) units and unit centers. 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 training of RBF network has been made still faster by applying adaptive learning rate and momentum.

Fig. 5 shows graphically the RBF neural network estimates for ATC as compared to exact values of ATC as determined from AC load flow method.

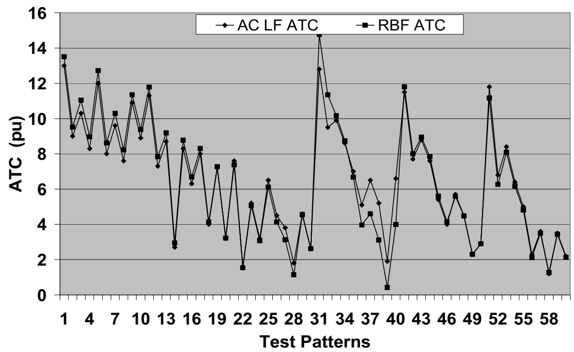

Fig. 5. Comparison of RBFN ATC and AC LF based ATC.

C. Adaptive Neuro Fuzzy Inference System (ANFIS)

ATC between a given pair of source-sink buses in a large system is determined using the same inputs as given in BPA and RBFN methods, except instead of taking binary input variables for outage conditions, a single variable is taken and it is given a separate integer value to distinct each outage case. Hence for the same problem discussed in previous two methods, the inputs thus become Sink bus injection (P_s), neighboring bus injection (P_n), Loading Index (γ) and category Index (C). The C value has been specified as follows

C=1 for Base case
C=2 for outage of Line 7
C=3 for outage of Line 18
C=4 for outage of Line 37

These four inputs are fuzzified and ATC has been calculated. The numbers of fuzzy sets (attributes) chosen are respectively 3, 5, 3 and 4 for P_s, P_n, γ and C. The linguistic attributes corresponding to three levels are low, medium, and high respectively. Since the neighboring bus may also have generation in excess of its local load, its membership levels are five implying negative high, negative low, zero, positive low, and positive high, respectively. For training by ANFIS, the MATLAB Fuzzy Toolbox [17] was used. Fig 6 shows graphically the ANFIS estimates the ATC as compared to exact values as determined from AC load flow based calculation.

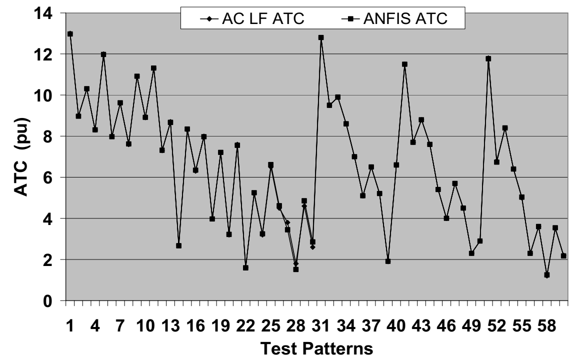

Fig. 6.Comparison of ANFIS ATC and AC LF based ATC.

The ATC values calculated for different test cases by the three methods are given in Table-1 and Table-2 for Base case and line outage cases along with the AC Load Flow based ATC values. Out of 60 test patterns 30 patterns presented in Table-1 correspond to normal operating condition. While the remaining 30 cases in Table-2 correspond to line outages with 10 cases for each line.

TABLE I
ATC BETWEEN BUS 23 TO BUS 16 FOR VARIOUS LOAD VARIATION TEST CASES UNDER NORMAL OPERATING CONDITION (PU)

Test patters	AC LF ATC	BPA ATC	RBF ATC	ANFIS ATC
1	13.00001	13.053	13.506985	12.97
2	9	8.9914	9.518487	8.97
3	10.3	10.281	11.043727	10.309
4	8.3	8.2917	8.965892	8.3094
5	12.00001	12.039	12.720891	11.975
6	7.99999	8.0358	8.613604	7.9748
7	9.6	9.6559	10.296741	9.6234
8	7.6	7.6841	8.222308	7.6237
9	10.90001	10.809	11.352566	10.913
10	8.9	8.8253	9.379425	8.9124
11	11.30001	11.415	11.786911	11.315
12	7.3	7.3441	7.835326	7.3142
13	8.7	8.7402	9.192936	8.6707
14	2.7	2.6969	2.946276	2.6687
15	8.3	8.3976	8.770634	8.3445
16	6.3	6.3528	6.688462	6.3451
17	7.99999	7.9974	8.302246	7.9698
18	4	4.0289	4.134586	3.9714
19	7.2	7.1004	7.273947	7.2113
20	3.2	3.2284	3.222071	3.2188
21	7.6	7.495	7.373643	7.5562
22	1.6	1.73	1.535939	1.5938
23	5.2	5.2348	5.062666	5.2498
24	3.2	3.1999	3.068753	3.2468
25	6.5	6.5503	6.115197	6.6203
26	4.5	4.4658	4.138824	4.6191
27	3.8	3.4563	3.128177	3.4477
28	1.8	1.4665	1.144288	1.5144
29	4.6	5.1265	4.550518	4.8551
30	2.6	2.9055	2.621739	2.8556

Table II

ATC BETWEEN BUS 23 TO BUS 16 FOR VARIOUS LOAD VARIATION TEST CASES UNDER SINGLE LINE OUTAGE (PU)

Test patterns	AC LF ATC	BPA ATC	RBF ATC	ANFIS ATC
31	12.80001	12.964	14.77582	12.801
32	9.5	9.952	11.346738	9.5025
33	9.9	10.141	10.166296	9.9001
34	8.6	8.9781	8.73677	8.6016
35	7	7.1053	6.681277	7
36	5.1	4.9325	3.966622	5.0999
37	6.5	6.4989	4.601788	6.4999
38	5.2	5.3608	3.105386	5.2077
39	1.9	1.9331	0.414151	1.9096
40	6.6	6.614	3.990614	6.5997
41	11.50001	11.34	11.803089	11.501
42	7.7	7.8051	8.00868	7.7019
43	8.8	8.81	8.951054	8.8002
44	7.6	7.444	7.837973	7.6012
45	5.4	5.3226	5.604135	5.4016
46	4	4.0617	4.146664	4.002
47	5.7	5.594	5.592674	5.6999
48	4.5	4.3272	4.477858	4.5004
49	2.3	2.2584	2.302838	2.3005
50	2.9	2.8876	2.897452	2.8998
51	11.80001	11.694	11.165541	11.768
52	6.8	6.5329	6.266925	6.7367
53	8.4	8.4842	8.085509	8.4004
54	6.4	6.3507	6.172842	6.4003
55	5	4.8195	4.810942	5.0366
56	2.3	2.3278	2.116342	2.3004
57	3.6	3.5195	3.495235	3.5999
58	1.2	1.2906	1.269242	1.2505
59	3.5	3.5012	3.433395	3.5455
60	2.2	2.162	2.135205	2.1744

*case 31-40: outage of Line 7
*case 41-50: outage of Line 18
*case 51-60: outage of Line 37

V.CONCLUSIONS

In this paper to utilize ATC calculations in real time, Artificial Intelligent methods viz., Back Propagation Algorithm, Radial Basis Function Neural Networks and Adaptive Neuro Fuzzy Inference System are used and compared with the Full AC Load Flow method. To compute ATC between source and sink three inputs are considered

i) Sink bus injection (P_s)
ii) Neighboring bus injection (P_n) and
iii) Defined Load index (γ).

Whereas for the line outage cases apart from these three inputs two more additional inputs are considered in case of BPA and RBFN whereas only one additional input is considered in case of ANFIS to identify a particular line outage. The proposed method has been tested on IEEE 24-bus Reliability Test System.

In case of Back Propagation Algorithm, the maximum absolute error for base case was found to be 0.5265(pu) and for line outage case was found to be 0.452(pu). For the Radial Basis function (RBF) neural network the maximum absolute error for base case was found to be 0.7437(pu) and for line outage case was found to be 2.609(pu). Whereas for the Adaptive Neuro Fuzzy Inference System (ANFIS) the maximum absolute for base case was found to be 0.3523(pu) and for line outage case was found to be 0.06(pu).

As the ANFIS has minimum error for the base case and line outage case of ATC computations, it can be used in real-time applications.

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