Online estimation of control parameters of FACTS devices for ATC enhancement using artificial neural network

M Karuppam Pandiyam¹, V Agnes Idhayaselvi², D Danalakshmi³, A Sheela⁴

¹² Department of Electrical and Electronics Engineering, Kalasalingam Academy of Research & Education, Krishnankoil, Tamil Nadu, India
³ Department of Electrical and Electronics Engineering, GMR Institute of Technology, Rajam, India
⁴ Department of Electrical and Electronics Engineering, Kongu Engineering College, Perundurai, Erode

* Corresponding author email: agnesvelusamy@gmail.com

Abstract. The deregulated electricity sector needs an improvement in the Available Transfer Capability (ATC) towards the maintenance of power network at balanced condition and to utilize the system in effective manner. Independent System Operator (ISO) maintains the ancillary services by ensuring the reliability of the power system. One of the major functions of ancillary service provider is to maintain the voltage and power flow at stable level. To improve the ATC, both the line power flow and bus voltage profile have to be modified and it is taken care by the ISO. The major limiting criterion for ATC is bus voltage profile. It is well known that the device Thyristor Controlled Series Compensation TCSC which is one of the Flexible AC Transmission System (FACTS) devices can modify the line flow by adjusting the line reactance and Static VAR compensator (SVC) can improve the bus voltage profile by injecting reactive power to the bus. In this research, an Artificial Neural Network (ANN) based estimation of control parameter of FACTS devices such as TCSC and SVC for ATC enhancement is used. The proposed approach uses two different ANN network to find the different TCSC and SVC control parameters to improve the ATC values without violating its voltage constraints for real time transactions. The ANN algorithms such as Radial Basis Function (RBF) as well as Back Propagation Algorithm (BPA) were used to find the TCSC and SVC Parameters and the results are compared. The proposed methods are demonstrated through Reliability Test System (RTS) of IEEE 24 bus. The simulation output represents the suitability of the anticipated method for Real Time estimation of FACTS devices control parameter settings for ATC Enhancement.

Keywords: Available Transfer Capability, Back Propagation Algorithm, Radial Basis Function, Repeated Power Flow

1. Introduction

Towards attaining the effective application of electrical utilities in the advanced electricity market, the power system quantities are operated to its maximum limits. But in deregulated environment, all GENCO’S companies try to maximize their profit. So, they wish to produce and sell more power, which need effective transmission system for transferring power. Due to the environmental aspects and economical consideration, construction of new line is limited. So, effective utilization of existing transmission line without violating its limit is more important. There are many constraints which have been considered when determining the ATC values which are stability limit, voltage limit and thermal limit. This limit can stop the Total Transfer Capability (TTC) even there are surplus amount power available at seller bus and high demand at buyer bus. This difficulty can be rectified by the advent of FACTS devices; which are able to improve the stability and security of the system [1]. Further, it
reduces the power loss, maximizes the transfer capability of power and thereby leads to maximize the usage of existing transmission system.

ATC is a capacity of transmission line to transfer power from seller bys (GENCO) to buyer (DISCO) towards the future activities as well as their existing users [2]. It is obtained for each control area and can make open-access for public communication [3]. Several existing methods are available to calculate the ATC value [4-9]. In [10], it is proposed that the algorithm to find the active ATC as hop bifurcation point as limiting criteria.

Various methods are available towards the improvement of ATC using FACTS devices in the literature. In [11], an Optimal Power Flow (OPF) based ATC enhancement using FACTS devices is discussed and it is implemented in 118 bus system. The author introduced FACTS devices for ATC enhancement but for the determination of ATC by OPF method, takes more time to find the values. To optimally find the location of FACTS devices such as SVC for ATC enhancement, genetic algorithm is used [12]. Similarly, a real coded GA (RGA) and Intelligent water droplets algorithm is applied with settings of FACTS devices like TCSC and SVC for ATC enhancement [13,24]. But, still the optimization algorithms are time consuming process. In [14] a sensitivity based approach for the determination of optimum location of UPFC is presented based on continuation power flow. Towards the ATC enhancement, an OPF based method is presented in [15] for determining the Interline Power Flow Controller's (IPFC) optimal location.

All the above mentioned methods use the optimization technique to find suitable control and location settings for FACTS devices. But in real time, the buyer needs to get huge power from the energy provider which can be limited by the voltage violation. At this situation the DISCO struggling to compensate the demand so the ISO comes into the picture to sort out the complication. The ISO decided to make transaction through some other seller even the existing GENCO has surplus power. This particular problem can be solved through the proposed method, where the FACTS devices are ready to enhance the ATC of the particular transaction with optimal parameter setting. The ANN based online methods estimate the parameters fast and give information to the ISO, from there it can be posted to OASIS for the fast response. The power system consists of dynamic loading and the operating loads are changing for every hour. In this proposed method, different loading conditions (75% to 105%) are considered and the corresponding ATC values and FACTS device parameters are calculated by Repeated Power Flow method (RPF).

The are several methods available to find the On – line ATC but for the authors knowledge there is no paper about the compensating parameter values of FACTS devices for the particular transaction loading condition. The accurate FACTS parameter values can save the operational cost of the devices. A novel ANN based online model is developed in this research to estimate the control parameter settings of SVC and TCSC devices for ATC enhancement. The input for the ANN is loading conditions in percentage, 13 load buses and ATC value. The output for the ANN is the parameter setting of the FACTS devices. The proposed approach makes use of feed forward neural network trained by BPA and RBF models. The data sets are developed using ANN models and it is presented in section 5. The validity of the proposed method is verified through IEEE RTS 24 Bus system.

2. Mathematical representation of DC motor

2.1 Modelling of TCSC

TCSC is one among the FACTS devices that is joined with the transmission line in series. TCSC is a static capacitor/reactor with impedance XTCSC inserted in transmission line that compensates the line
reactance. Thereby, reduces the reactance between the buses. This results an increase in maximum power in the line [16]. Figure 1 shows the TCSC bus connection from 'i' to 'j' in the transmission line model.

![Figure 1 Model of TCSC](image)

In power flow equation, the normal and TCSC lines are differentiated based on the Controllable reactance $X_c$. Reactance change has been introduced by TCSC in the transmission line.

\[ x_{ij} = x_I + x_t \]  

\[ x_t = r_t + x_I \]

where, $x_l$ is the line reactance and $r_t$ is the coefficient related to compensation of TCSC. In this work, the degree of compensation offered by TCSC is taken between 0 and 0.4 p.u, since the TCSC raise the problem of series resonance, it should be only 40 % of the line reactance value.

2.2 Modelling of SVC

SVC is a static VAR compensator connected with shunt in which the output is varied for maintaining the bus voltage [17]. The equivalent circuit of the SVC with susceptibility $B_{svc}$ at bus-i is represented in Figure 2. The injected reactive power at bus $i$ is represented as

\[ Q_{SVC} = B_{svc} \times V^2 \]

where $V$ is the bus voltage magnitude at which the SVC is connected. In this work, the compensation offered by SVC is taken as 0 to 0.8 (p.u) i.e., $B_{svc}$. 
2.3 TCSC Location

The procedure for selecting the locations to place TCSC involves the following steps:

i. Identify the line which is overloaded for each critical contingencies

ii. Among those lines, select most overloaded line to place TCSC.

2.4 SVC Location

The SVC is to be located in optimal place which involves the following steps:

i. Identify the buses which has low voltage level below the rated value for each critical contingency,

ii. Among the buses, the bus which has lowest voltage is selected to place the SVC.

In this work, minimum bus voltage rating is chosen as 0.95 p.u.

3. Problem formulation

The ATC is mathematically written as in Eq. 4,

\[ ATC = TTC - ETC \]  

Where,

TTC - Total Transfer Capability

ETC - Existing Transmission Commitments

The TTC values are calculated by running power flow up to voltage limit violation. In this paper the voltage limit considered is between 0.95 and 1.05.

The constraints are given below.
3.1 Equality Constraints

Transaction power balance and balance equation of the real and reactive power becomes the equality constraints.

\[ F(x, y, T) = 0 \]  \hspace{1cm} (5)

\[ G(x, y, T) = 0 \]  \hspace{1cm} (6)

\[ \sum P_{Gi}^k - \sum P_{Dj}^k = 0 \quad k = 1, 2, 3, t_k \]  \hspace{1cm} (7)

\[ X_{TCSC} = (0.4 - 0.4) X_{line} \]  \hspace{1cm} (8)

where,\( PD_j \) - the power to the buyer bus-\( j \), \( PG_i \) - the power from the seller bus-\( i \), and \( t_k \) is the total number of transactions.

4. Review of neural network

The architecture of ANN has 3 layers which are Input, Hidden and Output layers [18]. The input and output layer has its own neurons depends upon the application. But the hidden layer has \( n \) number of neurons which is randomly defined by users. The number of hidden neuron for each application is different and it will be chosen by trial and error method. There are different algorithm available in ANN based on the weight updation and training of the input output pair. In this proposed approach, two different ANN based supervised learning algorithms are analyzed.

4.1 BPA based ANN

Back Propagation Algorithm (BPA) is most widely used method for pattern recognition problem [19]. The network architecture for the BPA is given in Figure 3. The input data is given to the input layer, with initialized weight updation the values are reached hidden layer. The net input for hidden layer is binary or bipolar sigmoidal function, it is depends upon the pattern problem chosen. The net input entering to the output layer is calculated by Eq. 9.

The mathematical representation is,

\[ out = f(net) = f \left[ \sum_{i=1}^{n} w_{ij} out_j + b_i \right] \]  \hspace{1cm} (9)

where out, and out, are the outputs of i-th and j-th neuron in the present and previous layer. \( w_{ij} \) is the weight from i-th neuron to j-th inputs and \( b_i \) is a bias.
Figure 3 Structure of BPA based neural network

The output is calculated by the nonlinear activation function. This is called forward process of BPA. Now, the output is compared with target and the deviation is updated in the weight vectors between output and hidden layer which is given in Eq. 10.

In equation form,

$$W_{ij}(k+1) = W_{ij} + \Delta W_{ij}$$  \hspace{1cm} (10)

$\Delta W_{ij}$ is the change in weight into the input layer.

The updated weight values are further propagated to the weight vectors between input layer and hidden layer. This is second stage in BPA called Back Propagation. This process is continued till the error is minimized.

### 4.2 RBF BASED ANN

The RBF network is special type of ANN network which has more advantage over BPA. The training time of RBF network is faster than BPA networks. Based on the performance of radial basis function, the network is less prone to problems with non-stationary inputs [20]. The activation function used here is radial basis function so it is called as RBF network. Figure 4 represents the RBF neural network where the inputs are given through the input layer and propagated to hidden layer without weight. The hidden nodes has the transfer function of multivariate Gaussian density function,

$$\phi(y) = \exp\left(-\frac{\|y-u_k\|^2}{2\sigma^2}ight)$$ \hspace{1cm} (11)

where $y$ is input vector, $\|y-u_k\|$ implies the Euclidean distance between input vector, $y$ and Gaussian function centre, $u_k$. $\sigma$ is the spread of Gaussian function [21].

At $k_{th}$ node, $y_k$ is given by,

$$y_k(x) = \sum_{j=1}^{n} w_{kj} \phi(x) + w_{k0}$$ \hspace{1cm} (12)
where \( w_{kj} \) is the weight between the \( k \)th output node and \( j \)th hidden node and \( w_{k0} \) is the bias term.

![Figure 4 Structure of RBF Neural Network](image)

The RBFNN algorithm is.

i. Based on clustering algorithm [22], identify the unit centers.

ii. Obtain width of the unit using a heuristic method by maintaining the continuity and quality of the fitted function.

iii. Based on the least-squares objective function in the linear regression method, the weighting factor has to be obtained in the second layer.

5. Development of ANN for estimating control parameter setting of FACTS devices

The proposed method for estimating control parameter setting of FACTS devices towards enhancing ATC is by using BPANN and RBFNN. The aim is to obtain control parameter setting of FACTS devices for normal and contingency condition in order to improve ATC. The neural network has training and testing phases that are used for calculating the parameters. The data set has been generated through RPF method for different operating conditions from 75% to 105%. The neural network is trained using pre-processed data set. The normalization between input and output data are binary values. After normalization, the input values are applied for training the network. Further, the network is evaluated with various input and output data sets. After the training, real-time data sets can be applied in the network. The development of ANN for the proposed work is detailed in this section. The steps involved in the formulation of ANN – based estimation of control parameter setting of FACTS devices for ATC enhancement model are detailed below.

5.1. Data generation for Training

An imperative step in ANN model is the training data set generation. It is generated based on the following procedure [23],

a. Identify the transaction where ATC needs to be calculated.
b. Generate different loading conditions between 75% and 105%.
c. Calculate the ATC for different loadings using RPF algorithm.
d. Find location of FACTS devices using procedure as discussed in section 2.
e. For TCSC, modify line reactance using Eq. 1 and Eq. 2.
f. Calculate the ATC using RPF algorithm [10].
g. Repeat the steps for different compensation provided by TCSC and calculate respective ATC values.
h. Similarly for SVC inject reactive power to the corresponding bus using Eq. 3 to modify bus voltage magnitude
i. Calculate ATC using RPF algorithm
j. Repeat the steps for different compensation provided by SVC and calculate respective ATC values.

A separate training data is generated for TCSC and SVC. ANN uses percentage of loading and corresponding ATC values as an input and respective FACTS device control parameter setting as an output.

5.2. Data normalization

In the training phase, the input variables of larger value, suppresses the lesser one. Once the real data is functional, then the possibility of risk is there for saturated condition for neuron. Saturated neuron will not produce any change in the input value or output value. Normalization of real data is required to avoid this. The following expression Eq. 13 are used to normalize the data

\[ x_n = \frac{(x - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}})} + \text{starting value} \]

where, \( x_n \) is the normalized value, and \( x_{\text{min}} \) and \( x_{\text{max}} \) are the limits of variables.

5.3 Network development

Once the training is completed in the ANN networks by giving normalized inputs, the network is being evaluated by giving various data. After training and testing, they are ready for generating control parameter setting for FACTS device to enhance the ATC.

6. Simulation results

This section details the results obtained from IEEE 24-bus RTS [25] towards estimating the control parameter settings in the FACTS devices for enhancing ATC using the proposed method. For framing the models in MATLAB, the neural network toolbox has been used.

6.1 Incorporating TCSC in IEEE 24 bus RTS system

IEEE RTS 24 bus system has 11 generator and 13 load buses respectively with 38 transmission lines. Based on the transaction and line outage, the FACTS devices are incorporated with the system. In this proposed method, ANN based network has been developed to check the ATC values for dynamic loading condition and the corresponding TCSC line for the contingency condition. For developing the ANN model, 250 I/O sets have been produced by existing RPF based ATC calculation method in which 200 training and 50 testing data sets are assigned. The input for the ANN is 13 load buses, percentage of loading and corresponding ATC values. Output is TCSC and SVC values. The proposed method is tested for the transaction between the source bus 21 to sink bus 10. By using algorithm presented in section 5, the location of TCSC for a line outage of 3-9 is identified. The identified location of TCSC is line 14-16. TCSC has offered a compensation amount from 0 to 0.4 p.u. In the result section, the RBF and BPA of ANN have been compared. The MSE value, number of epochs and training period are compared. Table 3 shows the network parameter and performance analysis of the BPA and RBF network.
Table 1 Details of network parameter and performance analysis of BPA and RBF

| S. No | Network Parameters | BPA | RBF |
|-------|--------------------|-----|-----|
| 1.    | Number of hidden neurons | 35  | 67  |
| 2.    | Learning rate       | 0.4 | 0.67|
| 3.    | Number of epochs    | 873 | 858 |
| 4.    | MSE                 | 0.0012 | 0.0009 |
|       | Training time       | 15 sec | 11 sec |

From Table 1, it is inferred that the number of hidden neuron which is randomly chosen by users by trial and error method is 35 and 67 for BPA and RBF respectively. The number of hidden neuron is nonlinear for the output. The amount of weight updation can occur in each step of training network is decided by the learning network. The larger learning rate speedup the convergence but overshoot the result. At the same time lower value will decrease the accuracy. So the optimum value of learning rate is important for training. It is user defined variable; the range is between 0 and 1. In this proposed approach, it is given as 0.4 and 0.67 by trial and error method for BPA and RBF respectively. Figure 5 shows the performance analysis of BPA and RBF network. From the Figure 5, it is inferred that the MSE of RBF is slightly less than BPA with minimum time period. Number of epochs is less in RBF network which shows the accuracy of the RBF Network for online applications.

![Figure 5 Performance Analysis](image)

Table 2 shows the compensation needed to obtain particular ATC between source bus 21 and sink bus 10. The compensation obtained by actual procedure (RPF method), BPANN and RBFNN are listed in the above table. With the line outage of 3-9, the ATC is 316.38 MW for the transaction between 21-10 at base case. If the power transfers increases beyond 316.38 MW, the line 14-16 gets overloaded and it violates the voltage stability limit. So in order to enhance power transfer between 21-10, some special arrangements such as new line addition or inserting FACTS devices should be needed. Compared to new line addition, inserting the FACTS devices can be implemented very quickly.

To transfer the power more than 316.38MW between 21-10, TCSC is located optimally between14-16. According to ATC value, TCSC control parameter can be set. At base case, for the ATC value of
322.84MW, the control parameter setting obtained using training data generation procedure is 0.1142p.u which does not violate any constraints. The TCSC Coefficient “r” below the value 0.1142 is violated by voltage stability limit of the line. The estimation of TCSC parameter setting using online methods such as BPANN and RBFNN is produced the same result of RPF with minimum time. The load considered in the proposed system is dynamic behavior which changes with respect to time, so the impact of this dynamic change, the transaction MW is changed for every hour. In this proposed method, different load conditions are considered and ATC is calculated for different percentage of loading.

The Table 2 shows the 75% to 105% load changes, corresponding ATC values and its FACTS parameter settings. When the percentage of loading decreased, the ATC values increased at certain transaction point, it violates the voltage limits of the line. So the TCSC coefficients are increased. At 75% loading, without TCSC the ATC value is 345.43MW, the further increase in the ATC may violate the power flow constraints. But with the integration of TCSC with 0.3455 r coefficient integration, the seller can transmit upto 365MW power. Similarly for 105% over loading, the ATC values slightly decreased to 309MW which is less than base case. To improve the ATC values of 342MW, the TCSC parameter needed is 0.3954. It means, the line reactance of 14-16 has been added 37% of its reactance additionally.

The ANN networks are compared with RPF method in Table 2. The TCSC parameter value given by BPA and RBF is very close to the RPF method. The RPF method consumes more time to calculate the ATC values for the suitable TCSC values, since it runs power flow and check the transaction limits for each one step increment of ATC transaction. Compared with BPA, RBF give accurate result of TCSC parameter for different loading conditions.

| S. No. | Percentage of loading | ATC (MW) | r TCSC setting (p.u) |
|-------|----------------------|----------|---------------------|
|       |                      | By RPF Method | BPA based ANN | RBFNN |
| 1     | Base case            | 316.38   | 0.00 (Without TCSC) | 0.0021 | 0.0012 |
| 2     |                      | 322.84   | 0.1142              | 0.1201 | 0.1118 |
| 3     | 95%                  | 350.23   | 0.3712              | 0.3709 | 0.3711 |
| 4     |                      | 319.60   | 0.00 (Without TCSC) | 0.0003 | 0.0001 |
| 5     |                      | 333.65   | 0.2696              | 0.2682 | 0.2671 |
| 6     |                      | 359.08   | 0.3981              | 0.3960 | 0.3976 |
| 7     | 85%                  | 328.43   | 0.00 (Without TCSC) | 0.0062 | 0.0019 |
| 8     |                      | 341.65   | 0.2174              | 0.2164 | 0.2179 |
| 9     |                      | 367.93   | 0.3886              | 0.3850 | 0.3873 |
| 10    | 75%                  | 345.43   | 0.00 (Without TCSC) | 0.0009 | 0.0004 |
| 11    |                      | 358.17   | 0.1573              | 0.1594 | 0.1600 |
| 12    |                      | 365.10   | 0.3455              | 0.3507 | 0.3498 |
| 13    | 105%                 | 309.76   | 0.00 (Without TCSC) | 0.0015 | 0.0019 |
| 14    |                      | 314.23   | 0.1142              | 0.1201 | 0.1118 |
| 15    |                      | 342.43   | 0.3954              | 0.3939 | 0.3951 |
6.2 Incorporating SVC in IEEE 24 bus system

By using algorithm presented in section 2, the location of SVC for a line outage of 3-9 is identified. The identified location of SVC is bus 3. Total costs offered by SVC are 0 to 0.8p.u. Here selected transaction is between the source bus 23 to sink bus 3. Table 3 shows the compensation of Bsvc needed to obtain particular ATC between source bus 23 and sink bus 3. The compensation obtained by RPF, BPA and RBF are listed in the below table. With the line outage of 3-9 at base case, the ATC is 55.80 MW for the transaction between 23-3. For the further increment of ATC has violated the voltage limit at bus 5. So in order to improve the voltage, the SVC is connected at bus 3. The ATC of 81.6MW has been attained by connecting the SVC of 0.7084 Bsvc. Similarly the SVC parameter is estimated for different loading condition and the values are compared with ANN networks. The ATC values for overloading condition (105%) has given slightly lesser ATC values compared with other dynamic loading condition. So the SVC compensation needed for 105% is more comparatively. From the results it is inferred that, the ANN has predicted the control parameter setting of SVC more accurately within less period of time, specifically RBF based ANN has given closer values with RPF. The proposed ANN based BPA and RBF is best suited for online estimation of FACTS parameters for real time deregulated power system.

| S. No. | Percentage of loading | ATC (MW) | TCSC setting (p.u) | By RPF Method | BPA based ANN | RBFNN |
|--------|-----------------------|----------|-------------------|---------------|---------------|-------|
| 1      | Base case             | 55.80    | 0.0000 (without SVC) | 0.0012 | 0.0009 |
| 2      | 69.2                  | 0.3737   | 0.3727            | 0.3734 |
| 3      | 81.6                  | 0.7084   | 0.7081            | 0.7080 |
| 4      | 95 %                  | 58.25    | 0.0000 (without SVC) | 0.0009 | 0.0017 |
| 5      | 67.1                  | 0.348    | 0.3466            | 0.3490 |
| 6      | 76.7                  | 0.6245   | 0.6212            | 0.6241 |
| 7      | 85 %                  | 63.67    | 0.0000 (without SVC) | 0.0004 | 0.0002 |
| 8      | 81.75                 | 0.6972   | 0.6965            | 0.6971 |
| 9      | 82.95                 | 0.7039   | 0.7058            | 0.7047 |
| 10     | 75 %                  | 66.75    | 0.0000 (without SVC) | 0.0011 | 0.0006 |
| 11     | 72.03                 | 0.2826   | 0.2841            | 0.2836 |
| 12     | 81.9                  | 0.5777   | 0.5759            | 0.5781 |
| 13     | 105 %                 | 53.87    | 0.0000 (without SVC) | 0.0003 | 0.0002 |
| 14     | 59.38                 | 0.3954   | 0.3939            | 0.3951 |
| 15     | 63.08                 | 0.4372   | 0.4381            | 0.4377 |
7. Conclusion

In this article, the authors have illustrated the control parameter settings of FACTS devices using an ANN based estimation technique for online applications. By simulation, results have been taken on IEEE 24-bus system. The performance of BPA and RBF based approaches have been analyzed for accurate estimation of control parameter settings of FACTS devices to enhance ATC for single line outage condition. ISO is whole responsible for maintaining ancillary services of deregulated power system. The ATC has enhanced by incorporating the suitable FACTS devices at suitable places with accurate values. By estimating the FACTS device parameters with accurate value with minimum period has enhanced the stability of the system. The proposed method is suitable for online estimation of FACTS parameter for the integration with deregulated power system.

8. References

[1] Narain G., Hingorani, and Laszlo Gyugyi, “Understanding FACTS: concepts and technology of flexible AC transmission systems”, IEEE press, 2000.

[2] Force T T C T North American Reliability Council (NERC), Available Transfer Capability Definitions and Determination, Princeton, New Jersey, 1996

[3] Federal Energy Regulatory Commission, Open access same-time information system and standards of conduct Docket No. RM 95-9-000, Order 889, Washington, 1996

[4] Christie R D, Wollenberg B F, Wangensteen I, Transmission management in the deregulated environment. Proceedings of the IEEE, 88:170-195, 2000.

[5] Kumar A, Srivastava S C, Singh S N, Available transfer capability (ATC) determination in a competitive electricity market using AC distribution factors Electric Power Components and Systems, 32, 927-939, 2004.

[6] Ejebe, Gabriel C J, Tong J G, Waight J G, Frame, X Wang, W F Tinney, "Available transfer capability calculations IEEE Transactions on Power systems, 13: 1521-1527, 1998.

[7] Gravenor M H, Nwankpa C, Available transfer capability and first order sensitivity IEEE Transactions on Power Systems, 14: 512-518, 1999.

[8] Luo X, Patton, A D, Singh, C, Real power transfer capability calculations using multi-layer feed-forward neural networks IEEE Transactions on Power Systems, 15: 903-908, 2000.

[9] Gan D, Luo X, Bourcier D V, Thomas R J, Min-max transfer capability: preliminary results IEEE Power Engineering Society Winter Meeting. Conference Proceedings, 1:66-71, IEEE, 2001.

[10] Selvi V A I, Banu R N, Devaraj D, Karuppasamy Pandiyan M, Estimation of dynamic available transfer capability including Hopf bifurcation limit using step by step algorithm, International Journal of Power and Energy Conversion, 8-113-131, 2017.

[11] Xiao Y, Song Y H, Liu C C, Sun Y Z, Available transfer capability enhancement using FACTS devices IEEE transactions on power systems, 18: 305-312, 2003.

[12] Farahmand H, Rashidi-Nejad M, Foutahi-Firoozabadi M, Implementation of FACTS devices for ATC enhancement using RPF technique, In 2004 Large Engineering Systems Conference on Power Engineering, 30-35, IEEE, 2004.
[13] Babu P S, Ram B S, Babu M S, Optimal Location of TCSC and SVC for ATC Enhancement in a Deregulated Environment Using Real Genetic Algorithm International Journal of Engineering Research Applications (IJERA) 2: 917-923, 2012.

[14] Donapati S R, Verma K, An approach for optimal placement of upfc to enhance voltage stability margin under contingencies, In Fifteenth National power systems conference (NPSC), IIT Bombay, 441-446, 2008.

[15] Zhang J., Yokoyama A, Application of interline power flow controller to ATC enhancement by optimal power flow control, In 2007 IEEE Lausanne Power Tech.1226-1231. IEEE, 2007.

[16] Banu R N, Devaraj D, Enhanced genetic algorithm approach for security constrained optimal power flow including facts devices, International Journal of Electrical and Electronics Engineering, 3:552-557, 2009.

[17] Gerbex S., Cherkaoui R., Germond, A J, Optimal location of multi-type FACTS devices in a power system by means of genetic algorithms, IEEE transactions on power systems 16:537-544, 2001.

[18] Haykin S Neural Networks: A comprehensive foundation Prentice Hall, New Jersey, 1999.

[19] Devaraj D, Roselyn P, Rani R U, Artificial neural network model for voltage security based contingency ranking, Applied Soft Computing 7:722-727, 2007.

[20] Bishop C M Neural networks for pattern recognition Oxford University Press, New York, 1996.

[21] Devaraj D, Roselyn J P, On-line voltage stability assessment using radial basis function network model with reduced input features, International Journal of Electrical Power & Energy Systems, 33:1550-1555, 2011.

[22] Devaraj D, Yegnanarayana B, Ramar K., Radial basis function networks for fast contingency ranking, International journal of electrical power & energy systems, 24:387-393, 2002.

[23] Selvi V A I, Karuppasamypandiyan M, Narmathabanu R, Devaraj D, Artificial neural network approach for on-line ATC estimation in deregulated power system , In 2014 International Conference on Power Signals Control and Computations (EPSCICON) , 1-5, IEEE, 2014.

[24] Sheela A, Sowmya M , Gowrishankar V, Optimal placement and sizing of renewable energy generation considering uncertainties using intelligent water drops algorithm, International conference on innovations in information, embedded and Communication systems,2017

[25] Christie R, Dabbagchi,I, IEEE 30 bus test case. Internet, www. ee. washington. edu/research/pstca/pf30/pg_tca30bus. htm, 1993.