

# Short-Term Estimation of Transmission Reliability Margin Using Artificial Neural Networks

V. Khatavkar, D. Swathi, H. Mayadeo and A. Dharme

**Abstract** This paper proposes a novel approach for estimation of transmission reliability margin (TRM) by using artificial neural networks (ANN). The laws of deregulated electricity industry have made mandatory to publish the hourly available transfer capability (ATC) values for planning, reliability, and secure system operation. Hence the accurate determination of ATC values is of utmost importance, but is challenging as well. ATC comprises of marginal values such as TRM and capacity benefit margin (CBM) with the existing commitments (EC). Since TRM itself is composed of factors like network parameters, load changes, outages; it not only helps in accurate determination of ATC, but also plays a vital role in system congestion management. Therefore, this paper emphasizes on a method of determination of TRM. The tool used is ANN with back propagation algorithm (BPA) radial basis function (RBF). This work is based on the data of Alberta electric system operator, Canada.

**Keywords** Artificial neural networks • Deregulated power system operation  
Transmission reliability margin • Congestion management

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# 1 Introduction

The deregulated and restructured environment of the power system is enabling power transactions from various generating stations to diverse customers. This facility helps the power producers to generate more energy from the cheaper source for greater profit margins. It also helps customers for choosing more reliable and cheaper power. Although the power producers and customers are different, both of them utilize the same transmission network. Because of all the power transactions from point of production to point of utilization take place simultaneously cause contingency and congestion on transmission network. Power wheeling transactions within the same zone is slightly easier for forecasting and planning as compared to interzone transactions. For making interzone transactions safe and secure the timely posting of cross-border capacities become indispensable. Cross-border capacities of an interconnected system can be labeled as available transfer capabilities in interconnected system.

Available transfer capability (ATC) is made available to all utilities through open access information system (OASIS), so that further committed loads can be interfaced ensuring the system security. This provides a signal to the market participants about the capability of transmission network that is available for the period under consideration.

ATC is defined additional amount of inter-area power that can be transferred without violating the system security [1, 2]. ATC inherently contains some marginal values in it. It is mathematically defined as,  $ATC = TTC - TRM - CBM - EC$  [3, 4]. The TRM accounts for uncertainty in transmission, and CBM accounts for uncertainty in generation. So, appropriate quantification of TRM is essential for accurate determination of ATC.

TRM can be defined as the amount of transfer capability that is necessary for secure operation of interconnected system considering uncertainties at a particular operating condition. Network parameters, load changes, planned and unplanned outages, fluctuations in the prices are the some of the contributing factors of the uncertainty. Gamut of methods is available for calculation and estimation of TRM. J. Zhang discusses a formula which can determine the TRM based on the sensitivities of transfer capabilities and probabilistic uncertainties [5]. The method proposed by the M.M. Othman for determining the TRM with large uncertainty in transfer capability uses the parametric bootstrap technique [6]. In [7], a new concept is devised to estimate the TRM on border values. In this paper, initially the relevant uncertainties are considered and their respective independent time series is derived. Later, each uncertainty is statistically analyzed and their probability density functions are derived. Finally, convoluting all these PDFs the respective TRM values are obtained. All these methods provide accurate and efficient results. But as the power transactions have to be updated periodically and frequently, they fail in fast computation and repetitive analysis. These methods consume excessive computational time and use complex energy management system (EMS) computers.

These can be avoided by using ANN. The complex structure of the problem, inherent uncertainty, and number of factors affecting the system make it difficult to analyze using stochastic methods. This makes ANN more suitable for the problem due to its inherent ability of pattern recognition. This work has been carried out using back propagation algorithm (BPA) and radial basis function (RBF) and validated accordingly.

The paper is organized as follows. Section 1 introduces the paradigm of the problem. Section 2 speaks about problem formulation. Section 3 provides brief review of artificial neural network and related algorithms. Section 4 has the test case and results. Section 5 is about the analysis of results obtained. Ultimately, Sect. 6 concludes the paper with concluding remarks on the work done and possible future scope.

## 2 Problem Formulation

### 2.1 Problem Description

Due to simultaneous use of transmission network by all participants, overloading and congestion on the transmission network occur. This causes the violation of transmission limits such as thermal, voltage, and stability limits which in turn cause the hindrance in the system security and reliability. Therefore, it is necessary to determine the available transfer capability accurately so that the system doesn't lose its reliability while operating on the multilateral transactions. As TRM accounts for considerable part in ATC, it is essential to determine it dynamically [8]. TRM is the amount transmission margin that is set aside for the uncertain conditions that transmission network has to deal with. When the uncertain condition such as line outage occurs this margin is added to that relevant ATC value to prevent jeopardizing the system security. Generally all independent system operators (ISO) allocate certain percentage of margin, i.e., 2–5% of total transfer capability as per NERC regulations [9]. In this paper, an attempt has been made to estimate the TRM at continuous time intervals using the real-time data. And this estimated data is verified against the real-time data.

### 2.2 Methodology

The TRM in real-time application is estimated using the artificial neural networks by back propagation algorithm. Considering the BC-Alberta system bilateral transactions (i.e., historical data), different inputs (uncertainties) are mapped to output to form training pattern. Then this pattern is tested using ANN functions and finally validated using real-time data. The uncertainties considered are planned and unplanned outages and load variations.

### 3 Artificial Neural Networks

ANN has evolved as a great promising statistical tool in solving power engineering problems. It has made it possible to obtain solutions in complex environments in the power systems area where the speed of system security and simultaneously, accurate analysis are ultimate objectives. ANNs have the capability of learning from the large input data, forming a pattern of relationship between the input and the target outputs. The two different multilayer perceptron models applied here are BPA and RBF

#### 3.1 Back Propagation Algorithm (BPA)

The back propagation algorithm is the best method for the feed forward networks. There are two passes allowed in BPA, a forward pass and backward pass. The forward pass evaluates the input layer and hidden layer results and backward pass compares the target outputs and estimated outputs.

The activation function used in BPA can be given as,

$$f(x) = (1 + e^{-x})^{-1}. \quad (1)$$

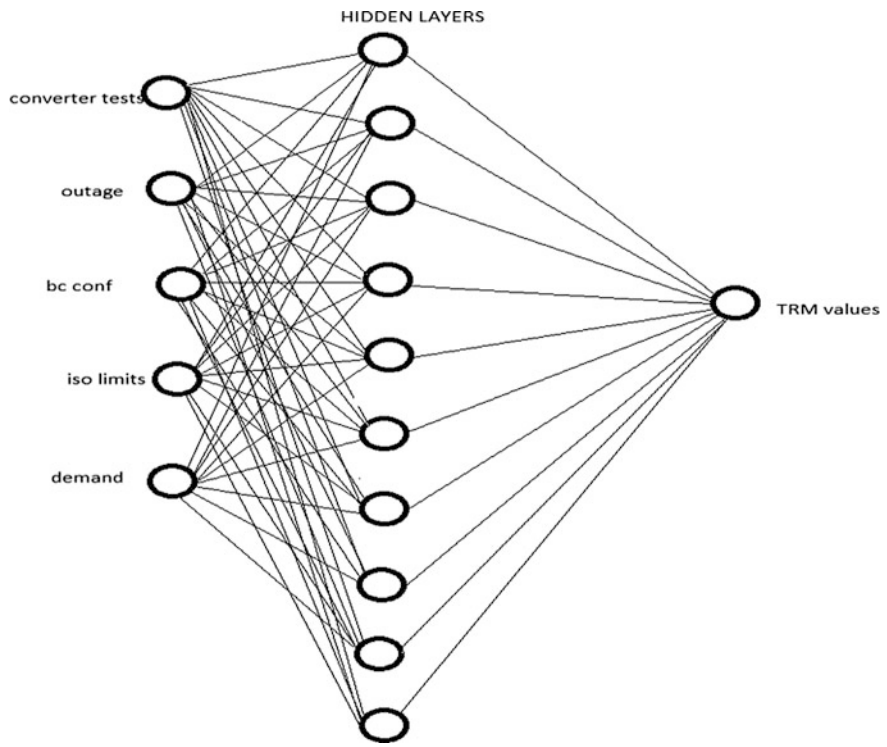
Here, the input signal is given by the  $X_i$  ( $i = 1, 2, 3 \dots n$ ), which is multiplied by the weight  $W_{ij}$ . These are operated using the activation function  $f(x)$  to reproduce the weights of the hidden layer ( $b_j$ ). Where

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

These are forward pass operations. Similarly backward pass operation is also performed.

Here, a training procedure is followed such that the differences between the desired values and the outputs of hidden layers are minimized. Certain part of input data (70%) is reserved for training the network, and the remaining part of it (30%) is used for validation and testing.

The schematic diagram for back propagation algorithm is shown in Fig. 1. This network consists of five inputs neurons, one target output neuron, and hidden layer of 10 intermediate neurons. The five typical inputs taken into consideration are line outages, British Columbia Configuration (BC-conf), converter tests, ISO limits, and demand. Line outages, BC-conf comes under the unplanned outages and converter tests, ISO limits comes into category of forced outages [10]. The components of the neural network are as follows,



**Fig. 1** Back propagation algorithm architecture

1. Input Vector:

Inputs	Limits applied	Limited unapplied
ISO limits	1	0
BC-CONF	1	0
Converter test	1	0
Outages	1	0
Demand conditions	The actual demand at every time interval is considered above the base case transfer	

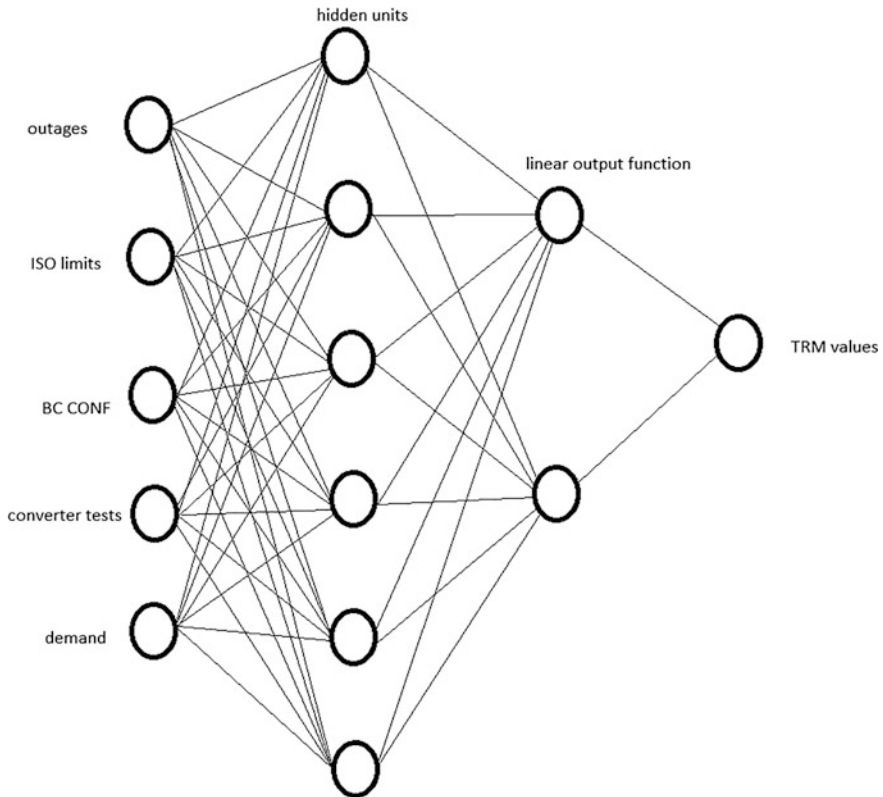
2. Output Vector: The output vector is TRM for stipulated time intervals between sending area and receiving area.
3. Network architecture: As mentioned earlier, 10 hidden layers are used. The sample size of the data is 750. The activation function is used here is Levenberg-Marquardt optimization.

### 3.2 Radial Basis Function

Radial basis function network has input layer, output layer, and only one nonlinear hidden layer. In the process of training, all the inputs are directly applied to hidden layer without weights getting assigned to them. An error signal is generated for the weights of hidden layer and output layer. Hence, it requires less computational time. The schematic diagram of radial basis function implementation is shown in Fig. 2.

The RBF network has nonlinear Gaussian function which acts on the hidden layer which is defined as central position and width parameter. This controls the rate of decrease or increase of function. The output of the  $i$ th unit  $a_i(x_p)$  in the hidden layer is given by,

$$a_i(x_p) = \exp\left(-\sum_{j=1}^r \frac{|x_{jp} - \bar{x}_{ji}|}{\psi_i^2}\right), \quad (3)$$



**Fig. 2** Radial basis function architecture

where  $X_{ij}$  is center of the  $i$ th RBF unit of input variable  $j$ ,  $\psi_i$  is the width of  $i$ th RBF unit,  $X_{jp}$  is  $j$ th variable of input pattern  $p$ , and  $r$  is dimension of input vector. The output value  $O_{qp}$  of the  $q$ th output node for  $p$ th is given by,

$$O_{qp} = \sum_{i=1}^H W_{qi} a_i(X_p) + W_{qo}, \quad (4)$$

where  $W_{qi}$  is the weight between  $i$ th RBF unit and  $q$ th output node,  $W_{qo}$  is the biasing term, and  $H$  is the number of hidden layer (RBF) nodes [8].

The inputs and their values remain same as considered in BPA. The only difference lies in the activation function.

## 4 Test Case and Results

For testing purpose, historical data of Alberta electric system Operator (AESO), Canada, is taken. The system chosen represents a modern power consuming society. Further description about the system is given in subsequent sections.

### 4.1 Test Case

Alberta electric system is taken as the test case. It is a commercial hub and represents peculiar load characteristics of a modern commercial load center. For purpose of testing, the proposed method is performed on AESO import and export TTC values. The system is divided into two areas. Dominant power flow is from British Columbia to Alberta. TRM is estimated between these two areas (Fig. 3).

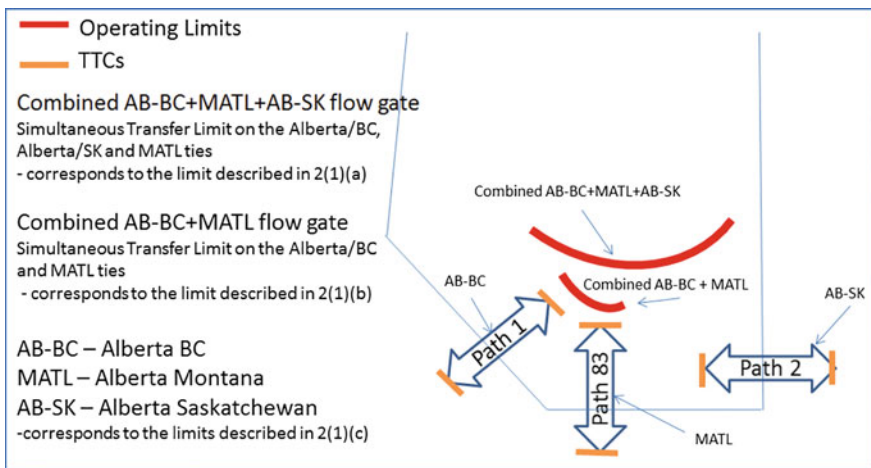


Fig. 3 Test system topology [9]

Testing patterns of neural network are representative of BC and Alberta path transaction. The planned, unplanned, and system parameters are taken into consideration of an independent system operator. Hence, individual transmission line status cannot be updated. So the uncertainties considered here are for the overall system transfer capabilities [10].

4.2 Results

Estimated TRM for every hour is obtained in 24 h window. Here, the TRM comprises of both the marginal values, i.e., CBM and TRM. Since CBM remains constant throughout, the TRM is the only variable; therefore, the whole marginal value is considered as TRM. Figures 4 and 5 give comparison of estimated values and real-time values of TRM for both the algorithms used.

To evaluate the performance of both the algorithms, we have considered relative error as the parameter of comparison. The performance of both the algorithms is given in Table 1.

The comparison of both the algorithms from computational efficiency point of view is given in Table 2.

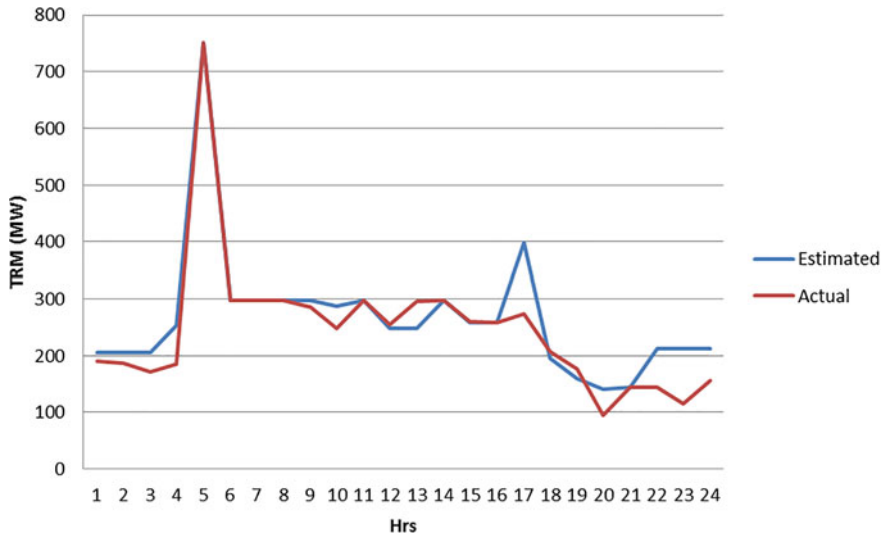


Fig. 4 Estimated versus actual TRM (BPA)



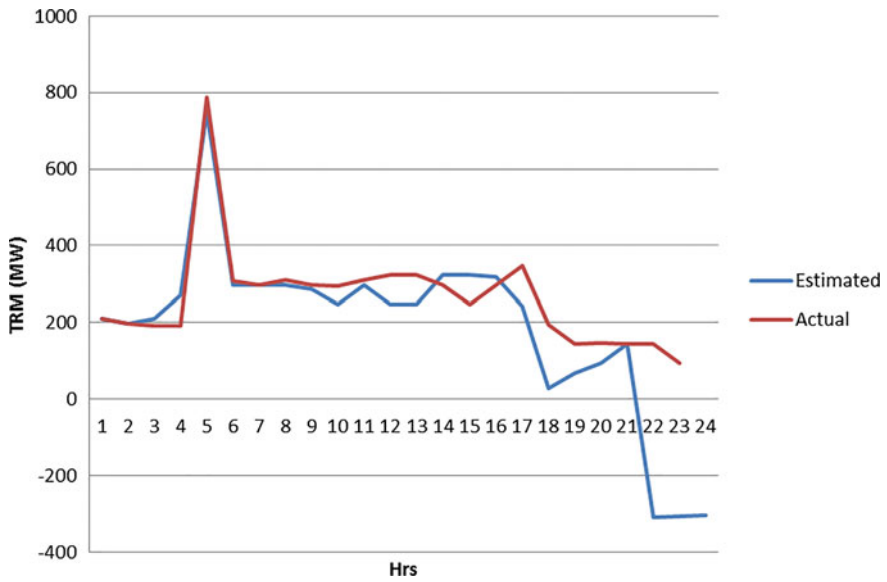


Fig. 5 Estimated versus actual TRM (RBF)

Table 1 Performance comparison

Statistical parameter of $\epsilon$	BPA	RBF
Mean	-0.1337	0.5593
Standard deviation $\sigma$	0.2360	1.2784
Variance $v$	0.0557	1.6344

Table 2 Comparison of computational efficiency

Parameter	BPA	RBF
EPOCH	7 iterations-1000	7 iterations-1000
Performance	193-32.098	256-32.098
Gradient	0.98e-05	0.98e-05
MU	100e+11	100e+10
Validation check	6	6

5 Discussion

From Figs. 4 and 5, it is evident that the vagaries in the difference between estimated TRM and actual TRM are prominent toward the end of the 24 h window. While using RBF algorithm, the estimated values tend to stray away from the actual values after 6th hour mark, but similar phenomenon is observed for BPA from 16th hour. The comparison of performance of the two algorithms shows that BPA is front runner in giving accurate solution to the problem under consideration. The RBF algorithm has much higher relative error especially in the trailing end of

the time window (Tables 1 and 2). This is due the unidirectional flow of the algorithm. The BPA algorithm due to its inherent feedback architecture has a self-correcting ability and fares better against the RBF algorithm.

## 6 Conclusion

The artificial neural network is a handy tool for estimation and prediction of various variables in power systems due to its inherent learnability from pattern forming and experience-based learning. In this work, it is observed that a feedback type algorithm gives better results in comparison with a unidirectional algorithm. Hence, BPA algorithm can be used to estimate and predict TRM values with acceptable accuracy. This helps in quick and reliable planning and operation of transactions with the consideration of TRM.

Further to this study a comparison of other algorithms and statistical method with neural network method can be made. Also, this study is an ex-post study. A similar study can be done for ex-ante estimation or prediction of TRM using both, the neural network tool and statistical tool.

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