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Voltage Collapse Prediction Based on Artificial Neural Network

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Abstract

Stability analysis electric power system is a significant issue for a robust and reliable electric power system and it is a subject of concern throughout the world. Voltage stability can be defined as the ability of electric power system to sustain steady allowable voltages of all buses in the power system operating at usual conditions and when exposed to a different disturbance. Continuously increasing in load demand day by day that leads to low voltage profile and forcing generators to operate near to their maximum limits will lead to voltage collapse and to a blackout conditions. In this paper a line stability Index (Lmn) evaluation can indicate accurately the closeness of the power system to voltage collapse or voltage instability. Lmn index value was also considered as an effective indicator to find stressed line in the power system, where its value ranges from 0 to 1, where zero represents no loads and one represents voltage collapse. Artificial Neural Network (ANN) applied for the evaluation of Lmn Index for all transmission lines in the power system because of its ability in solving non-linear equations, the input-output data set of ANN are yield from the well-known power flow analysis method Newton-Raphson in the MATLAB /Simulink environment. The proposed approach is carried out on the real 132KV, 48-Bus Kurdistan rejoin power system and the results are analyzed and reported.

1. Introduction

Nonstop increasing in electricity demands associated with a lack in installing capacities have led the power systems to operate at low voltage and closer to their security limits, hence voltage instability problem raised[1]. Voltage instability is major reason for most of power systems blackout that accrued worldwide in the past [2]. Whenever power systems heavily loaded and it companied by perturbation in a part of the network, the system faces voltage collapse problems, but other reasons like system exposed to a disturbance, loading characteristics, power generators limits and voltage controlling devices also led to instability in voltage [3, 4]. Power system operators should be supplied by correct and fast information for predicting voltage collapse limits so as to maintain a power system in stability margin and initiate the necessary control steps to protect the system from damage [5]. Voltage stability studies are essential to assess systems performance [6], and also to make sure that voltage magnitudes at all buses in the power system maintain a stable values [2]. Occurring of many voltage collapses in last years, has led to many blackouts that have a significant effect on the society growth and the economy in countries, so the question is how to immediately access the voltage stability of a system and improve unstable operating conditions [7]. Previously, various methods have been proposed for predicting power system voltage instability and its closeness to collapse conditions based on traditional methods [5]. Voltage stability indices (VSI) which can predict early possible voltage collapse in power systems [9], have become important tools that power system engineers used in monitoring systems stability limits for offline, indices such as a line stability index (Lmn), fast voltage stability index (FVSI), and line voltage stability index (LVSI) are the most common ones that used by researchers [10].

Classical methods of voltage stability studies have depends on and continuation power flow method [11] and conventional load flow method, that computes PV and VQ curves which are the most commonly used method for predicting power systems voltage stability[12], mentioned methods involve significant computation efforts and require considerable large time for calculations, hence it is not suitable for online monitoring [13], in online applications quick estimation of voltage stability is vital in order to take acceptable and correct response to avoid voltage collapse [14]. At present, non-conventional techniques such as artificial neural networks (ANNs) have been suggested for voltage stability assessment, ANNs has the ability to solve nonlinear equations associated with voltage stability, so it can immediately analyze the voltage stability hence it is an effective and powerful tool for online monitoring especially in case of urgent situations, furthermore, when creating a good ANNs model, complex algorithms and programming are not necessary and it is simple to implement [15]. The author in [16] proposed neural network model to monitor the VSIs of IEEE 9 buses power system and verified the results validity of the of the proposed neural network model by the conventional load flow analysis method Newton raphson for different types of reactive load conditions, precision and ability of Neural Network to monitor the stability of the power system has been approved. To find the closeness of system operating point from voltage collapse point, ANN has been proved to have better accuracy, efficiency and reliability [9]. In [17] load flow calculations conducted using ANN to overcome the draw backs of conventional N-R,G-S methods that contain iterative calculations, time consuming and nonlinear complex equations, results of ANN used to calculate the line-stability index which is used to maintain the system in stable limits. Predicting voltage stability margin of a power transmission system has been studied in [17] using ANN, the system overloaded, voltage drop noticed in load buses that causes voltage collapse, and weakest bus in the system identified. The paper presented in [5] used convolutional neural network (CNN) for predicting static voltage stability index in transmission power system, input data for the CNN model was active and reactive load values in electric power system. Another indicator named voltage collapse proximity that related to power systems load points was investigated in [1] and it is proved that ANN can be used for early predicting voltage instability. Researchers in [20] applied ANN techniques to provide system operators by accurate and reliable information about voltage stability limits of the system in various operating conditions using voltage stability index. Voltage stability limit enhancement has been studied by proposing an ANN model in [21], the proposed ANN model used to identify weakest lines of a system and then installing FACTS devices for enhancement.

In this study a proposed artificial Feed Forward Neural Networks (FFNN) applied for predicting voltage collapse, using Lmn index as an indicator for voltage stability, effectiveness of the proposed index is investigated on the Kurdistan high voltage power system for different load conditions. Further, the study suggests proper parameters as input – output data set for the structure and training of the ANN where load changes used as an input dataset to the FFNN and Lmn is used as an output data set and as an indicator to the status of the system. Validity of the results from the (FFNN) are verified by those obtained from the load flow using N-R, comparison shows that the proposed method is efficient in estimating the stressed lines with minimum error.

Organization of this paper is as the following: section II presents the methodology of the work, and describes the static voltage stability Lmn index, also describes an introduction to the ANN, training data Generation, ANN Structure, training ANN model and performance of ANN. Section III shows the Simulation of the of the proposed model and Results of simulation compared with N-R method . Finally, Section V concludes the study.

2. Methodology

In this work and for the purpose of voltage collapse prediction a common static stability index, known as Lmn is used, the value of this Lmn index varies from 0 to 1 and the transmission line which has highest value of Lmn index is considered as the weakest line in the power system network, The aim is predicting the closeness to voltage instability and then ranking the obtained voltage collapse in the case of occurrence according to its severity.

Voltage instability occurs in the system when the indicator reaches the value of 1. This index gives a reasonably accurate and more practical means of the estimation and can indicate the voltage stability analysis in a simple way; the indices values are predicted by constructing suitable neural network.

1- Voltage Stability Index

The bus voltage profile for stability analysis can be conducted by evaluating the VSI; static VSIs estimates the systems operating point proximity to voltage collapse point [9]. In this article inorder to assess voltage stability, a popular static stability index, known as line voltage stability index Lmn index [20] is analyzed. This index has been chosen rather than others indexes because of their noticeable precision and low complexity in calculations [7], and also, they have a quick response for changing of reactive power and indirectly affected by active power [21]. Lmn index value ranges between 0 and 1; higher L-index value indicates weakest bus and closer to voltage collapse. When the Lmn indicator reaches the value of 1this means voltage collapse occurs [20]. As soon after Lmn indicators are calculated from load flow analysis for various load conditions, the aim is to use ANN to apply previously calculated Lmn indicators as training and testing data sets [21]. Fig.1 represents two bus power system, the voltage stability for this system may be accessed by Lmn index which may be defined by equations (1) [22],

$$L_{mnij} = \frac{4x_{ij}\,Q_{ij}}{(V_i \sin(\Theta_{ij} - \delta_{ij}))^2} \qquad (1)$$

Where;

Xij = line reactance

Vi= sending end voltage, Vj= receiving end voltage,

Qji = reactive power at receiving end

δ= line impedance angle and Ɵij = power angle

2- Review of Artificial Neural Network

The ANN is well known tool and widely used in power system [23], it can play an effective role in enhancing the voltage stability of electrical power systems with high precision [24]. Artificial Neural Network (ANN) is an effective information processing network that works similarly as biological neurons of human brain which consists of a very large number of highly interconnected artificial neurons that receives input signals processing them using different activations functions based on ANNs application and sends out the obtained signal, the architecture of ANN are organized as three layers; input layer, hidden layer (one or more), and output layer [25], [21]. At starting, ANNs go through learning process, at which weight coefficients are adjusted to fulfill ANN's outputs, learning process classified in to two types; supervised training; in which Ann's output target is known and weights adjusted according to it, and unsupervised training target output is unknown[17,18]. The ANNs main advantages are ability for modeling nonlinear and complex data without needing for understanding mathematical relation between them, also it does not require complex algorithms and programming [16], but they required large amount of data of training [15]. The ANNs can quickly analyze the voltage collapse and monitor it online. An ANN configuration is used to predict the closeness of the 132KV high voltage of Kurdistan rejoin power systems working point to voltage collapse point, the whole process begins as data collection for training and testing, and it ends by evaluating the ANNs performance using mean square error.

A. Training data Generation

Once NN has been constructed for a specified application, it will be ready for training. Large set of data needed for training [26], in this paper the data set are generated using off line well known Newton-Raphson load flow analysis by changing the active load and reactive load of all load buses in the system form base case to about %100 of base case value, voltage stability index are calculated at each step for all buses.

B. ANN Structure

Figure2 represents the construction of a multilayer feed forward neural network. The structure used consists of one input layer, one hidden layer and one output layer. The input layer has 3 neurons since the number of variables in the input neural network is 3 for 41 transmission line in the system, the number of hidden neurons is set to 30 during the real system training by trial-and-error procedure and one output neuron for Lmn index. Input features selection for the training purpose is important while designing ANNs, selecting important parameters has great effect on the learning capability of the NN, absence of these parameters can limit its precision [27]. Total of (2074) input-output dataset features are created. Out of these, 1555 patterns (%75) are used as training data set the rest patterns are used as testing dataset. For this study, the value of voltage magnitude, inductance of the transmission line, reactive loads at all buses were required as an input set data, for the output data set Lmn used. For the simulation the data sets collection process, the active, reactive load values are randomly changed, and load flow analysis using newton Raphson performed and Lnm determined are organized as input-output data set for ANN. The collected features have been normalized and then used to train the NNs [28]. a feed forward neural network with one input layer, one output layer and a single hidden layer is represented in the Fig.2 is selected for the task.

C. Training ANN model

When acceptable amount of training data is generated, next step is the training of ANN's model [29], Training process of NNs involves updating all interconnected weights in the ANNs until the best result is reached which can be observed noting mean square error [24], the following step is testing NNs, in this step weights have been frozen which means that the NNs has successfully learned and it is time to test and predict outputs [30]. Time taken to learn the ANN depends on many factors such as learning rule, number of layers , number of neurons and activation function of neurons[21]. During training different training algorithms can be used, such multi-layer feed forward back propagation (BP) algorithm which is very slow and time consuming so a better algorithm like, Levenberg-Marquardt algorithm are improved to train ANNs that has the ability to converges faster than BP algorithm may be used [26]. In the present paper, the MATLAB neural network toolbox (nntool) is used to train the NN with Levenberg-Marquardt algorithm. If the training set is successful and the algorithm works effectively, the NN will be able to estimate Lmn directly, even inputs are not existed in the training set [12].

D. Performance of ANN

A reliable ANN should be able to generate best output results [31], Root Mean Squared Error (RMSE), which defined as the error between the obtained outputs compared with the desired outputs, is used to evaluate the performance of the feed forward propagation neural network [6], for additional identifying the precision of the developed network, correlation coefficient(R) value must be checked, when the R value is close to one indicates that ANN is trained accurately [32], also indicates a that zero RMSE error. RMSE expressed as a mathematical expression represented as in equation (2).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_{o,i} - y_{d,i})^2}{n}} \quad (2)$$

Where

n is defined as all observation numbers (for this case in this work, it represents amount of data in the testing dataset), $y_{o,i}$ = the predicted output, $y_{d,i}$ = the desired output [6].

3. Simulation of the system and results

Recently in this section simulation details presented; The proposed ANN configuration model based Lmn Index for voltage stability assessment is simulated and verified on a 48 bus, 132 kV Kurdisan region power system, A single line diagram of the high voltage power system is shown in Fig.3; it is consisting of a slack bus, 8 voltage-controlled buses, 39 load buses and 61 interconnected transmission lines, The data used in this research was officially obtained from the General Directorate of Control and Transmission Lines, which operates under the Ministry of Electricity in the Kurdistan Region, Iraq[33]. Load flow analysis is conducted using conventional Newton-Raphson method; the power-flow outputs are used for calculating the Lmn Index for the system and used to define voltage stability. Lmn indices were calculated for different loading conditions, then Training dataset samples was produced to be trained by the ANNs. Changing the reactive loads from 0% to 100% of the base values in all load buses, the Lmn index for all 61 transmission lines were calculated. Training ANN models using Levenberg Macquardit algorithm were finished when maximum of 1000 iteration was reached, mean-squared error lower than 1e-6, or 6 validation checks are performed. Obtained results from the simulation showed that the proposed ANN structure was capable to reach the target value in 25 epochs as its clear in Fig. 4. The correctness of the proposed ANN network was verified by using Mean square error value where index value for any condition is estimated by ANN and compared with the actual value of the index. Obtained test results are listed in Table 1. The Lmn indexes were predicted for all the transmission lines.

To approve the power of the proposed ANN models, three cases are considered.

Case A -Base case load where active and reactive load at load buses at nominal values

Case B- Reactive load at load buses increased by %50 of the base case.

Case C- Reactive load at load buses increased by %100 of the base case.

Fig.5 shows the Lmn for all transmission lines for cases A, index values, for base loading case represented shows that, all lines are within the stable limits except lines (8, 38, 28, 3, 59) have the critical values (equal or higher than 0.9), which means that those lines is prone to voltage collapse (especially line 8 followed by line 38) when compared to other lines. Other line index values estimated by ANN falls in a save range, The ranking of the critical lines depending up on the index values is represented in table 1, where estimated values obtained by ANN are approved by Lmn values computed by NR method. Fig.6 and7 show the performance of NNs and its regression plot respectively. The performance plots show that mean square error reaches 2.11*10-5 comparing predicted and desired outputs, and validation reaches 0.998 which means that outputs of ANN fit the desired output very much. The trained NN is further employed to estimate the Lmn index value of all transmission line under various load condition. Fig.8 represents case B, in which the Lmn index of load buses assessed under an increasing reactive load by %50 in all load busses, considerable increasing number of unstable lines and increasing in values of indexes observed when reactive load continuous to increase by %50 the sequence of the critical lines on the basis of index values is showed in table 2, line number 39 also joint to lines exist in table 1 to become another unstable line of the power system. Further increasing in reactive load as in case C, the L-index gradually increases and reaches very close to 1, hence these lines loses its stability and reaches to collapse point, hence suitable response needs to be taken by insulting correct voltage control devices .Fig.9 indicates that 15 lines are very close to collapse point The sequence of the critical lines which for now becoming more (15 transmission lines) on the basis of index values is showed in table3. So, the used indicator can clearly identify the most unstable and close to unstable lines of the system. For the Line 58 that is connecting bus 2 to 14, The reactive power has been increased on the load bus number 14 from the value of 0.3 p.u to 0.6 p.u, and this will lead to value of 0.99 as the Lmn index, the line number 58 connecting to the bus 14 is going to be critical first when compared to other lines as its Lmn index value is very close to 1. Fig.10 illustrated the increasing of Lmn index for different value of reactive power in p.u. at bus number 40. From the tables and figures above, it can be concluded that using ANN was able to predict the Lmn –index value in a different case of reactive power with very high precision and low RMSE, also the predicted result was approved based on the power flow analysis using conventional N-R method which certifies that the trained NNs can be used for identifying critical lines and voltage stability indication.

4. Conclusion

The conventional voltage stability methods can give accurate results, but these methods are time consuming and very complex , to deal with this problem, an implementation of ANN based technique for predicting voltage collapse using the Lmn index is applied to estimate voltage collapse of 48-bus Kurdistan high voltage power system, the results shows An extremely fast response of the ANN model and simplicity in calculating Lmn index on the bases of reactive load demand in the power system, bus voltages and inductance of the transmission lines as input data, and Lmn index as output data , the values of Lmn Index are appropriate in indicating the most critical transmission line in the power system , and it is validated by the standard Lmn index calculated using results of conventional N-R method, comparing results of both method same lines stability ranking observed, with high degree of accuracy. The proposed off line trained ANN model has proved to be very fast and excellent for the analyzing of systems voltage collapse and effectively monitor on line voltage stability of the power system under various heavy load conditions that will assist the electrical power system engineers in making quick and correct decisions while operating power systems. Simulation results show that both ANN and N-R give required results; furthermore, complex calculation is much reduced when ANN is used. Further works can focus on training ANN for enhancement of voltage stability of Kurdistan high voltage power system to predict optimal size and location of FACTS devices in the power system.

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التنبؤ بانهيار الجهد الكهربائي المعتمد على الشبكة العصبية الاصطناعية

المستخلص

يعد تحليل استقرار نظام الطاقة الكهربائية مشكلة مهمة لنظام طاقة كهربائية قوية وموثوقة، كما أنه موضوع اهتمام في جميع أنحاء العالم. يمكن تعريف استقرار الجهد على أنه قدرة نظام الطاقة الكهربائية على الحفاظ على الفولتية الثابتة المسموح بها لجميع الناقلات في نظام الطاقة التي تعمل في الظروف المعتادة وعندما تتعرض لاضطرابات مختلفة. إن الزيادة المستمرة في طلب الحمل يوماً بعد يوم مما يؤدي إلى انخفاض الجهد وإجبار المولدات على العمل بالقرب من حدودها القصوى سيؤدي لاحقا إلى انهيار الجهد وظروف انقطاع التيار الكهربائي. في هذا البحث يمكن أن يشير تقييم مؤشر استقرار الخط (Lmn) بدقة إلى مدى قرب نظام الطاقة من انهيار الجهد أو عدم استقرار الجهد. كما اعتبرت قيمة مؤشر Lmn مؤشرا فعالا لإيجاد الخطوطو المجهدة في نظام القدرة، حيث تتراوح قيمته من ٠ إلى ١، حيث يمثل الصفر عدم وجود أحمال والواحد يمثل انهيار الجهد. تم تطبيق الشبكة العصبية الاصطناعية (ANN) لتقييم مؤشر Lmn لجميع خطوط النقل في نظام الطاقة بسبب قدرتها على حل المعادلات غير الخطية، ومجموعة بيانات المدخلات والمخرجات لـ . ANN هي ناتجة عن طريقة تحليل تدفق الطاقة المعروفة Newton-Raphson في بيئة MATLAB / Simulink.يتم تنفيذ النهج المقترح على نظام الطاقة الحقيقي ١٣٢ كيلو فولت، ٤٨ حافلة في كردستان ويتم تحليل النتائج وجدولتها.

:الكلمات المفتاحية

التنبؤ بانهيار الجهد، شبكات التغذية العصبية الأمامية، الشبكة العصبية الاصطناعية، MATLAB، مؤشر Lmn.

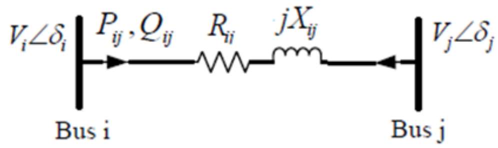

Fig.(1): Two buses single line equivalent network.

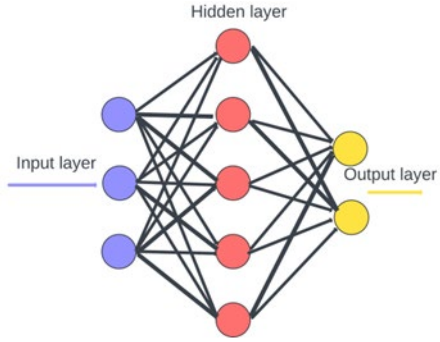

Fig. (2): Feed forward NN architecture.

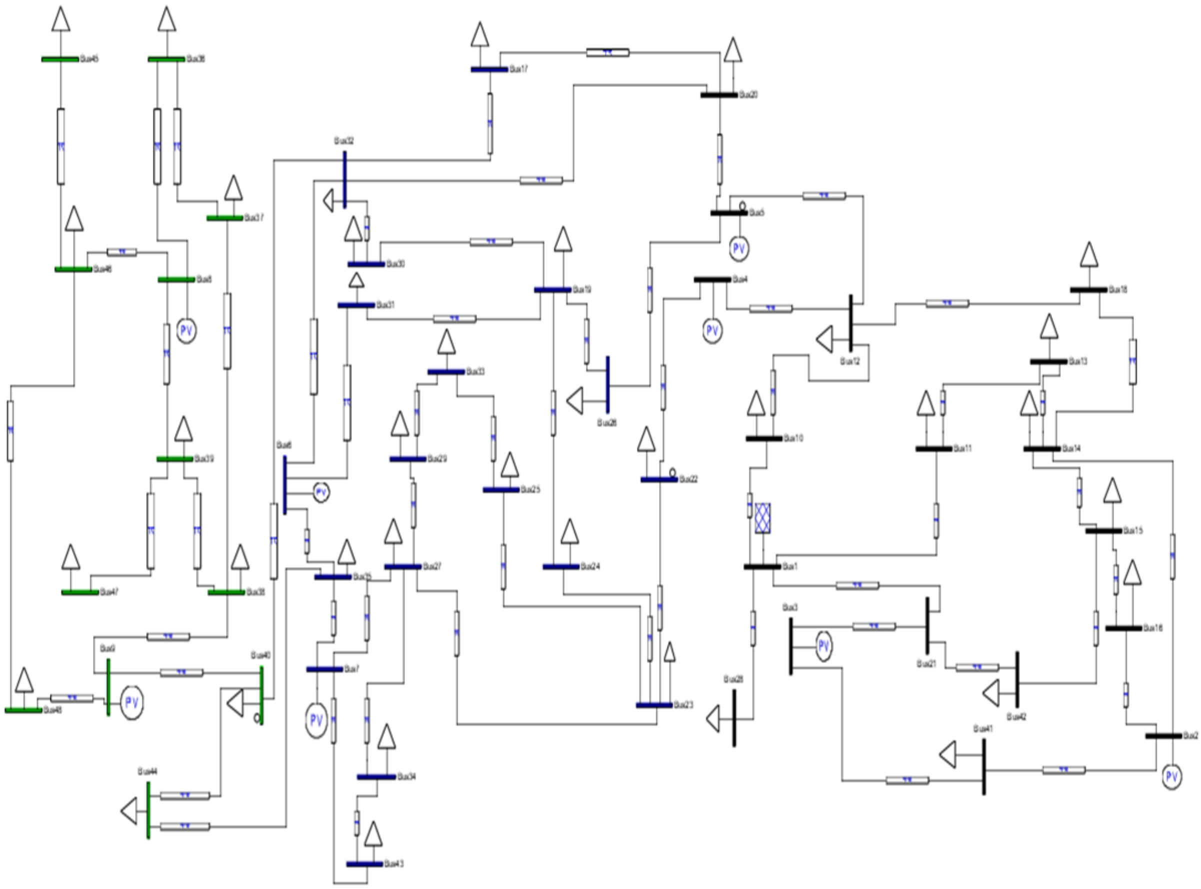

Fig. (3): Kurdistan Region High Voltage Power System.

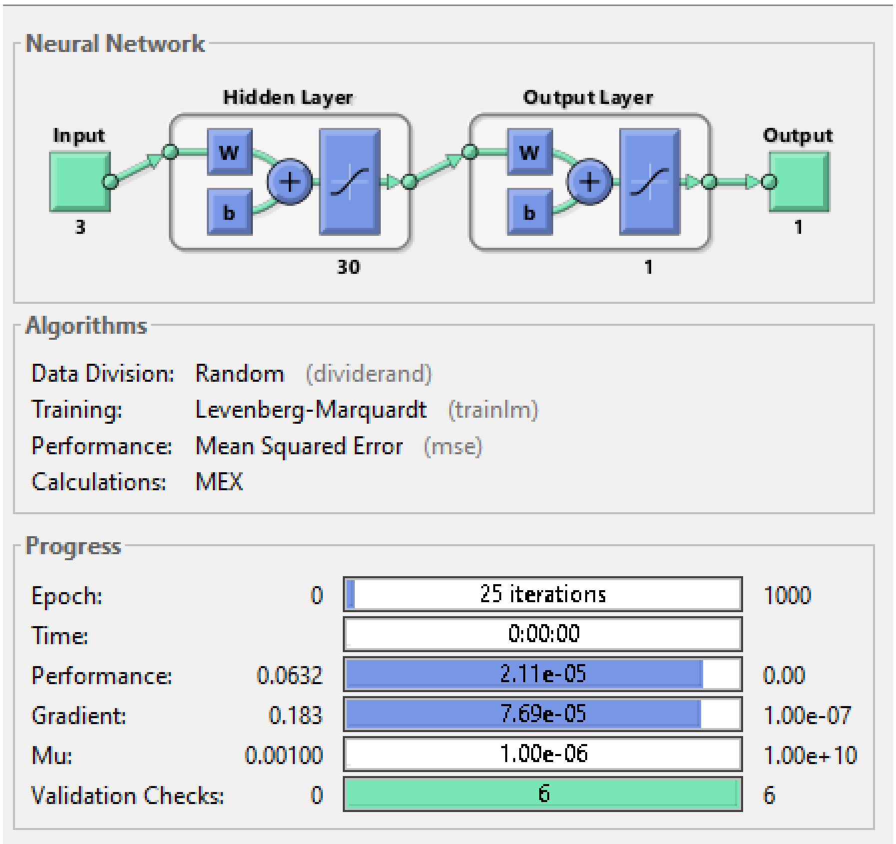

Fig. (4): Trained Neural Network.

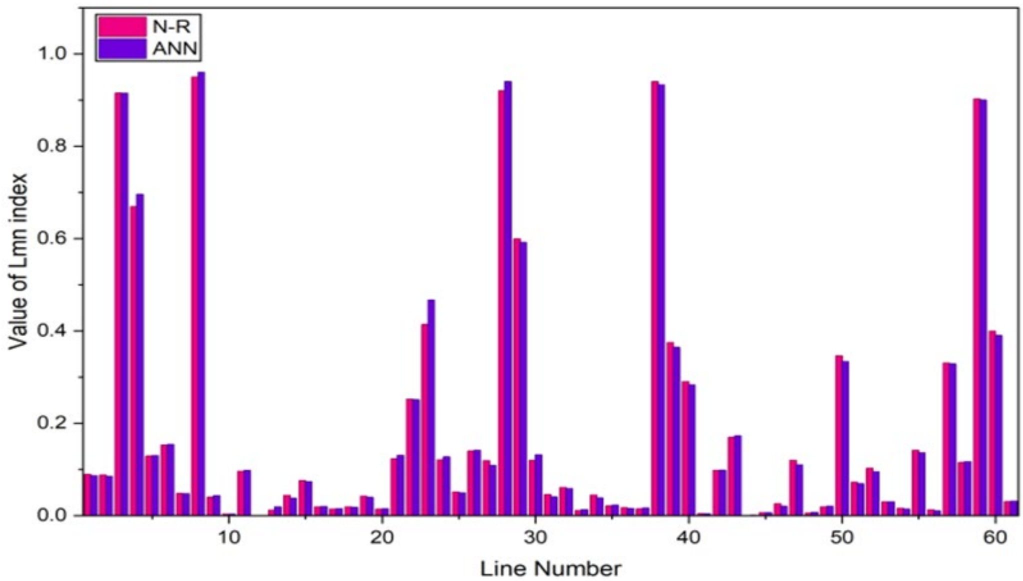

Fig. (5): Lmn index of the base case load.

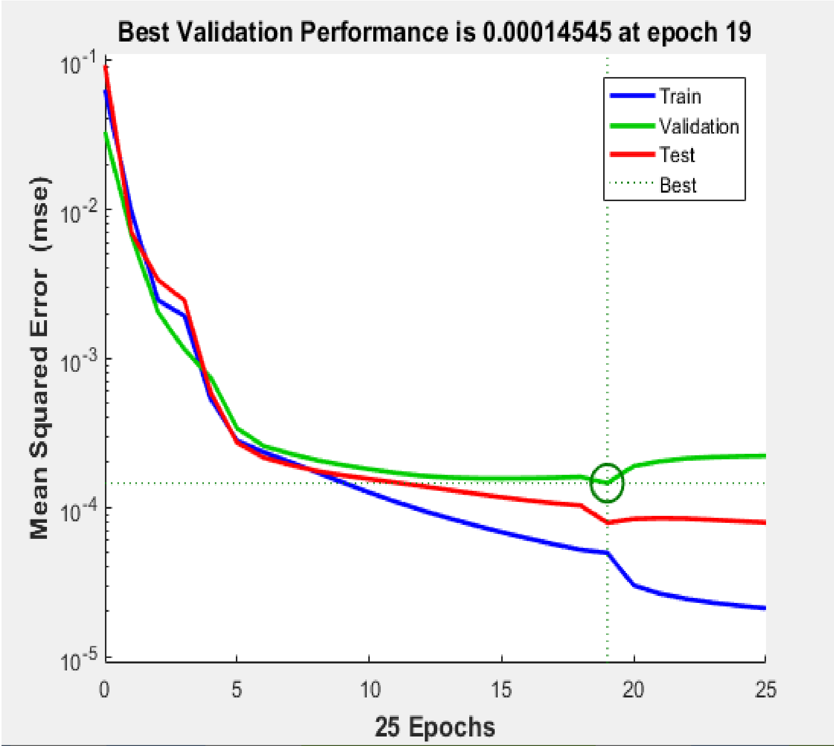

Fig. (6): The mean square error of ANN.

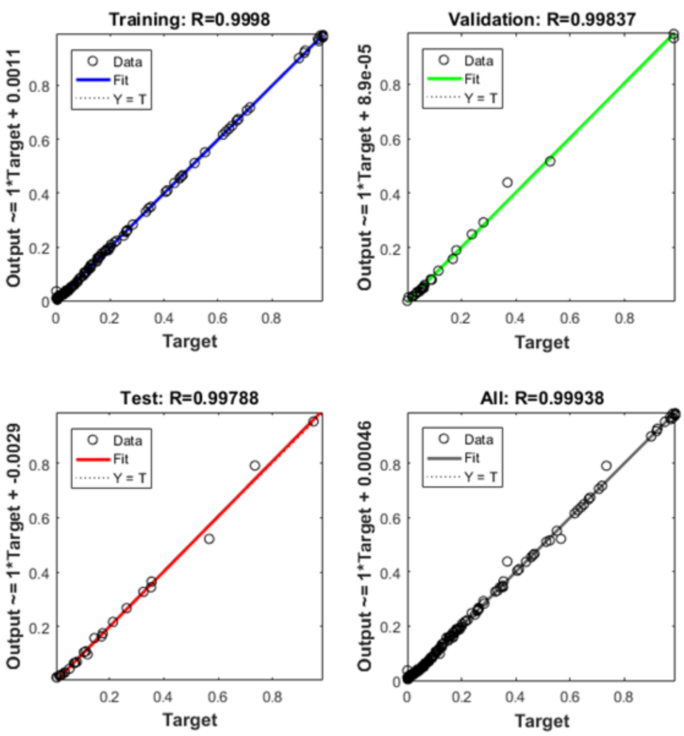

Fig. (7): The regression value of the neural network.

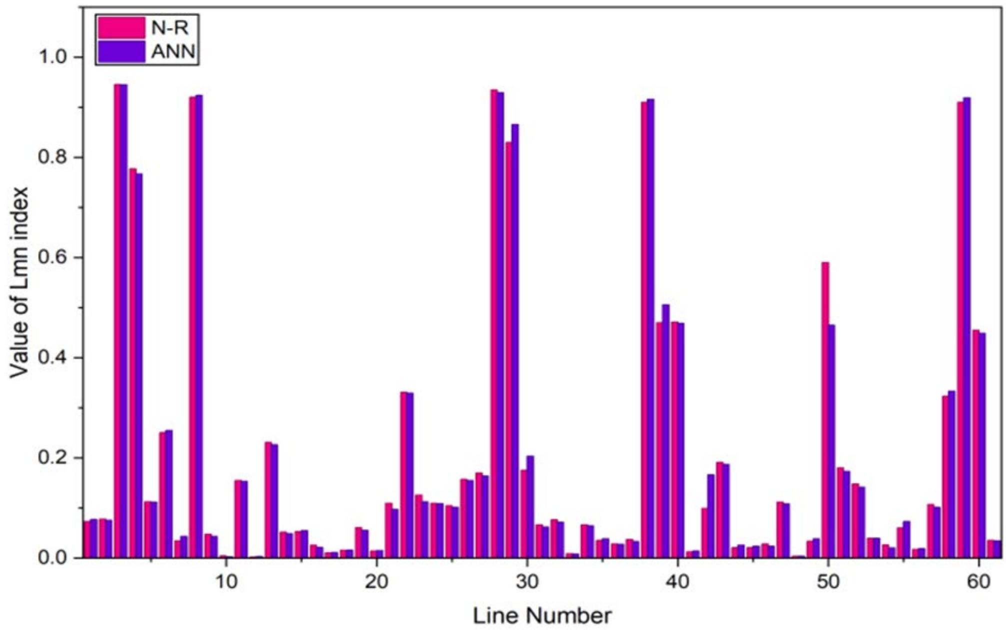

Fig. (8): Lmn index for increasing load by %50 of base case.

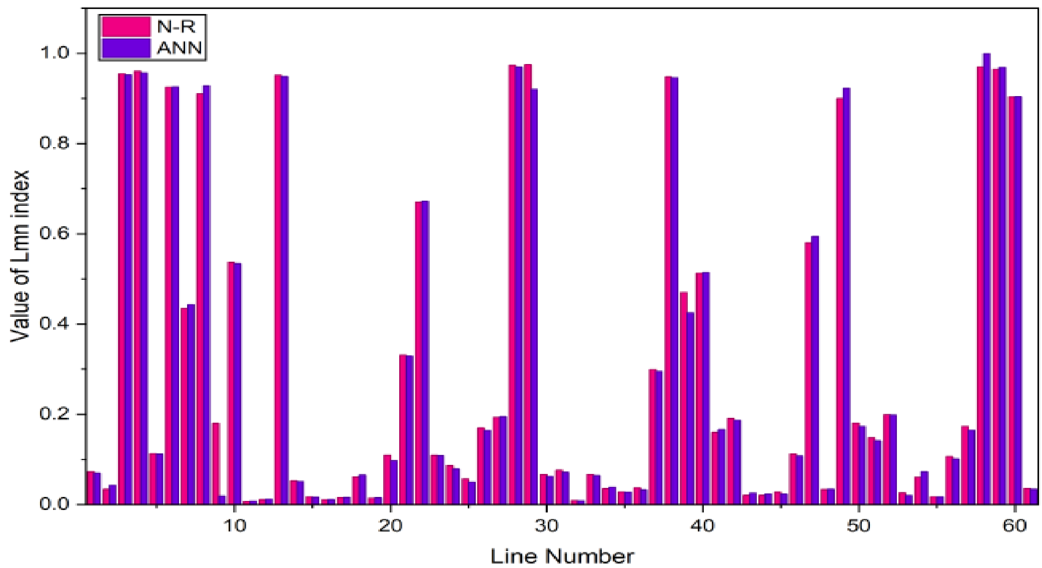

Fig . (9): Lmn index for increasing load by %100 of base case.

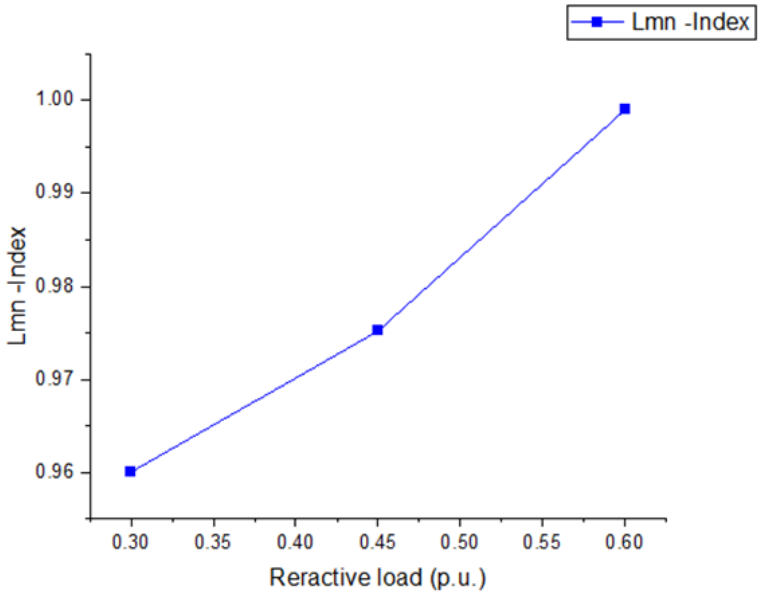

Fig. (10): Lmn index value as a function in x axis able (reactive load) for transmission line number 58.

Table1. Comparison of results of ranking weakest line obtained from classical calculation and ANN algorithm.

Line No.	Lmn by ANN	Lmn by N-R
8	0.95	0.960
38	0.94	0.933
28	0.92	0.940
3	0.9151	0.914
59	0.902331	0.900
4	0.669	0.69566
29	0.599317	0.592

Table 2. Ranking of the weakest lines for base case load.

Line NO.	ANN	N-R
3	0.9452	0.945473
28	0.9294	0.935
8	0.9235	0.92
59	0.919	0.91
38	0.916055	0.91
29	0.8659	0.83
4	0.76697	0.776931
39	0.50568	0.47

Table 3: Ranking of weakest line when load increased by %50.

Line NO.	ANN	N-R
58	0.999	0.97
28	0.96959	0.9733
59	0.9689	0.9645
4	0.9566	0.960
3	0.952	0.954727
13	0.9484	0.95142
38	0.94568	0.948
8	0.92798	0.91
6	0.92547	0.925021
29	0.92034	0.975171
60	0.90438	0.903548
22	0.672	0.67
47	0.59405	0.58
10	0.534	0.536282
40	0.5138	0.51251