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Voltage stability using ANN Combined with Multilinear Regression Models

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ABSTRACT
This paper combined artificial neural network and multilinear regression models to predict voltage stability for power system. An approach for power system is considered by varying loads. Therefore, a modified model, depending on artificial neural network (ANN) dealed with estimated linear regression, is implemented on the 14-bus system electrical network dependent on its load flow data to estimate the maximum loading point and contingency ranking. This technique was compared with conventional methods (also with basic linear regression models). Application of simulation results shows that the proposed methods are feasible and effective. The application of neural networks for online voltage stability. The programming is done in MATLAB-SIMULINK environment.

Keywords: IEEE 14 bus system; neural networks; multiple regression models, MATLAB.

1. INTRODUCTION

The increase of power systems related to have been obtained worldwide by engineers, customers and utilities. As demands for energy is rising rapidly, in power system is increasing to accommodate the rapid loading factor changing by load flow control analysis for different contingencies. This continues expansion and persistent active power make power system more complex or may be vulnerable and difficult to maintain its stability and ensure its security. Voltage stability and its margin are well-defined and classified in [10]. While indicated an appropriate load flow analysis for voltage stability phenomena among engineering and researches are still debatable. Voltage stability has been studied using two main approaches: steady state and dynamic analysis, where voltage instability as fact is considered as transient and sdynamic phenomenon.

Although the transient/dynamic analysis is preferable by most utilities, the steady state voltage stability approach is basically used in research and on-line regression for applications providing an insight into voltage stability problems with high speed analysis.

II. VOLTAGE STABILITY ANALYSIS

PV and QV curves-Voltage profiles shown in the well-known PV and QV curves are of the practical use for determining the proximity to collapse so that operators can take proper preventive control actions to safeguard the system. Q-V curve technique is a general method of evaluating voltage stability. It mainly presents the sensitivity and variation of bus voltages with respect to the reactive power injection. Q-V curves are used by many utilities for determining proximity to voltage collapse so that operators can make a good decision to avoid losing system stability. In other words, by using Q-V curves, it is possible for the operators and the planners to know the maximum reactive power that can be achieved or added to the weakest bus before reaching minimum voltage limit or voltage instability. The P-V curves, active power-voltage curve, are the most widely used method of predicting voltage security. They are used to determine the MW distance from the operating point to the critical voltage.

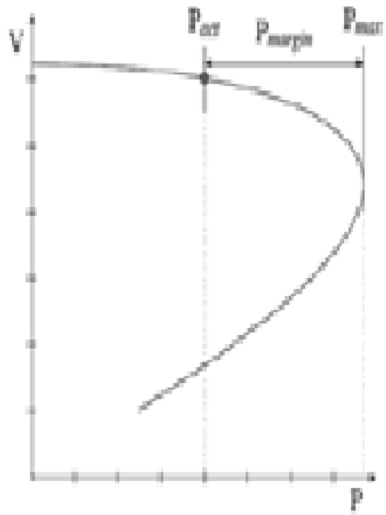

Fig 1: Power Margin

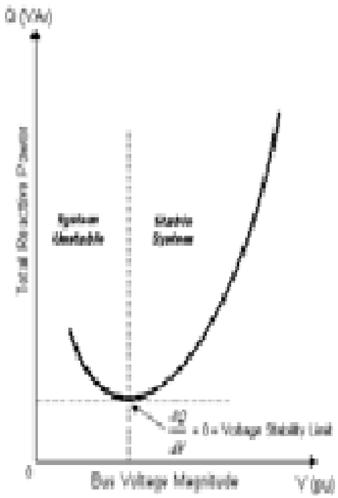

Fig 2: Q-V curve

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In this region, several voltage stability indicators are estimated. It should be indicated at implementing these already proposed indicators by ANN networks for back propagation algorithm.

The adoptability of testing proximity to voltage stability/collapse was tested beforehand for IEEE 14 bus system. On-line determination of proximity of power system to voltage collapse is essential for operating the system with an adequate security margin.

The voltage stability, also called as load stability refers to the ability of the system to maintain load bus voltages within acceptable limit, following some disturbance or change in power demand [12]. IEEE has given the formal definition of voltage stability as: It is the ability of a power system to maintain voltages so that when load admittance is increased, load power will increase, i. e., both voltage and power are controllable [4]. Voltage stability in its simplest form can be illustrated by considering the two terminal network of fig. 1. It consists of a constant voltage source *ETH* supplying a load *ZL* through series impedance *ZTH*. This is representative of a simple radial feed to load or a load area served by a large system through a transmission line because any complex supplying system may always be reduced to the Thevenin's equivalent circuit shown in fig. 2.

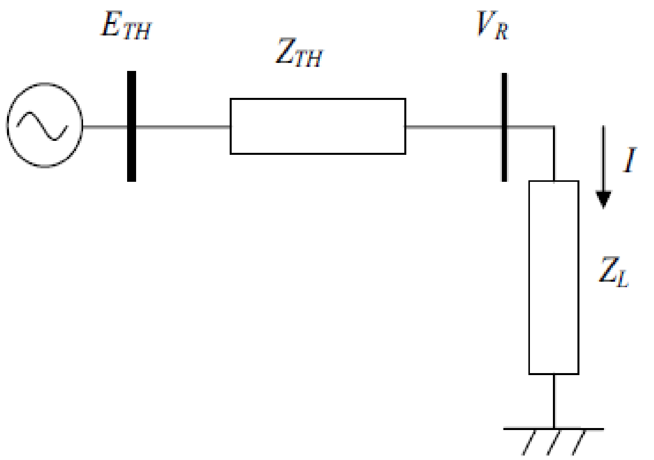

Fig 3: Equivalent circuit as Thevenin equivalent

Simplified equivalent circuit of a local bus and rest of the system treated as a Thevenin equivalent.

The magnitude of the current is given by –

$$I = \frac{E_{TH}}{\sqrt{(Z_{TH}\cos\theta + Z_L\cos\phi)^2 + (Z_{TH}\sin\theta + Z_L\sin\phi)^2}} \qquad (1)$$

This may be expressed as -

$$I = \frac{E_{TH}}{\sqrt{Z_{TH}^2 + Z_L^2 + 2\,Z_{TH}\,Z_L\cos(\theta-\phi)}} \qquad (2)$$

Where -
θ = phase angle of impedance Z_{TH} and
ϕ = phase angle of impedance Z_L

The magnitude of the receiving end voltage is given by

$$V_R = Z_L I = \frac{E_{TH} Z_L}{\sqrt{Z_{TH}^2 + Z_L^2 + 2Z_{TH} Z_L\cos(\theta-\phi)}} \qquad (3)$$

The apparent power supplied to the load is

$$S = V_R^2 Y \qquad \text{where } Y = \frac{1}{Z_L}$$

$$\therefore S = \frac{E_{TH}^2 Z_L}{Z_{TH}^2 + Z_L^2 + 2\,Z_{TH}\,Z_L\cos(\theta-\phi)} \qquad (4)$$

III. ARTIFICIAL NEURAL NETWORKS

A basic Artificial Neural Network (ANN) of power system is a computational model that requires to account for the parallel in connection of the human brain. Specifically, it is a network of highly interconnecting processing elements (neurons) operating in parallel connection, Fig. 4. An ANN can be utilized to solve numerical problems involving complex relationships between parameters. The basic type of ANN used in this load flow study is a supervised learning one, wherein the observation (target) is specified, and the ANN is trained with adjusting different gains to reduce the absolute error between the ANN output and the target, resulting in an optimal solution (assuming the absolute and global minimum is obtained). This is accomplished by varying the connections between the elements, which involves an adjustment to the weights (w1, 1…w11, z).

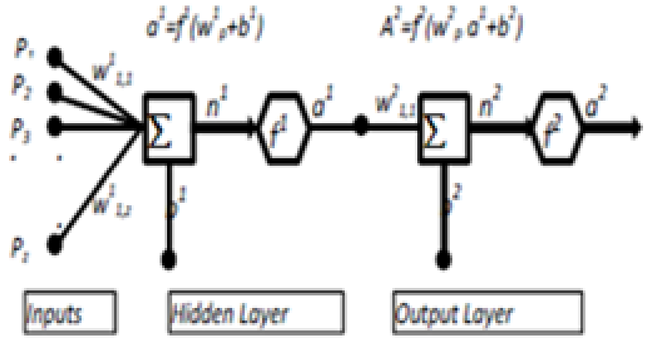

Fig 4: A two-layer ANN with multi-input and single hidden layer and output layer

In normal theory, this adjustment process can be viewed as a form of 'learning'. Thus, the ANN is considered to be a form of artificial intelligence. ANNs were selected for this study owing to their ability to model non-linear relationships. The relationship between the input and output parameters in this study is highly non-linear.

IV. Mathematical formulation of MLRMs

The general formulation of a MLRM for a given observation *i* is given, with all variables described in the sequence. The variable *y* represents the dependent variable (VSM), the*n* variables represent system RPRs, the variables α , β and γ represent the coefficients for each RPR in the model and ε*i* represents the error term. The index *i* accounts for the number o samples available, whereas the indexes *j*, *l* and *k* account for the number of RPRs available.

$$y_i = \alpha_0 + \alpha_j x_{ij} + \gamma_{kl} x_{ik} x_{il} + \omega_j x_{ij}^2 + \varepsilon_i ,$$

$$for \{ i = 1,...,n; j = 1,..., p; l = 1,..., p; k = 1,\mathrm{L} \;, p; \; with \; k \neq l \} \quad \textbf{(5)}$$

Although quadratic and crossed terms are present (*xi*2*j* and *xik xil)*, the model is still linear on the coefficients α , γ and ω and hence can be solved by the method of least square or robust least square, In case several observations or samples are available to the model, equation (5. 1) can be represented in the vector-matrix form as shown in (5. 2), where the *coefficient vector* β is given

$$\text{by}\, \boldsymbol{\beta} = [\alpha_0, \mathrm{L} \;, \alpha_p, \gamma_1, \mathrm{L} \;, \gamma_{p(p-1)/2}, \mathrm{L} \;, \omega_1, \mathrm{L} \;, \omega_p]^T .|$$

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \quad \textbf{(6)}$$

Adapting the formulation given in (5. 2) to the problem at hand, vector **y** will represent VSM measurements obtained from offline system simulation; **X** will be a matrix containing monitored RPRs and ∑ represents the residual or errors.

The first column of matrix **X** is formed by a unitary vector (it contains 1's from the first until the last vector position) to account for the linear interception coefficient 0 〈. All the remaining columns of **X** represent a RPR, a product of RPRs, or a squared RPR as described in (5. 1). Each row of matrix **X** and row of vector **y** represents a sample of the RPRs and system VSM, respectively. The samples of RPRs and VSM are taken at different points along the PV curve, enabling the MLRM to be used at different loading levels along the LID. The *coefficient vector* β is found by minimizing the sum of the square of the residual as follows.

$$\underset{\beta}{Min} \| \boldsymbol{\varepsilon} \|^2 = \underset{\beta}{Min} \frac{1}{2} \| \mathbf{y}\text{-}\mathbf{X}\boldsymbol{\beta} \|^2 \quad \textbf{(7)}$$

The solution of problem (5. 3) is defined as the least square solution, The best linear unbiased estimation (BLUE) for the vector of coefficients β is given by equation.

$$\hat{\boldsymbol{\beta}} = \left(\mathbf{X}^T \mathbf{X} \right)^{-1} \left(\mathbf{X}^T \mathbf{y} \right) \quad \textbf{(8)}$$

Once the vector of coefficients β is found, the MLRM regression model can be used online to estimate VSM. An estimation of the VSM vector (ŷ) is obtained by multiplying the vector of coefficients β by the matrix of monitored regressors **X** as follows.

$$\hat{\mathbf{y}} = \mathbf{X}\hat{\boldsymbol{\beta}} \quad \textbf{(9)}$$

The difference between the estimated VSM values (ŷ) and the actual VSM values (**y**) is defined as *residuals* or *errors* (∑).

$$\boldsymbol{\varepsilon} = \mathbf{y} - \hat{\mathbf{y}} \quad \textbf{(10)}$$

Confidence intervals for the estimated VSM (ŷ) can be obtained by modeling the residual probability density function (*pdf*). Once obtained, the confidence interval (c. i.) can then be used to handle uncertainty of VSM estimation in the following manner.

$$\hat{y} = X\hat{\boldsymbol{\beta}} \pm c.i. \quad \textbf{(11)}$$

Equation (11) represents how the MLRM are to be used in the online environment to estimate VSM. The online monitored RPR vector (*X*) is multiplied by the regression coefficient vector (β) to get an estimation of VSM. The confidence interval is obtained by modeling the residual *pdf* and is later added as bounds to the estimated VSM.

- Uncertainty in system stress direction
- Power system modeling and simulation
- Using MLRMs to relate RPRs and system VSM
- MLRM developmental procedure
- Homoskedasticity
- Normality of the residuals
- Hypothesis test
- Multicollinearity

V. APPLICATIONS AND RESULTS

This simulation approach deals a step by step approach that initiates load flow study with different multilinear regressions. The proposed algorithm consists of a series combination of two methods for

Modeling and study of power systems stability. The two methods are: Artificial neural network and linear regression models. The step by step procedure of power system could be derived as follows:

1. A neural network was applied using electric load data and the output is fed to neural network training regression.
2. A linear regression models were derived for all cases (by varying loading factor, for different contingencies and etc).
3. Then, the load of power systems was estimated as the indicated artificial neural network (Step 1) moved by the find out mean value obtained using (Step 2).

The commonly used as the coefficients which are nearby to minimum values will be found during the different learning methods/rules even though the number of iterations is obtained at a reference value. Therefore, the estimated performances of the estimated models are obtained with further efficiency terms. Each parameter is estimated from the

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estimated values of the simulation model and the measured data (targets). The accuracy of the proposed method is tested for IEEE 14 bus test for power systems.

Each simulation model will be tested by four types of error to guarantee the maximum accuracy and to ensure that the load flow control analysis is near as possible to the actual load. This will summed more complications to the problem but in the same time. Since the mathematical values of the load flow data entity improves at each and every iteration, in order to make a fair comparison in terms of the squared error, we also present a' normalized RMSE", which leads to the RMSE value normalized.

The basic characteristic of voltage stability is illustrated with IEEE 14-bus for power system. The generator produces active power, which is transferred through a transmission line to load. The reactive power capability of the generator is infinite. Thus the generator terminal voltage V_1 is constant.

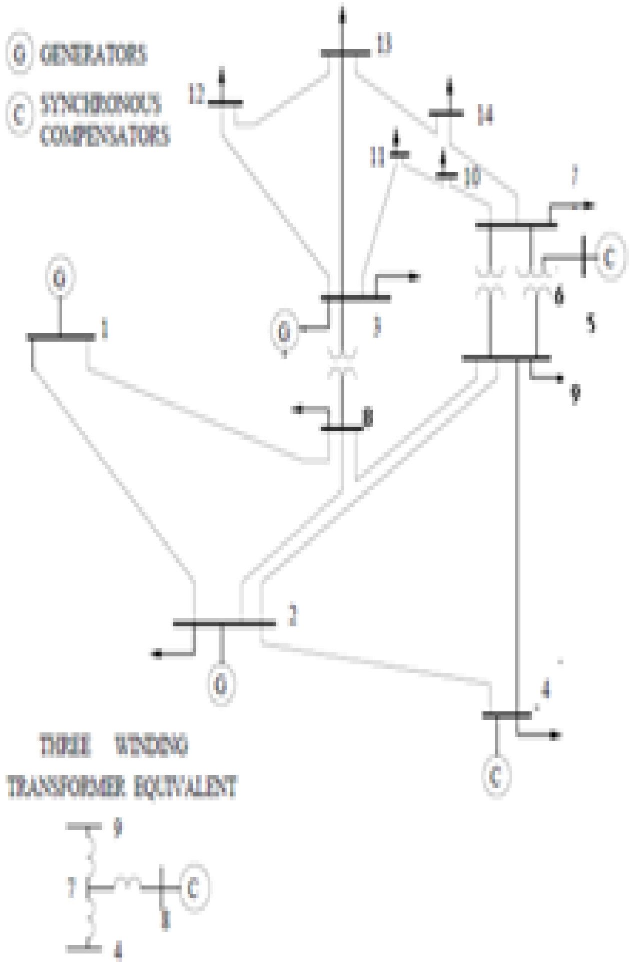


Fig 5: Line diagram of IEEE14-bus test system

$$V_2 = \frac{\sqrt{((V_1^2 - 2QX) \pm \sqrt{(V_1^4 - 4QXV_1^2 - 4PX^2)}}}{2} \quad (12)$$

$$Pi = \Sigma ViVjYij \cos(\delta i - \delta ij Yij)$$

$$Qi = \Sigma ViVjYij \sin(\delta i - \delta ij Yij)$$

For i,j =1 to n

Where Pi and Qi are active and reactive powers injected at load.

VI. ILLUSTRATIONS

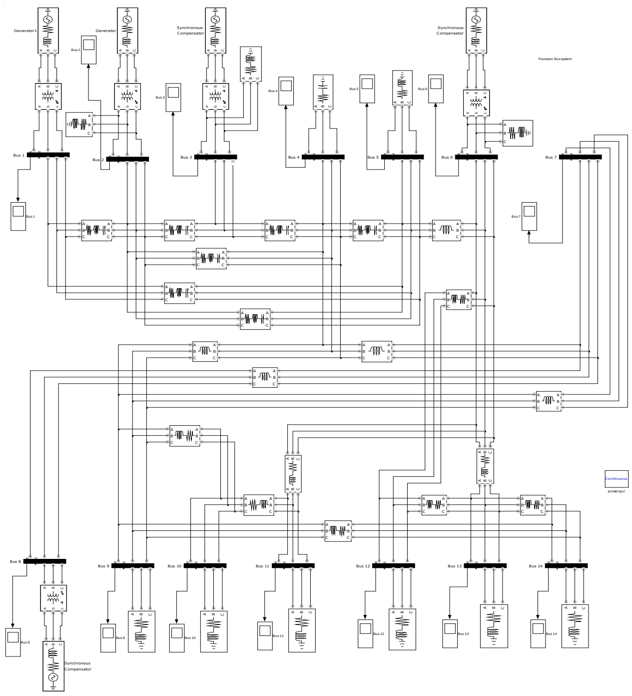


Fig 6. Simulation Model for IEEE 14-BUS system

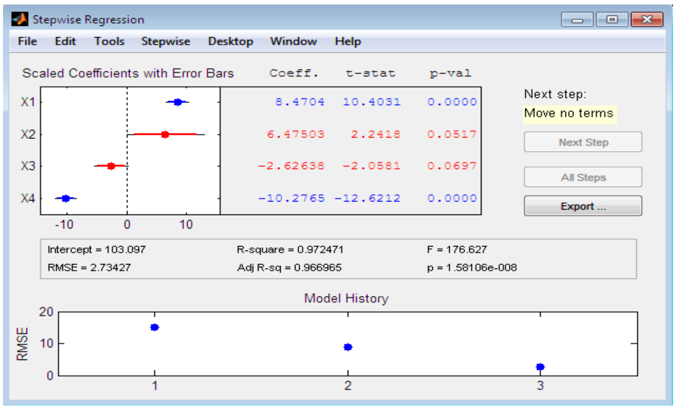


Fig 7: step wise regression

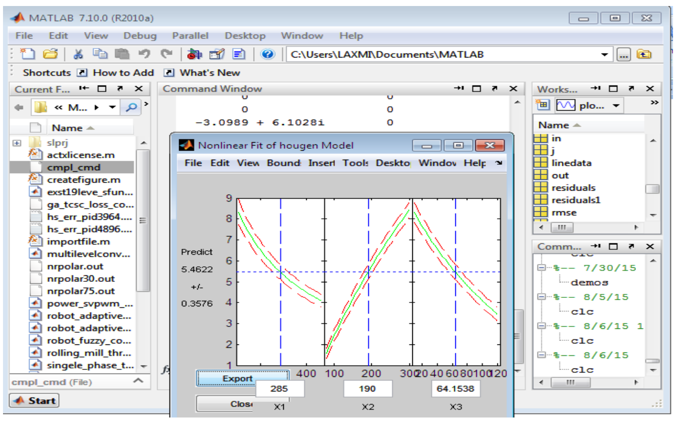


Fig 8: nonlinear regression

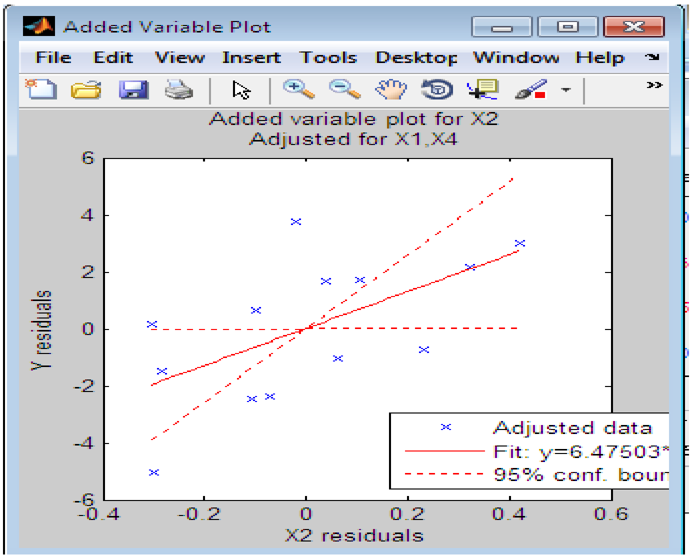


Fig 9: X_2 axis estimation

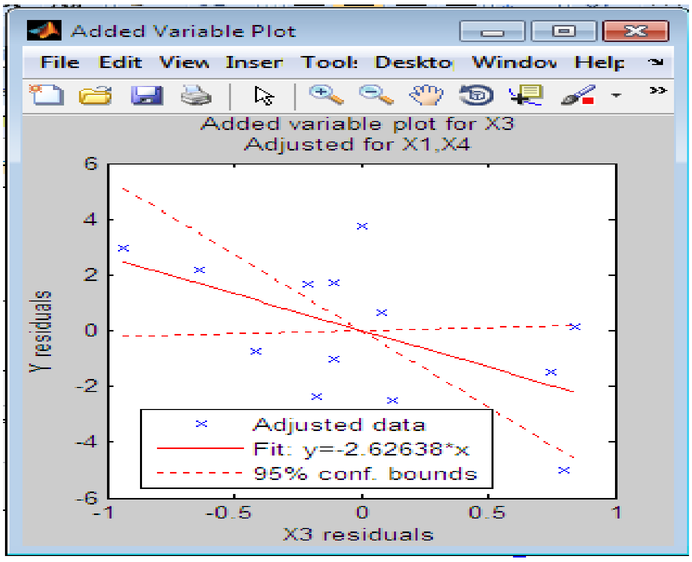
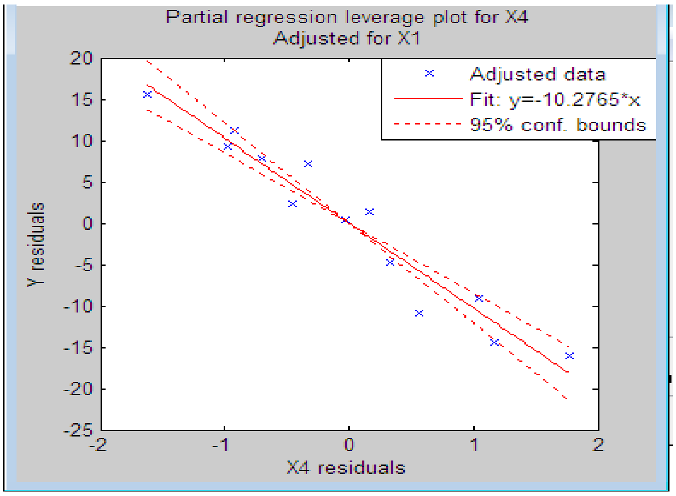
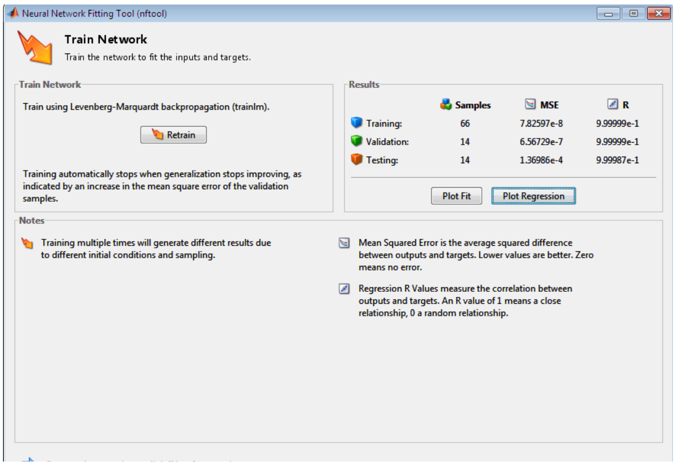


Fig 10: X3 axis estimation



F ig 11: X4 axis estimation



F ig 12: Neural networks tool box

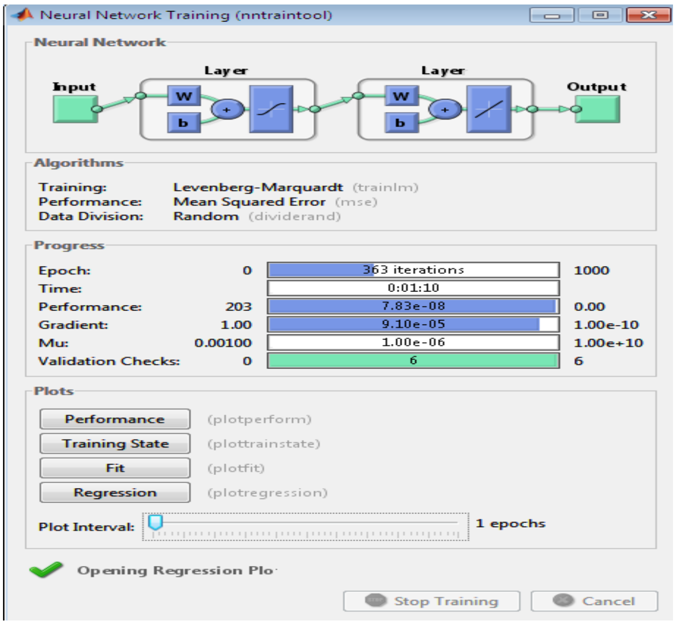


Fig 13: Training of NN

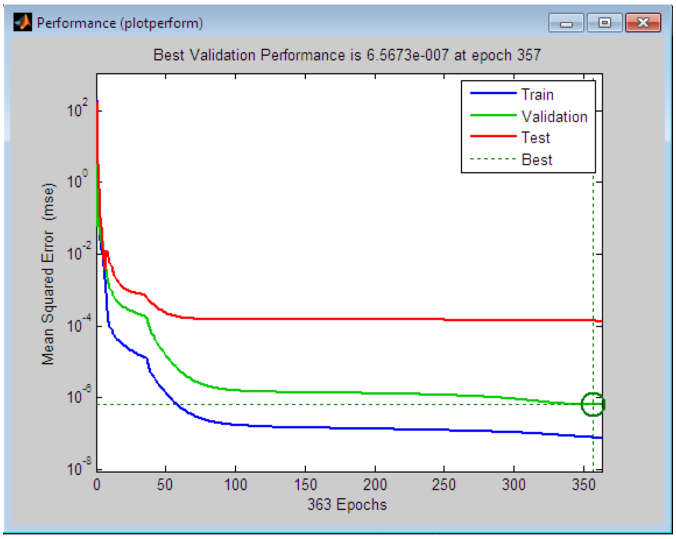


Fig 14: Performance and testing of NN-MLRM

Fig 15: Regression analysis of NN-MLRM

The estimated simulation results are derived for the proposed load flow with different load variations and Ybus formation of, root mean square error (RMSE), normalized root mean square error (NRMSE) and coefficient of correlation (R), whose definitions are indicated, can be recalculated by precise if MAPE, RMSE, NRMSE and the estimated parameter R are nearer to series of data 0, 0, 0 and 1 simultaneously.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(L_f - L_a)^2} \quad \textbf{(13)}$$

$$R = \sqrt{\frac{\sum_{i=1}^{N}(L_f-\bar{L}_a)^2-\sum_{i=1}^{N}(L_f-L_a)^2}{\sum_{i=1}^{N}(L_f-\bar{L}_a)^2}}$$

where: N = Number of observations

(14)

Each model will be checked by four different types of absolute error to estimate the accuracy is maximum and to obtain that the loading factors are varied. This will summed large complications to the mathematical formulation but in the same time it summed more guarantee for the load flow analysis. Since the numerical estimation of the load flow entity improves for every year, in order to make a suitable comparison in terms of the squared error estimation, in terms as a 'normalized RMSE".

Table 1: Comparison of estimated regressions in terms of RMSE and R

	RMSE	**R**
Linear regression	8. 963e8	0. 98
Step wise regression	2. 73e8	0. 9724
Partial regression	6. 567e7	0. 99999
Neural networks with MLRM	1. 3e5	0. 95

VII. CONCLUSION

One of the works which are of power systems is too exactly to estimate different load necessities at all instant of times. Simulation Results developed from linear regression and ANN toolbox combination are utilized in voltage stability and its assessment. Neural Network algorithm used is back propagation can understand to assume any operation just by using load flow output as input. They are simulation model free nonlinear estimators, which understand of resolving mathematical formulation based on the presentation of a huge number of training of weights. Artificial Neural Networks estimate and describe a mathematical function of how the outputs are functionally vary with the inputs and disturbance. They represent a good approach that is potentially robust and fault tolerant. In this work, an electric load flow analysis based on artificial neural network combined with basic linear regression model was determined using MATLAB-SIMULINK environment. The system performs better results than some other systems. The Improvement of accuracy more than one of the parameters (active power, voltage, reactive power, data analysis) as reference input, which is huge enough to incorporate assll the effects which can be quantified.

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