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ARTIFICIAL NEURAL NETWORK MODELING TECHNIQUE FOR VOLTAGE STABILITY ASSESSMENT OF RADIAL DISTRIBUTION SYSTEMS

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ABSTRACT
This paper presents an Artificial Neural Network (ANN) based modeling technique for predicting the voltage stability of radial distribution systems. The modeling technique is based on a new voltage stability index for assessment of radial distribution systems \( L_v \). The index is implemented to investigate a 33-bus distribution system. An ANN model which has an input layer with two input vectors \((P, Q)\), one hidden layer, and an output layer, which gives the predicted value for the voltage stability index \( L_v \), is suggested to predict the value of this index. The performance of the ANN model is tested by using the results of the 33-bus distribution system. Then the ANN model is checked by two model evaluation indices namely mean absolute percentage error and actual percentage error. Plotting of the simulated results with the ANN output is used to evaluate visually the accuracy of simulation. Extensive testing of the proposed ANN based technique have indicated its viability for voltage stability assessment.

INTRODUCTION
Distribution systems are distinctly different, in both their operation and characteristics from transmission systems. Modern power distribution systems are constantly being faced with an over-growing load demand. Distribution systems experience distinct change from a low to high load level every day. In certain industrial areas, it has been observed that under certain critical loading conditions, the distribution system may experience voltage collapse [1]. Radial distribution systems having low reactance to resistance \((X/R)\) ratio causes a considerable IX and IR voltage drops in these systems which may lead them to voltage collapse. Therefore, they are categorized as ill conditioned systems [2].

Artificial neural networks provide techniques for solution of some engineering problems. Their flexible nature allows representation of many types of data for analysis. Since training is based on the past as well as existing data of different parameters, the results obtained can be more reliable. Also, the computational difficulty is reduced by considerable extent and recent data can be obtained for further analysis [3]. In recent years, ANN have emerged a promising technology, which has the capability to solve some long-standing power system problems where conventional approaches have difficulty. ANN has already been applied to some power system problems such as security assessment, real time control of capacitors, protection, and load forecasting. ANN has also been applied to the voltage stability assessment problem [4].

El-Kady et. al [4] introduced an ANN based technique for prediction of voltage stability in electrical power systems. Selection of input variables for training ANN is obtained using a performance index, which reflects the proximity of system from voltage collapse. Abd El-Aziz et. al [5] investigated the application of artificial neural networks in voltage stability assessment using the energy function method. This technique is used for calculation of voltage stability margins. El-Keib et. al [6] used the ANN’s for determining the voltage stability margins based on energy function method. A systematic method for selecting the ANN’s input variables was developed using sensitivity analysis. Jeyasurya [7] used the ANN’s for evaluation of on-line voltage stability in modern energy control centers based on an energy measure, which is an indication of the power system’s proximity to voltage collapse. Salama et. al [8] applied the ANN’s to predict the voltage instability based on a voltage collapse proximity indicator, which was presented in [9].

This paper suggests an ANN network modeling technique based on a novel voltage stability index derived and presented in [10,11]. This ANN technique has been implemented to investigate a 33-bus distribution system.

VOLTAGE STABILITY INDEX
A new index \( L_v \) was derived and implemented for the two bus-equivalent model of any N-bus distribution system. This index is defined as [10,11]:

\[
L_v = \frac{4S_0 \cos (\theta + \varphi)}{Y_{22} [V_1 \cos (\delta)]^2}
\]  

(1)
Where
\[ \begin{align*}
V_1 & : \text{Voltage at bus No. 1, and its angle is } \delta, \\
S_2 & : \text{Load apparent power, and its angle is } \varphi, \\
Y_{22} & : \text{Sum of admittances connected to bus No. 2, and its angle is } \theta.
\end{align*} \]

\( L_v \) is a stability index that indicates the status of the system and shows how close the operating point to the point of collapse. When the value of the index equals to zero that means there is no load, and between zero and one the system operates in the stable region and the values greater than one mean that the system is unstable.

**ANN ASSESSMENT OF VOLTAGE STABILITY BASED ON \( L_v \) INDEX**

A multi-layer feed forward artificial neural network with back-propagation learning is proposed for the prediction of the \( L_v \) voltage stability index which reflects the proximity of the distribution system to voltage collapse. The ANN based technique maps the relationship between the load total active and reactive powers of the distribution system and the voltage stability index \( L_v \), according to the present load pattern. A neural network model depends on the variables used for predicting the \( L_v \) index. The \( L_v \) index is obtained on each bus by using certain reconfiguration of the distribution system [10, 11]. Therefore, it is obvious to model the data of reconfigured system by a certain neural network pattern. This technique helps to study the effect of the load at each bus on voltage stability index. Its implementation is effective especially when the load variation can be monitored at each bus or at a certain bus.

**DESIGN OF ANN MODEL**

The topology of a multi-layer feed-forward ANN consists of an input layer, one or several hidden layers and an output layer. The proposed multi-layer neural network structure is shown in Figure 1. As seen in Eq. 1 the value of \( L_v \) index depends on many factors but the most effective factor is the total load apparent power (active and reactive power). Therefore the load total active and reactive powers govern the voltage stability of a radial distribution system. Thus they are chosen as inputs to the ANN. The number of input nodes “n” is two for total active and reactive powers. The number of neurons in the hidden layer depends on the number of training vectors and the number of unknown weights and biases to be evaluated. The number of output layer neuron is one, which is the voltage stability index \( L_v \). The input of training patterns has a size of \( 2 \times R \) where “R” is the number of data used for training. The value of R has been varied at each bus under study. The output “G” is the voltage stability index \( L_v \). The training process has been carried out using back-propagation learning algorithm.

**GENERATION OF TRAINING SET SAMPLES**

A 33-bus [12] distribution system is employed in this study. Instead of choosing all buses to be studied with the proposed technique it is better to choose the weakest buses that affect the voltage stability of the 33-bus distribution system. By computing the value of the index found in [1] at all buses of the 33-bus system. It is found that the area containing buses 13, 14, 15, 16, 17, and 18 is the weakest area. A gradual increase of the active power load at these buses by a step of 10 kVA at the same power factor of the base load is implemented. Then the value of the \( L_v \) index is computed for each bus.

**EVALUATION OF MODELING TECHNIQUE**

Two model evaluation indices have been implemented. They are mean absolute percentage error (MAPE) [13, 14] and actual percentage error (APE) [15]. These indices have been computed for predicted values. They are defined as follows:

\[ \text{MAPE} = \left\{ \frac{1}{N} \sum_{i=1}^{N} \left| \frac{Y_{ac} - Y_{pr}}{Y_{ac}} \right| \times 100 \right\} \times 100 \frac{1}{N} \sum_{i=1}^{N} \left| \frac{Y_{ac} - Y_{pr}}{Y_{ac}} \right| \times 100 \]

where,

- \( Y_{ac} \): The actual value of voltage stability index,
- \( Y_{pr} \): The predicted value of the index and
- N : The total number of values predicted and also the limit of the summation process.

Low values of MAPE satisfy the statistical evaluation of prediction validity [15]. A pre-specified acceptable error is justified by APE.
Neural network model is trained by applying the supervised learning procedure. The Neural Network Toolbox in MATLAB [16] is used to implement the proposed ANN technique. Each input vector and the corresponding voltage stability index $L_v$ are used to train the ANN model. During training the weights and biases are iteratively adjusted to minimize the network performance function [16]. The trained network is used to predict the value of the $L_v$ index for new input vectors, which were not used for training the ANN models, and ANN results compared with the simulation results obtained for these new input vectors. The network is retrained if the global error is not within the specified limit. Once the network is satisfactory trained it is ready for use in the prediction mode. Table 1 illustrates the values of the total active and reactive power loads used for training and predicting procedures.

### RESULTS AND DISCUSSION

#### A. Voltage Stability Index $L_v$

Figures from 2 to 7 show the predicted and simulated values of voltage stability index $L_v$ where the load increases at the weakest buses No. 13, 14, 15, 16, 17 and 18 respectively. The values shown in the figures are the simulated and predicted values. The prediction of $L_v$ index is carried out for total active and reactive power up to the critical values while the load increases at a certain bus. These critical values are the limit values after which the voltage collapse will occur. Table 2 illustrates the number of training pair's vectors, number of testing vectors, and the figure number at which results are presented. Figures from 2 to 7 show the output of the proposed ANN model for each bus and the simulated values of the $L_v$ index. The ANN outputs and simulated values of $L_v$ index are plotted against the total apparent power load of the distribution system for each bus. It can be observed that the output of the ANN (predicted values of $L_v$) for each bus is coincident with the simulated values of the $L_v$ index.

#### B. Actual Percentage Error (APE)

To evaluate the accuracy of predicted values, the actual percentage errors at the weakest buses have been calculated. The values of APE for the predicted values with the loads increase at buses No. 13, 14, 15, 16, 17 and 18 are given in Figure 8. From Figure 8 it can be seen that the APE varies over a very limited range less than ± 0.5%, which can be considered as indication of validity of the proposed ANN model.

#### C. Mean Absolute Percentage Error (MAPE)

Figure 9 shows the mean absolute percentage error MAPE for the predicted values while the loads increase at buses No. 13, 14, 15, 16, 17 and 18. Figure 9 shows small values of MAPE. These values approximately zero. Small values of MAPE indicate good prediction from the view point of statistical evaluation of the model. A summary of maximum and minimum actual percentage errors and mean absolute percentage errors at the weakest buses of the 33-bus system are illustrated in Table 3. From Table 3 it can be seen that the results obtained for MAPE and APE justify the applicability and validity of the proposed ANN model. The proposed ANN model can be used for the assessment of voltage stability based on $L_v$ index.

### Table 1 Data used for training and prediction of the proposed ANN model at the weakest buses of the 33-bus system (step of $P_L$ is 10 kW for constant power factor)

<table>
<thead>
<tr>
<th>Bus No.</th>
<th>From</th>
<th>To</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_L$</td>
<td>$Q_L$</td>
<td>$P_L$</td>
</tr>
<tr>
<td>13</td>
<td>3715</td>
<td>2290.01</td>
</tr>
<tr>
<td>14</td>
<td>3715</td>
<td>2290.01</td>
</tr>
<tr>
<td>15</td>
<td>3715</td>
<td>2290.01</td>
</tr>
<tr>
<td>16</td>
<td>3715</td>
<td>2290.01</td>
</tr>
<tr>
<td>17</td>
<td>3715</td>
<td>2290.01</td>
</tr>
<tr>
<td>18</td>
<td>3715</td>
<td>2290.01</td>
</tr>
</tbody>
</table>

### Table 2. Training and testing pair's vectors at each bus

<table>
<thead>
<tr>
<th>Bus No.</th>
<th>No. of training vectors</th>
<th>No. of testing vectors</th>
<th>% of load increase</th>
<th>Results in Fig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>80</td>
<td>89</td>
<td>19.8</td>
<td>2</td>
</tr>
<tr>
<td>14</td>
<td>75</td>
<td>75</td>
<td>16.7</td>
<td>3</td>
</tr>
<tr>
<td>15</td>
<td>100</td>
<td>75</td>
<td>15.9</td>
<td>4</td>
</tr>
<tr>
<td>16</td>
<td>82</td>
<td>70</td>
<td>15.4</td>
<td>5</td>
</tr>
<tr>
<td>17</td>
<td>61</td>
<td>61</td>
<td>16.2</td>
<td>6</td>
</tr>
<tr>
<td>18</td>
<td>50</td>
<td>69</td>
<td>16.4</td>
<td>7</td>
</tr>
</tbody>
</table>
Figure 2: Simulated and predicted values of the $L_v$ index. (With the load increase at bus No. 13)

Figure 3: Simulated and predicted values of the $L_v$ index. (With the load increase at bus No. 14)

Figure 4: Simulated and predicted values of the $L_v$ index. (With the load increase at bus No. 15)

Figure 5: Simulated and predicted values of the $L_v$ index. (With the load increase at bus No. 16)

Figure 6: Simulated and predicted values of the $L_v$ index. (With the load increase at bus No. 17)

Figure 7: Simulated and predicted values of the $L_v$ index. (With the load increase at bus No. 18)
CONCLUSIONS

The contribution of this paper is the application of the artificial neural networks for the prediction of the inception of voltage instability in radial distribution systems. An ANN model has been trained and implemented for the prediction of the voltage stability index $I_v$, and the results show that: ANN structure of an input layer with two input vectors $(P, Q)$, one hidden layer, and an output layer, which gives the predicted value for the voltage stability index $I_v$, has proved to be reliable. Two model evaluation indices (APE and MAPE) were implemented to justify the validity and applicability of the proposed ANN models.

REFERENCES


