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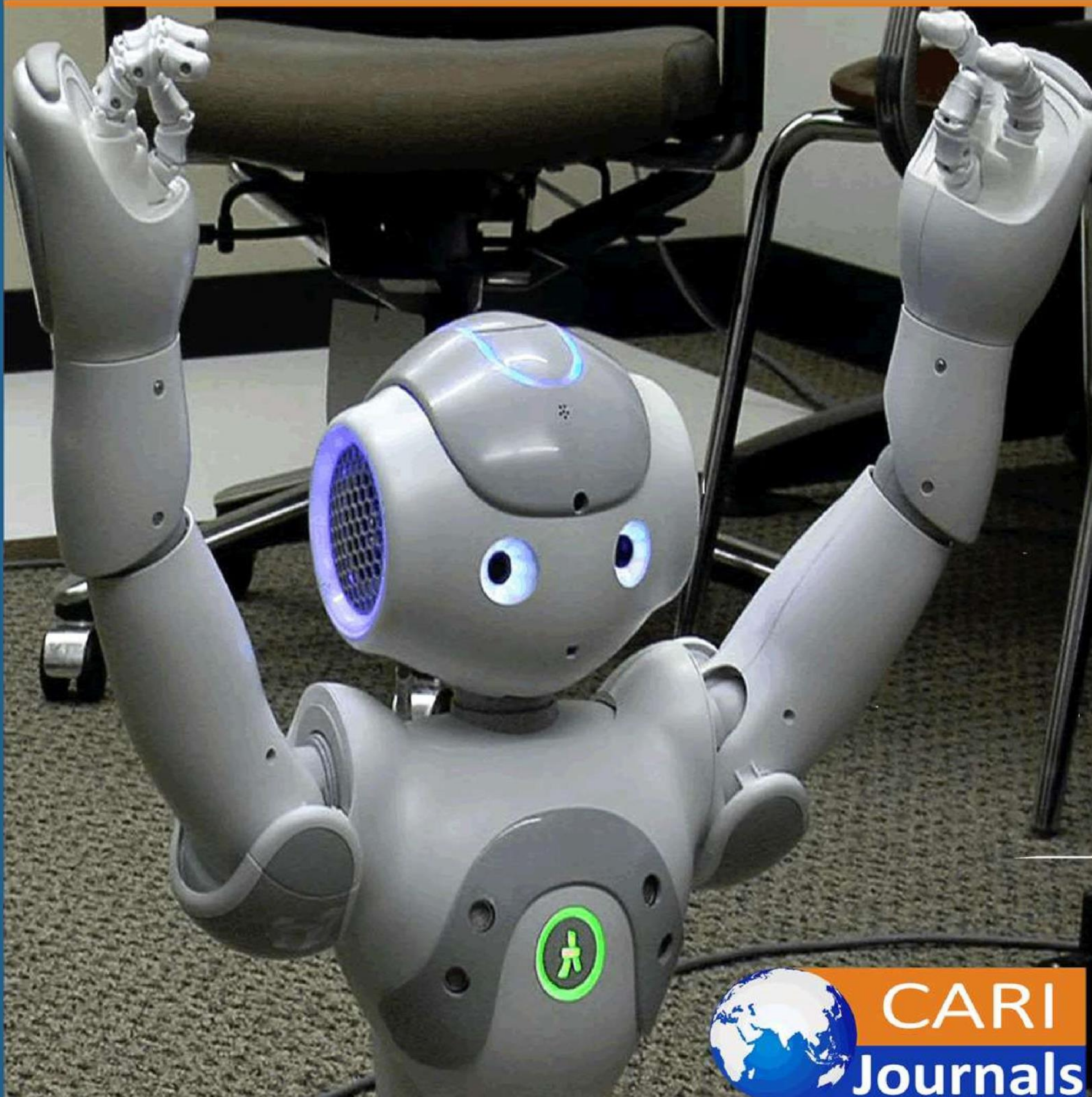

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Artificial Neural Networks for Online Voltage Stability Assessment of Saudi Power Grid

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Abstract

This paper proposes and compares various techniques based on artificial neural networks for the on-line assessment of voltage stability of Saudi power grid in terms of a voltage collapse proximity index computed from the knowledge of the real and reactive power injections at various buses in the system. Various ANNs investigated include MLFFNN), RBFN and RNN-LSTM. The input-output training patterns required for the respective learning algorithms are generated by performing conventional Newton-Raphson load flow analysis (NRLF) of the power grid for various load conditions. The proposed models are assessed in terms of solution accuracy and computation time. The simulation results show that the ANN based methods can offer fast assessment of voltage stability as accurate as the NRLF method but without repeated iterative load flow calculations. Among the investigated models, the RBFN shows better performance in terms of both solution accuracy and computation time for on-line voltage stability assessment.

Keywords: *Voltage Stability, Artificial Neural Network, MLFFNN, RBFN, RNN-LSTM, Saudi Power Grid*

JEL Codes: *C45, C61, L94*

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1. Introduction

Voltage instability occurs when the system cannot sustain the growing demand of reactive power, and the bus voltages start to decrease gradually. Failure to take corrective measures in time may cause this process to cause voltage collapse, causing a partial or total blackout of the system. Several changes in structure and operation of the modern power systems are contributing to higher exposure to the voltage stability issues. The steady increase in load demand has resulted in overloaded transmission systems which frequently run near to thermal and stability boundaries. Modern power systems are increasingly operating under stressed conditions due to growing electricity demand and limited expansion of transmission infrastructure. These factors have increased the risk of voltage instability and hence it is important to have reliable and fast voltage stability assessment methods.

Traditionally, voltage stability has been evaluated using numerical techniques such as Newton Raphson load flow analysis [1], continuation power flow [2], and sensitivity-based methods such as modal analysis [3]. Although these methods provide accurate results, These require recurring computational cycles leading to significant computational overhead, and thus restricting the their relevance for online voltage stability assessment. This has necessitated the interest of researchers in alternative methods to minimize the complexity of the computational process without compromising the solution accuracy. Artificial neural networks (ANNs) have been found useful for the voltage stability assessment because of their inherent parallel and distributing approach in learning the nonlinear relationship between system operating variables and stability indicators [4]. Once trained, ANN models can perform the system voltage stability assessment without performing repeated load flow calculations. This paper proposes ANN based voltage stability assessment techniques utilizing the voltage collapse proximity index (VCPI) given by

$$\mathrm{VCPI}_{\mathrm{System}} = \max\left(\mathrm{VCPI}_{\mathrm{P,ij}}\ ,\ \mathrm{VCPI}_{\mathrm{Q,ij}}\right) \tag{1}$$

Where

$$\mathrm{VCPI}_{\mathrm{P,ij}} = \frac{P_{ij}}{P_{ij(max)}} \tag{2}$$

$$\mathrm{VCPI}_{\mathrm{Q,ij}} = \frac{Q_{ij}}{Q_{ij(max)}} \tag{3}$$

Where P_{ij} and Q_{ij} are the real and reactive power flows through the transmission line i-j.

A VCPI close to zero signifies a stable operating state, while a value nearing one suggests closeness to voltage collapse. The system is considered to be operating in a voltage-critical region when the VCPI reaches a value between 0.9 and 1.0. In this paper, the voltage stability assessment of a typical 5-generator, 4-load, 21-bus 380-kV Saudi power grid [5], shown in Fig. 1, is

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investigated using three ANN models. The base-case NRLF solution [1] is used for generating the input-output patterns for the training of the ANNs. The effectiveness of the ANN models is established in terms of solution accuracy and computational overhead. ANN models and the corresponding simulation results are discussed in the following sections.

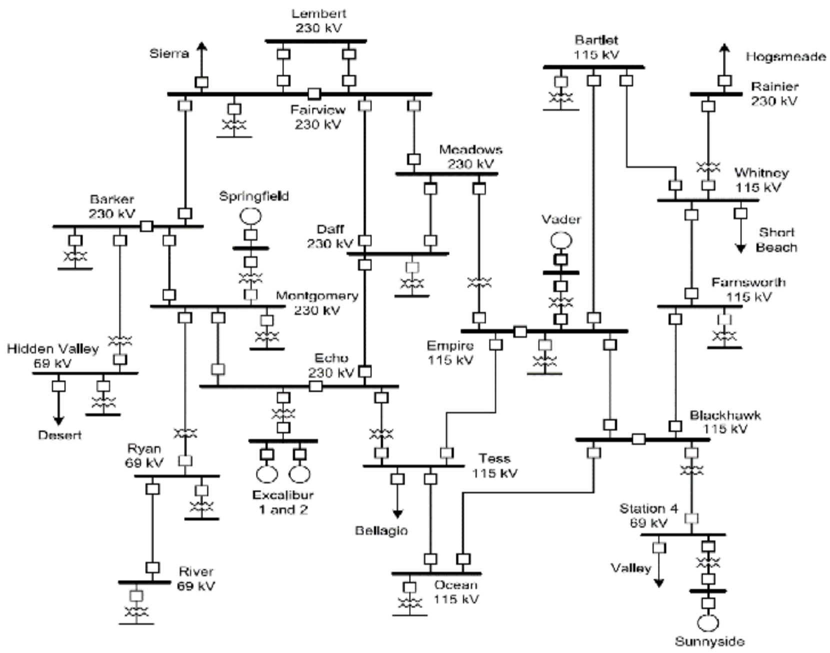

Fig. 1: 5-Generator, 4-load 21-bus 380kV Saudi Power Grid

2. Proposed Artificial Neural Network Models

The voltage stability of the system is assessed using three different ANNs: Multilayer Feedforward Neural Network (MLFFNN), Radial Basis Function Network (RBFN) and Recurrent Neural Network with long short-term memory (RNN-LSTM). In order to develop a training data set, load demand at various buses varies within a certain range. The load scaling factor (λ) is used to represent different load levels where λ ranges from low load to stressed scenarios. The training set is generated by scaling each load bus demand as

$$\left[P_{\{D,i\}}=\lambda_i P_{\{D,i\}}^{\{base\}},\quad Q_{\{D,i\}}=\lambda_i Q_{\{D,i\}}^{\{base\}}\right] \qquad (4)$$

Here λ is the load scaling factor. In this study, the value of λ used represents light-load, normal-load, and stressed operating conditions, with values set at 0.5, 1.0, and 1.5, respectively. The loading scenarios were uniformly distributed and non-uniform loading, so that the ANN models could be trained with a variety of loading data.

At each load level, the NRLF analysis is performed to determine the bus voltages, power flows, and the corresponding VCPI value and this process is repeated to produce a few thousand input–output data samples for the training and validation of the ANNs. The data set includes samples of

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normal, stressed and near-collapse operating conditions of the system. The input and output variables are normalized for better convergence and training of the ANN models.

Multilayer Feedforward ANN Model

The architecture of the Multi-layer Feed forward ANN (MLFFNN) proposed for the online voltage stability assessment is shown in Fig. 2. As shown in this figure, the input layer of the MLFFNN receives the respective normalized values of the real and reactive power generation and the load demand at each of the 21 buses. So, there are 84 neurons in the input layer. The first hidden layer of the developed model MLFFNN has 20 neurons and the second hidden layer has 10 neurons. The values have been chosen after a few training trials to obtain good convergence and prediction. The hidden layer of the neural network employs Tanh activation function to enhance its ability to learn mapping of the non-linear input-output patterns. The voltage collapse proximity index value is given by the neuron in the output layer.

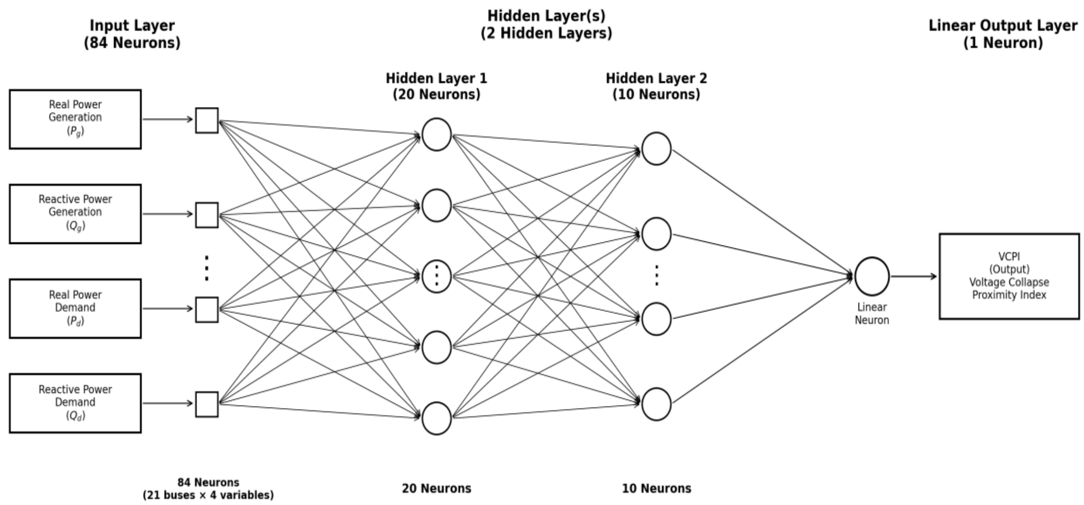

Fig. 2: Proposed Multilayer Feedforward ANN Model

The back propagation algorithm is used to train the network using the Levenberg–Marquardt optimization method, which is widely employed for the fast and efficient training of neural networks [6,4]. The network weights are updated during the learning process to minimize the mean squared error given by

$$MSE=\frac{1}{N}\sum_{k=1}^{N}(VCPI_K(actual)\text{- }VCPI_K(ANN))^2 \tag{5}$$

Radial Basis Function ANN Model

As shown in Fig.3, the RBF network is a three-layer ANN with the hidden layer neurons having a Gaussian activation function given by

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$$\phi(x)=\frac{\exp\left(-\left\|x-c^{2}\right\|\right)}{2\sigma^{2}} \tag{6}$$

The Gaussian activation function is used to calculate the Euclidean distance between the input data and the cluster centers [6]. The inputs to this network is the same as that of the MLFFNN. The hidden layer processes these inputs, while the output layer neuron produces the corresponding normalized value of the Voltage Collapse Proximity Index (VCPI). RBF network training is carried out in two main steps. Initially, the centers of the radial basis functions are determined identified using the k-means clustering method [7]. After that the output-layer weights are computed using a linear optimization process [8]. This two-step training procedure makes the RBF network faster to train than multi-layer feed forward neural networks [7,9].

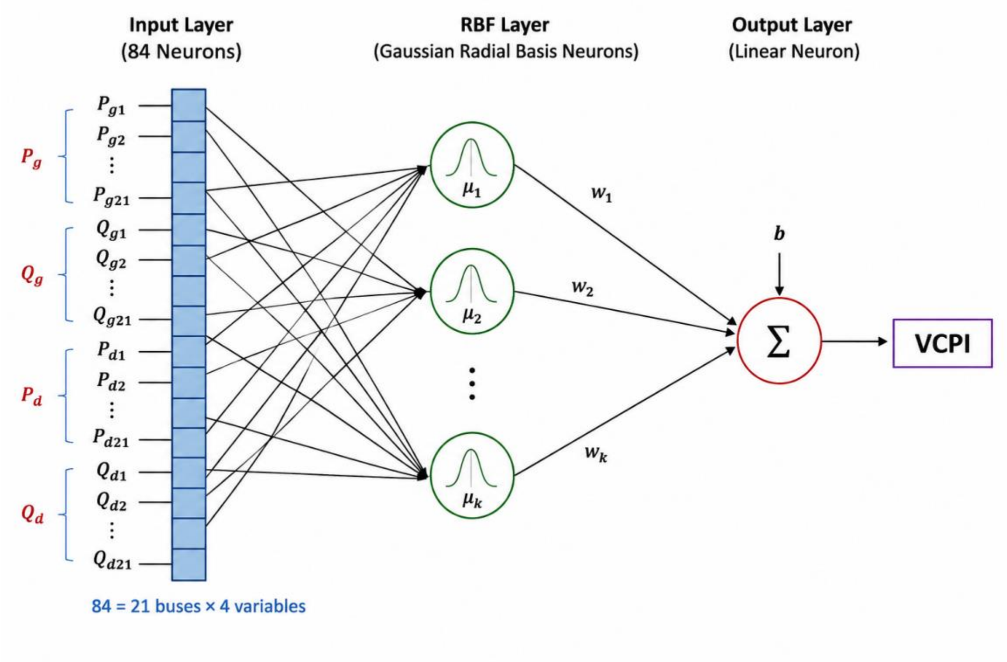

Fig. 3: Proposed Radial Basis Function ANN Model

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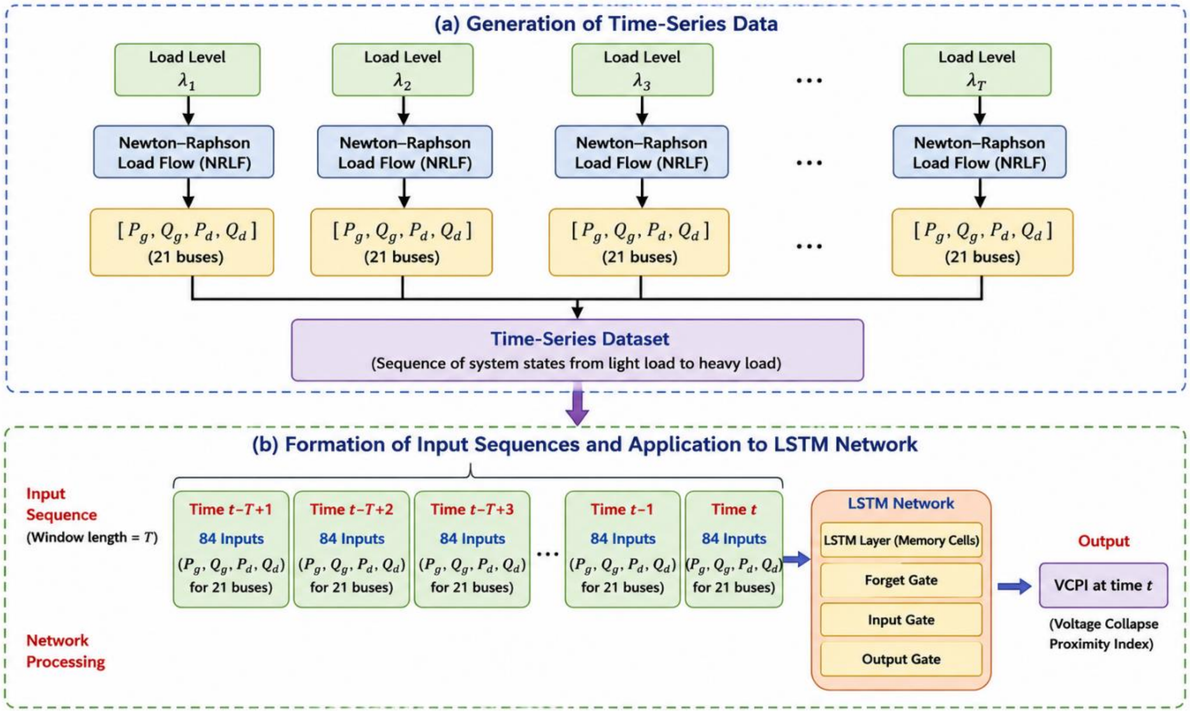

Figure 4: Generation of Time series Data

The time-series data for the RNN-LSTM model has been generated as shown in figure 4. The different load levels are simulated by the Newton-Raphson Load Flow (NRLF) analysis and the system states obtained are displayed in the form of sequential data. The temporal patterns of these sequences are then introduced into the LSTM network to train the network to predict the Voltage Collapse Proximity Index (VCPI) under different operating conditions.

Recurrent Neural Network with Long Short Term Memory Model

Long Short-Term Memory (LSTM) is developed to understand long-term relationships in sequential information, overcoming the "vanishing gradient" problem of standard RNNs. By utilizing an internal memory cell and three gates (forget, input, output), LSTMs selectively retain or discard information. As shown in Fig.5, the key components of an LSTM Unit are

- Cell State (C_t): running straight down the entire chain to store long-term memory with minimal linear interactions.
- Hidden State (h_t): representing short-term memory and the output of the cell.
- Forget Gate (f_t): deciding what information from the previous cell state to discard, using a sigmoid function (outputs 0 to 1).
- Input Gate (i_t): determining which new information from the input to add to the cell state [11].

- Output Gate (o_t): controlling which part of the cell state to output as the new hidden state.

The Recurrent Neural Network (RNN) with LSTM is investigated for voltage stability assessment because of its ability to capture dynamic system behavior and provide accurate solutions in real-time applications. As shown in Fig. 6, the RNN-LSTM model is used to analyzes time-dependent variations in system voltage behavior. Unlike feed forward neural networks, the RNN-LSTM model can retain information from previous time steps and learn patterns in sequential data. This makes it suitable for tracking voltage variations as system loading conditions change [3]. The time-series data generated from load flow simulations are used to train the model. The model processes a sequence of system measurements and predicts the voltage stability state at each time step. The RNN-LSTM network is trained using Adam optimization algorithm with the back propagation \through time algorithm [11].

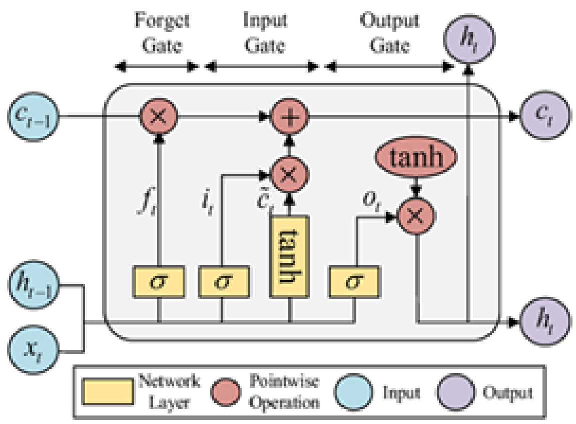

Fig.5: Long Short Term Memory Model

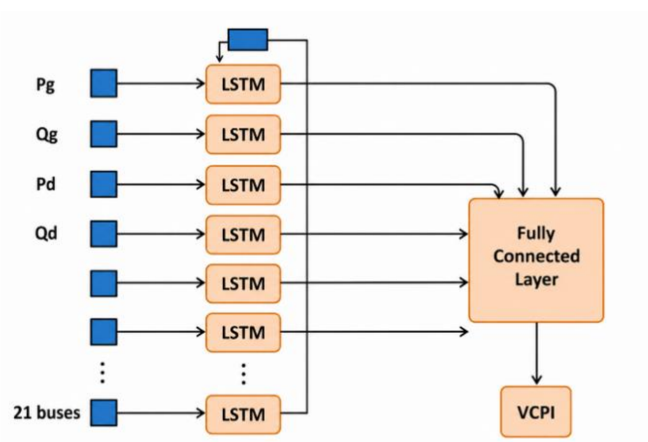

Fig.6: Proposed RNN-LSTM Model

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3. Simulation Results

The performance of the proposed ANN models for the voltage stability assessment of practical power systems is assessed using the conventional statistical error measures and computational speed measures. These are employed to determine the assessment capability and consistency of the models in estimating the Voltage Collapse Proximity Index (VCPI). The convergence performance of the proposed ANN models is verified by observing the percentage error of the Voltage Collapse Proximity Index (VCPI) while training the models. The error convergence graphs for the three models MLFFNN, RBFN and RNN-LSTM are shown in Fig. 7. From these figures, it can be observed that the network needs more iterations of learning to learn stochastic temporal patterns in the input before a stable solution is found due to the influence of the recurrent architecture and memory cells. Fig. 8 compares the VCPI computed by various proposed ANN models with that of the conventional NRLF method, for more than 200 load conditions. The figure indicates that the VCPIs calculated by the ANN closely matches with the actual values obtained from using NRLF [12].

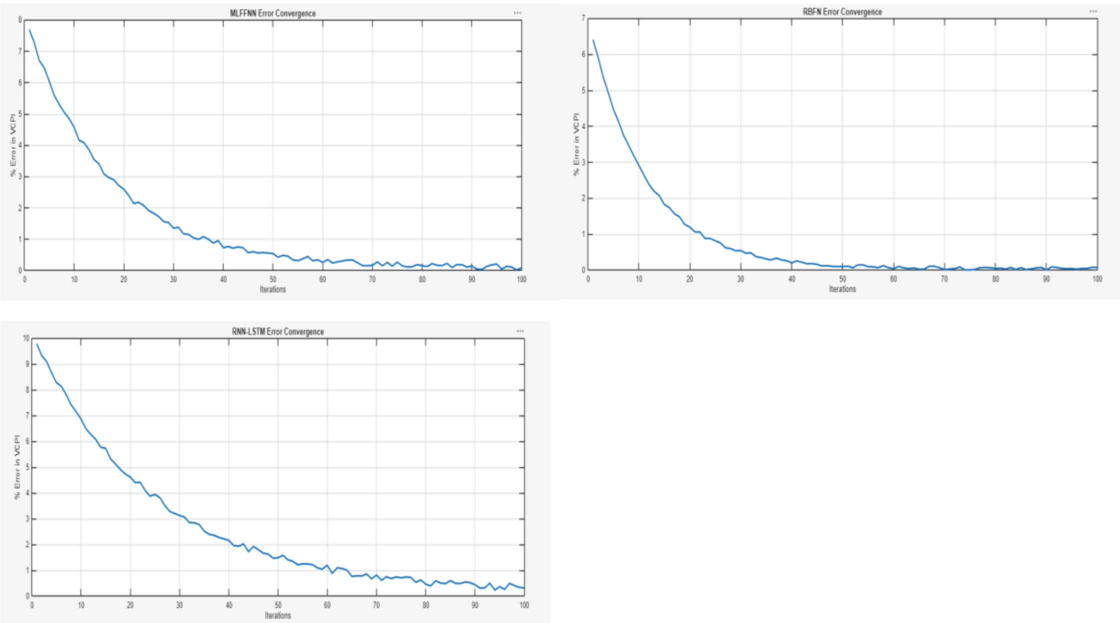

Fig. 7: ANN Learning Convergence

a. MLFFNN b. RBFN c. RNN with LSTM

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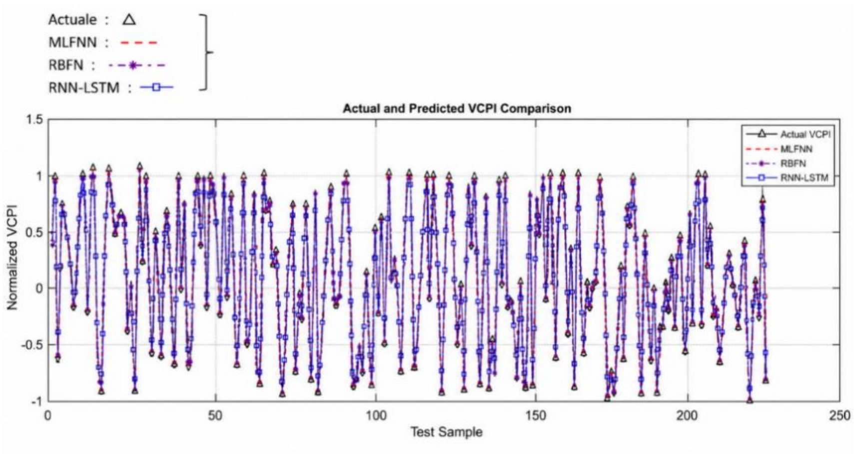

Fig. 8: Comparison of Proposed ANN model results for various load conditions

The solution accuracy of the proposed ANN models in the evaluation of the VCPI values is measured in terms of Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and coefficient of determination (R^2) of the voltage collapse proximity index as

$$\mathrm{MSE}=\frac{1}{N}\sum_{k=1}^{N}(\mathrm{VCPI}_K(\mathrm{actual})\text{- }\mathrm{VCPI}_K(\mathrm{ANN})^2 \quad (7)$$

RMSE =

$$\sqrt{\left(\left(\frac{1}{N}\right)\sum_{i=1}^{N}[\mathrm{VCPI}_i(\mathrm{actua})\text{-}\mathrm{VCPI}_i(\mathrm{predicted})]^2\right)} \quad (8)$$

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{N}[\mathrm{VCPI}_i(\mathrm{actua})\text{-}\mathrm{VCPI}_i(\mathrm{predicted})]^2}{\sum_{i=1}^{N}[\mathrm{VCPI}_i(\mathrm{actua})\text{-}\mathrm{VCPI}^{-}]^2}\right] \quad (9)$$

The coefficient of determination (R^2) is a statistical metric used to evaluate how well the actual values fit between the actual values of Voltage Collapse Proximity Index (VCPI) obtained by using the Newton-Raphson Load Flow (NRLF) method [12] and the values predicted by the ANN models. The test data set corresponding to the complete range of operating conditions starting from the light load levels up to the heavily loaded highly stressed conditions bordering the voltage collapse. These values computed for each of the proposed ANN models are presented in Table 1.

Table 1: Comparison of ANNs for voltage stability assessment

Model	MSE	RMSE	R^2	Number of Iterations for Convergence During Learning Process
MLFFNN	2.34×10^{-5}	0.00484	0.987	≤ 100
RBFN	1.12×10^{-5}	0.00335	0.994	95
RNN-LSTM	3.87×10^{-5}	0.00622	0.976	≤ 100

R^2 is a number between 0 and 1. The better the agreement between the ANN output and the actual values, the closer the R^2 value is to 1, while the closer its value is to 0, the poorer the prediction capability is. Finally, considering the voltage stability assessment, the high value of R^2 indicates that the ANN model identifies the relationship between system operating conditions and Voltage Collapse Proximity Index. The RBFN had the highest value for R^2 of 0.994, which was higher than that of the MLFFNN and RNN-LSTM models as shown in Table 1, thus predicting the accuracy was greatest. The R^2 values of all the ANN models obtained are greater than 0.97, which represents more than 97% of the variation in VCPI values that is explained by the proposed neural network models. This validates their applicability for online voltage stability assessment of Saudi power grid.

The simulation results indicate that the RBFN achieves optimal performance with the lowest MSE (1.12×10^{-5}), lowest RMSE (0.00335), highest R^2 (0.994) and fastest convergence of 95 iterations. The MLFFNN model showed also good performance with high prediction accuracy and moderate convergence speed (185 iterations). The RNN-LSTM model, on the other hand, needed the most iterations (320) and had a relatively low prediction performance. Hence, it is found that RBFN is the most suitable model for this dataset because of its high accuracy, as well as its high computation speed. It can be seen from this Table that the proposed MLFFNN, RBF, and RNN–LSTM networks estimates voltage stability conditions, as accurately as the conventional NRLF approach. Further, it can be seen that the RBF network-based voltage stability assessment is more accurate than the other ANNs investigated [15-16].

4. Conclusion

This paper has proposed artificial neural network (ANN) models for the online voltage stability assessment of a typical utility grid in Saudi Arabia. The ANNs involves the computation of the Voltage Collapse Proximity Index (VCPI) from the current values of power generation and load demand at various buses in the system. Input-output patterns required for training the ANNs have been generated by conducting Newton-Raphson load flow analysis for various loading conditions from normal to stressed conditions. The ANN models proposed for the voltage stability assessment are MLFFNN, RBFN and RNN-LSTM. The investigations reveal that all the investigated ANN models are capable of performing voltage stability assessment of practical power grids significantly faster and also as accurately as the conventional Newton-Raphson load flow algorithm. Even though all the three models can perform the task satisfactorily, RBFN outperforms other models regarding solution accuracy and computational efficiency, while the RNN-LSTM model was found to be suitable for time-dependent system conditions [14,11]. This indicates high applicability of the RBFN model in online voltage stability assessment of the Saudi power grid as it delivers high accuracy and a lower computational effort.

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