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Neural Network Based Approach for Steady-State Stability Assessment of Power Systems

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Abstract: The quest for an intelligence compliance system to solve power stability problems in real-time with high predictive accuracy, and efficiency has led to the discovery of deep learning (DL) techniques. This paper investigates the potency of several artificial neural network (ANN) techniques in assessing the steady-state stability of a power system. The new voltage stability pointer (NVSP) was employed to parameterize and reduce the input data to the neural network algorithms to predict the proximity of power systems to voltage instability. In this study, we consider five neural network algorithms viz. feedforward neural network (FFNN), cascade-forward neural network (CFNN), layer recurrent neural network (LRNN), linear layer neural network (LLNN), and Elman neural network (ENN). The evaluation is based on the predictability and accuracy of these techniques for dynamic stability in power systems. The neural network algorithms were trained to mimic the NVSP dataset using a Levenberg-Marquardt (LM) model. Similarly, the performance analyses of the neural network techniques were deduced from the regression learner algorithm (RLA) using a root-mean-squared error (rmse) and response plot graph. The effectiveness of these NN algorithms was demonstrated on the IEEE 30-bus system and the Nigerian power system. The simulation results show that the FFNN and the CFNN possess a relatively better performance in terms of accuracy and efficiency for the considered power networks.

Keywords: voltage stability; machine learning (ML); neural network (NN); new voltage stability pointer (NVSP); steady-state stability

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1. Introduction

The intricacy of an interconnected power network has forced most power systems to be operating close to their stability breakpoint [1]. This is because power systems with much uncertainty are vulnerable to voltage instability, especially when faced with contingency. However, accurate and timely prediction of voltage instability could avert voltage collapse or blackout if properly managed [2]. The conventional practice of deploying numerical methods for assessing a power network seems not to yield convincing results [3], mostly, for early detection of possible voltage breakdown. Aside from that, numerical methods of solving power stability problems are growing out of phase, as they are less effective in the analysis of a complex interconnected power network [4]. The complexity of most power systems could be traced to the adverse effect of matching up with the increasing rate of power demand through the penetration of renewable energy [5–9]. Conversely, these renewable energy injection schemes have their inherent dynamic characteristics, thereby, altering the stability of the existing power system [10]. In such a context, a more reliable and smart controlling mechanism is needed to ensure a secured power system.

For this reason, machine learning (ML) is now being predominantly used in the analysis of power systems because of its high accuracy and efficiency [11]. Moreover, with the advent of the smart grid, an intelligent compliance system is desirable [12]; essentially for the sustainable delivery of qualitative and quantitative power to end users [13]. Similarly, ML techniques are found to be promising in applications where fast and smart decisions are required without compromising the accuracy of the output result [11,14]. ML is often regarded as artificial intelligence (AI) and deep learning (DL) [15]. These approaches are somewhat efficient and reliable tools for the assessment of power system stability [11]. As a branch of ML, artificial neural networks (ANN) have gained application in power systems due to their flexibility [11], easy adaptability to nonlinear variables [16], and better performance [17]. The advantage of ANN algorithms lies in their ability to accurately define the security status, [18] and control the network through the optimal placement of flexible AC transmission system (FACTS) devices [19]. This is to ensure a responsive, spontaneous, and smart power system capable of taking intelligent decisions with little or no supervision.

The objectives of this research are to (a) evaluate the voltage stability set-points of the power network buses using a new voltage stability pointer (b) train the result in ANN using different algorithms (c) assess the steady-state stability of the NN techniques and (d) rank the performance of the NN techniques based on their accuracy and predictability via the regression learner algorithm (RLA).

2. Related Work

In recent times, ML has been widely used in power system analysis especially, the ANN for transient and steady-state stability assessment. Reference Zhu L. et al. [20] presented a convolutional neural network-based approach to analyzing the transient stability of a power network. The research employs the power stability margin using a 'divide and conquers' technique for the evaluation of transient stability. The result shows that ML is a better method for the prediction of transient stability in a power network. Similarly, authors Zhao T. et al. [21] proposed a new control method for power stability problems using the Lyapunov model. The proposed model possesses a two-unit framework designed to mimic the pattern of the Lyapunov function through a neural network. The model was validated on different power control problems. More recently, Wang T. et al. [22] presented an intelligent technique for the control of voltage stability using a back-propagation neural network. The study explored the high precision characteristics and speed of the neural network to control the load margin and voltage stability problems. The simulation result was tested with the IEEE 118-bus test data.

Furthermore, authors Yang Y. et al. [23] presented a control technique for a small stability problem using an extreme gradient boosting model. The technique served as a correctional tool to compensate for the variance in active power until the stability of the power system is attained. Moreover, a new control model presented by S. Naderi et al. [24] ensures that a power system is prevented from possible transient stability problems using a DL technique. The study considers the response time of the rotor cycle to voltage instability under post-fault and pre-fault conditions. Several loading patterns were mapped and trained with an integer linear programming algorithm on transient stability restrictions. The practicability of this model was tested with the IEEE 39-bus test data and the 74-bus Nordic data. Similarly, Bento M. [25] presented a hybrid technique of ANN and genetic algorithm methods to solve power system loading problems. The ANN data was derived from the phasor measurement units and the genetic algorithm was employed to choose a sizable number of buses for the ANN.

The process of identifying the weak buses in a power network could be time-consuming; however, it is one of the ways to prevent voltage collapse [26]. The authors Goh H. et al. [27] examined several voltage stability indices for the identification of the weakest bus in a power system. The results were trained on an artificial neural network with the IEEE 9-bus and IEEE 14-bus data. The simulation results show a close prediction value between the calculated indices and the ANN-trained results. In the paper presented by Bai X. and Tan J. [28], several contingency problems were analyzed using the NN algorithm. The simulation result was tested with the IEEE 39-bus data. The results show that the proposed deep learning neural network model is accurate for the monitoring of voltage stability. In the same vein, Wang T. and Liua J. [22] presented an ANN model that is based on the surrogacy theorem for the control voltage stability problem in power systems. The control of the voltage stability margin through the proposed model experimented with the IEEE 188-bus data. The results show the accuracy and time-effectiveness of the neural network method to control voltage stability issues. In addition, Shi Z. et al. [29] introduced a classification model through a neural network algorithm to assess the transient stability status of every bus in an interconnected power network. The classification was based on the vulnerability of the network to oscillatory stability and non-periodic stability. The results from the newly proposed model were proved to be accurate.

Similarly, Abdullah A. et al. [30] presented a technique to determine the stability status of a distribution network using an artificial neural network. The ANN was trained to predict the maximum loading point as it affects the stability of the distribution network. Reference, Calma E. and Pacis, M. [31] compared different voltage stability indices on steady-state stability assessment through the injection of load perturbation. The ANN was employed to train the line stability index and fast voltage stability index. The result was demonstrated on IEEE 14-bus, IEEE 30-bus, and IEEE 57-bus data. Authors Khurana B. and Titare L. [32] presented an improved stability technique using an artificial neural network for the reduction of voltage instability and enhancing the voltage profile of a power network. In the same vein, Bingi K. and Prusty B. [33] proposed a prediction method based on an artificial neural network to suggest vulnerable buses in a power network. The result from the simulation was compared with the existing numerical methods. The results proved to be more accurate. In addition, Zhang H. et al. [34] proposed a combined method of NN and an easy ensemble learning algorithm for the transient stability analysis in a power network. The multilayer perceptron neural network was deployed for the assessment of the network's performance. Also, Ramachandran B. et al. [35] proposed a convolutional neural network to classify the power network based on its transient stability status. The proposed model was confirmed to be better than the existing deep learning techniques with improved accuracy.

From the literature, it is clear that the neural network technique is seen as an essential tool for the performance assessment of a power network. This research is aimed at examining the best neural network technique from the selected algorithms for the prediction of voltage stability problems in power systems. The performance indices of this study are accuracy, predictability, and training time through the RLA. The framework of this study is to (a) define the security status of a power network through the new voltage stability pointer (b) synthesize the dataset into the neural network models (c) evaluate the performance of the surrogate data using root mean squared error (rmse).

3. Methodology

In this study, we employed the new voltage stability pointer (NVSP) proposed by Badrudeen T. et al. [36] to define the voltage security status of each line and bus in the power network under the steady-state condition. In addition, these datasets were synthesized into the NN algorithms for better and faster prediction of power instability. The sequence diagram of the proposed methodology is presented in Figure 1.

3.1. Mathematical Modeling of the New Voltage Stability Pointer

The mathematical modeling of the NVSP was formulated from Figure 2. The 2-bus network in Figure 2 depicts a reduced power network with the P-V and P-Q bus systems. In addition, this line voltage stability index, NVSP, will be used to determine the stability breakpoint of each transmission line as regards the steady-state stability of the considered power systems. The power networks considered in this research are the IEEE 30-bus system and the Nigerian power system (NGP).

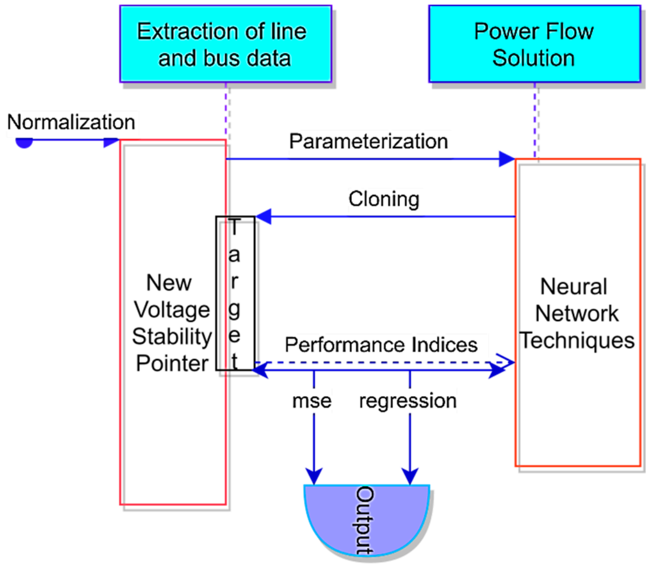


Figure 1. Sequential diagram of the proposed technique.

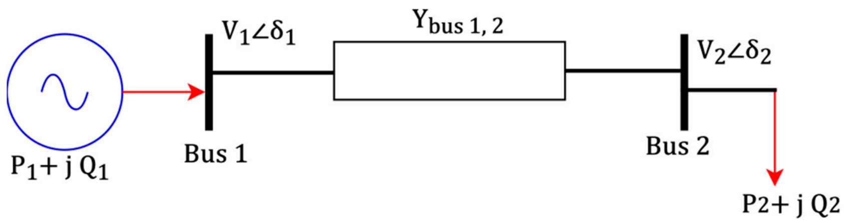


Figure 2. One line diagram [36].

The line current (I) from bus 1 is

$$I = (V_1 - V_2) \times Y_{bus} \tag{1}$$

The load current at the bus 2 is given as:

$$I = \left(\frac{S_2}{V_2}\right) = \frac{P_2 - jQ_2}{V_2\angle - \delta_2} \tag{2}$$

If the line loss is neglected, then the current at bus 1 will be equal to the load current in bus 2, i.e.:

$$P_2 - jQ_2 = |V_1 V_2 Y_{bus}|\angle(\theta - \delta_2) - |V_2|^2 \times |Y_{bus}|\angle\theta \tag{3}$$

Equation (3) can be reduced to

$$\frac{P_2 - jQ_2}{|Y_{bus}|\angle\theta} = |V_1 V_2|\angle - \delta_2 - |V_2|^2 \tag{4}$$

Then, Equation (4) can be rearranged as

$$|V_2|^2 - |V_1 V_2|\angle - \delta_2 + \frac{P_2 - jQ_2}{|Y_{bus}|\angle\theta} = 0 \tag{5}$$

From Equation (5):

$$V_2 = |V_1|\angle - \delta_2 \pm \frac{\sqrt{|V_1|\angle - \delta_2\ |^2 - 4\frac{P_2 - jQ_2}{|Y_{bus}|\angle\theta}}}{2} \tag{6}$$

Assume $\left(|V_1|\angle - \delta_2\,|^2 - 4\frac{P_2 - jQ_2}{|Y_{bus}|\angle\theta}\right)$ is set to zero, the real roots of V_2 will be evaluated as $|V_1|\angle - \delta_2\,|^2 - 4\frac{P_2 - jQ_2}{|Y_{bus}|\angle\theta} \leq 0$; and

$$\frac{4(P_2 - jQ_2)}{|G - jB|\angle\theta|V_1|\angle - \delta_2\,|^2} \leq 1 \tag{7}$$

If the voltage angle (δ_2) is presumed to be ignored, then the imaginary part of Equation (7) will be approximately equal to $\frac{4Q_2|Z|}{|V_1|^2} \leq 1$.

Conclusively, the *NVSP* is given as Equation (8)

$$NVSP = \frac{4Q_2|Z|}{|V_1|^2} \leq 1 \tag{8}$$

where Q_2 and V_1 denote the load reactive power and the generator bus voltage, respectively, and Z represents line impedance between buses 1 and 2.

The NVSP between the transmission lines is a value that must be less than 1 to keep the power network free from voltage collapse. However, in any case where the value of the NVSP between the transmission lines is equal or greater than 1, then, it is a clear indication of voltage instability and corrective measures must be ensued imminently to prevent large system disturbances. In summary, the NVSP value must be maintained far below 1 for all lines at all times to ensure a stable power system.

3.2. Neural Network Algorithms

In this research, we propose to investigate the potency of the selected neural network techniques to assess the steady-state stability of a power network. This investigation will be based on the predictability and accuracy of these neural networks for steady-state stability assessment. The input data to the NN are the load reactive power, line impedance, line susceptance and generator voltage as shown in Figure 3, and the target data are the NVSP indexing values between the transmission lines. The selected NN algorithms are cascade-forward neural network (CFNN), Elman neural network (ENN), linear layer (Design) neural network (LLNN), layer recurrent neural network (LRNN), and feedforward neural network (FFNN) as shown in Figure 4. The evaluation of the NN algorithms will be ranked based on the accuracy and predictability of steady-state stability in power systems.

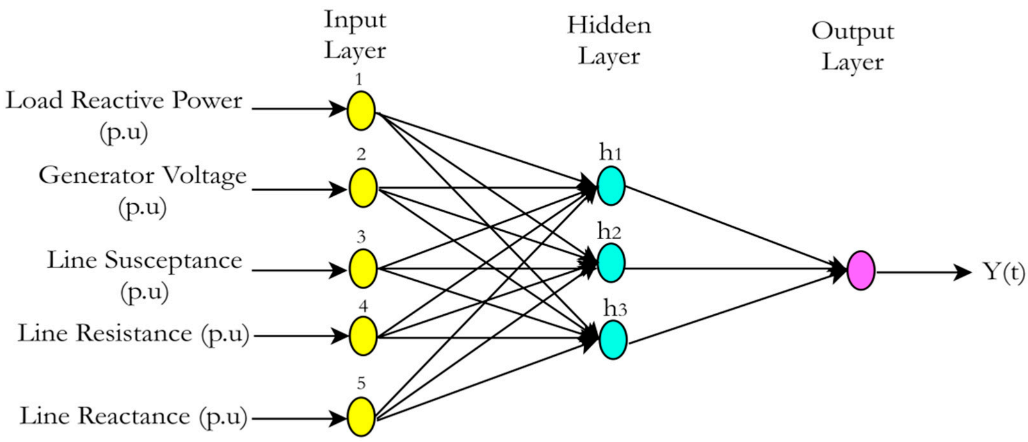


Figure 3. The Neural Network Architecture.

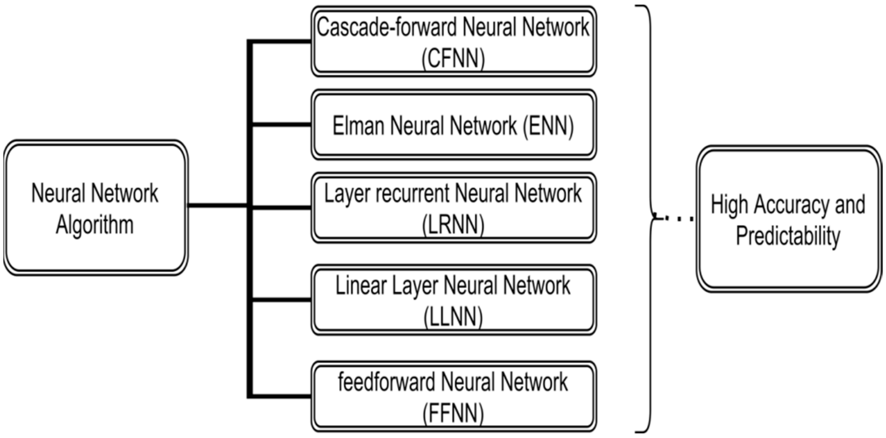


Figure 4. Neural Network Algorithm Selection.

3.2.1. Cascaded-Forward Neural Network (CFNN)

The CFNN is widely accepted as one of the neural techniques in machine learning modeling [37]. It has input and output layers, and possesses some neurons as a hidden layer. The mathematical representation of the CFNN is presented in Equation (9).

$$x_k = \sum_{i=1}^{p} g^i \omega_i^0 y^i + g^0 \left(\sum_{j=1}^{p} \omega_i^0 x^i g_i^h \left(\sum_{i=1}^{p} \omega_{jH}^h y_i \right) \right) \tag{9}$$

where g_i^h, g^i and ω_j^h are hidden, output layer functions and weight of hidden layer, respectively and x_k is the output of the trained NN.

3.2.2. Elman Neural Network (ENN)

The Elman neural network (ENN) has a better feature for real time performance evaluation of nonlinear functions. [38]. The mathematical representation of the ENN is shown in Equation (10).

$$x_k = g \left(\sum_{i=1}^{p} \omega_{ki}^0 g_{ki} \right) \tag{10}$$

where g, ω_k^0, and g_k represent the logsig function, weight of the hidden layer and output of the hidden layer, respectively.

3.2.3. Layer Recurrent Neural Network (LRNN)

The LRNN are best mathematical soft tool for processing data that are in sequential order [39]. The mathematical expression for the LRNN is given in Equation (11).

$$x_k = g^0 \left(v_i^0 + \sum_{j=1}^{p} g_{ij}^0 y_j^{(t)} + \sum_{i=1}^{p} \omega_{ij}^0 g_j^{(t-1)} \right) \tag{11}$$

where g^0, v^0, ω^0 represent biases, input weights, and recurrent weights, respectively, while $g^{(t)}$ and y^t denote the hidden layer (vector) and input functions, respectively.

3.2.4. Linear Layer Neural Network (LLNN)

The mathematical modeling expression for the LLNN is presented in Equation (12).

$$x_k = g^0 \left(\sum_{i=1}^{p} y_i \omega^0 + \sum_{j=1}^{q} y_j \omega_{ji}^h \right) \tag{12}$$

where g_i^h, g^i and ω_j^h are hidden, output layer functions and weight of hidden layer, respectively and x_k is the output of the trained NN

3.2.5. Feed-Forward Neural Network (FFNN)

The FFNN is different from the recurrent types of the NN. However, the neuron communication channel is monodirectional, thereby, making it simple and fast to train with [40]. The FFNN mathematical modeling is presented in Equation (13).

$$x_k = g^0\left(\sum_{j=1}^{p}\omega^0 y^i g_j^h\left(\sum_{i=1}^{p}\omega_{ji}^h y_i\right)\right) \quad (13)$$

where g_i^h, g^i and ω_j^h are hidden, output layer functions and weight of hidden layer, respectively and x_k is the output of the trained NN.

3.3. Levenberg-Marquardt Model (LMM)

In this research, we employ the LMM for the training of the neural network algorithms due to its fast training time. The change of weight of the vector using LMM is given in Equation (14).

$$\Delta(w) = -\left[J\left(w^T J(w) + \mu I\right)\right]^{-1} J^T(w)e(w) \quad (14)$$

where $J(w)$, and I denote the Jacobian matrix, and identity matrix, respectively, and μ is the parameter (damping).

4. Results and Analysis

4.1. Results

The steady-state analysis of the IEEE 30-bus system and the NGP system on the vulnerable buses using the NVSP are presented in Tables 1 and 2, respectively. The Tables describe the safe operating range of the power network in steady-state stability scenarios. This includes the contingency and base case conditions. It is shown from the Table that the safe range of active power at the load bus 30, 26, and 29 are 10.6–25.6 MW, 10.5–20.3 MW, and 10.4–10.9 MW, respectively. Meanwhile, the steady-state stability range of the reactive power at the same load bus 30, 26, and 29 are given as 10.9–25.9 MVar, 10.3–20.3 MVar, and 10.9–25.9 MVar, respectively. The NVSP values of these buses are kept below 1. Any further increase in load demand outside the defined range of safe operating limit may result in voltage collapse if there is no compensation or control mechanism.

Table 1. Steady-state stability assessment using NVSP on IEEE 30-bus.

Bus No	Minimum Load				Maximum Load			
	P (MW)	Q (MVar)	NVSP	Voltage Mag. (p.u)	P (MW)	Q (MVar)	NVSP	Voltage Mag. (p.u)
30	10.6	10.9	0.3053	0.919	25.6	25.9	0.9832	0.609
26	10.5	10.3	0.1943	0.912	20.5	20.3	0.4651	0.711
29	10.4	10.9	0.2110	0.945	25.4	25.9	0.6458	0.691

Table 2. Steady State Stability Assessment using NVSP on NGP.

Bus Name	Minimum Load				Maximum Load			
	P (MW)	Q (MVar)	NVSP	Voltage Mag. (p.u)	P (MW)	Q (MVar)	NVSP	Voltage Mag. (p.u)
Gombe	90.6	50.9	0.1242	1.174	125.0	135.0	0.1711	1.000
Jos	40.3	55.7	0.1372	1.140	120.0	105.0	0.3936	0.962
Kano	80.6	90.9	0.2091	1.112	250.0	150.0	0.4006	0.933

As shown in Table 2, the NGP P-Q buses Gombe, Jos, and Kano have a safe operating limit of active power between 90.6–125.00 MW, 40.3–120.0 MW, and 80.6–250 MW, respectively. However, the safe operating range of 50.9–135.0 MVar, 55.7–105.0 MVar, and 90.9–150.0 MVar are reactive power for Gombe, Jos, and Kano buses, respectively.

The data presented in Tables 3 and 4 depict the response of the NN algorithms to the trained data of the IEEE 30-bus system and NGP system, respectively. The target is the NVSP dataset of the vulnerable lines and buses, and the corresponding neural networks dataset mimicking the target data is presented for IEEE 30-bus and NGP systems.

Table 3. Steady-State Stability Assessment using NN on IEEE 30-bus.

Target	Neural Network Algorithm				
	Cascade-Forward	Feed-Forward	Linear Layer (Design)	Layer Recurrent	Elman
0.0134	0.0359	0.0434	0.0198	0.0184	0.0306
0.0535	0.0319	0.0610	0.0169	0.0196	0.0313
0.0763	0.0248	0.0559	0.0226	0.0198	0.0355
0.0000	0.0221	0.0116	0.0231	0.0226	0.0369
0.0405	0.0351	0.0604	0.0222	0.0254	0.0371
0.0000	0.0323	0.0590	0.0196	0.0189	0.0319
0.0000	0.0817	0.0000	0.0417	0.0139	0.0344
0.0161	0.0271	0.0167	0.0274	0.0233	0.0369
0.0493	0.0588	0.1145	0.0344	0.0257	0.0452
0.0385	0.0324	0.0341	0.0288	0.0239	0.0374
0.0436	0.0385	0.0527	0.0540	0.0378	0.0470
0.0000	0.0036	0.0000	0.1114	0.0214	0.0081

Table 4. Steady-State Stability Assessment using NN on NGP bus.

Target	Neural Network Algorithm Training Output				
	Cascade-Forward	Feed-Forward	Linear Layer (Design)	Layer Recurrent	Elman
0.3689	0.0000	0.4646	0.2162	0.4708	0.2768
0.0389	0.0389	0.0094	0.0895	0.0466	0.2037
0.2223	0.2223	0.2013	0.3538	0.2495	0.2037
0.1797	0.1797	0.1112	0.4036	0.1058	0.3234
0.0000	0.0000	0.0020	0.1266	0.0080	0.1793
0.0000	0.0000	0.0714	0.4860	0.1085	0.3540
0.0000	0.0000	0.0010	0.1000	0.0039	0.1984

The training data comprises about seventy percent of the total dataset while the remaining dataset was used as the target data. In the performance evaluation of the neural network models, we consider root mean squared error (rms). The degree of closeness between the target and the trained results from the neural network algorithms was used to describe the accuracy of the NNs. However, the training time and the computed ratio of the trained data of each NN technique to the target data was employed to define the efficiency of each NN.

4.2. Performance Analysis of the Regression Learner Algorithm

In the performance evaluation of the neural network models, we consider root mean squared error (*rmse*). The *rmse* was derived using the regression learner algorithm. However, Equations (15) and (16) describe the numerical expression for the *mse* and *rmse*, respectively.

$$mse = \frac{1}{P}\sum_{k=1}^{P}(x_k - l_k)^2 \tag{15}$$

$$rmse = \sqrt{\frac{1}{P}\sum_{k=1}^{P}(x_k - l_k)^2} \tag{16}$$

where x_k and l_k are the trained output from the neural network and the target, respectively.

Tables 5 and 6 present the analysis of the trained output of the neural network models for the IEEE 30-bus system and the NGP system, respectively. The table comprises the rmse, training time, iteration, gradient, and regression performance of the considered neural networks.

Table 5. Performance Analysis of the NN Algorithms on the IEEE 30-bus.

Neural Network Model	Rmse	Training Time (s)	No of Iteration	Gradient	Regression	Rank
CFNN	0.029316	0.82864	12	0.000117	0.000983	2nd
ENN	0.031560	0.84766	6	4.84×10^{-5}	0.000225	5th
LRNN	0.030479	0.92653	7	0.000633	0.000633	4th
LLNN	0.028165	2.92024	1000	-	0.000547	3rd
FFNN	0.026290	0.89757	6	0.000234	0.000327	1st

Table 6. Performance Analysis of the NN Algorithms on the NGP.

Neural Network Model	Rmse	Training Time (s)	No. of Iteration	Gradient	Regression	Rank
CFNN	0.14979	0.93095	6	0.00693	0.000333	1st
ENN	0.16124	0.77200	6	0.00905	0.000663	4th
LRNN	0.16480	0.86549	8	0.00206	0.000121	5th
LLNN	0.15717	4.97786	1000	-	0.000446	3rd
FFNN	0.15141	0.95489	20	0.00206	0.000350	2nd

The ranking of the NN algorithms was based on the training time, accuracy, and efficiency of the target data (NVSP). The results presented in Table 5 depict that the FFNN has the best performance in terms of accuracy, predictability, and adaptability as it is ranked first for the IEEE 30-bus system. Meanwhile, the CFNN is ranked second on the assessment of steady-state stability on the IEEE 30-bus system. Conversely, as shown in Table 6, the CFNN is ranked first while FFNN is ranked second for the assessment of steady-state stability on the NGP system.

The response plot showing the degree of closeness between the target data and the trained data of different neural network techniques on the IEEE 30-bus is shown in Figure 5. The weighted sample of the target data and the neural network's predicted output is represented with blue and yellow dots, respectively, while the marginal difference (error) between the two set points is described by red lines.

The response plot showing the degree of closeness between the target data and the trained data of different neural network techniques on the NGP is shown in Figure 6. The weighted sample of the target data and the neural network's predicted output is represented with blue and yellow dots, respectively, while the marginal difference (error) between the target data and the trained ANNs output is described by red lines.

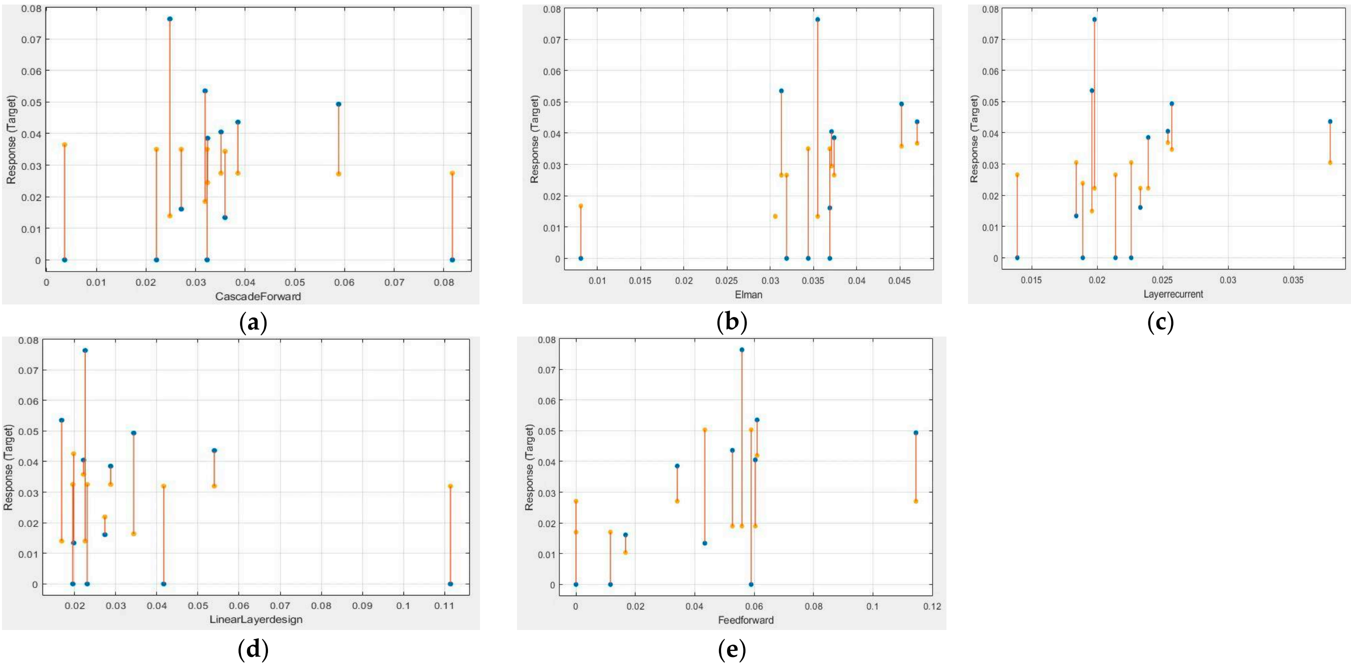


Figure 5. Response plot from the regression learner algorithm (IEEE 30-Bus system). (**a**) CFNN (**b**) ENN (**c**) LRNN (**d**) LLNN (**e**) FFNN.

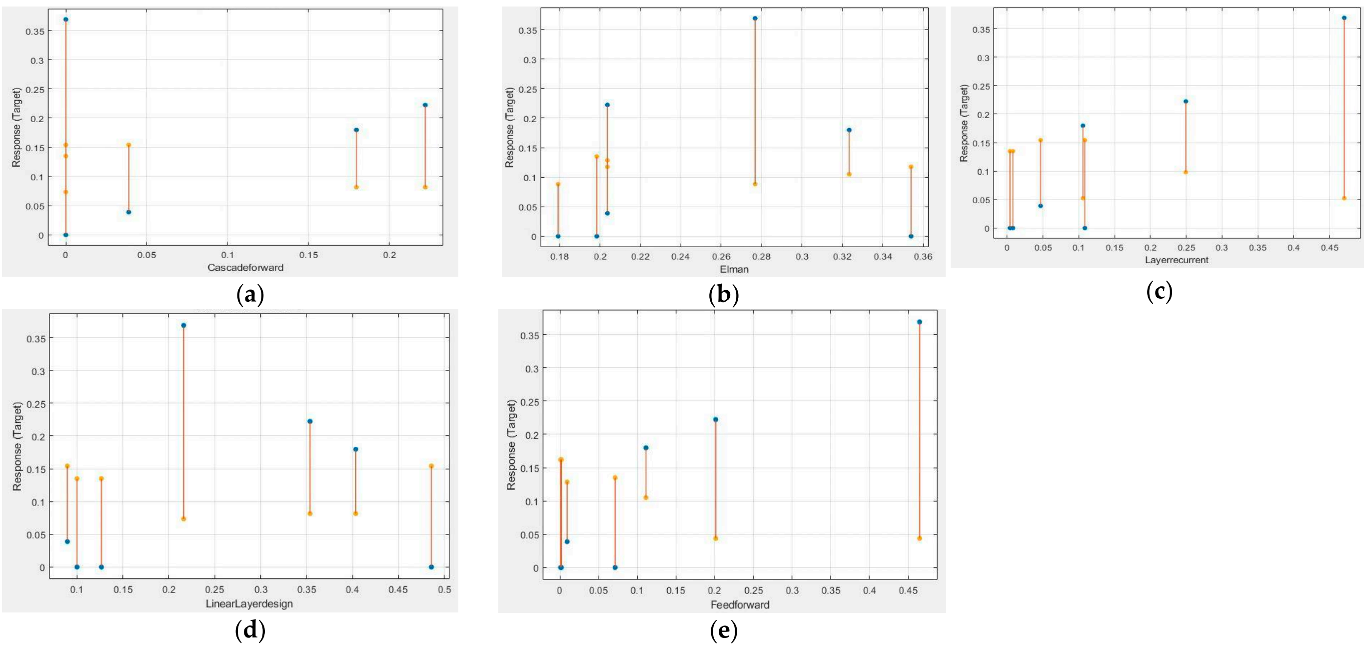
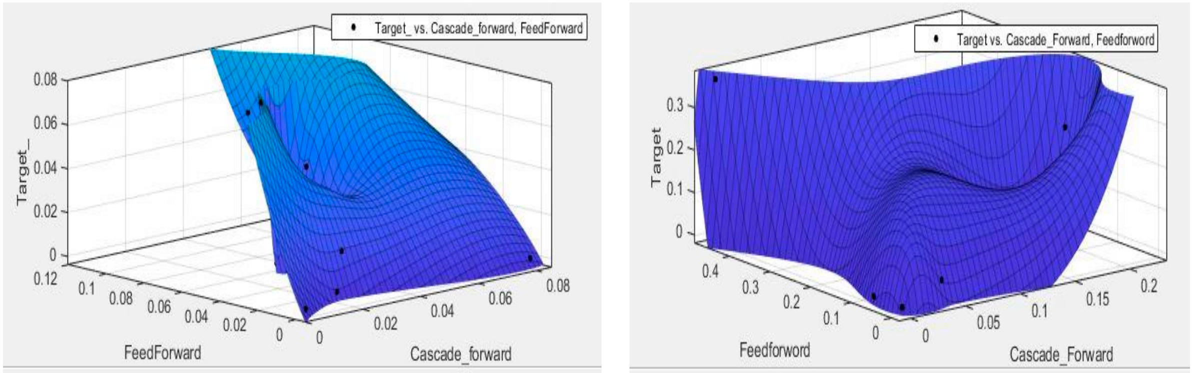


Figure 6. Response plot from the regression learner algorithm on the NGP, 28-bus system. (**a**) CFNN (**b**) ENN (**c**) LRNN (**d**) LLNN (**e**) FFNN.

4.3. Comparative Analysis of the Neural Networks

The results from the response plot show that the FFNN has a very close predictive performance to the CFNN for the considered power systems. This implies that both approaches are good for the assessment of power systems [31,37,41,42]. Sometimes, researchers combine more than one neural network algorithm for a better accurate result [43,44].

Figure 7 describes the interpolant nearest neighbor plot comparing the FFNN and CFNN with the target result on steady state-stability prediction on the IEEE 30-bus system and NGP system, respectively. From the information presented in Figure 7, the FFNN has similar traits to the CFNN for the considered power networks. More importantly, the NGP is classified as a complex interconnected power network because of its nonlinear loading feature [36]. However, the IEEE 30-bus system is an improved American power subsystem [45]. Both CFNN and FFNN are good techniques for the assessment of the steady state stability assessment in a power network. Meanwhile, in a complex interconnected power system, it is recommended to employ the CFNN and the FFNN for an ideal network that is free of uncertainty.



(**a**) (**b**)

Figure 7. Nearest neighbor plot comparing CFNN and FFNN on (**a**) IEEE 30-bus system. (**b**) NGP system.

5. Conclusions

This paper has investigated different neural network techniques for the assessment of steady-state stability in a power network. In this study, we consider five neural network algorithms namely: cascade-forward neural network (CFNN), Elman neural network (ENN), layer recurrent neural network (LLNN), linear layer neural network (LLNN), and feedforward neural network (FFNN). The performance ranking of the NN algorithms was achieved through the regression learner algorithm (RLA) using a root mean squared error (rmse) and response plot graph. The assessment was performed on the IEEE 30-bus and the NGP system. The FFNN and CFNN have close prediction values for both the IEEE-30 bus system and NGP system. The data presented in Table 5 ranked the FFNN as the first based on accuracy and predictability and CFNN ranked second for the IEEE 30-bus system. Conversely, the CFNN is ranked first and FFNN ranked second for the NGP system as presented in Table 6. LLNN is ranked third for the two cases-IEEE 30-bus and NGP. ENN is ranked fifth for the IEEE 30-bus and fourth for the NGP. LRNN is ranked fourth and fifth for the IEEE 30-bus and NGP systems, respectively.

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