**DEVELOPMENT OF A DEEP LEARNING**

**NEURAL**

**NETWORK MODEL FOR TRANSIENT**

**AND SMALL**

**SIGNAL STABILITY ASSESSMENT**

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#  ABSTRACT

This research recommends employing a deep learning neural network (DLNN) technique to analyze both transient and small signal stability, in contrast to other studies that only looked at transient stability. The complexity of power system dynamic features has increased due to the introduction of new components like power electronics, electric vehicles, and renewable energy generation, making TSA and SSA essential considerations. Today, the stability and security of the electrical network are impacted by the growing development of renewable energy sources. Wide area monitoring systems for the electrical system have emerged, creating "big data," which has ushered in new paradigms for tackling these issues. A wide range of stakeholders are paying attention to transient stability and small signal stability issues because they have the potential to create catastrophic outages. This study's objective is to evaluate the numerous stability issues relating to the electrical system using feature selection and DLNN methodology. The 28-bus test case power system's dynamic simulations were used to provide Nigerian time-domain data. A data processing pipeline for feature selection is built using the Relief-F feature selection approach. If a system is transiently stable, the prediction model will advise the power system operator of the damping This research recommends employing a deep learning neural network (DLNN) technique to analyze both transient and small signal stability, in contrast to other studies that only looked at transient stability. of low frequency local and interarea oscillations. The DLNN approach also provides information on the system's oscillatory dynamic response and transient stability, enabling the application of essential control measures. Calculations are made to determine the proper amount of adjustment, the correct minimum damping ratio, and system stability under the constraints of stability and power balance. The DIgSILENT/Python tool, which is powered by an Intel Pentium core i5 2GHz CPU, is used to carry out this study. The better performance of the proposed model is tested on the Nigeria 28 bus system, and confirmed on the IEEE 9 bus system. The 28-bus system in Nigeria was evaluated as having an accuracy performance of 90.16 percent for TSA and 100 percent for SSA. This study evaluates and validates the strength of the proposed model.

**Keywords-** Small Signal stability assessment, Transient stability assessment, Deep Learning Neural Network, Long Short-Term Memory, Transient stability, Power system stability, Relief F, Recurrent Neural Network

#  I. INTRODUCTION

Power system stability refers to a power system's ability to recover from a disruption, reach equilibrium, and resume normal operations. The instability problem has long been associated with rotor angle instability brought on by synchronism loss [7]. Rotor angle instability caused by synchronism loss has long been linked to the instability issue [7]. Rotor angle stability can also be split into small signal and transient signal stability depending on the strength of the disturbance. Small signal stability and transient stability, respectively, are terms used to describe a power system's capacity to sustain synchronism in the face of minor and significant disruptions [2]. The behavior of synchronous generators in relation to their associated control systems, loads, renewable energy output, flexible AC transmission devices (FACTs), and the transmission network is described by a collection of highly nonlinear Differential and Algebraic Equations (DAE) [2] and [7]. When there is little change in the power system, the DAE model can be linearized all the way around the equilibrium point. Electrical torque variations in synchronous machines with the appropriate synchronizing and dampening torque component enable small-signal stability. Since the DAE model cannot be linearized around an operational point when a power system experiences significant changes, each situation must be handled numerically using time domain simulations [7]. If there is not enough synchronizing and damping force, the rotor angle of a synchronous generator may occasionally drift and oscillate [2]. The primary cause of power outages is transient instability, which has the potential to lower a power system's overall performance [4]. In especially for big power systems with an almost infinite number of operating points and eventualities, TSA, a sort of time domain simulation, is expensive and computationally challenging. To achieve these objectives, the prediction model is trained using a Deep Learning technique (LSTM) and a data set for a variety of operating conditions. The considerable weekly damped low frequency oscillation is gradually captured by the Long Short Term Memory (LSTM), which is trained to remember the oscillatory response of a projected stable system. The computational complexity of the TSA and SSA is steadily reduced, improving prediction accuracy, and the same is true for the LSTM. The Nigeria 28 Bus System is used to demonstrate the suggested model's improved performance, and information about how the IEEE 9 Bus system supports it is provided.

#  II. TRANSIENT AND SMALL SIGNAL STABILITY OF A POWER SYSTEM

In this study, a prediction model for the transient and tiny signal stability concerns in Nigeria's 28 bus system is built using deep learning neural network methodologies. The mathematical process for transient and tiny signal stability is described in this section.

# A. Transient Stability

Rotor angle stability describes a synchronous machine's capacity to keep synchronism in a power system after a disruption. Because different power system disruptions have different effects on generation, some generators will slow down as a result of an increase in load from adaptive operation, while the other generators will accelerate up to maintain grid frequency. An increase in generator speed causes a change in the tilt of the rotor with regard to the stator [6]. To keep the mechanical input torque and electrical output torque in balance, the rotor continuously accelerates and decelerates alternately. This activity reduces the generator's capacity to generate electricity and damages the transformers, prime mover, and generator as a whole. Therefore, it is crucial to safeguard the synchronous machine [8].

A group of DAE control the dynamic response of a power system to disturbances, and their compact form is:





The state as well as the algebraic variables x and y are shown. Additionally, h and g display the vectors of the relevant DAE. To obtain time-varying trajectories, the algebraic variables y, such as bus voltages and active power injections, and the state variables x, such as rotor angles and frequencies, are solved. To do this, the set of differential equations is discretized using numerical methods, such as the trapezoidal approach equation (1). At each time step (2), the created algebraic equations and the remaining algebraic equations are solved using the Newton's method. The dynamic trajectories over the simulation time window are observed to assess transient stability. This approach offers a precise evaluation of the temporary for a particular circumstance [1]

# B. Small signal stability

Insufficient oscillation Small signal stability is indicated by damping in frequency, rotor angle, or voltage stability indications. The amplitude of oscillatory activity is constant across time when damping is zero. Negative damping raises the oscillations' amplitude regardless of the initial disturbance. High damping ratios make the power system's critical mode larger and decrease oscillation behavior. This is because it is the component of the system that is least stable [7]. The smallest damping ratio can be used to test the stability of small signals. Small signal stability problems can be local or worldwide in scope. Interarea mode oscillations are larger disturbances created by a group of generating stations than local mode oscillations, which are smaller disturbances brought on by a single producing station. Power System Stabilizer (PSS) and Flexible AC Transmission System (FACTS) controllers are widely used to improve oscillation stability in multi-machine power systems. By generating additional signals to combat oscillations in generator excitation systems, these devices [5] and [7] reduce damping. The main factor affecting how synchronous machines respond to oscillations is their electrical torque. Electrical torque is made up of two components: The Synchronizing Torque (TS), which oscillates in phase with the rotor angle deviation, and the Damping Torque (TD), which oscillates in phase with the components that affect the speed deviation. Both kinds of torques have an effect on the stability of tiny signals [5]. The set of algebraic and differential equations stated in (1) - (2) can be linearized around an equilibrium point for mild disturbances, as shown in equations (3) - (4).



To investigate small signal or local stability at an equilibrium point in the presence of a slight disturbance in a power system, the linearized model in (3) – (4) is utilized. To do this, one employs the Lyapunov first technique, which entails determining the eigenvalues of the characteristic equation as follows. [3].

det(𝐴𝑠𝑦𝑠 − 𝐼) = 0 (6)

Where, 𝐴𝑠𝑦𝑠=𝐴−𝐵 (𝐷−1)𝐶 𝑎𝑛𝑑 =(1, 2…………………………….𝑛)

Either real or complex estimated eigenvalues result in non-oscillatory or oscillatory responses. Additionally, conjugate pairs of complex eigenvalues are present, each of which indicates an oscillatory mode [5].

# C. LSTM NETWORK FOR TSA AND SSA

The RNN variants known as LSTM networks are capable of retrieving historical data from time series data. By encoding incremental temporal domain inputs into long-lasting internal hidden states, the network learns. Recalling earlier information over time is a typical behavior. LSTMs are helpful for time-series prediction because they can remember prior inputs [7]. LSTMs interact in a variety of ways thanks to their chain-like structure and four interacting layers. LSTMs are frequently employed in voice recognition, music production, and pharmaceutical research in addition to time-series predictions [7] and [10]. LSTM is used to address the long-term dependency problems. At each point, LSTM offers the choice to read, write, or reset the sale [10]. Equation 7 displays the mathematical computations for the LSTM.

 

(

7)



The operator denotes the pointwise multiplication of two vectors, where ct stands for the state of the LSTM cell, and Wi, Wc, and Wo are the weights. The input gate selects what fresh information can be entered while updating the cell state, while the output gate selects what information can be output based on the cell state. The LSTM cell shown in equation 8 can be mathematically characterized as follows based on the connections:

(

8

)



Information from the state of the cell been destroyed is decided by the forget gate. The forget gate, ft, has a value of 1, this information is kept, and when it has a value of 0 it is fully discarded [10]. The structure of the LSTM is shown in Figure 1.



**Figure 1: LSTM Network Diagram [11].**

#  III. NETWORK STRUCTURE OF THE MODEL

In order to develop a DLNN for TSA and SSA, this chapter builds the six-layered network model are explained below

1. Data collection: Appropriate data for modeling the 28-bus Nigeria network are acquired from the National control center (NCC) Oshogbo.
2. Using DIgSLIENT, the Nigeria 28 bus system was well modeled.
3. Data collection for DLNN: The Relief-F technique is applied to remove unusual data from useful data.
4. DLNN (LSTM): A DLNN based on LSTM is well modelled using the data that is available, trained, tested, and confirmed to complete the required TSA and SSA evaluation.
5. Performance evaluation: The effectiveness of the LSTM model is then assessed using the Root Mean Squared (RMS), Specificity, Accuracy, and Precision metrics.
6. Compare outcomes: The results are evaluated against the IEEE 9 bus and other bus system.

Figure 2, shows the proposed model for assessing transient and small signal stability. It is made up of two different model. The two model contains four inputs namely, voltage, rotor angle, active power and reactive power.

In

TS

A

SSA

X

1

X

2

X

3

X

4

Y

1

Y

2

Y

3

Y

4

Stable/

unstable

Stable/

unstable

 Bias=1

 **Figure 2: Schematic design model of TSA & SSA**

#  IV. DATA PREPARATION

The NCC provided the bus and transmission line data to the 330KV, 28 bus networks in Nigeria that was utilized as the case study (TCN). Figure 3 shows the 28-bus power network, which consists of 28 buses, 9 generation stations, and 52 transmission lines. Table 1 displays the transmission line and bus data. The modeling is done in the DIgSILENT power facility. The bus bars were either PV or PQ models when it came to the transmission lines, depending on where the load and generator were positioned. The loads were lumped loads based on PQ data. Using the required information and synchronous generator characteristics, the generators were accurately modeled.

 **Figure 3: The Nigerian 28 bus power system** [9].

**Table 1: Network Data of the Nigerian 28 Bus Power System** [9].

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Bus Identification**  | **Bus Loads**  |  | **Transmission Lines Data**  |  |
| **NO**  | **Name**  | **MW**  | **MVAR**  | **Bus**  | **R(pu)**  |  **X(pu)**  |
| 1 Egbin  | 68.90  | 51.70  | **FROM**  | **TO**  |   |   |

1. Delta 0.00 0.00 1 3 0.0006 0.0044
2. Aja 274.40 205.80 4 5 0.0007 0.0050
3. Akangba 244.70 258.50 1 5 0.0023 0.0176
4. Ikeja-West 633.20 474.90 5 8 0.0110 0.0828
5. Ajaokuta 13.80 10.30 5 9 0.0054 0.0405
6. Aladja 96.50 72.40 5 10 0.0099 0.0745
7. Benin 383.30 287.50 6 8 0.0077 0.0576
8. Ayede 275.80 206.8 2 8 0.0043 0.0317
9. Osogbo 201.20 150.90 2 7 0.0012 0.0089
10. Afani 52.50 39.40 7 24 0.0025 0.0186
11. Alaoji 427.00 320.20 8 14 0.0054 0.0405
12. New-Heaven 177.90 133.40 8 10 0.0098 0.0742
13. Onitsha 184.60 138.40 8 24 0.0020 0.0148
14. B/Kebbi 114.50 85.90 9 10 0.0045 0.0340
15. Gombe 130.60 97.90 15 21 0.0122 0.0916
16. Jebba 11.00 8.20 10 17 0.0061 0.0461
17. Jebba G 0.00 0.00 11 12 0.0010 0.0074
18. Jos 70.30 52.70 12 14 0.0060 0.0455
19. Kaduna 193.00 144.70 13 14 0.0036 0.0272
20. Kanji 7.00 5.20 16 19 0.0118 0.0887
21. Kano 220.60 142.90 17 18 0.0002 0.0020
22. Shiroro 70.30 36.10 17 23 0.0095 0.0271
23. Sapele 20.60 15.40 17 21 0.0032 0.0239
24. Abuja 110.00 89.00 19 20 0.0081 0.0609
25. Makurdi 290.10 145.00 20 22 0.0090 0.0680
26. Mambila 0.00 0.00 20 23 0.0038 0.0284
27. Papalanto 0.00 0.00 23 25 0.0038 0.0284

 12 26 0.0071 0.0532

 19 26 0.0059 0.0443

 26 27 0.0079 0.0591

 5 28 0.0016 0.0118

#  V. RESULT AND DISCUSSION

The test is run using the Relief-f algorithm and the LSTM. Python/DIgSLIENT is utilized to carry out this study's implementation. The Nigerian 28-bus power system for TSA and SSA is depicted in Figure 4 below using a DIgSILENT model. Data were collected from DIgSILENT for TSA and SSA purposes under various situations.



#  Figure 4: Modelling of Nigerian 28-Bus System

In this study the user interface gives user the privilege to load several dataset, select relevant information from the large amount of data, using the Relief-F feature selection algorithm. Table 2 shows the loaded data.

# Table 2: Loaded Data Nigerian 28-Bus System

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **V(p.u)**  | **P(KW)**  | **Q (KVAr**  | **(ϴ)**  | **TSA** **Targ**  | **SSA Targ**  |
| 0.388583  | -271.618  | 0.454232  | -63.3957  | 0  | 1  |
| 0.469965  | 563.2468  | -306.641  | 97.48929  | 0  | 1  |
| 0.255932  | -209.335  | 151.7141  | -102.012  | 0  | 1  |
| 0.533196  | 409.5992  | -385.232  | 58.1159  | 0  | 1  |
| 0.147646  | 19.65125  | 190.0627  | -142.138  | 0  | 1  |
| 0.540542  | 127.6128  | -338.973  | 17.22918  | 0  | 1  |
| 0.220532  | 318.4933  | 72.08323  | 176.2186  | 0  | 1  |
| 0.484492  | -151.327  | -180.955  | -25.1795  | 0  | 1  |
| 0.370508  | 535.4349  | -148.529  | 133.0507  | 0  | 1  |
| 0.366197  | -274.478  | 26.74668  | -69.1091  | 0  | 1  |
| 0.489727  | 539.7334  | -341.938  | 88.36538  | 0  | 1  |
| 0.209501  | -156.153  | 174.4907  | -114.545  | 0  | 1  |
| 0.543035  | 309.6819  | -389.185  | 42.17829  | 0  | 1  |
| 0.154649  | 150.4527  | 153.4337  | -161.475  | 0  | 1  |
| 0.514599  | -27.5849  | -260.075  | -5.50633  | 0  | 1  |
| 0.310105  | 458.6298  | -49.8561  | 150.0938  | 0  | 1  |
| 0.403731  | -252.811  | -30.6135  | -54.6958  | 0  | 1  |
| 0.465345  | 553.8266  | -304.05  | 100.1514  | 0  | 1  |
| 0.233219  | -197.255  | 154.0606  | -105.39  | 0  | 0.135  |
| 0.54455  | 350.7548  | -412.666  | 48.70475  | 0  | 0.135  |
| 0.261644  | -207.228  | 163.5346  | -100.006  | 1  | 1  |
| 0.533944  | 476.4872  | -393.262  | 69.36015  | 1  | 1  |
| 0.18805  | -114.21  | 196.6741  | -121.668  | 1  | 1  |
| 0.558244  | 357.5287  | -423.106  | 46.91436  | 1  | 1  |
| 0.143834  | 28.34095  | 192.7953  | -144.893  | 1  | 1  |
| 0.557052  | 193.1078  | -381.217  | 22.91489  | 1  | 1  |
| 0.174444  | 207.5377  | 142.6571  | -169.663  | 1  | 1  |
| 0.529761  | 5.899559  | -279.595  | -2.62709  | 1  | 1  |

The loaded data in this study includes 81,802 instances and 6 attributes, with the targets stable/unstable and eigen values. The loaded data is preprocessed and analyzed using relief-f with DLNN. Relief-F is used to preprocess the loaded data before passing the chosen or pertinent feature to DLNN. The DLNN consists of input layers, hidden layers, and LSTM-based output layers. The ANN Fitting perspective for the data is shown in Figure 5.

X

1

X

4

Y

X

3

X

2

# Figure 5: Fitting Layers of the Data

The results of TSA and SSA are either stable or unstable. For a stable system the TSA is denoted as 1, and for an unstable, it is denoted as 0. In contrast, for SSA, the system is stable or oscillatory free if the real portion of the eigenvalue is negative and the damping ratio is positive, but unstable if the real part of the eigenvalue is positive. The deep learning neural network architecture of TSA and SSA is displayed in Table 3.

Table 3: Deep learning Neural Network Data and Structure of TSA & SSA

|  |  |
| --- | --- |
| **Feature and Structure Of LSTM** | **TSA AND SSA** |
| Number of inputs | 4  |
| Number of neurons in the hidden layer  | 6  |
| Output  | 1 each  |
| Training data  | 66560  |
| Testing data  | 8256  |
| Validation data  | 6273  |
| Training algorithm  | LSTM  |
| Epoch  | 31  |
| Transfer function Relu and Sigmoid  |

The model confusion matrix obtained is to determine the evaluation performance of the developed model, including accuracy and precision, using the DLN technique is shown in Figure 6. After 10 epochs, the system converges, and the model accuracy for TSA and SSA achieves 90.16 percent and 100 percent, respectively. Tables 4 and 5 display the model evaluation performance of the methodology.



**Figure 6: Confusion Matrix for the TSA Developed Model. TP=14335; TN=275; FP=225; FN=1526**

# Table 4: Evaluation Performance for TSA

|  |  |  |
| --- | --- | --- |
| **Measure**  | **Evaluation (%)**  | **Derivations**  |
| Sensitivity  | 90.38  | TRP=TP/(TP+FN)  |
| Precision  | 98.45  | PPV=TP/(TP+FP)  |
| Accuracy  | 90.16  | ACC+(TP+TN)/(P+N)  |



 **Figure 7: Confusion Matrix for the SSA Developed Model. TP=7251; TN=9110; FP=0; FN=0**

# Table 5: Evaluation Performance for SSA

|  |  |  |
| --- | --- | --- |
| **Measure**  | **Evaluation (%)**  | **Derivations**  |
| Sensitivity  | 100  | TPR=TP/(TP+FN)  |
| Precision  | 100  | PPV=TP/(TP+FP)  |
| Accuracy  | 100  | ACC=(TP+TN)/(P+N)  |

#  A. Compare Results on IEEE 9 Bus System

This part is illustrated in Figure 8 and uses modeling of the IEEE 9 bus system in the DIgSILENT power factory to validate the assessment outcomes from the TSA and SSA. For these systems, time-domain simulations and eigenvalue computation are performed using DIgSILENT. The generator rotor angle, voltage level, active power, and reactive power at all buses are also reported along with the oscillation modes. Additionally, a time difference of 0.3 seconds is used during the simulations' 10 second run. Table 6 displays loaded data for the IEEE 9 bus system developed and utilized for training and testing, consisting of 62,500 target values, because neural networks require a lot of data to train. For the IEEE 9-Bus system, recovered samples included 18,750 testing samples and 43,750 training samples with appropriate target values. This system exhibits oscillations with eigenvalues that are compatible with both local and inter-area modes. The simulation for SSA indicated significant eigenvalue errors. The LSTM forecasts for this system were accurate and closely corresponded with the dynamics of the simulated oscillatory modes, in contrast to the TSA, whose LSTM predictions provided straightforward evaluation performance estimates.



 **Figure 8: Modelling of IEEE 9 Bus System in DIgSILENT**

#  Table 6: Loaded data for IEEE 9 bus system

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| V(p.u)  | P(KW)  | Q (KVAr)  | (ϴ)  | TSA Target  | SSA Target  |
| 0.17958  | -123.513  | 171.9536  | -121.034  | 0  | 1  |
| 0.541271  | 191.1149  | -377.243  | 26.03689  | 0  | 1  |
| 0.21862  | 312.9513  | 61.45572  | 172.7484  | 0  | 0  |
| 0.437684  | -202.49  | -101.296  | -40.9198  | 0  | 0.982346655  |
| 0.441616  | 528.1544  | -257.218  | 105.0707  | 0  | 0.982346655  |
| 0.210953  | -162.216  | 160.9706  | -109.329  | 0  | 0.10730671  |
| 0.542129  | 238.5471  | -392.568  | 35.91947  | 0  | 0.10730671  |
| 0.194307  | 277.8757  | 75.5049  | -179.199  | 0  | 0.085283166  |
| 0.459572  | -195.994  | -154.359  | -34.6968  | 0  | 0.085283166  |
| 0.428978  | 542.6657  | -250.911  | 109.4685  | 0  | 0  |
| 0.228289  | -186.864  | 148.0511  | -106.753  | 0  | 0  |
| 0.534469  | 254.3771  | -375.392  | 36.6825  | 0  | 0  |
| 0.198982  | 272.5964  | 83.33363  | 179.7563  | 0  | 0  |
| 0.441242  | -197.513  | -114.59  | -37.5489  | 0  | 0  |
| 0.445292  | 530.6067  | -272.797  | 104.8101  | 0  | 0  |
| 0.194562  | -150.778  | 160.4638  | -113.223  | 0  | 0  |
| 0.542532  | 191.7196  | -392.29  | 28.39765  | 0  | 0  |
| 0.227462  | 338.5404  | 33.06602  | 169.661  | 1  | 0.982346655  |
| 0.418274  | -235.976  | -78.9364  | -49.4565  | 1  | 0.982346655  |
| 0.468614  | 509.4048  | -308.579  | 91.10054  | 1  | 0.10730671  |

The TSA model confusion matrix, which was calculated using the DLNN technique to determine the evaluation performance of the developed model, including accuracy and precision, is shown in Figure 9 and Table 7. The outputs of the TSA's confusion matrix model are TP=2300, TN=5900, FP=4000, and FN=370. After 82 epochs, the system converges, and the model accuracy for TSA is 65%.



#  Figure 9: Confusion matrix for the TSA IEEE 9 bus system

**Table 7: Evaluation Performance for TSA of IEEE 9 bus system**

|  |  |  |
| --- | --- | --- |
| **Measure**  | **Evaluation (%)**  | **Derivations**  |
| Sensitivity  | 94  | TPR=TP/(TP+FN)  |
| Precious  | 86  | PPV=TP/(TP+FP)  |
| Accuracy  | 65  | ACC=(TP+TN)/(P+N)  |

Because the goal values have so many floats and so few integers, the SSA outcome is a Regression method. After 40 epochs, the system converges, producing a Mean Squared Error of 0.183 and a Root Mean Squared Error of 0.4277849927. Figure 10 depicts the Residual Distribution Curve, where the prediction is both over and under estimated because the majority of the estimated values fall between -0.5 and 0.5.

print (‘MSE: ‘ + str(mse) ) print (‘MSE: ‘ + str(rmse) ) print (‘Epochs: ‘ + str(5) )

MSE: 0.183

 RMSE: 0.4277849927



#  Figure 10: Residual Distribution Curve

A number of studies on TSA and SSA were compared to the outcomes utilizing different machine learning approaches. The accuracy of various methods for predicting TSA and SSA is compared in Table 8. The proposed method is tested utilizing the IEEE 58, IEEE 60, and New England 39 bus systems after being compared to CNN and LSTM in Table 8 to anticipate TSA and SSA. The MSE, RMSE, Accuracy, Sensitivity, and Precision are the primary comparing measures. The Nigeria 28 bus system has faultless assessment performance for both TSA and SSA because to the usage of LSTM to increase its accuracy, sensitivity, and precision. Because there were so many floats in the input data, TSA's accuracy was low. The accuracy of the evaluation performance when using the IEEE 9 bus system was 65%. To improve TSA accuracy in this case, random hyperparameter tweaking can be employed, although a longer training period is required. While in SSA, the MSE can be improved by using random search hyperparameter adjustment and can also be improved by adding more LSTM layers to make sure that it won't overfit the data.

# Table 8: Comparison of performance with TSA and SSA methods

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Related works on (TSA and** **SSA)**  | **Method**  | **Accuracy****(****)****%**  | **Sensitivit****y****(****)****%**  | **Precision****(****)****%**  | **MSE**  | **RMSE**  |
| Nigeria 28 Bus System (proposed work)  | LSTM  | 90.16 100  | 90.8 100  | 98.45 100  |  \_  |  \_   |
|  IEEE 9 Bus System (proposed work)  |  LSTM  |  65  |  94  |  86  |  0.183  |  0.42778  |
|  IEEE 50 Bus System [7].  |  CNN and LSTM  |  98.31  |  \_  |  \_   |  0.00000016   |  0.0004  |
|  New England 39 Bus System [7].   |  CNN and LSTM   |  94.5   |  \_   |  \_   |  0.00001024    |  0.0032   |
| IEEE 68 Bus System [7].  | CNN and LSTM  | 97.22   | \_  | \_  | 0.00001681  | 0.0041  |

#  VI. CONCLUSION

Thanks to the integration of power electronics technology and renewable energy sources, it is now easier to convert the existing power systems into a new generation of power systems with a high penetration of renewable energy and power electronics. The evaluation of the electrical networks' transient and tiny signal stability is significantly hampered by this modification. In contrast to traditional time domain simulation and energy function methods, datadriven TSA with SSA methods establish a relationship between system operational parameters and stability status before determining stability results without the need for a power system's physical model or parameter information. Transient stability and small signal stability are necessary for the reliable and safe operation of energy networks. This study introduces feature-based deep learning algorithms (LSTM) to assess small signal stability and transient stability. The study's conclusions will help people who are interested in the subject by deepening their grasp of how LSTM evaluates the stability of transient and small signals.

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