

DEVELOPMENT OF A DLNN MODEL FOR TRANSIENT STABILITY ASSESSMENT OF NIGERIA 28 BUS SYSTEM

John Obiajulu Onyemenam
Department of Electrical and Information
Engineering,
Landmark University, Omu-Aran, Nigeria
john.obiajulu@lmu.edu.ng

Paul Kehinde Olulope
Department of Electrical and Information
Engineering,
Ekiti State University, Ekiti, Nigeria
paulade001@yahoo.com

Nnaemeka Uchenna Okeke
Department of Electrical and Information
Engineering,
Landmark University, Omu-Aran, Nigeria
okeke.uchenna@lmu.edu.ng

Emmanuel Osaji
Department of Electrical and Information
Engineering,
Landmark University, Omu-Aran, Nigeria
osaji.emmanuel@gmail.com

ABSTRACT

This article suggests using a Deep Learning Neural Network (DLNN) approach to forecast transient stability. Transient Stability Assessments (TSA) have long been acknowledged as being crucial for maintaining the reliable and secure operation of power systems. Due to the introduction of new components such as power electronics, electric vehicles, and renewable energy sources, the complexity of power system dynamic features has increased, causing serious worries among TSA. The development of renewable energy sources is currently having an impact on the reliability and security of the electrical network. Wide area monitoring systems have been used in the electrical system, producing large amounts of data that have ushered in new approaches to resolving these problems. Due to the possibility of catastrophic outages, transient stability issues are grabbing the attention of a wide spectrum of stakeholders. The objective of this study is to investigate TSA concerns in the electrical system using data collecting and DLNN. The Nigerian 28 Bus system was modeled using the DIGSILENT environment using data from the National Control Center (NCC) Oshogbo. The Relief-F feature selection method is used in a Python environment to create a data processing pipeline for feature selection. To forecast transient stability on Python, the chosen feature will be fed into a particular form of DLNN. The DLNN reduces the time complexity of TSA, increasing accuracy. The accuracy value produced for the Nigeria 28 bus system is 90.16 percent once the system converges after 31 epochs. The IEEE 9 bus test system is used to validate the DLNN approach, which is used to evaluate transient stability. The outcome of this work is compared with similar work in the conclusion in terms of some evaluation performance.

Keywords- Transient stability assessment, Deep Learning Neural Network, Long-short Term Memory, Transient stability, Power system stability, Artificial Intelligence, Neural Network, Relief F, Recurrent Neural Network.

I. INTRODUCTION

Power system stability refers to a power system's capacity to return to an equilibrium state and perform as intended in the wake of a disturbance. Rotor angle instability caused by synchronism loss has long been linked to the

instability issue [4]. Transient stability is the capacity of a power system to retain synchronism in the face of significant distractions [12]. It is crucial in this case that TSA is efficient and precise. Thanks to the quick development of artificial intelligence techniques, data-driven TSA procedures have gained a lot of attention in recent years, and numerous research findings have been made public. So that relevant academia can have a better awareness of the research state, key technologies, and current difficulties in the field [7], a thorough evaluation of the available data-driven TSA approaches is required. The three types of TSA methods offered are time domain or traditional simulation method, direct method, and data-driven artificial intelligence approach. The behavior of synchronous generators in connection to their related control systems, loads, renewable energy output, flexible AC transmission devices (FACTS), and the transmission network is described by a set of highly nonlinear Differential and Algebraic Equations (DAE). When a power system experiences significant variations, the DAE model cannot be linearized around an operational point thus, it must be numerically solved for each situation using time domain simulations. Power outages are mostly caused by transient instability, which can also lower a power system's overall performance [15]. Time domain simulations, a type of TSA, are costly and computationally challenging, particularly for large power systems with a nearly infinite number of operating points and contingencies [13], [14.] To achieve these objectives, the prediction model is trained using a Deep learning technique (LSTM) and a data set for a range of operating conditions. The LSTM reduces the TSA's time complexity, improving prediction accuracy even more. The Nigeria 28 Bus System is used to show off the improved performance of the suggested model, and the IEEE 9 Bus System is used to corroborate it.

II. TRANSIENT POWER SYSTEM STABILITY

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

A. Transient Stability TS

Rotor angle stability is the capacity of a synchronous machine in a power system to retain synchronism following an interruption. The consequences of power system disruptions on generation could not always be the same, thus some generators would experience increased load as a result of adaptive operation and will slow down, while the remaining generators will speed up to maintain grid frequency [6–9]. As the generator's speed increases, the tilt of the rotor in relation to the stator varies. To maintain balance between the mechanical input torque and the electrical output torque, the rotor continuously alternates between accelerating and decelerating [10], [11]. This behavior reduces the generator's capacity to generate electricity and damages the generator, prime mover, and transformers. The synchronous machine needs to be secured as a result [2]. The dynamic reaction of a power system to disturbances is controlled by a collection of DAE, and their compact form is:

$$\dot{x} = h(x, y) \quad (1)$$

$$0 = g(x, y) \quad (2)$$

Indicated are the state and algebraic variables x and y . Additionally, h and g denote the corresponding DAE's vectors [4], [5]. 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 get time-varying trajectories. This is accomplished by discretizing the set of differential equations using numerical techniques like the trapezoidal approach (1). The generated algebraic equations and the remaining algebraic equations are solved by the Newton's technique at each time step (2). To evaluate transient stability, the dynamic trajectories over the simulation time window are monitored. This method provides an accurate assessment of temporary for a specific situation [16].

B. Long Short Term Memory Network in TSA

Recalling information from the past in time series requires LSTM because, LSTMs are capable of remembering previous inputs, they are useful for time-series prediction and are used to follow data across time.

LSTMs, which have a chain-like structure and four interacting layers, interact in various ways. In addition to time-series predictions, LSTMs are commonly used in speech recognition, music production, and pharmaceutical research [17]. LSTM is used to address the long-term dependency problem's problems. LSTM networks are a subset of RNNs. At each stage, LSTM has the choice to read, write, or reset the transaction [3]. Equation 3 displays the LSTM's mathematical formulas;

$$\begin{aligned}
i_t &= \sigma(W_{ih}h_{t-1} + W_{ix}X_t + b_i), \\
\hat{c}_t &= \tanh(W_{ch}h_{t-1} + W_{cx}X_t + b_c), \\
c_t &= c_{t-1} + i_t \cdot \hat{c}_t, \\
O_t &= \sigma(W_{oh}h_{t-1} + W_{ox}X_t + b_o), \\
h_t &= O_t \cdot \tanh(c_t),
\end{aligned} \tag{3}$$

Where c_t denotes the state of the LSTM cell and W_i , W_c , and W_o are the weights, the operator denotes the pointwise multiplication of two vectors. Based on the cell state, the output gate determines what data can be output, and the input gate determines what new data can be entered while updating the cell state [1], [3]. The LSTM cell shown in equation 4 can be mathematically characterized as follows based on the connections.

:

$$\begin{aligned}
f_t &= \sigma(W_{fh}h_{t-1} + W_{fx}X_t + b_f), \\
i_t &= \sigma(W_{ih}h_{t-1} + W_{ix}X_t + b_i), \\
\hat{c}_t &= \tanh(W_{ch}h_{t-1} + W_{cx}X_t + b_c), \\
c_t &= f_t \cdot c_{t-1} + i_t \cdot \hat{c}_t, \\
o_t &= \sigma(W_{oh}h_{t-1} + W_{ox}X_t + b_o), \\
h_t &= o_t \cdot \tanh(c_t).
\end{aligned} \tag{4}$$

The forget gate determines which information from the cell state will be deleted. This information is stored when the forget gate, f_t , has a value of 1, and it is completely discarded when it has a value of 0. The LSTM's structure is depicted in Figure 1.

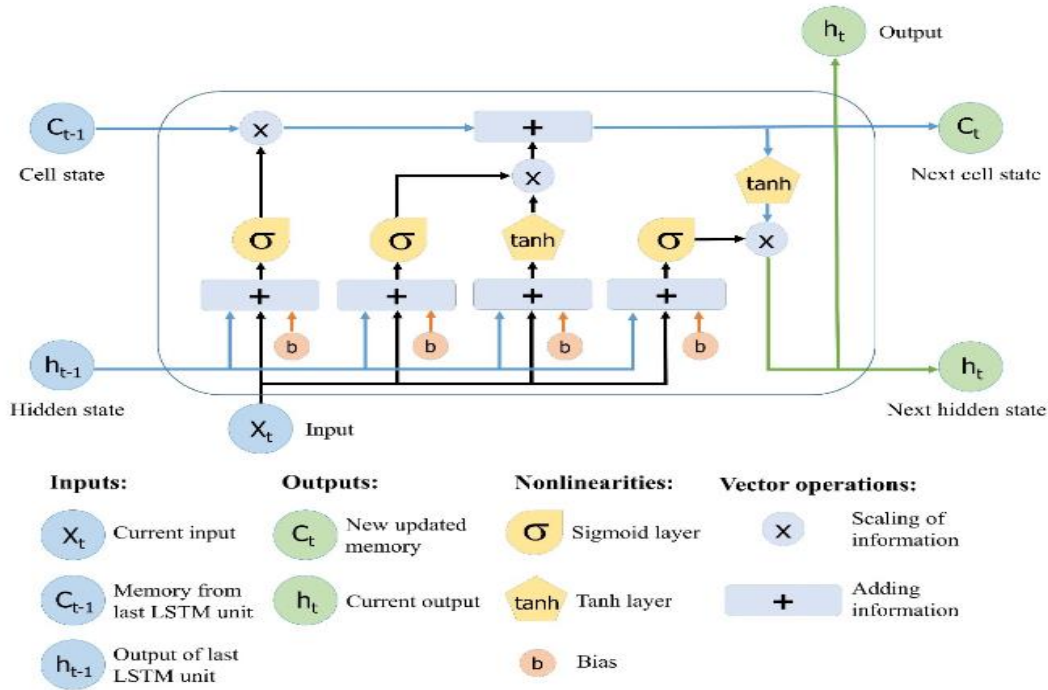


Figure 1: LSTM Network Diagram [17].

C. Network Structure of the Model

This study constructs a six-layer network model for a Deep learning NN for TSA, which is described below.

- Data collection: The National Control Center (NCC), Oshogbo, is where appropriate data for modeling the 28-bus Nigeria network are acquired.
- Using DIGSLIENT, the Nigeria 28 bus system was network modeled.
- Data collection for DLNN: The Relief-F technique is applied to remove irrelevant data from redundant ones.
- DLNN (LSTM): To perform the necessary Transient stability evaluation, a DLNN based on LSTM is modelled based on the data that is currently available, trained, tested, and validated.
- Performance evaluation: The Specificity, Accuracy, and Precision measures are then used to evaluate the performance of the LSTM model.
- Evaluate outcomes in the context of related research.

The suggested model for evaluating transient stability is depicted in Figure 2. The TSA model has four inputs: voltage, rotor angle, reactive power, and active power.

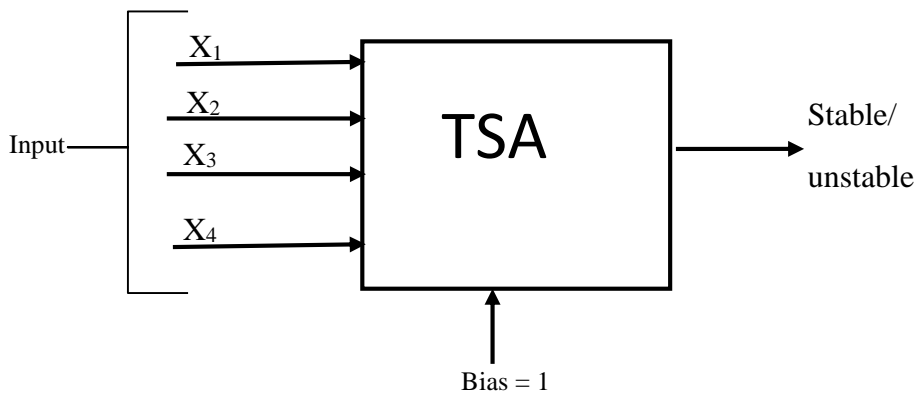


Figure 2: Schematic design model of TSA

III. RESULT AND DISCUSSION

The test is run using the LSTM and Relief-f algorithm. Python/DiGSILENT is utilized in this study to carry out the study. The Nigerian 28-bus power system for TSA is depicted in Figure 3 below in DiGSILENT model form. For TS, information was acquired via DiGSILENT under various scenarios.

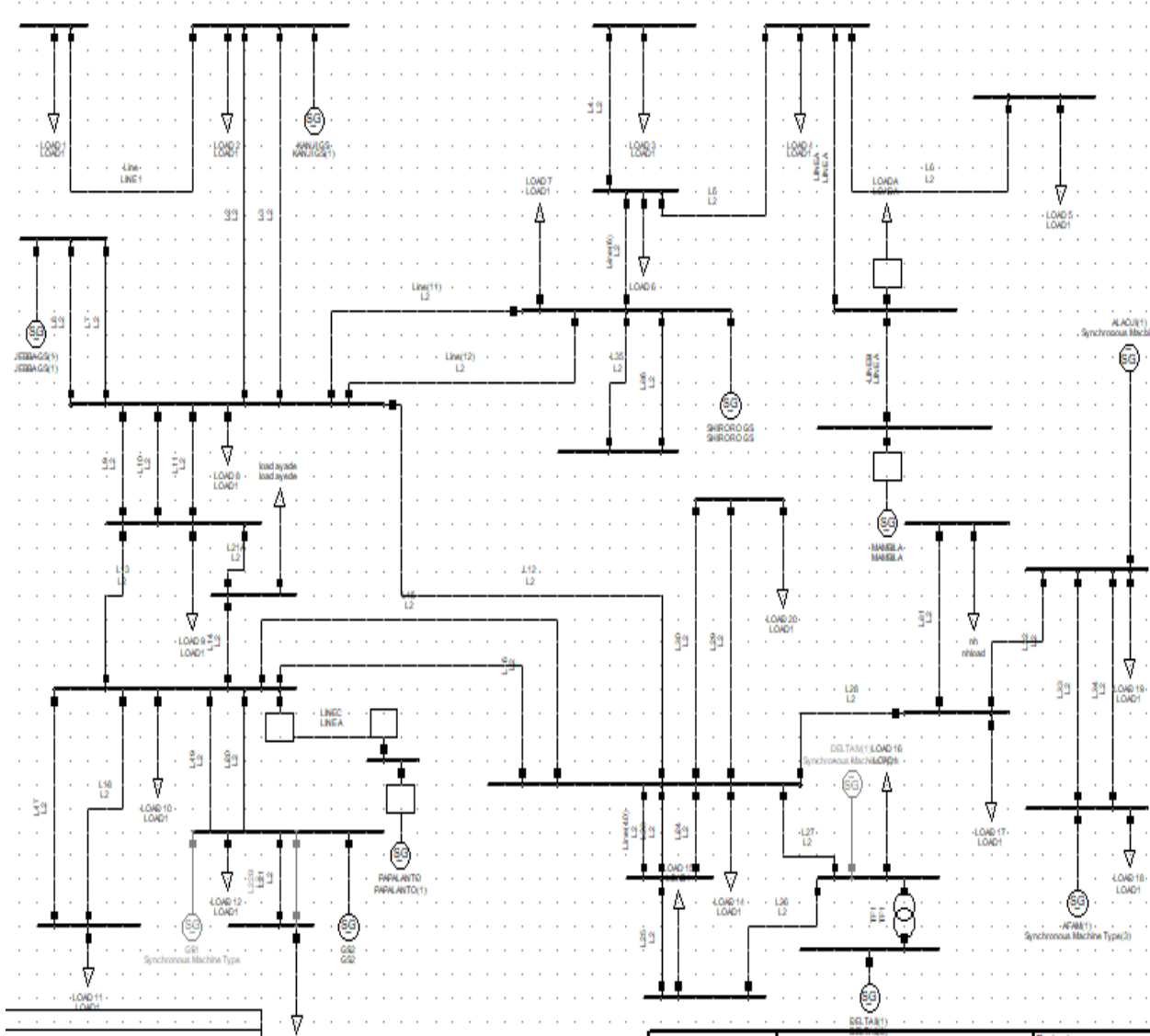


Figure 3: Modelling of Nigerian 28-Bus System

The user interface in this study allows users to import datasets, choose pertinent information from the enormous amount of data, and preprocess and choose pertinent subsets of the data using the Relief-F feature selection method. Table 1 displays loaded data for the 28 bus system in Nigeria.

Table 1: Loaded Data Nigerian 28-Bus System

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

In this study, the preprocessed, Relief-f with DLNN-analyzed loaded data contains 81,802 instances classified as stable or unstable. Relief-F is used to preprocess the loaded data, and the Python LSTM is then given the specified feature. The DLNN is made up of input layers, hidden layers, and LSTM-based output layers. The model confusion matrix utilized to determine the evaluation performance of the developed model, including accuracy, sensitivity, and precision using the LSTM, is shown in Figure 5. After 31 epochs, the system converges, and the model accuracy for TSA hits 90.16 percent. Table 2 displays the model evaluation performance of the method.

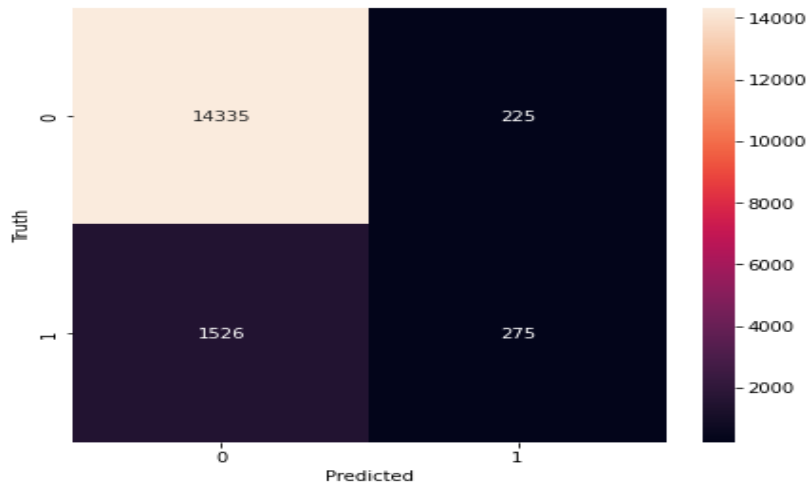


Figure 5: Confusion Matrix for the TSA Developed Model. TP=14335; TN=275; FP=225; FN=1526

Table 2: Evaluation Performance for TSA

Measure	Evaluation (%)	Derivations
Sensitivity	90.38	$TRP=TP/(TP+FN)$
Precision	98.45	$PPV=TP/(TP+FP)$
Accuracy	90.16	$AC=(TP+TN)/(P+N)$

The Target value of TSA acquired on DigSILENT is displayed in Table 3 and is subsequently placed into a Long Short Term Memory (LSTM). To obtain a projected value for TSA, the LSTM is trained. Whether TSA is stable or unstable can be determined by the projected value that was attained. When the rotor angle is between 0 and 120 degrees, as predicted, the system is stable; however, when the rotor angle exceeds 120 degrees, the system is unstable.

Table 3: Target and Predicted values for TSA

S/N	Target for TSA	Predicted value\n",
"16345	0	0.0\n",
"16346	0	0.0\n",
"16347	0	0.0\n",
"16350	0	0.0\n",
"16351	0	0.0\n",
"16352	0	0.0\n",
"16353	0	0.0\n",
"16354	0	0.0\n",
"16355	0	0.0\n",
"16356	0	0.0\n",
"16357	0	0.0\n",
"16358	1	0.0\n",
"16359	0	1.0\n",
"16360	1	1.0\n"

A. Compare Results of IEEE 9-bus test system

This portion, as shown in Figure 5, depicts the modeling of the IEEE 9 bus system in the DIgSILENT power factory, which is used to confirm the accuracy of the TSA evaluation results. According to where the load and generator were located, the bus bars were either modelled as PV or PQ when it came to the transmission lines. The loads were PQ data-based lumped loads. The generators were accurately modeled using the appropriate data and synchronous generator characteristics. For these systems, time-domain simulations are performed using DIgSILENT. The input comprises the generator's rotor angle, the magnitude of the voltage, as well as the active and reactive power at each bus. Additionally, these simulations are run for 10 seconds at a temporal offset of 0.3 seconds.

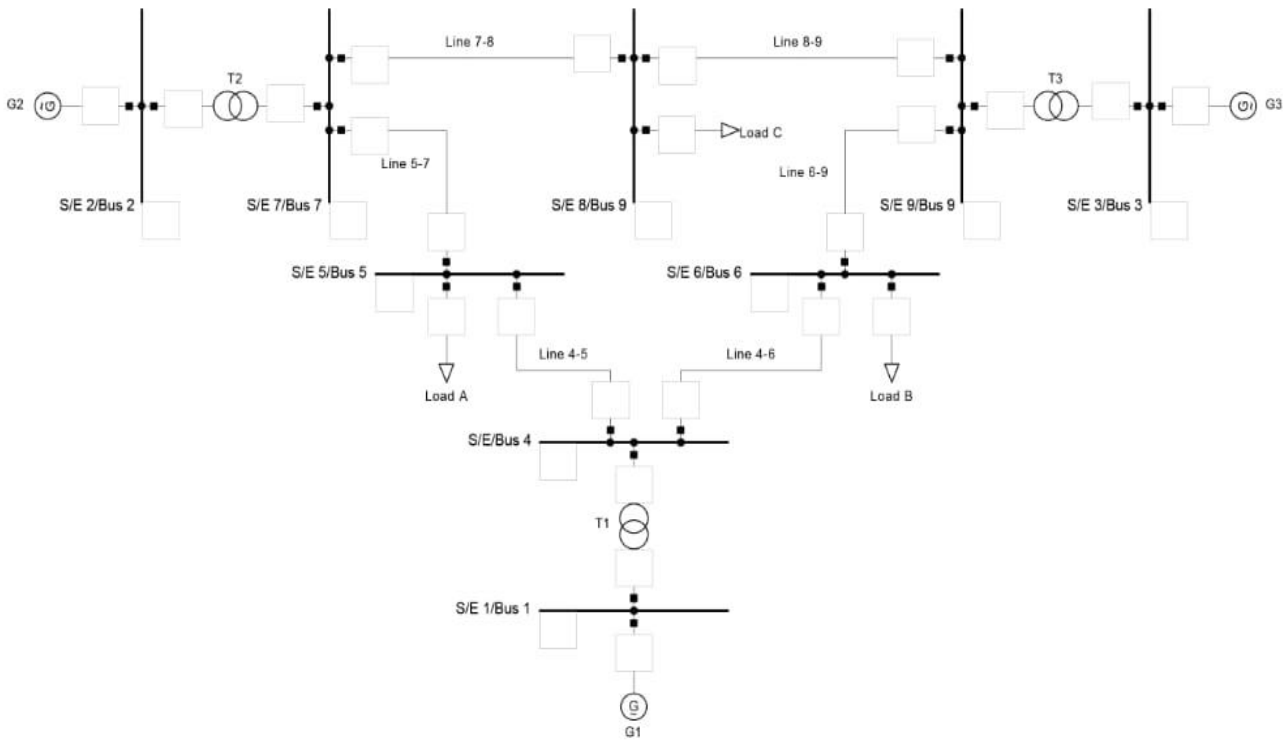


Figure 5: Modelling of IEEE 9 Bus System in DIgSILENT

Table 4 displays the loaded data for the IEEE 9 bus system developed and utilized for training and testing, consisting of 62,500 target values. This is because neural networks need a lot of data to be trained. With appropriate goal values, the IEEE 9-Bus system recovered 18,750 testing samples and 43,750 training samples.

Table 4: Loaded data for IEEE 9 bus system

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

Figure 6 displays the TSA model confusion matrix that was utilized to compute the evaluation performance of the developed model, such as accuracy, sensitivity, and precision, using the DLNN technique. TP=2300, TN=5900, FP=4000, and FN=370 are the outcomes of the confusion matrix TSA created model. After 82 epochs, the system converges, and for TSA, the model accuracy is 65%.

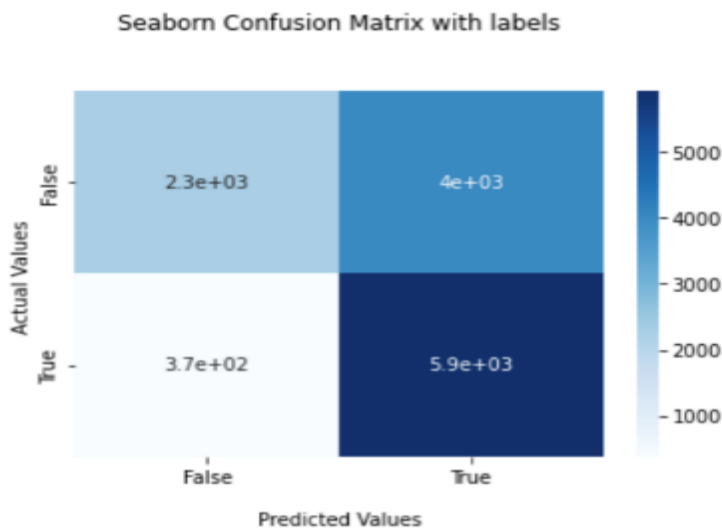


Figure 6: Confusion matrix for the TSA IEEE 9 bus system

Table 5: 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	$ACC=(TP+TN)/(P+N)$

The results were compared with other works on TSA using various machine learning techniques. Table 6 compares the effectiveness of several techniques for predicting TSA. Accuracy, sensitivity, and precision are the main comparison criteria. The TSA's accuracy, sensitivity, and precision in the created LSTM for the 28 bus system in Nigeria have excellent evaluation performance. The low accuracy in TSA is due to the input data acquired, which included so many floats. Meanwhile, utilizing the IEEE 9 bus system, the evaluation performance for accuracy was 65%. In this scenario, random hyperparameter adjustment can be used to increase TSA accuracy, but a longer training period is necessary.

Table 6: Comparison of performance with TSA methods

Related works on TSA	Method	Accuracy	Sensitivity	Precision
		(%)	(%)	(%)
Nigeria 28 Bus System (proposed work)	LSTM	90.16	90.8	98.45
IEEE 9 Bus System (proposed work)	LSTM	65	94	86
IEEE 39 Bus System (Baoqin et., al 2020)	LSTM	99.73	99.72	99.73
New England 68 Bus System (Zhou et.,al 2016)	SVM	97.31	-	-

IV. CONCLUSION

The integration of power electronics technology with renewable energy sources has made it easier to turn the current power systems into a new generation of power systems with a high penetration of renewable energy and power electronics. It is quite challenging to evaluate the transient stability of electricity networks because of this change. In contrast to conventional time domain simulation and energy function methods, data driven TSA methods establish a relationship between system operational parameters and stability status prior to determining stability results without requiring a power system's physical model or parameter information. Understanding transient stability is crucial for the dependable and secure operation of electricity networks. In this research, feature-based deep learning algorithms (LSTM) are presented for the evaluation of transient stability. By giving them a better grasp of the current level of research in the domains of power system transient stability assessment, the study's findings will be helpful to researchers interested in the topic.

REFERENCES

- [1] Baoquin Li, J. Wu, L. Hao, M. Shao, R. Zhang & W. Zhao (2020). Anti-jitter and Refined Power System Transient Stability Assessment Based on Long-short Term Memory Network. DOI: 10.1109/ACCESS.2020.2974915, IEEE ACCESS
- [2] Krištof, V., & Mešter, M. (2017). Loss of excitation of synchronous generator. *Journal of Electrical Engineering*, 68(1), 54–60. <https://doi.org/10.1515/jee-2017-0007>
- [3] Mikolov, T., Joulin, A., Chopra, S., Mathieu, M., & Ranzato, M. 'A. (2015). Learning longer memory in recurrent neural networks. *3rd International Conference on Learning Representations, ICLR 2015 - Workshop Track Proceedings*
- [4] Nan Li, Baoluo Li & Lei Gao (2017). Transient Stability Assessment of Power System Based on XGBoost and Factorization machine. DOI:10.1109/ACCESS.2020.2969446, IEEE Access
- [5] Noor, I., Abdul, W., & Azah, M. (2008). Transient Stability Assessment of a Power System Using Probabilistic Neural Network. *American Journal of Applied Sciences*, 5(9), 1225–1232.
- [6] Olulope, P., Folly, K. ., Chowdhury, A. ., & Chowdhury, S. . (2010). Transient stability Assessment using Artificial Neural Network Considering Fault Location. *Iraq Journal of Electrical and Electronic Engineering*, 6(1), 67–72.
- [7] Ren, C., Xu, Y., & Zhang, Y. (2018). Post-disturbance Transient stability assessment of power system towards optimal accuracy-speed trade-off. *Protection and control of Modern Power Systems*, 3(1), 19. <https://doi.org/10.1186/s41601-018-0091-3>
- [8] Sarajcev, P., Kunac, A., Petrovic, G., & Despalatovic, M. (2022). Artificial Intelligence Techniques for Power System Transient Stability Assessment. *Energies*, 15(2), 507. <https://doi.org/10.3390/en15020507>
- [9] Sawhney, H., & Jeyasurya, B. (2006). A feed-forward artificial neural network with enhanced feature selection for power system transient stability assessment. *Electric Power Systems Research*, 76(12), 1047–1054. <https://doi.org/10.1016/j.epsr.2005.12.026>
- [10] Sedat, N., Issa, A., & Alyaseh, A. (2021). Improvement of Power System Small-Signal Stability by Artificial Neural Network Based on Feedback Error Learning. *Tehnicki Vjesnik - Technical Gazette*, 28(2). <https://doi.org/10.17559/TV-20191011133311>
- [11] Shi, Z., Yao, W., Zeng, L., Wen, J., Fang, J., Ai, X., & Wen, J. (2020). Convolutional neural network-based power system transient stability assessment and instability mode prediction. *Applied Energy*, 263, 114586. <https://doi.org/10.1016/j.apenergy.2020.114586>
- [12] Venkata, S. S. mani, Eremia, M., & Toma, L. (2013). Background of Power System Stability. In *Handbook of Electrical Power System Dynamics* (pp. 453-475). John Wiley & Sons, Inc. <https://doi.org/10.1002/9781118516072.ch8>
- [13] Yang, Y., & Wu, L. (2021). Machine learning approaches to the unit commitment problem: Current trends, emerging challenges, and new strategies. *Electricity Journal*, 34(1). <https://doi.org/10.1016/j.tej.2020.106889>
- [14] Zhang, S., Zhu, Z., & Li, Y. (2021). A Critical Review of Data-Driven Transient Stability Assessment of Power Systems: Principles, Prospects and Challenges. *Energies*, 14(21), 7238. <https://doi.org/10.3390/en14217238>
- [15] Nikolaev, N., Dimitrov, K., & Rangelov, Y. (2021). A Comprehensive Review of Small-Signal Stability and Power Oscillation Damping through Photovoltaic Inverters. *Energies*, 14(21), 7372. <https://doi.org/10.3390/en14217372>

- [16] BIN, Z., & XUE, Y. (2019). A method to extract instantaneous features of low frequency oscillation based on trajectory section eigenvalues. *Journal of Modern Power Systems and Clean Energy*, 7(4), 753–766. <https://doi.org/10.1007/s40565-019-0556-z>
- [17] Syafiq, K. A., Younes, J. I., Mohamed, S. El., Khaled, E. (2020). A Unified Online Deep Learning Prediction Model for Small Signal and Transient Stability. *IEEE Transactions on Power Systems*, 35(6)