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

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ABSTRACT

This work suggests using a Deep Learning Neural Network (DLNN) technique to predict transient stability. Transient Stability Assessment (TSA) have long been critical components in assuring the safe and reliable operation of power system. The development of new components such as power electronics, electric vehicles, and renewable energy generations has increased the complexity of power system dynamic features, making TSA serious concern. Today, the increasing development of renewable energy sources affects the electrical network reliability and security. The advent of wide area monitoring systems in the electrical system has given rise to large data, ushering in new methods for addressing these problems. Because of the potential for catastrophic outages, transient stability issues are capturing the attention of a wide range of stakeholders. The purpose of this research is to look at TSA concerns in the electricity system utilizing data gathering and DLNN. The Nigerian 28 Bus system data was gathered from the National control center (NCC) Oshogbo and modelled on DIgSILENT environment. The Relief-F feature selection method is used in a Python environment in order to create a data processing pipeline for feature selection. The selected feature will be passed into a type of DLNN to predict transient stability on Python. The DLNN improves the accuracy by reducing the time complexity of TSA. The system converges at 31 epochs and the accuracy result obtained for the Nigeria 28 bus system is 90.16 percent. The DLNN technique, which is used to assess transient stability, is validated using the IEEE 9 bus test system. At the end of this work the result is compared with other related work 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 is the ability of a power system to recover back to an equilibrium point and function properly after been subjected to a disturbance. The instability problem has long been associated with rotor angle instability brought on by synchronism loss [4]. The ability of a power system to maintain synchronism in the face of large disruptions, is referred to as transient stability [12]. TSA that is accurate and quick is becoming increasingly important in this situation. Data-driven TSA methods have become a hot issue in recent years, thanks to the rapid growth of artificial intelligence tools, and a considerable number of research results have been published. As a result, a serious review of existing data-driven TSA methods is needed so that relevant academia can have a better understanding of the research status, important technologies and current issues in the field [7]. Time domain or Traditional simulation method, Direct method and Data-driven artificial intelligence method are the three types of TSA methods available   A set of highly nonlinear Differential and Algebraic Equations (DAE), describes how synchronous generators behave in relation to their associated control systems, loads, renewable energy production, Flexible AC transmission devices (FACTs), and the transmission network. The DAE model cannot be linearized around an operational point when a power system undergoes large changes, hence it must be numerically solved for each circumstance utilizing time domain simulations. Transient instability is the root cause of power outages, which can also reduce a power system's overall performance [15].

Especially for large power systems with an almost unlimited number of operational points and contingencies, time domain simulations, a type of TSA, are expensive and computationally complex [13], [14]. The prediction model is trained utilizing a Deep learning technique (LSTM) and a data set for a variety of operating scenarios in order to accomplish these goals. The LSTM further increases prediction accuracy by lowering the time complexity of the TSA. The suggested model's enhanced performance is demonstrated using the Nigeria 28 Bus System, and it is confirmed using the IEEE 9 Bus System.

II. TRANSIENT STABILITY OF POWER SYSTEM

Using deep learning neural network approaches, a prediction model for the Transient stability in Nigeria's 28 bus system is built in this article. This section describes the mathematical procedure for transient stability.

A. Transient Stability TS

The ability of synchronous machine in a power system to maintain synchronism after a disruption is known as rotor angle stability. Due to the fact that power system disturbances may not always have the same effects on generation, certain generators will face increased load as a result of adaptive operation and will slow down, the remaining generators which will increase their speed to maintain grid frequency [6-9]. The tilt of the rotor with respect to the stator changes as the generator's speed rises. The rotor continuously alternates between accelerating and decelerating to maintain equilibrium between the mechanical input torque and the electrical output torque [10], [11]. The generator's ability to produce power is decreased by this behavior, which also harms the generator, prime mover, and transformers as a result, the synchronous machine needs to be protected [2]. A group of DAE control the dynamic response of a power system to disturbances, and their compact form is:

$$x = h\ (x, y) \qquad (1)$$

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

Where state and algebraic variables, x and y, are indicated. Additionally, h and g indicate the vectors of the relevant DAE [4], [5]. In order to create 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 like the trapezoidal approach (1). Each time step, the Newton's method is used to solve the resulting algebraic equations as well as the remaining algebraic equations (2). The dynamic trajectories over the simulation time window are observed to assess Transient stability. This approach offers a precise evaluation of transitory for a particular circumstance [16].

B. Long Short Term Memory Network for TSA

In order to recall knowledge from the past in time series da LSTMs are used to track data over time because they can remember prior inputs, they are helpful in time-series prediction. Four interacting layers of LSTMs, which have a chain-like structure, interact in unique ways. LSTMs are frequently employed in speech recognition, music production, and pharmaceutical research, in addition to time-series predictions [17]. The issues of long term dependency problem are solved using LSTM. LSTM networks are RNN variants. LSTM has the option to read, write, or reset the sale at each stage [3]. The mathematical formulae for the LSTM are shown in equation 3;

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

Where, Wi, Wc, and Wo are the weights, and the operator stands for the pointwise multiplication of two vectors where c_t represents the state of the LSTM cell. The output gate chooses what information can be output based on the cell state, and the input gate chooses what new information can be entered while updating the cell state [1], [3]. Based on the connections, the LSTM cell depicted in equation 4 can be mathematically defined as follows:

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

Which information from the cell state will be erased depends on the forget gate. When the forget gate, f_t, has a value of 1, it stores this information and when it has a value of 0, it discards all of it. Figure 1 shows the structure of LSTM

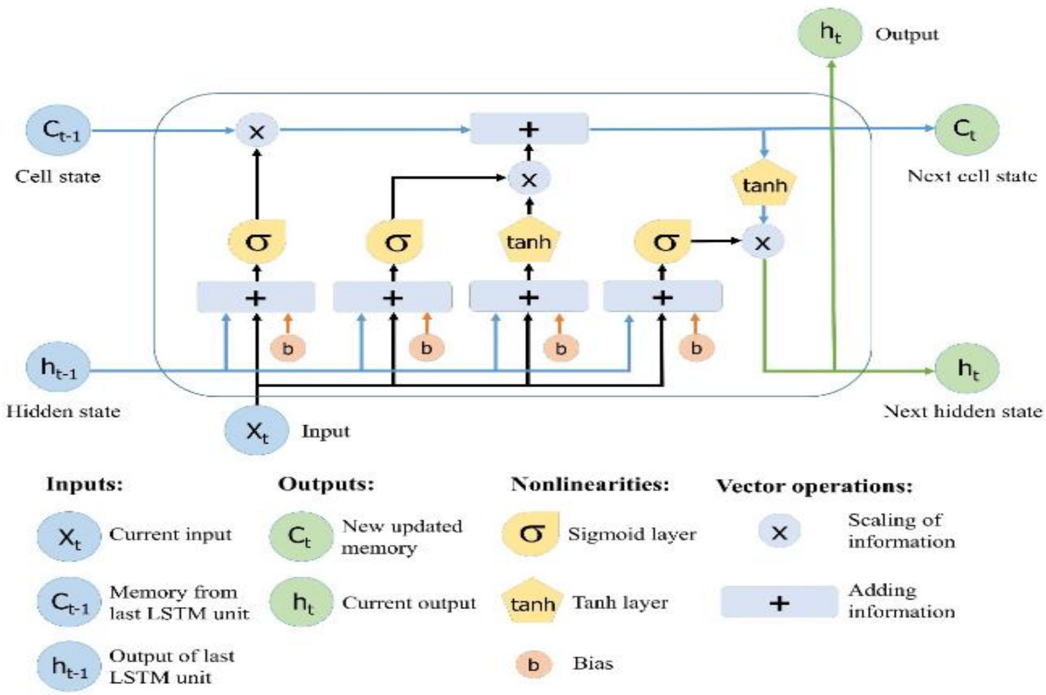

Figure 1: LSTM Network Diagram [17].

C. **Network Structure of the Model**

In order to create a Deep learning NN for TSA, this paper builds the six-layer network model are explained below

i. Data gathering: Appropriate data for the modelling of 28-bus Nigeria network is gathered from the National Control Center (NCC), Oshogbo.

ii. Network modeling: Nigeria 28 bus system was modelled using DIgSLIENT.

iii. Data gathering for DLNN: The Relief-F algorithm is used to filter redundant data so as to obtain relevant ones.

iv. DLNN (LSTM): A DLNN based on LSTM is modelled based on the available data, trained, tested and validated to carry out the required Transient stability assessment.

v. Performance evaluation: The LSTM model's performance is then assessed using the following metrics: Specificity, Accuracy, and Precision.

vi. Compare results with other related works.

Figure 2, shows the proposed model for assessing Transient stability. The TSA model contains 4 inputs namely, active power, reactive power, rotor angle, voltage.

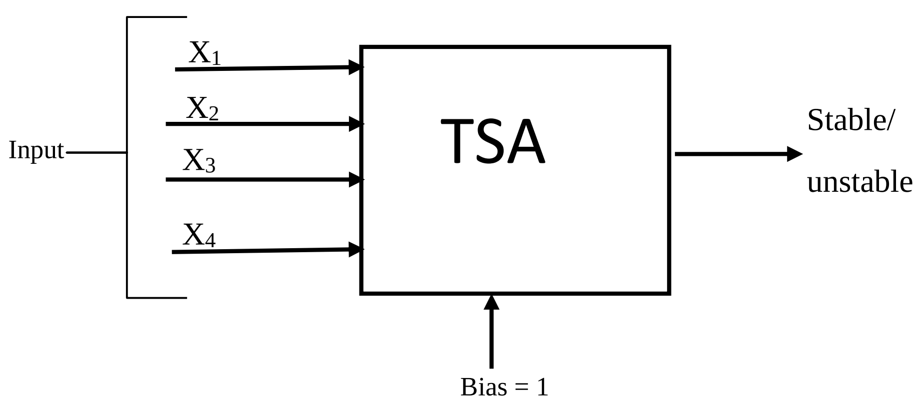

Figure 2: Schematic design model of TSA

III. RESULT AND DISCUSSION

The LSTM and Relief-f algorithm are used to conduct the test. In this study, Python/DIgSLIENT is used to implement the study. Figure 3, below shows DIgSILENT model of Nigeria 28-bus power system for TSA. Data were obtained from DIgSILENT under different contingencies for TS.

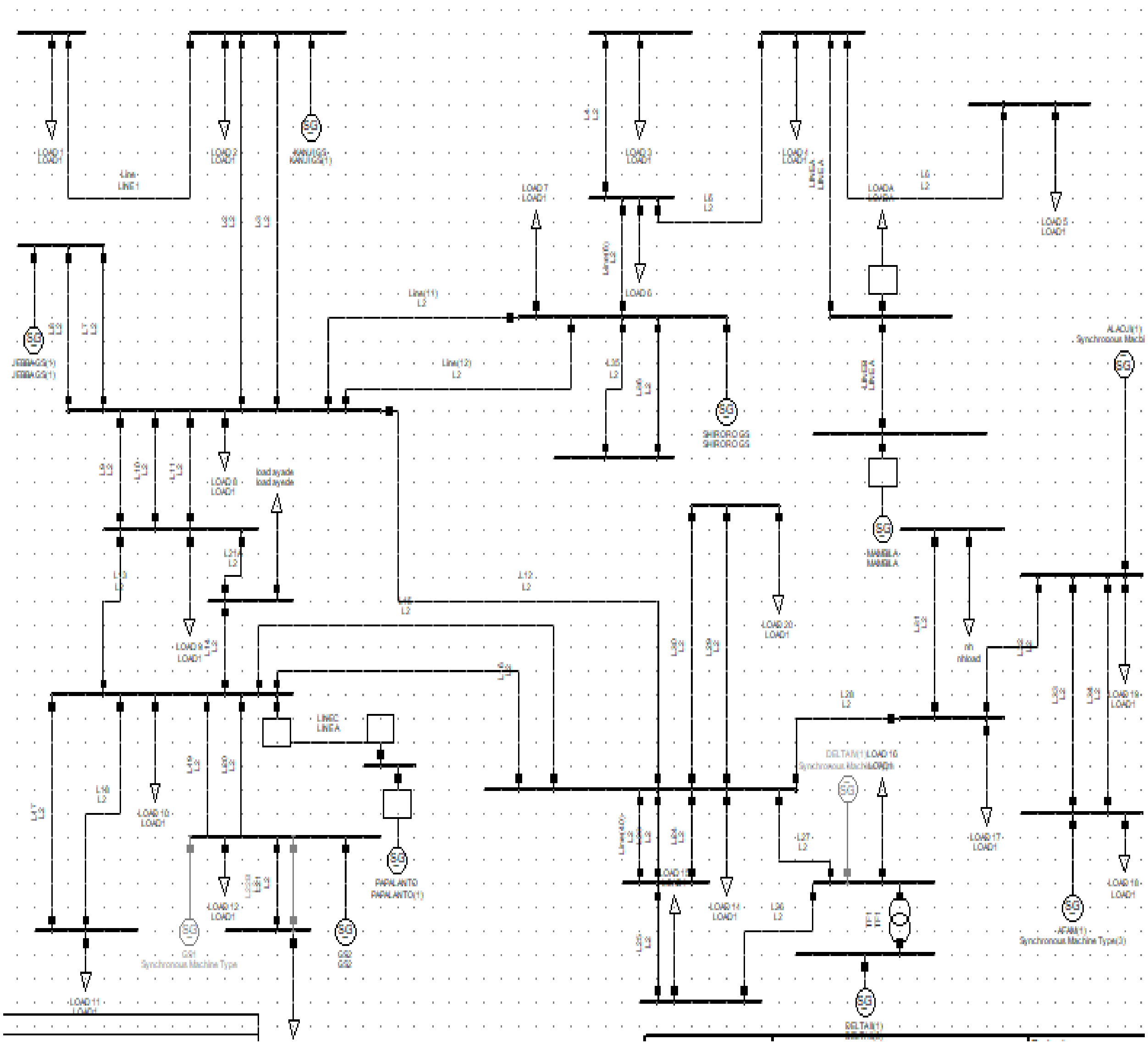

Figure 3: Modelling of Nigerian 28-Bus System

In this study the user interface gives user the privilege to load dataset, select relevant information from the huge amount of data, using the Relief-F feature selection algorithm, it helps preprocess and selects relevant subset of the data. Table 1 shows loaded data for Nigeria 28 bus sytem.

Table 1: Loaded Data Nigerian 28-Bus System

V(p.u)	P(KW)	Q (KVAr)	δ(Θ)	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 loaded data is preprocessed, analyzed using Relief-f with DLNN, the loaded data, comprises of 81,802 instances stated as Stable/Unstable. The loaded data is preprocessed using Relief-F, the selected feature is passed into the LSTM in Python. The DLNN comprises of input layers, hiden layers and output using the LSTM. Figure 5 shows the model confusion matrix used to calculate the created model's evaluation performance, such as accuracy, sensitivity and precision using the LSTM. The system converges after 31 epochs, and the model accuracy reaches 90.16 percent for TSA. The model evaluation performance of approach is shown in Table 2.

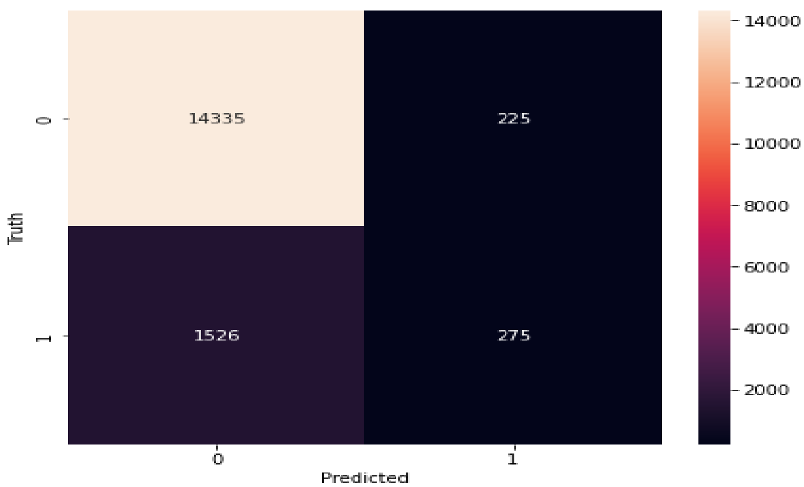

Figure 5: Confusion Matrix for the TSA Developed Model. TP=14335; TN=275; FP=225; FN=1526

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)

In Table 3 shows the Target value of TSA obtained on DIgSILENT which is then passed into a Long short term memory (LSTM). The LSTM is trained so as to get a predicted value for TSA. The predicted value obtained for TSA shows whether it is stable or unstable. The predicted value for TSA is known, if the rotor angle is at the range of 0 degree to 120 degrees the system is stable but when the rotor angle is more than 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",
"16348	0	0.0\n",
"16349	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 on IEEE 9-bus test system**

This section as shown in Figure 5, shows the modeling of IEEE 9 bus system in DIgSILENT power factory, which is used to verify the evaluation results obtained from TSA. The transmission lines were modeled as π network, the bus bars were modelled as PV or PQ depending on the location of load and generator. The loads were lumped loads consisting of PQ data. The generators were well modelled consisting of synchronous generator characteristics with the relevant data. DIgSILENT is used to run time-domain simulations for these systems. The input includes, generator rotor angle, voltage magnitude, active power, and reactive power at all buses are also noted. Additionally, these simulations are performed for 10 seconds with a 0.3 second time difference.

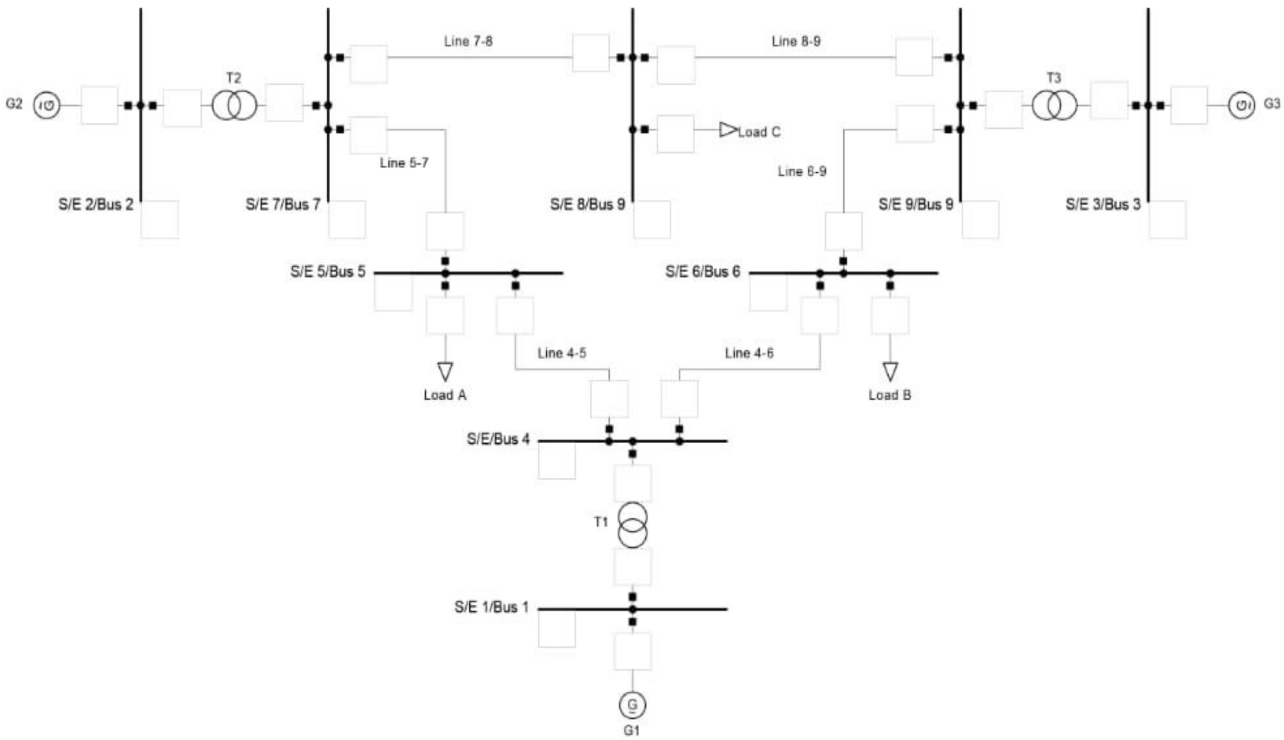

Figure 5: Modelling of IEEE 9 Bus System in DIgSILENT

Since neural network requires so much data to train, therefore, table 4 shows the loaded data for IEEE 9 bus system generated been used for the training and testing, consisting of 62,500 target values. With valid target values of 18,750 testing samples and 43,750 training samples were recovered for the IEEE 9-Bus system.

Table 4: Loaded data for IEEE 9 bus system

V(p.u)	P(KW)	Q (KVAr)	δ(Θ)	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

In Figure 6 shows, the TSA model confusion matrix used to calculate the created model's evaluation performance, such as accuracy, sensitivity and precision, using the DLNN technique. The confusion matrix TSA developed model results; TP=2300, TN=5900, FP=4000, FN=370.
The system converges after 82 epochs, and the model accuracy reaches 65 percent for TSA.

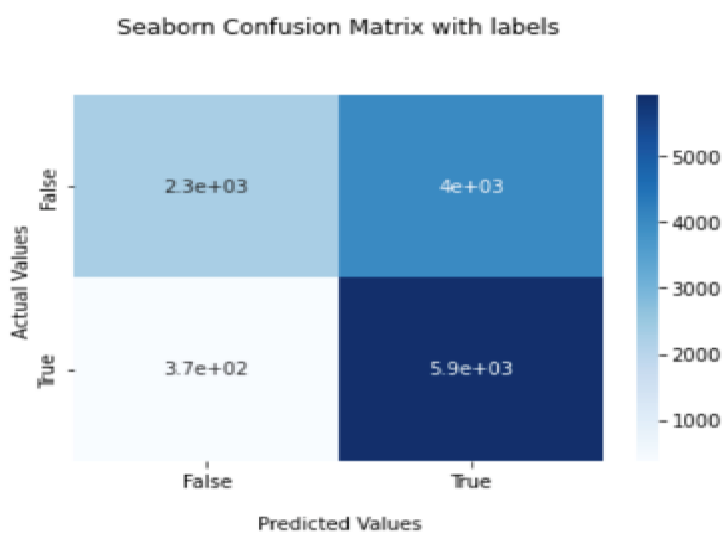

Figure 6: Confusion matrix for the TSA IEEE 9 bus system

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 result been obtained was compared with several works on TSA using different Machine Learning methods. Table 6 shows the comparison performance of using different methods in predicting TSA. These comparison is majorly focused on Accuracy, Sensitivity and Precision. The accuracy, sensitivity and precision for TSA in the Nigeria 28 bus system using LSTM developed, have a perfect evaluation performance. Meanwhile using the IEEE 9 bus system the evaluation performance for accuracy was 65 percent, the reason for the low accuracy in TSA, is as a result of the input data obtained which had so many floats. In this case the accuracy of TSA can be improved by using random hyperparameter tuning and a longer training time is required.

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 combination of power electronics technology and renewable energy sources has led to the evolution of the power systems of today into a new generation of power systems with a high penetration of renewable energy and power electronics. Because of this modification, it is now very challenging to evaluate Transient stability of electricity networks. In contrast to traditional time domain simulation and energy function methods, data driven TSA 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. Recognizing Transient stability is crucial for the dependable and secure operation of power networks. In this study, feature based Deep learning techniques (LSTM) is presented for assessing Transient stability. The study's results will aid scholars interested in the issue by improving their knowledge of the state in the areas of Transient Stability assessment for power systems.

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