Prediction of Electrical Grid Collapse Using Hybrid Deep Learning Model

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Abstract- ***Electrical power supply is crucial to the growth and development of every economy. Power system components including generators, transformers, transmission lines, buses and loads are interconnected to form an electrical grid. However, on large grids such as the Wide Area Synchronous Grid (WASG), a problem that occurs in one part of the network would result in disturbance across the entire grid leading to possible collapse of the grid and eventual blackout. Thus, an accurate and timely prediction of the power network instability is of utmost importance. This paper proposes a grid-collapse prediction model developed by hybridizing the One-Dimensional Convolutional Neural Network (1D-CNN) and Long Short-Term Memory Networks (LSTM) deep learning techniques. Historical real-time system frequency data of the national grid in the Nigeria Electricity System Industry (NESI) was used in this study. The system frequency data was divided into training and test datasets. The 1D-CNN was used to extract the features for training the LSTM network. Experimental results showed that the 1D-CNN-LSTM model gave RMSE, MAE and MAPE values of 0.0109 Hz, 0.0008 Hz, and 0.0015%, respectively, whereas using the LSTM model alone gave RMSE, MAE and MAPE values of 0.0194 Hz, 0.0099 Hz, and 0.0197%, respectively. The proposed 1D-CNN-LSTM model gives significant improvement over the LSTM model in prediction accuracy.***

Indexed Terms- ***Electrical Grid Collapse, System Frequency, 1D-CNN, LSTM, Nigeria Electricity System Industry (NESI).***

I. INTRODUCTION

An electrical power system is a system that consists of the generation, control, transmission and consumption of electrical energy. An electrical power system supplies electricity for different purposes such as lighting, heating, residential, commercial, transportation and industrial. Stable electricity (or power) supply is crucial to the growth and development of every sector of the economy, including institutions, health care, manufacturing, businesses and government [1, 2]. One of the main challenges facing the electrical power industry is the inability to store electricity in economical quantity; thus, powers generated are injected into the grid with a view to balance the amount of generated power with load demands across a given geographical area [3].

Electrical grid is a complex network that requires sophisticated monitoring and control to ensure that the amount of electrical power generated matches the consumers' demands [4]. An uncontrolled mismatch between the amount of power generated and the amount demanded would lead to grid collapse, and invariably national blackout [5, 6, 7]. This mismatch causes deviation from the nominal system frequency, which is 50 Hz in the case of the Nigeria Electricity Supply Industry (NESI), and a variation outside the $\pm 0.5\ \%$ tolerance would be inimical to the power network stability [8, 9]. The NESI experienced an average of 35 grid collapses between 2006 and 2015 as well as over 90 incidents in the last ten years [8, 9]. Moreover, the NESI witnessed over six occurrences of collapses between January and November 2024 [9]. The down times experienced before the restoration of power supply

are very significant and would have negative effects on the socio-economic well-being of the consumers. Thus, the need to have an effective grid-collapse prediction model for the prevention of collapses cannot be overemphasized.

Deep Learning (DL) is a branch of Machine Learning (ML) that involves Artificial Neural Network (ANN), and training using big data [10]. In addition, DL is useful for several engineering applications such as real-time prediction, time-series forecasting, computer vision, pattern recognition and classification of system events, provided that sufficient training data is available [11].

The goal of this study is to leverage Artificial Intelligence (AI) in developing a robust DL-based model for a more accurate prediction of system (or grid) frequency to forestall incidences of electrical grid collapse and to prevent blackout.

II. LITERATURE REVIEW

2.1 Grid Collapse:

Aside from grid failures triggered by natural disasters, some other major factors that trigger grid collapse are stability loss, load node voltage instability, outage of generators due to overload, multiple lines' faults, sudden load rejection, and frequency decline at active power [12]. Balance in the active power is of utmost importance to the power system's frequency stability. Thus, any change in demand of active power would lead to change in system frequency from the acceptable limits, which could invariably result in system collapse [13].

A three-phase (3-ϕ) generator produces electromotive force (emf) with a frequency, in Hertz (Hz), given as [1]:

$$f = \frac{NP_s}{120} \quad (1)$$

where N is the synchronous speed in rpm, and P_s is the number of poles in the stator winding. The grid frequency, f, and power deviation are related by the swing equation given as [1]:

$$\frac{H}{\pi f}\frac{d^2}{dt^2} = P_m - P_e \quad (2)$$

where H is the inertia constant;

P_m is mechanical power input; and

P_e is electrical power output

2.2 One-Dimensional Convolutional Neural Network (1D-CNN)

The standard CNN works on two-dimensional features like images, and it is best suited for image recognition; whereas the one-dimensional CNN (1D-CNN) is more suited for time-series prediction or forecast applications, and has lower computational complexity compared to the 2D CNN. The 1D-CNN extracts spatial features from the input sequence and outputs a sequence of feature vectors [14]. The architecture for 1D-CNN is shown in Figure 1.

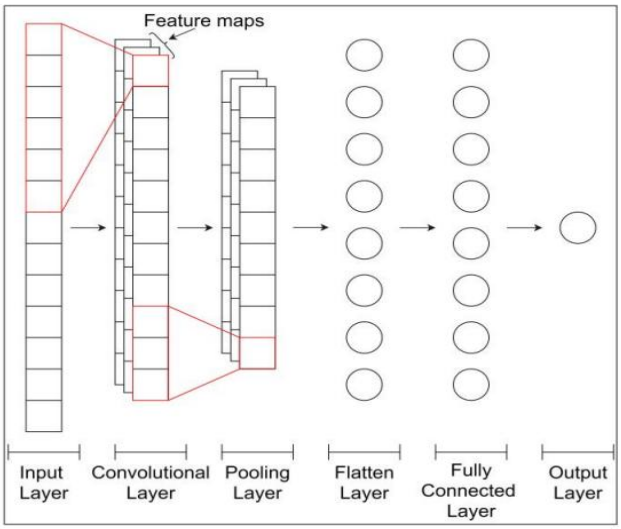

Figure 1: One-Dimensional Convolutional Neural Network (1D-CNN) Architecture [14]

2.3 Long Short-Term Memory Networks (LSTM)

The LSTM is a Recurrent Neural Network (RNN), and LSTM layers are particularly suitable for capturing temporal dependencies within data and are a preferred choice for building multi-step time series forecasting models [15, 18]. Figure 2 shows the LSTM cell architecture consisting of a forget gate, an input gate, an output gate, cell state $\boldsymbol{c_t}$, cell input $\boldsymbol{X_t}$, and cell output $\boldsymbol{h_t}$.

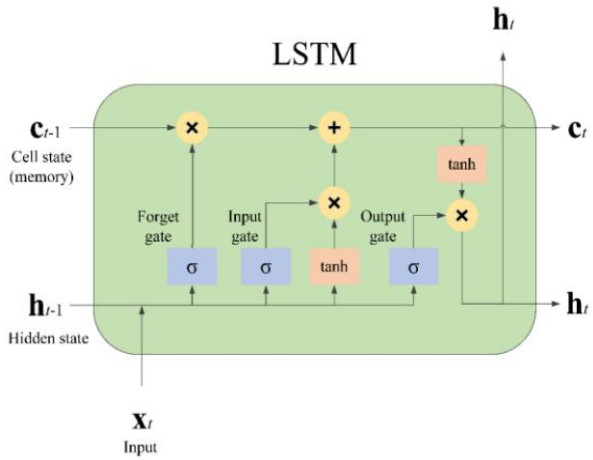

Figure 2: LSTM Cell Architecture [22]

III. RELATED WORK

Different methods for mitigating grid collapse have been proposed in the literature. [16] proposed a Markov chain model in which the transition matrix is dependent on the probability of power outage due to system overloads or unforeseen factors. A method that utilizes measured bus active and reactive powers for vector analysis in predicting voltage collapse was proposed in [17]. A DL-based model for predicting voltage instability using the LSTM was proposed in [18]. Bayesian optimization model for predicting system collapse on nonlinear dynamical systems was proposed in [19]. In [20], a combination of ML and the Kullback-Leibler difference was proposed for wide area monitoring of power grid dynamics. The model was trained using Phasor Measurement Units (PMU) information. A power grid monitoring indicator for predicting voltage collapse was employed in [21]. The proposed indicator utilizes apparent power and line impedance in power flow analysis to detect weakness of buses. In [22], a hierarchical control scheme was proposed for frequency, voltage and power stability.

Most of the existing works on grid-collapse mitigation have focused on voltage collapse, conventional power system models, or a single ML or DL technique whereas little attention has been given to the prediction of system frequency and the use of a hybrid DL technique. Hence, the goal of this study is to investigate this gap.

IV. MATERIALS AND METHODS

System frequency measurements of the NESI national grid logged every second from 24:0:0 hours of 10th December 2024 to 23:59:59 hours of 11th December 2024 were used in this study. The time format is Hours:Minutes:Seconds. The length of the entire data is 84,743 timesteps. The data of 10th December was one hour data, 24:0:0 to 24:59:59 hours, which gives 3,600 timesteps whereas the data of 11th December was one day's data, 1:0:0 to 23:59:59 hours, which gave a total of 81,143 timesteps. A segment of the data of 11th December in which the country experienced blackout from the national grid is presented in Table 1. The grid collapsed at 13:32:00 hours with system frequency of 55.93 Hz; and the system was restored at 13:53:00 hours as highlighted on the table. This shows that it took over 15 minutes before the supply was restored.

Table 1: Samples of the Measured System Frequency on 11th December 2024 [23]

Time (Hours)	System Frequency
13:32:10	50.23
13:32:11	50.22
13:32:12	50.23
13:32:13	50.19
13:32:14	49.97
13:32:15	49.69
13:32:16	49.45
13:32:17	49.15
13:32:18	48.84
13:32:19	48.55
13:32:20	48.34
13:32:21	48.13
13:32:22	47.85
13:32:23	47.52
13:32:24	47.52
13:32:25	46.41
13:32:26	45.04
13:32:27	46.83
13:32:28	49.35
13:32:29	52.33
13:32:30	55.93
13:53:49	51.13
13:53:50	51.13
13:53:51	51.18

A. Data Normalization and Denormalization

The raw input data was normalized so that the normalized data contains lower range of values but retains the properties of the original dataset. The formular used for obtaining the normalized data, X_{new}, is given as:

$$X_{new} = \frac{X - X_{mean}}{X_{std}} \quad (3)$$

The normalized data is denormalized to recover the original values using the formular given as:

$$X = (X_{new} * X_{std}) + X_{mean} \quad (4)$$

where X is the original raw data; X_{new} is the normalized data; X_{std} is the standard deviation of X; and X_{mean} is the mean of X.

B. Data Partitioning and Segmentation

The entire data of length 83,700 timesteps was segmented into the dimension 100-by-837; that is 100 observations. The 100 observations were subdivided into 80 observations (80-by-837) for training with validation and 20 observations (20-by-837) for testing, which translates to 70% for training, 10% for validation and 20% for testing. The training and validation datasets were used to train the prediction models. The test dataset was only used to test the trained models but not part of the training data.

C. The Proposed 1D-CNN-LSTM Model

The 1D-CNN architecture consists of a convolutional 1D layer, and time-distributed routing layer. The architecture has N filters, a stride of one, and Rectified Linear Unit (ReLU) activation. The 1D input sequence through this convolutional layer is converted into a feature map as:

$$X \in \mathcal{R}^{d \times N} \quad (5)$$

where X is the feature map; d is the data sequence which contains the system frequency samples and N is the number of filters. The filters help to extract significant features from the data.

The architecture of the proposed 1D-CNN-LSTM is shown in Figure 3. The architecture forecasts future values of a time series data as $\hat{x}_{t+1}, \ldots, \hat{x}_{t+T}$; where T is the consecutive time steps into the future.

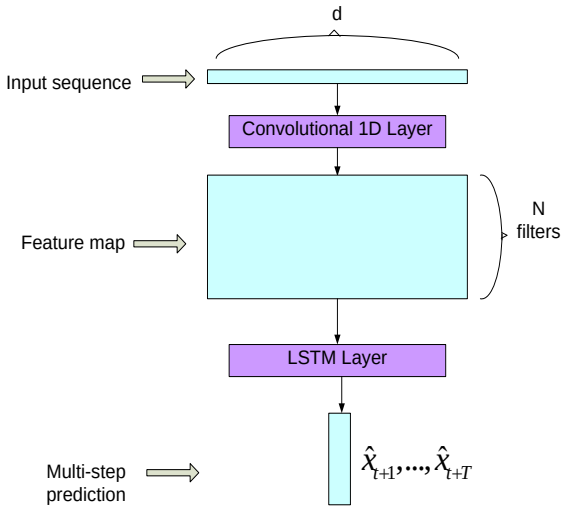

Figure 3: 1D-CNN-LSTM Architecture

Model implementation was carried out using MATLAB software package. The 1D-CNN network was used to extract features from the training data and the extracted features were used to train the LSTM network for time-series prediction of the system frequency and invariably grid collapse. This study used 50.25 Hz as the upper limit and 49.75 as the lower limit for the classification of system (or grid) frequency according to the Grid Code for NESI (NERC, 2024). The procedure for training the 1D-CNN network for feature extraction is presented in Algorithm 1; and the procedure for creating the 1D-CNN-LSTM model is presented in Algorithm 2.

Algorithm 1: Feature Extraction by 1D-CNN
BEGIN Load the historical system frequency data Trim data into multiple of 100 Reshape data into samples x sequence_length Normalize data Convert data sequence to cell array Partition the data into training, validation, and test datasets Create 1D-CNN network using training parameters Train the 1D-CNN network using the training and validation datasets Create Feature Extractor from the trained 1D-CNN network Save the Feature Extractor END

Algorithm2: Training of LSTM by features from 1D-CNN

BEGIN
Load the Feature Extractor
Load the Training with Validation datasets
Apply the Feature Extractor to extract the features
Training with Validation datasets
Create an LSTM regression network
Train the 1D-CNN-LSTM model
Save the 1D-CNN-LSTM model
END

The procedure for testing is presented in Algorithm 3. The targets are the data sequences with values shifted by one time step. The predicted values are obtained by the application of the function MATLAB function *predict()*. The proposed 1D-CNN-LSTM model learns to predict the system frequency value of the next time step. The 1D-CNN-LSTM model specifications are presented in Table 2. The adaptive moment estimation (adam) optimizer was used as the training algorithm due to its robustness for non-linearity in data.

Algorithm 3: Testing the 1D-CNN-LSTM model

BEGIN
Load the 1D-CNN-LSTM model
Load the Test dataset
Create Input and Target datasets from the Test dataset
Pass the Input dataset into the 1D-CNN-LSTM model for prediction of targets
Compare the Predicted targets and the Actual targets to evaluate performance
END

Table 2: Model Training Parameters

DL Network	Parameter	Specification
1D-CNN	Optimizer	adaptive moment estimation (adam) algorithm
	Maximum Epoch	50
	Network Layers	4
	Number of Filters	16
	Learning Rate	0.001
LSTM	Optimizer	adam
	Maximum Epoch	100
	Number of Hidden Units	128
	Number of Channels	16
	Training validation metric	root mean squared error (RMSE)

D. Performance Evaluation Metrics

Root Mean Square Error (RMSE): It estimates the prediction errors, and an RMSE value of 0 indicates a perfect fit. The formular used for calculating the RMSE is given as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{L}(x_i - \hat{x}_i)^2}{L}} \quad (6)$$

where x_i is the actual (or true) value at the time step i; $\hat{x}_i$ is the predicted (or forecast) value at the time step i; L is the number of time steps.

Mean Absolute Error (MAE): The MAE is a measure of the average of the absolute forecast errors between the prediction values and the actual values; and the formular is given as:

$$MAE = \frac{\sum_{i=1}^{L}|x_i - \hat{x}_i|}{L} \quad (7)$$

Mean Absolute Percentage Error (MAPE): The MAPE value of 1.5% implies that the average difference between the predicted value and the actual value is 1.5%. The MAPE formular is given as:

$$MAPE = \frac{100}{L}\sum_{i=1}^{L}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \quad (8)$$

V. RESULTS AND DISCUSSION

The system frequency data obtained from the National Control Centre (NCC) for December 10, 2024 is presented in Figure 4. The system frequency went above the upper limit 778 times and there was none below the lower limit.

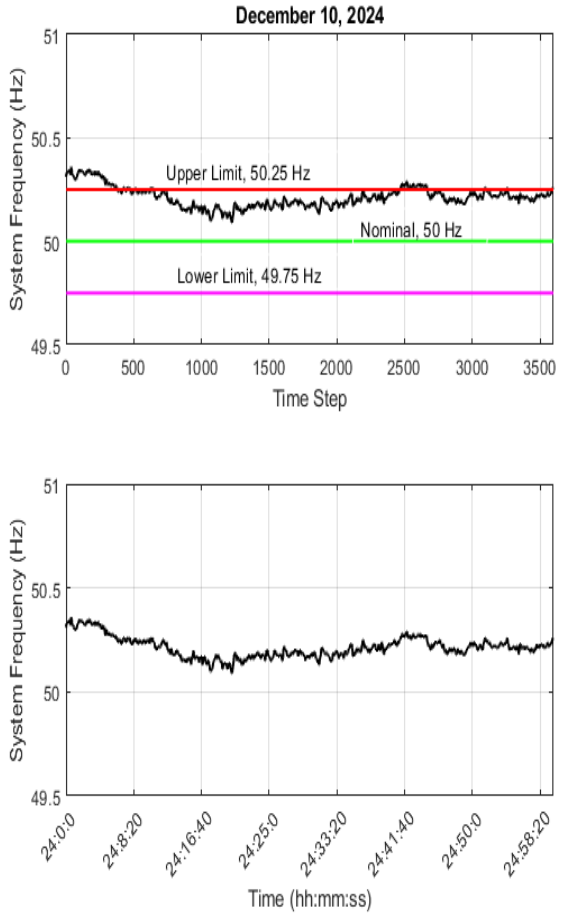

Figure 4: Visualization of the System Frequency Data Obtained from the NCC for December 10, 2024

The system frequency data for December 11, 2024 is presented in Figure 5. The system frequency went above the upper limit 41,044 times and went below the lower limit 950 times.

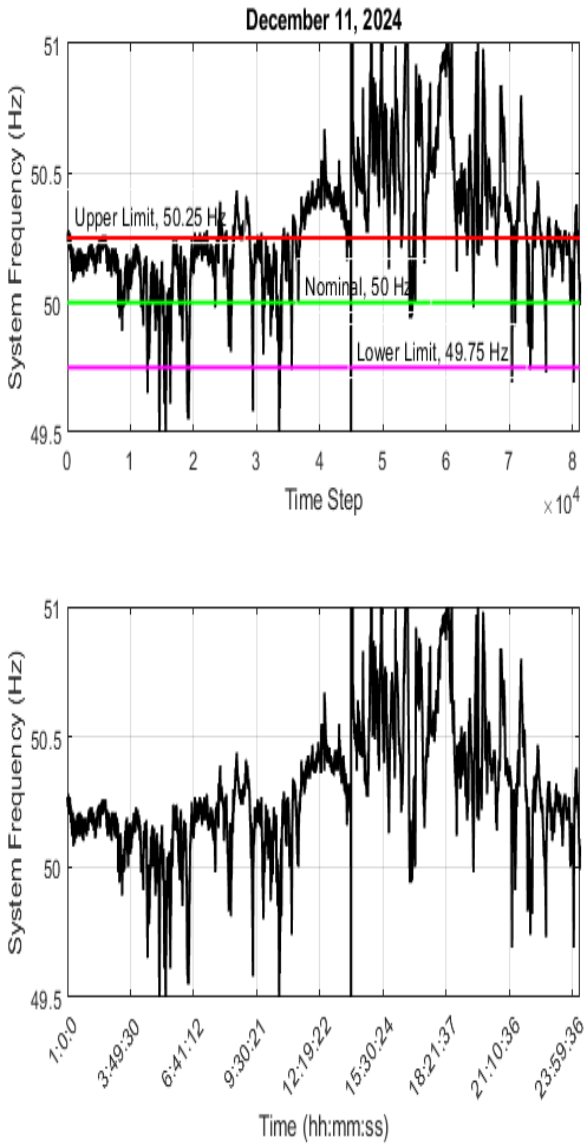

Figure 5: Visualization of the System Frequency Data Obtained from the NCC for December 11, 2024.

The RMSE, MAE and MAPE results for the proposed 1D-CNN-LSTM model compared with the existing LSTM model by [18] are presented here. The graphs of the prediction of system frequency by the proposed 1D-CNN-LSTM model and the LSTM model on the test dataset are shown in Figures 6 and 7, respectively. The 1D-CNN-LSTM model correctly predicted 16,712 instances whereas the LSTM correctly predicted 16,594 instances. This reveals that the 1D-CNN-LSTM model achieved higher prediction accuracy compared to the LSTM model by about 0.4%. Furthermore, the 1D-CNN-LSTM model gave RMSE, MAE and MAPE values of 0.0109 Hz,

0.0008 Hz, and 0.0015%, respectively, whereas the LSTM model gave RMSE, MAE and MAPE values of 0.0194 Hz, 0.0099 Hz, and 0.0197%, respectively. The results reveal that the proposed 1D-CNN-LSTM model gives relatively lower prediction errors compared to the LSTM model.

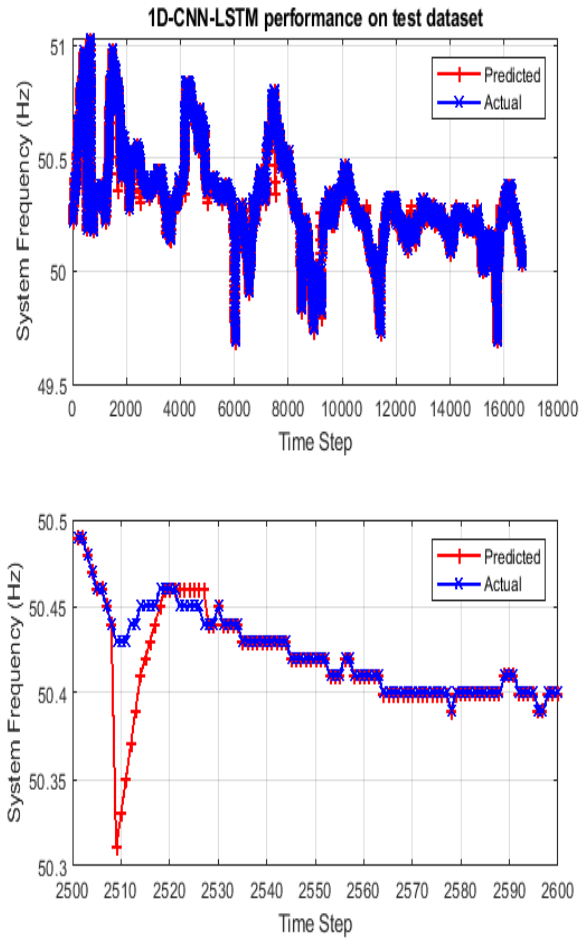

Figure 6: Prediction of System Frequency by the Proposed 1D-CNN-LSTM model

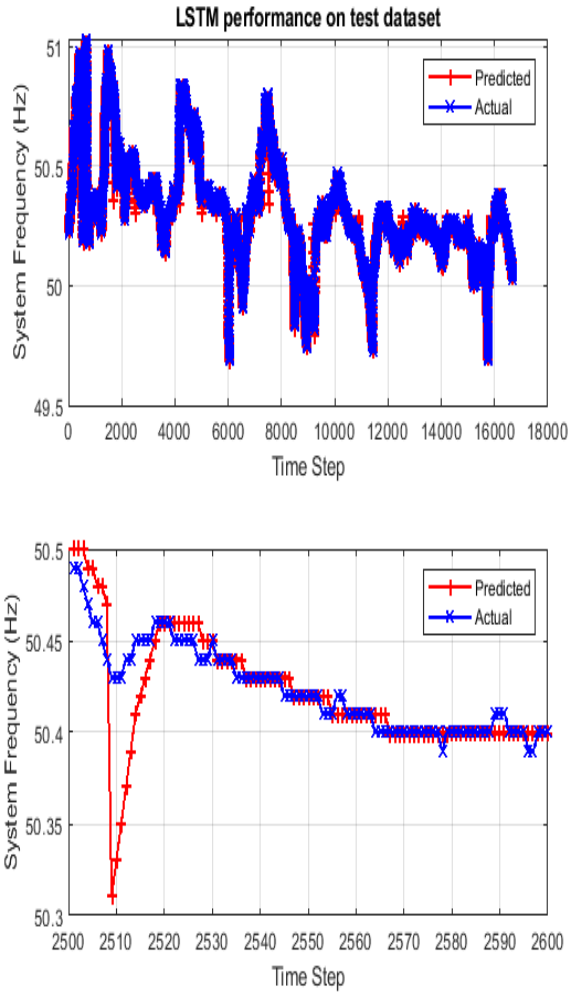

Figure 7: Prediction of System Frequency by the LSTM Model

CONCLUSION

The conventional methods of monitoring and managing the electrical grid are no longer effective due to the increasing grid network complexity, which invariably results in incessant incidences of grid collapse. In this paper, a hybrid DL model, named 1D-CNN-LSTM, was investigated for the prediction of electrical grid collapse based on the system (or grid) frequency forecasts. Historical real-time system frequency data was used to train and test the 1D-CNN-LSTM model which gives relatively lower prediction errors compared to the LSTM model in terms of the RMSE, MAE and MAPE. This study has shown that the hybrid 1D-CNN-LSTM model is an enhancement over the single LSTM model for the system frequency forecast, and invariably the

prediction of grid collapse. Thus, a rapid online preventive measure can be taken on the power network to mitigate incidences of blackout; thereby improving the economic benefits for both the consumers and the electricity providers.

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