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Prediction Of Gas Power Plant Combustion Turbine Exhaust Temperature And Wheel Space Temperature Using Hybrid Convolutional Neural Network And Long Short-Term Memory Model

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Abstract*—In this work, prediction of gas power plant (GPP) combustion turbine exhaust temperature (CTET) and wheel space temperature (CTWST) using hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) model is presented. The GPP dataset is obtained from a GPP located in Akwa Ibom State in Nigeria. In the model implementation, each of the baseline models; the CNN model and the LSTM model is used to predict the CTET and CTWST. Also the CNN-LSTM hybrid model is used to predict the CTET and CTWST. The prediction performance of the three models are compared and the best model is identified. The results show that there are 2004 records but the CTET has 1986 record with 18 missing data, the CTWET has 1973 record with 31 missing data, the power output has 1991 record with 13 missing data, while Day and Time have no missing data items. Also, in the CTET prediction, the hybrid CNN-LSTM model has the best prediction performance with the highest R^2 value of 0.9847, lowest RMSE of 12.8523 and lowest MAPE of 4.62%. Also, the LSTM performed better than the CNN model in the prediction of the CTET. Also, in the CTWST prediction, the hybrid CNN-LSTM model has the best prediction performance with the highest R^2 value of 0.97968, lowest RMSE of 21.14799 and lowest MAPE of 2.27%. Also, the LSTM performed better than the CNN model in the prediction of the CTWST. In all, the hybrid CNN-LSTM model is recommended for the prediction of the case study gas power plant Combustion Turbine Exhaust Temperature (CTET) and Combustion Turbine Wheel Space Temperature (CTWST)

Keywords*—Convolutional Neural Network (CNN), Gas Power Plant, Long Short-Term Memory (LSTM), Combustion Turbine Exhaust Temperature, hybrid CNN-LSTM mode, Combustion Turbine Wheel Space Temperature

1. Introduction

Across Nigeria, there has been steady effort to improve on the power generation to address the lingering power shortage and high proportion of population without access to electricity [1,2,3]. This has led to the installation of several power plants across the Nigeria [4,5]. Although the initial major energy source is in Nigeria is hydropower system, there has been diversification of the energy sources with growing adoption of gas power plants and related fossil fuel energy sources [6,7,8]. The renewable energy sources (not including the hydropower) are also increasing with the growing installation of solar power systems by various organizations and government agencies [9,10,11].

Notably, in this era of diversification of the energy generating source in Nigeria, one of the challenges is maintenance of the power plants [12,13,14]. Many plants are maintained using the routine approach coupled with breakdown maintenance. The need for regular power supply and for the power plants to operate at their installed capacity requires for efficient end proactive maintenance strategy [15,16]. In this case, predictive approach whereby, sensor derived datasets are used to predict the likelihood of plant breakdown so that maintenance can be effected to avoid the plant breakdown [18,19]. In the present smart system era, machine and deep learning models are employed for such plant parameter prediction.

Accordingly, in this work, selected temperature parameters associated with the gap power plant (GPP) combustion turbine are modeled using a hybrid Convolutional Neural Network and Long Short-Term Memory model (CNN-LSTM) model. The CNN-LSTM model is a data driven model that can be used in this case to predict the GPP combustion turbine exhaust temperature (CTET) and wheel space temperature (CTWST). These temperatures when approximately estimated can be used to detect the likelihood of abnormal behavior in the plant's operations. The hybridization of the CNN and the LSTM models is meant to harness the strength of each of the two baseline models so as to develop a hybrid model with better prediction performance. The performance of the hybrid model is compared with those of the baseline model.

2. Methodology

The essence of this work is to apply the hybrid Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) model in the prediction of gas power plant (GPP) combustion turbine exhaust temperature (CTET) and wheel space temperature (CTWST). The work first used the baseline models, namely the LSTM model and the CNN model to predict the GPP-CTET and the GPP-CWST after which the CNN-LSTM model is then applied in the prediction of the two temperatures. The prediction performance of the baseline models and the hybrid model are compared.

The GPP dataset is obtained from a gap power plant located in Akwa Ibom State in Nigeria. The dataset has 2,004 data records (rows) with four column representing the following four variables: Time in hours (TH), Power Output (PW), Combustion Turbine Exhaust Temperature (CTET) and Combustion Turbine Wheel Space Temperature (CTWST). The TH is further processed to create the additional variable denoted as Day (DY), thereby making it a total of five variables in the dataset.

In addition, missing data and outliers were identified through descriptive statistical analysis of the dataset. The data records with the missing data components were removed. The outliers identified in the CTET and CTWST were retained because the essence of the study is to present a model that can predict the CTET and CTWST including their outliers which is essential for detecting abnormal status of the GPP combustion turbine.

The system model for the prediction of the temperatures using the baseline and the hybrid models is presented in Figure 1. The structure of the CNN model is presented in Figure 2. Also, the cell structure of the LSTM model and the LSTM model architecture used are presented in Figure 3. Again, the architecture of the CNN-LSTM hybrid network is presented in Figure 4 while the flow diagram for the CNN-LSTM model training and validation is presented in Figure 5. The summary of the model performance evaluation metrics description and formular are is presented in Table 1.

In the model implementation, each of the baseline models; the CNN model and the LSTM model is used to predict the CTET and CTWST. Also the CNN-LSTM hybrid model is used to predict the CTET and CTWST. The prediction performance of the three models are compared and the best model is identified.

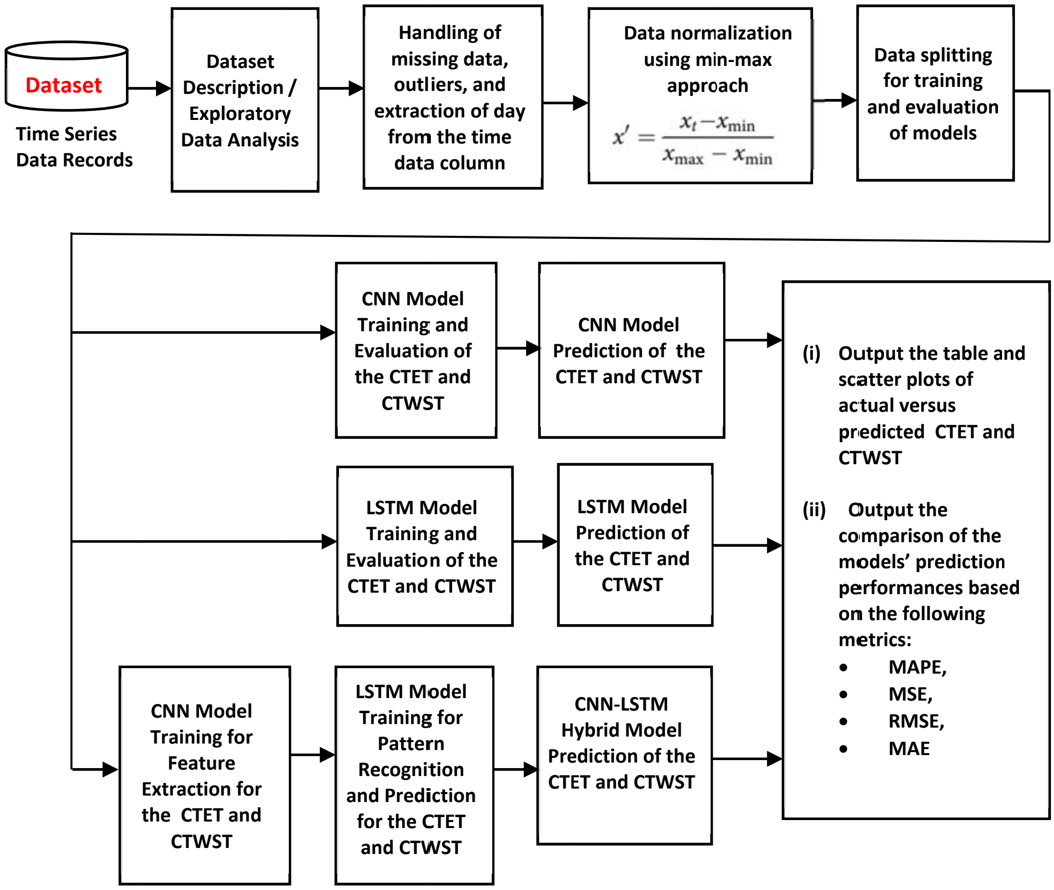

Figure 1 The system model for the prediction models development and evaluation

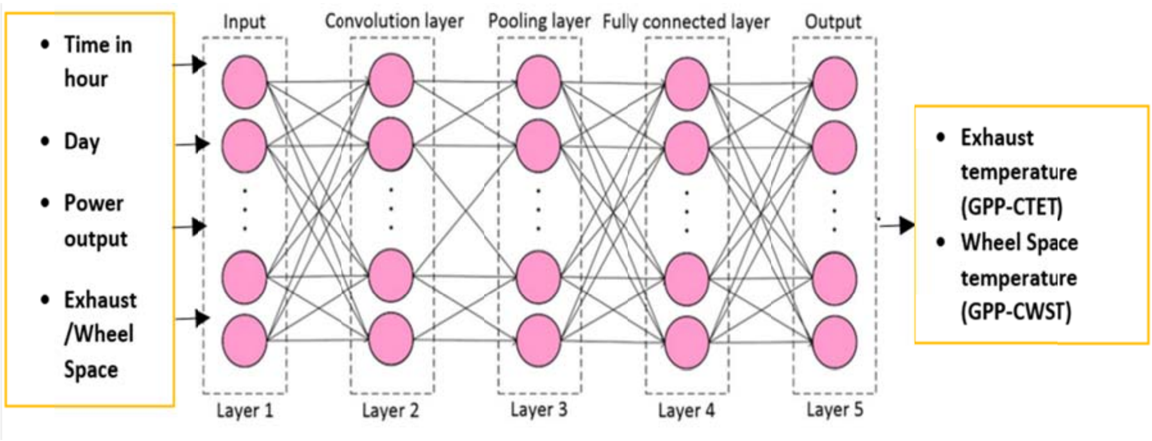

Figure 3 The structure of the CNN model (Adapted from **[19]**)

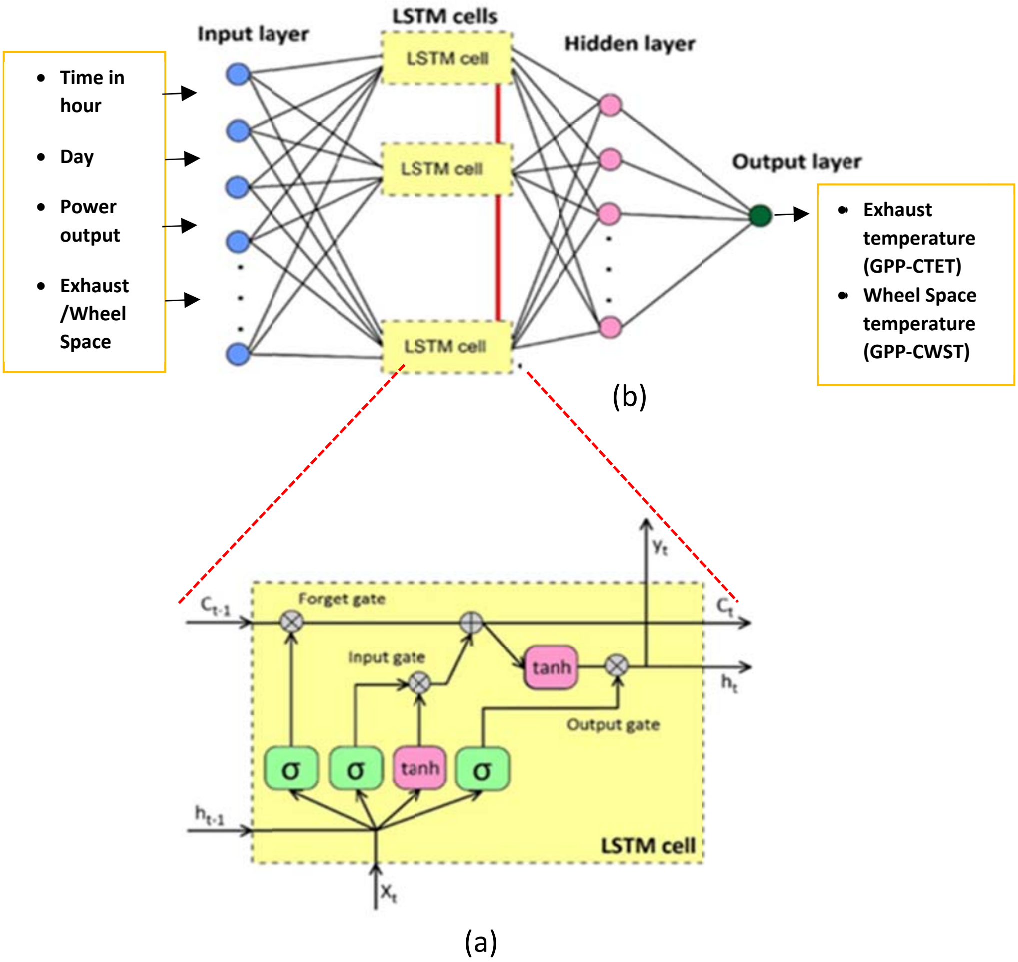

Figure 3 The cell structure of the LSTM (a) and the LSTM model architecture (b) (Adapted from **[19])**

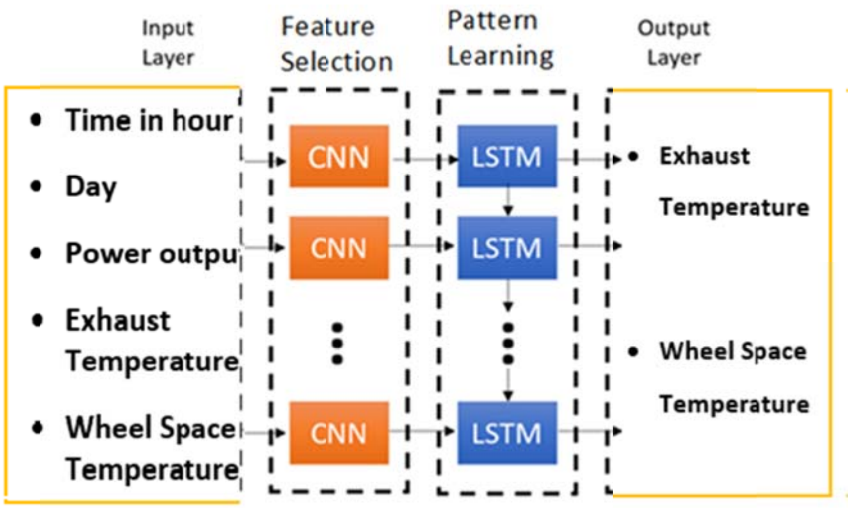

Figure 4 The architecture of the CNN-LSTM hybrid network (Adapted from **[20])**

Figure 5 The flow diagram for the CNN-LSTM model training and validation (Adapted from **[19])**

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Table 1 The model performance evaluation metrics description and formular

Model Performance Evaluation Metrics Description and Symbol	Model Performance Evaluation Metrics Symbol and Formular
Mean Absolute Percentage Error (MAPE)	$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left\|\frac{P_i - M_i}{M_i}\right\|$
Mean Squared Error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n}(M_i - P_i)^2$
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i - P_i)^2}$
Mean Absolute Error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n}\|P_i - M_i\|$
R-Squared (R^2 or the coefficient of determination)	$R^2 = 1 - \frac{SS_{\mathrm{res}}}{SS_{\mathrm{tot}}}$
Where P_i **denotes predicted,** M_i **denotes measured**	
$\bar{M} = \frac{1}{n}\sum M_i$,	$SS_{\mathrm{res}} = \sum (M_i - P_i)^2$, $SS_{\mathrm{tot}} = \sum (M_i - \bar{M})^2$

3. Results and discussion

The results of the dataset statistical analysis when missing data items are included and when the missing data records are excluded are presented in Figure 6, Figure 7, Figure 8, and Figure 9, as well as in Table 2 and Table 3. The results in Figure 6 and Figure 7 show that there are 2004 records but the CTET has 1986 record with 18 missing data, the CTWET has 1973 record with 31 missing data, the power output has 1991 record with 13 missing data, while Day and Time have no missing data items.

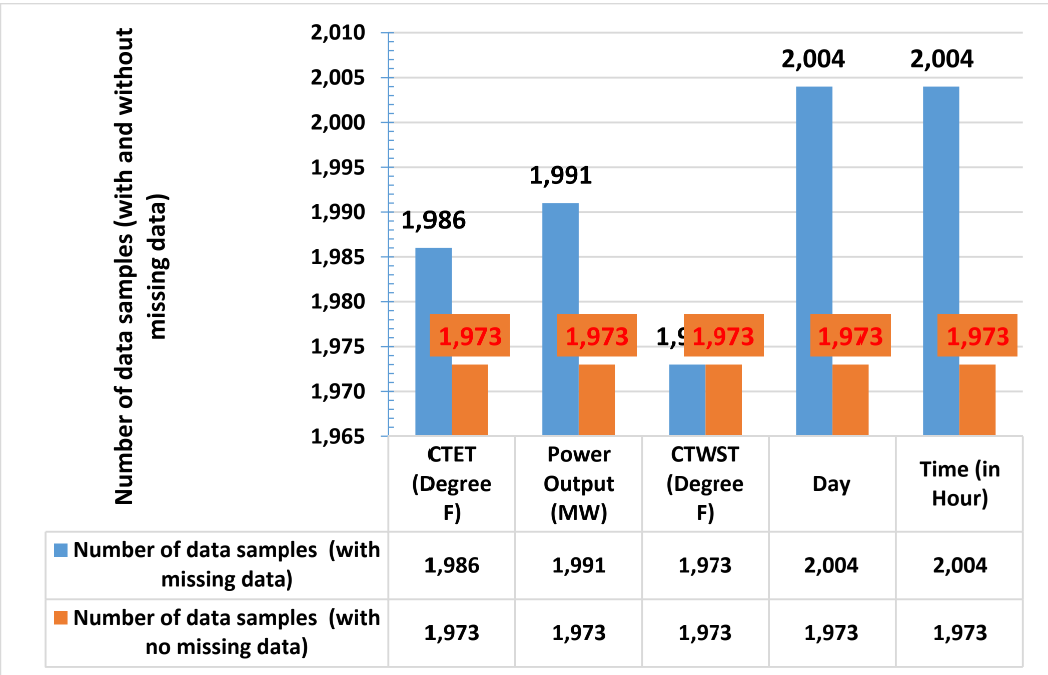

Figure 6 The number of data samples (with and without missing data)

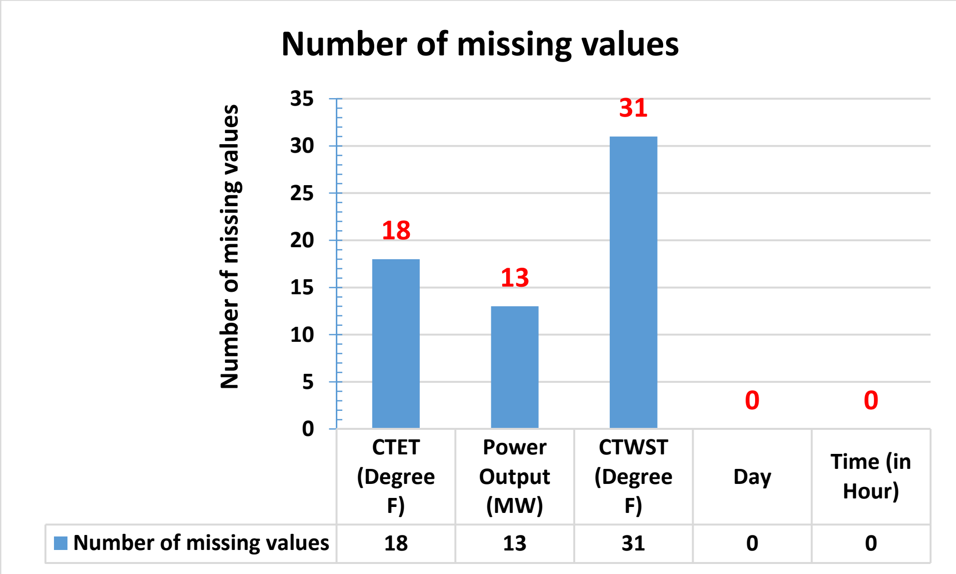

Figure 7 The number of missing values

When the missing or incomplete records in the dataset are removed, it affected the minimum, mean values and the outliers in the variables as shown in Figure 8 and Figure 9, as well as in Table 2, Table 2, Figure 10 and Figure 11. As shown in Table 2 for the Combustion Turbine Exhaust Temperature (CTET), the outlier was 79 in the original dataset but it reduced to 73 after the data records with missing data items were removed. Similarly, as shown in Table 3 for the Combustion Turbine Wheel Space Temperature (CTWST), the outlier was 86 in the original dataset but it reduced to 76 after the data records with missing data items were removed.

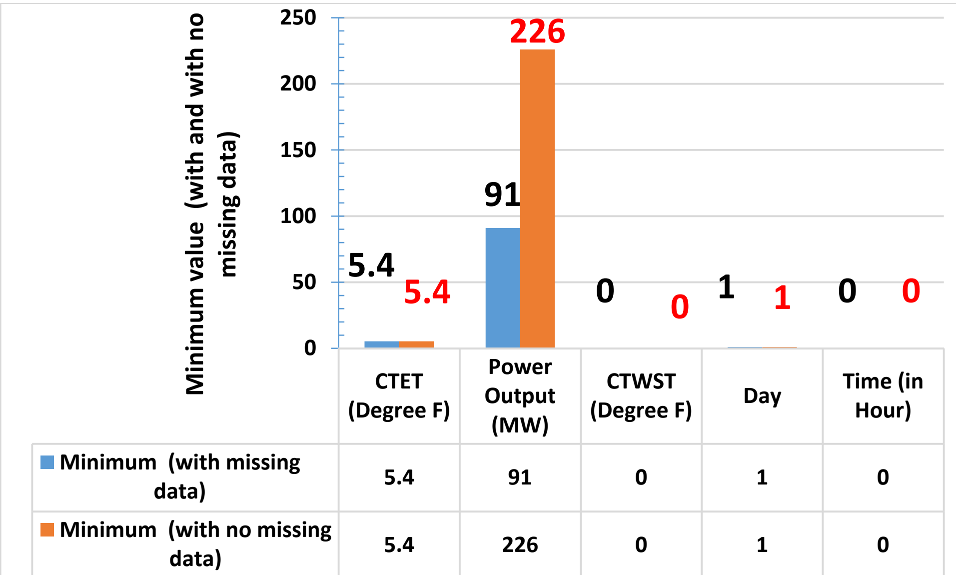

Figure 8 Minimum value (with and with no missing data)

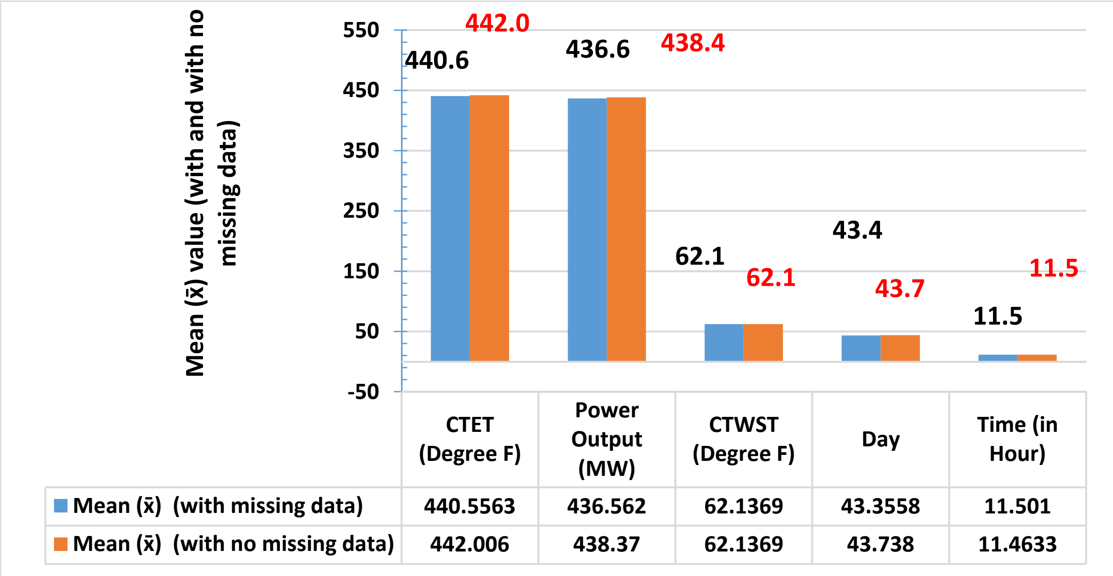

Figure 9 Mean (x̄) value (with and with no missing data)

Table 2 Summary of the results of the outlier analysis for the Combustion Turbine Exhaust Temperature (CTET) with and with no missing data

	Upper Outlier in CTET	Lower Outlier in CTET	Total Outlier in CTET
Outliers in CTET (With Missing Data)	71	8	79
Outliers in CTET (With No Missing Data)	71	2	73
The changes in number of outliers in CTET	0	6	6

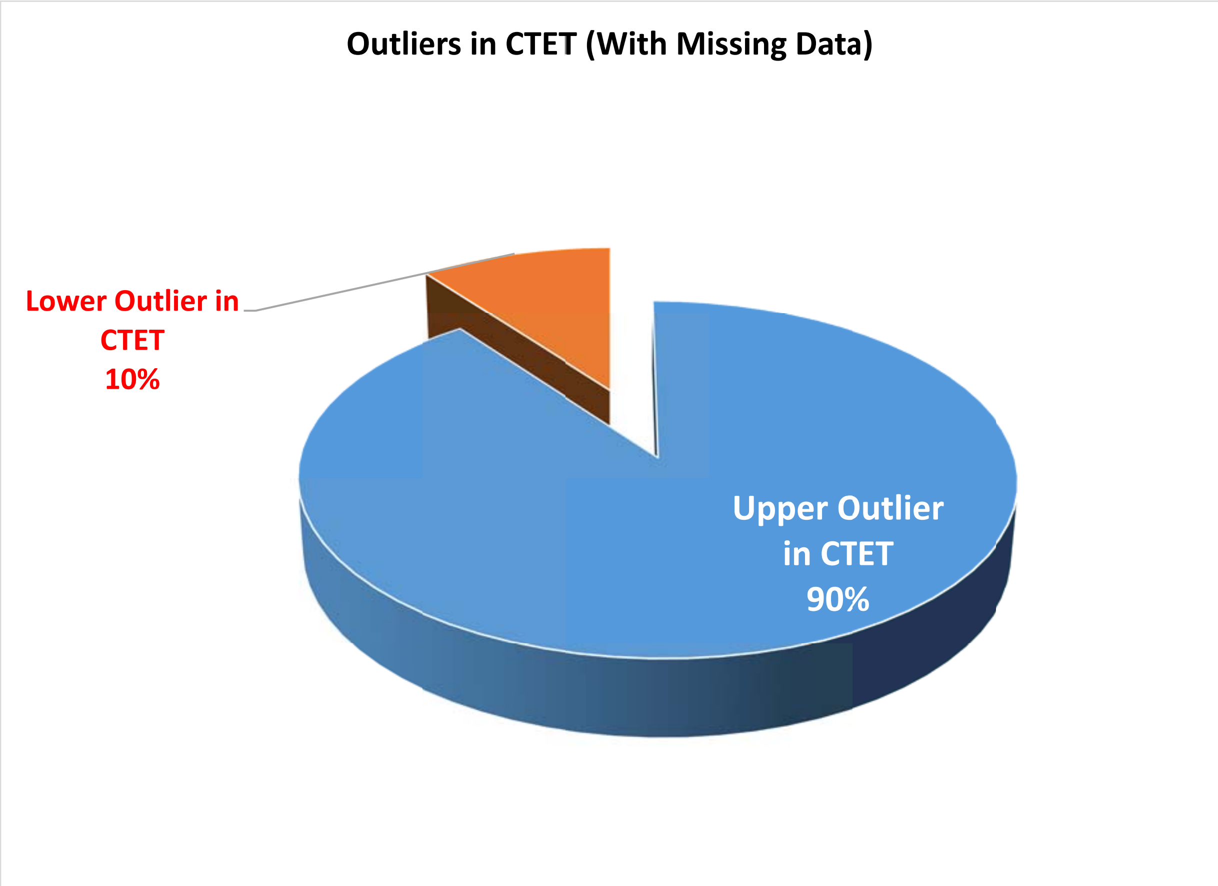

Figure 10 The pie chart showing the summary of the results of the outlier analysis for the Combustion Turbine Exhaust Temperature (CTET) with and with no missing data

Table 3 Summary of the results of the outlier analysis for the Combustion Turbine Wheel Space Temperature (CTWST) with and with no missing data

	Upper Outlier in CTWST	Lower Outlier in CTWST	Total Outlier in CTWST
Outliers in CTWST (With Missing Data)	71	15	86
Outliers in CTWST (With No Missing Data)	71	5	76
The changes in number of outliers in CTWST	0	10	10

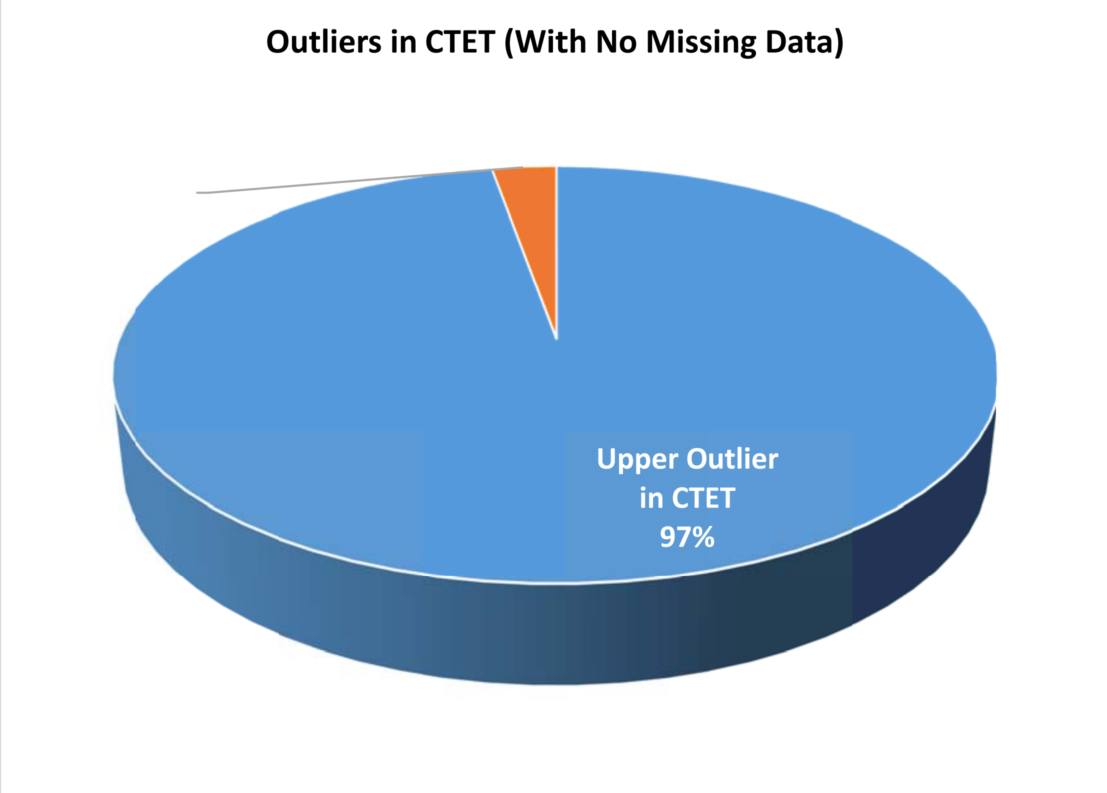

Figure 11 The pie chart showing the summary of the results of the outlier analysis for the Combustion Turbine Wheel Space Temperature (CTWST) with and with no missing data

The results of the prediction performance analysis of the models for the Combustion Turbine Exhaust Temperature (CTET) are presented in Figure 12, Figure 13, and Figure 14, and also in Table 2, Figure 15, Figure 16, and Figure 17. The scatter plots of the actual CTET versus predicted CTET are presented in Figure 12 for the CNN model, in Figure 13 for the LSTM model, and in Figure 14 for the hybrid CNN-LSTM model.

Again, the comparison of the RMSE, MAE, MSE and MAPE are presented in Table 4, as well as in Figure 15, Figure 16 and Figure 17. The results show that the hybrid CNN-LSTM model has the best prediction performance with the highest R^2 value of 0.9847, lowest RMSE of 12.8523 and lowest MAPE of 4.62%. Also, the LSTM performed better than the CNN model in the prediction of the CTET.

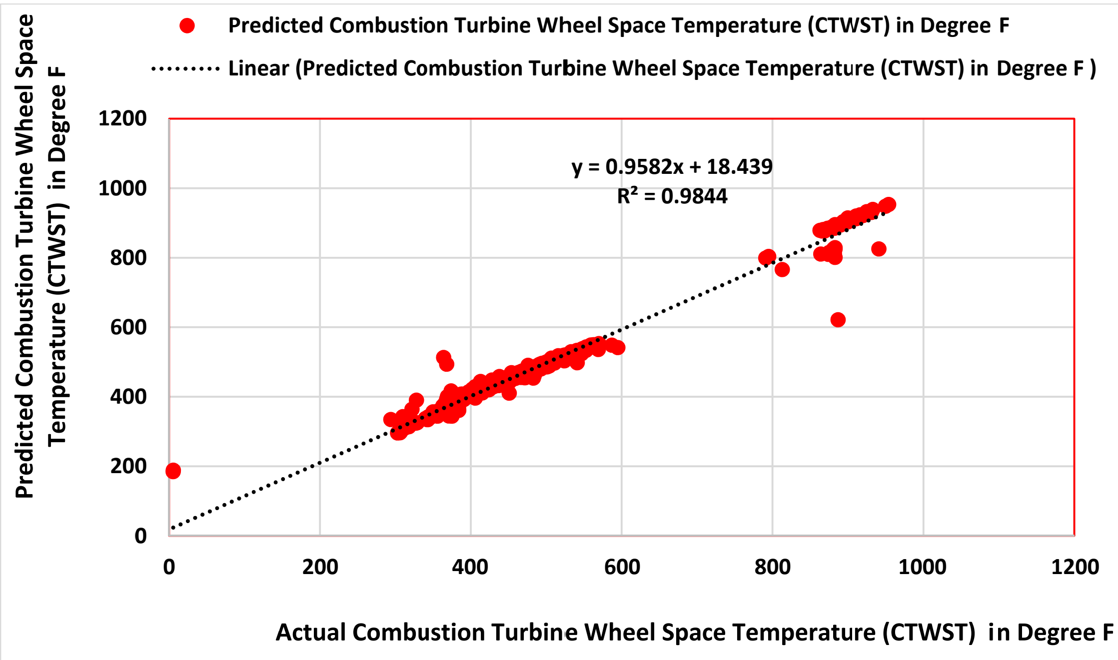

Figure 12 The scatter plot of the actual versus predicted Combustion Turbine Exhaust Temperature (CTET) using CNN model

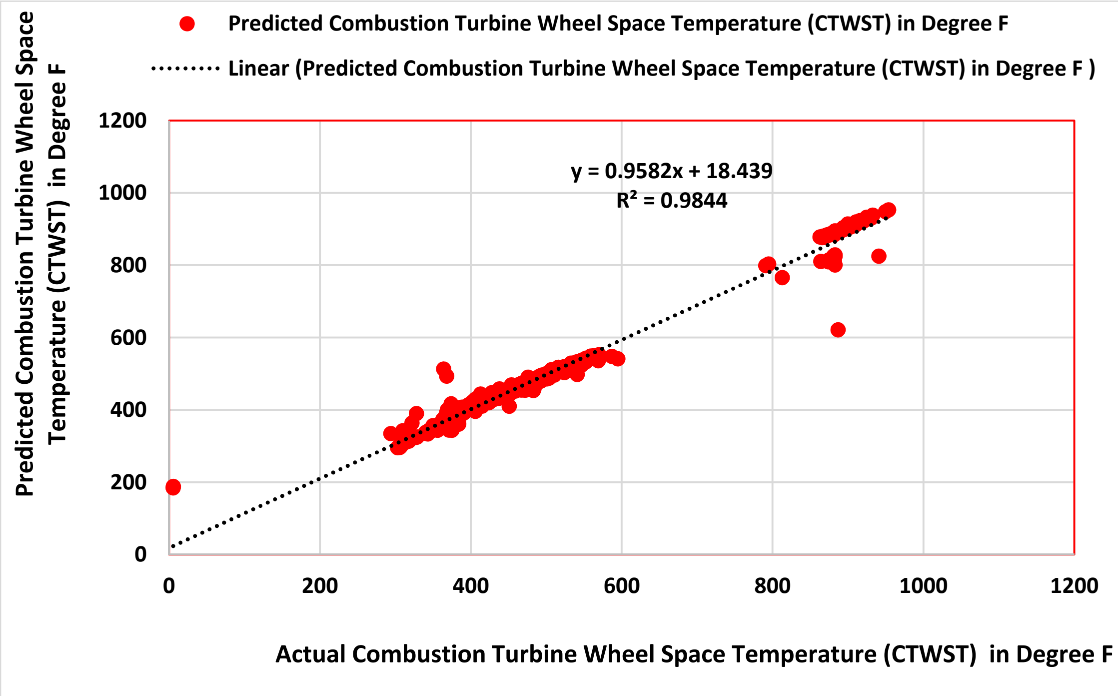

Figure 13 The scatter plot of the actual versus predicted Combustion Turbine Exhaust Temperature (CTET) using LSTM model

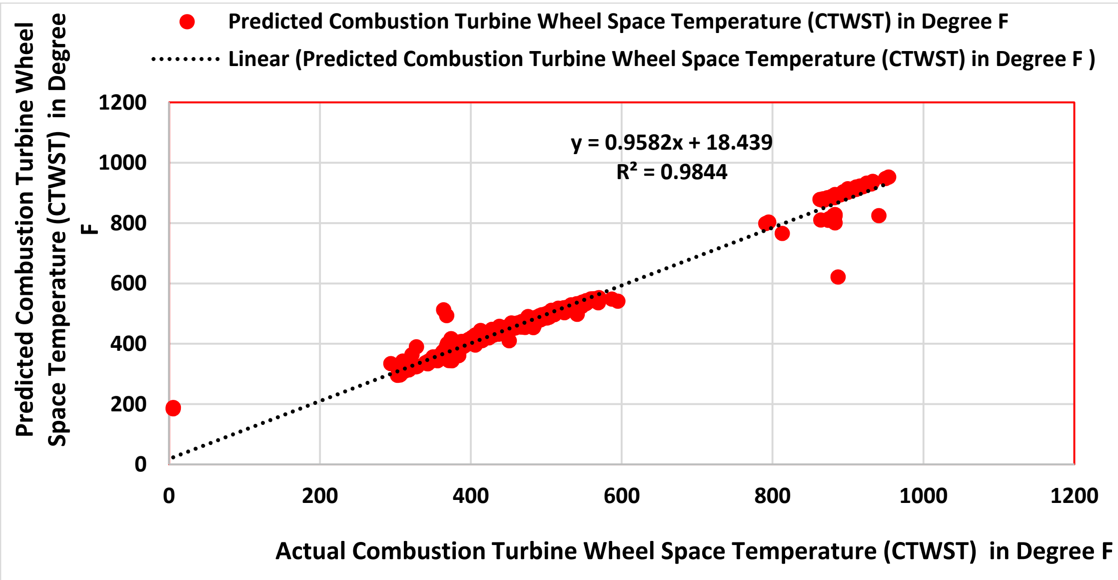

Figure 14 The scatter plot of the actual versus predicted Combustion Turbine Exhaust Temperature (CTET) using hybrid CNN-LSTM model

Table 4 Comparison of the CTET prediction performance of the CNN model, the LSTM model and the hybrid CNN-LSTM model

	MAE	MSE	RMSE	R^2	MAPE
CNN Prediction for CTET	11.81729	548.4993	23.42006	0.949093	8.10%
LSTM Prediction for CTET	11.00221	484.3508	22.00797	0.955047	8.33%
Hybrid CNN-LSTM Prediction for CTET	6.7296	165.1817	12.8523	0.984669	4.62%

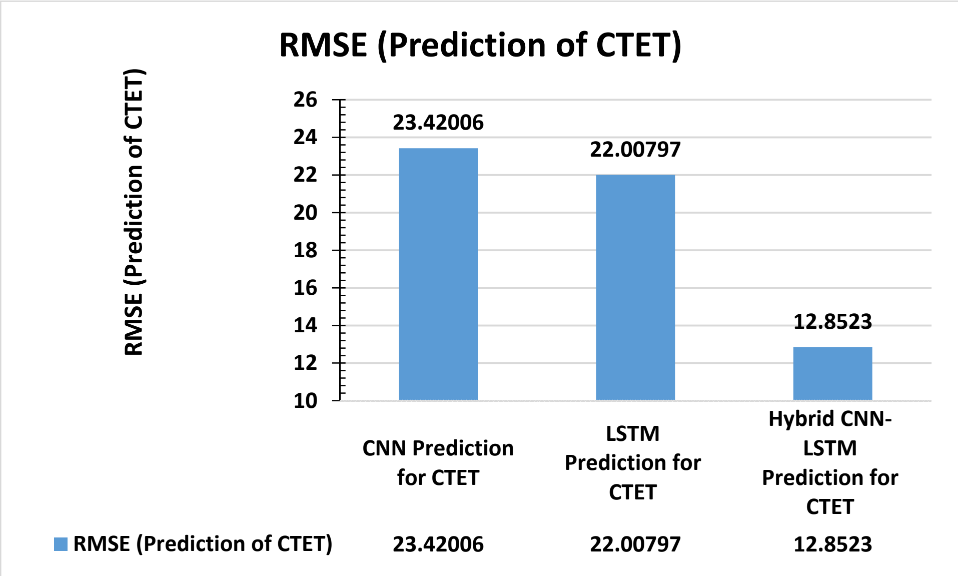

Figure 15 Comparison of the RMSE for the CTET prediction by the CNN model, the LSTM model and the hybrid CNN-LSTM model

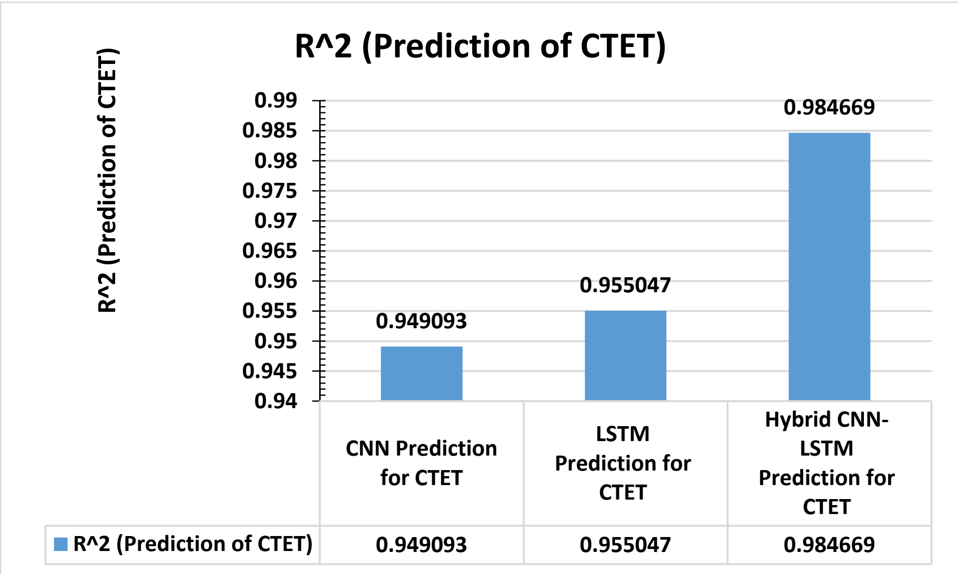

Figure 16 Comparison of the R^2 for the CTET prediction by the CNN model, the LSTM model and the hybrid CNN-LSTM model

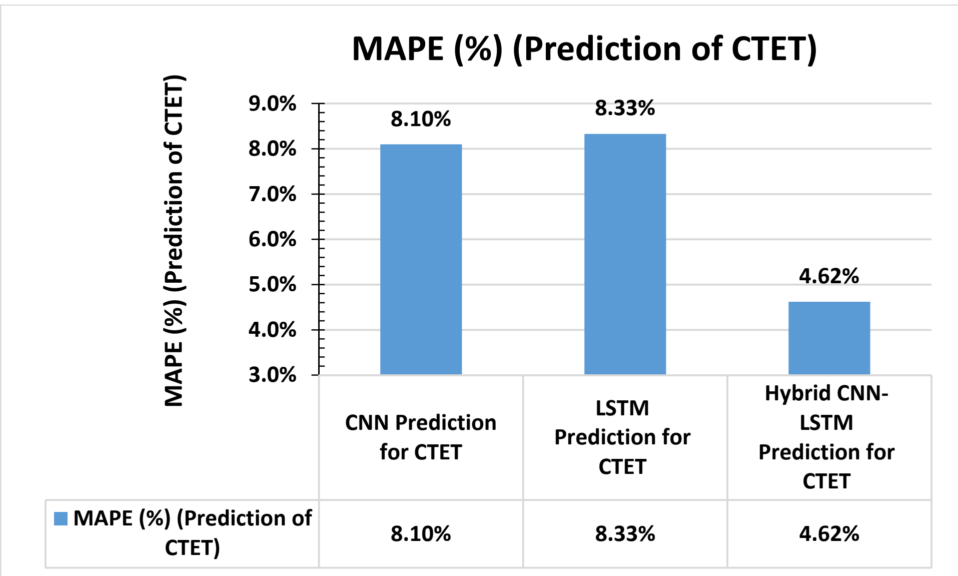

Figure 17 Comparison of the MAPE for the CTET prediction by the CNN model, the LSTM model and the hybrid CNN-LSTM model

Similarly, the results of the prediction performance analysis of the models for the Combustion Turbine Wheel Space Temperature (CTWST) are presented in Figure 18, Figure 19, and Figure 20, and also in Table 3, Figure 21, Figure 22, and Figure 23. The scatter plots of the actual CTWST versus predicted CTWST are presented in Figure 18 for the CNN model, in Figure 19 for the LSTM model, and in Figure 20 for the hybrid CNN-LSTM model.

Again, the comparison of the RMSE, MAE, MSE and MAPE are presented in Table 5, as well as in Figure 21, Figure 22 and Figure 23. The results show that the hybrid CNN-LSTM model has the best prediction performance with the highest R^2 value of 0.97968, lowest RMSE of 21.14799 and lowest MAPE of 2.27%. Also, the LSTM performed better than the CNN model in the prediction of the CTWST.

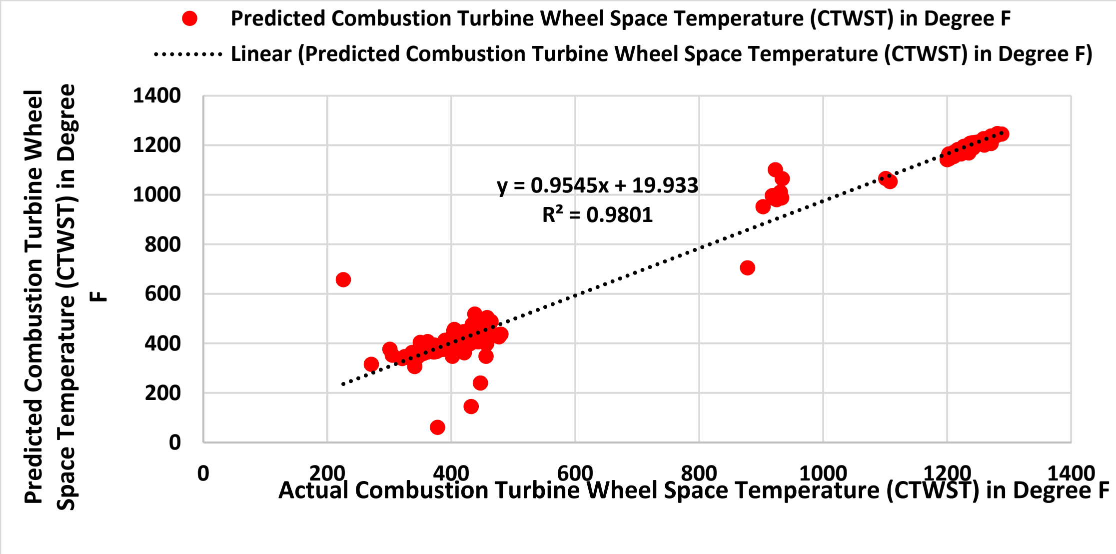

Figure 18 The scatter plot of the actual versus predicted Combustion Turbine Wheel Space Temperature (CTWST) using CNN model

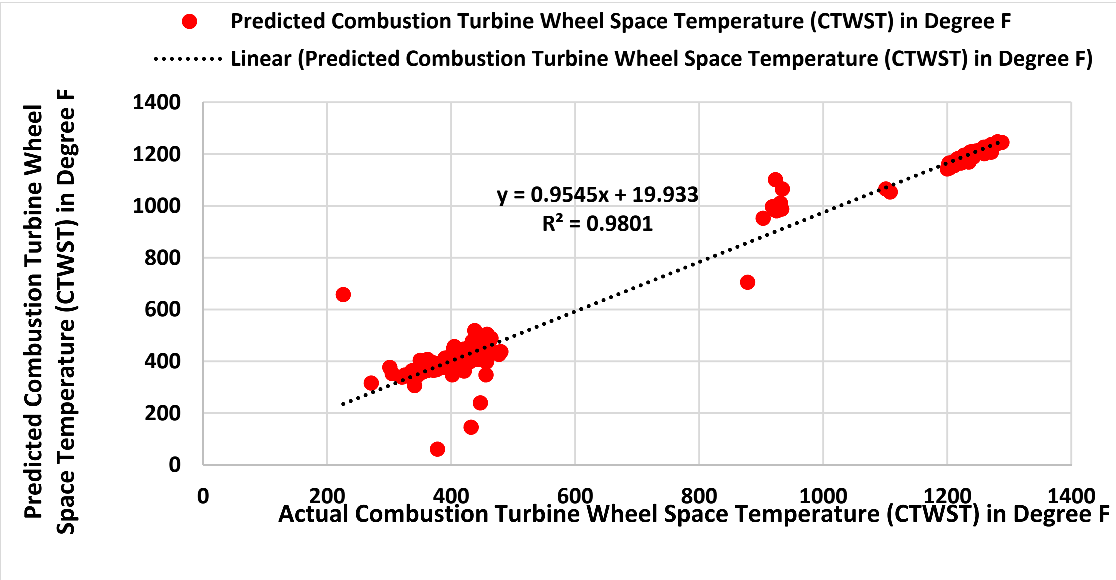

Figure 19 The scatter plot of the actual versus predicted Combustion Turbine Wheel Space Temperature (CTWST) using LSTM model

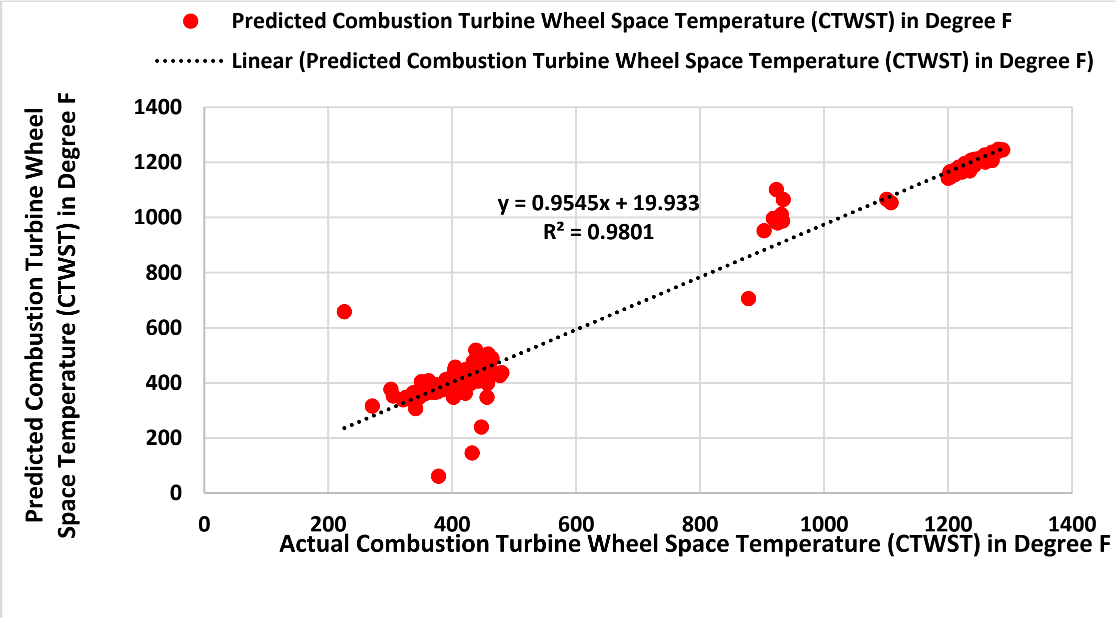

Figure 20 The scatter plot of the actual versus predicted Combustion Turbine Wheel Space Temperature (CTWST) using hybrid CNN-LSTM model

Table 5 Comparison of the **CTWST** prediction performance of the CNN model, the LSTM model and the hybrid CNN-LSTM model

	MAE	MSE	RMSE	R^2	MAPE
CNN for CTWST Prediction	17.95664	1291.016	35.93071	0.941344	3.99%
LSTM for CTWST Prediction	16.59755	995.5923	31.55301	0.954767	3.67%
Hybrid CNN-LSTM for CTWST Prediction	10.24535	447.2375	21.14799	0.97968	2.27%

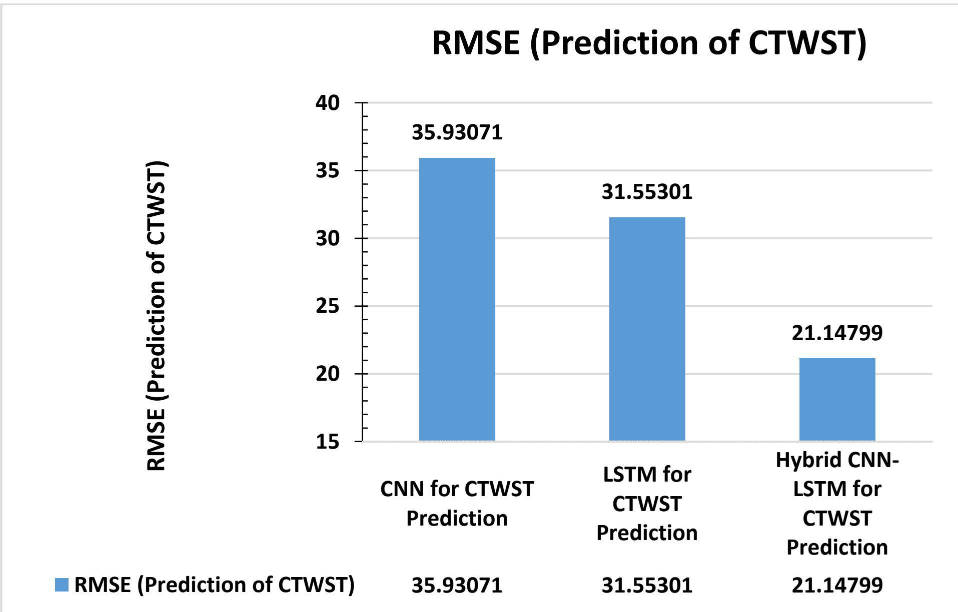

Figure 21 Comparison of the RMSE for the CTWST prediction by the CNN model, the LSTM model and the hybrid CNN-LSTM model

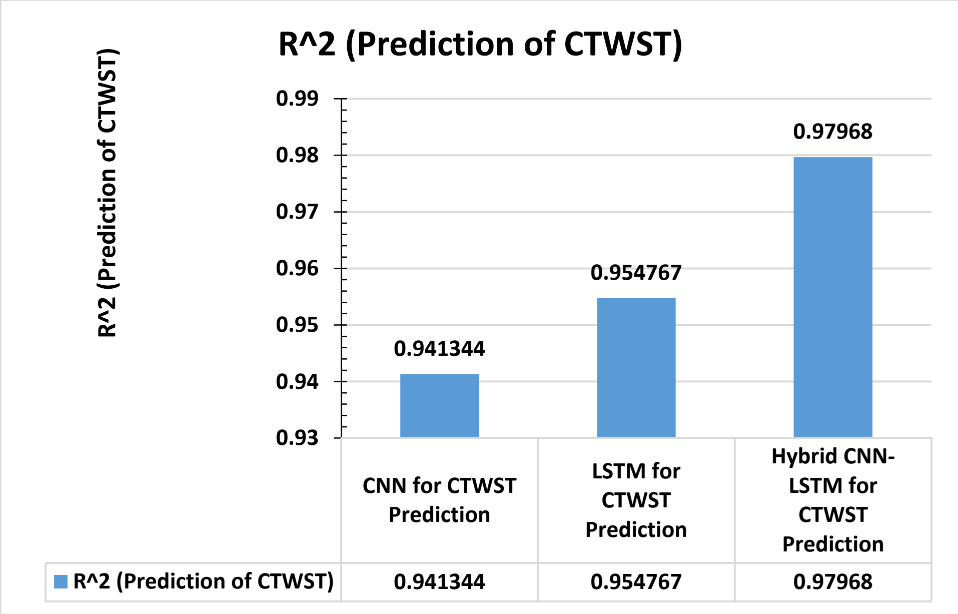

Figure 22 Comparison of the R^2 for the CTWST prediction by the CNN model, the LSTM model and the hybrid CNN-LSTM model

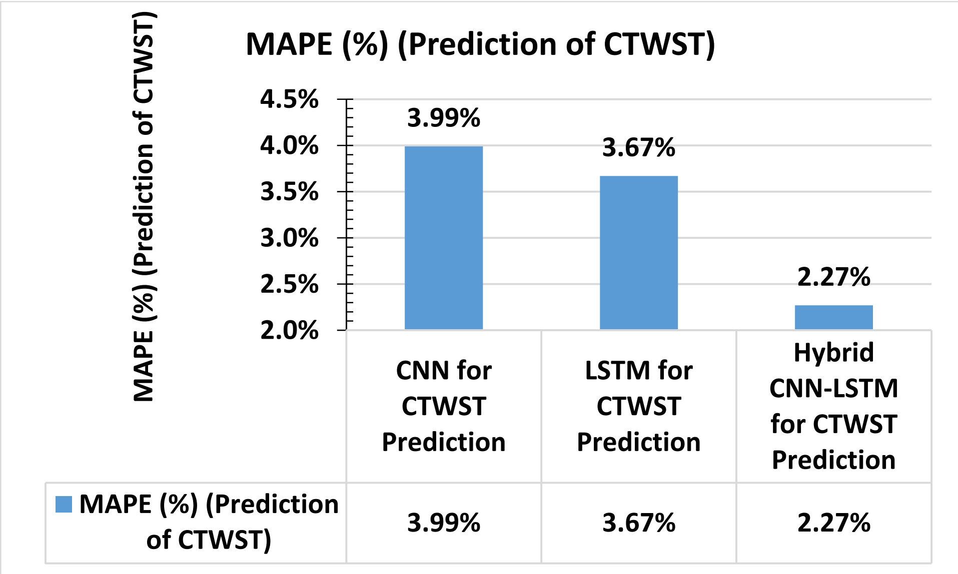

Figure 23 Comparison of the MAPE for the CTWST prediction by the CNN model, the LSTM model and the hybrid CNN-LSTM model

4. Conclusion

The prediction of gas power plant Combustion Turbine Exhaust Temperature (CTET) and Combustion Turbine Wheel Space Temperature (CTWST) using CNN model, LSTM and hybrid CNN-LSTM model is presented. The study utilized a dataset obtained from a gas power plant situated in Akwa Ibom State. The hourly power output with the attendant CTET and CTWST data records are used for the study. The results show that the hybrid model of CNN-LSTM performed btter than the baseline models (CNN and LSTM). Also, the LSTM model gave better prediction performance than the CNN model. As such, the hybrid CNN-LSTM model is recommended for the prediction of the case study gas power plant Combustion Turbine Exhaust Temperature (CTET) and Combustion Turbine Wheel Space Temperature (CTWST).

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