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Multiple Linear Regression-Based Model To Predict Power Gas Turbine Exhaust And Wheelspace Temperatures For Application In Predictive Maintenance Framework

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***Abstract*—In this work, multiple linear regression-based model to predict power gas turbine exhaust and wheelspace temperatures for application in predictive maintenance framework is presented. The cases study dataset from a gas power plant in Akwa Ibom State Nigeria has the following data columns; time of the day, power output of the turbine, the exhaust temperature and the turbine wheelspace temperature. The missing data records and incomplete data records were identified and removed. Afterwards, data spitting was done with 80 % reserved for training while 20% of the dataset was used for the model validation. The results of the descriptive statistics analysis of the dataset show that there are up to 2004 records in the dataset but some variables have missing data which were removed and then all the variables have 1,973 data samples each. The correlation matrix results show that only the Wheelspace Temperature and the Exhaust Temperature have very strong correlation value above 0.5. In the dataset used for the model training and validation, the Exhaust Temperature has 2 lower outliers and 71 upper outliers which is a total of 73 outliers while the Wheelspace Temperature has 5 lower outliers and 71 upper outliers which is a total of 76 outliers. The MLR model for the Exhaust Temperature has MAE of 13.49557, RMSE of 26.92566 and R-squared value of 0.932712 while the MLR model for the Wheelspace Temperature has MAE of 25.56581, RMSE of 49.74893and R-squared value of 0.887554. The prediction MLR models obtained in the work are essential for application in predictive maintenance framework.**

***Keywords*—power Gas Turbine, Predictive Maintenance Framework, Turbine Exhaust Temperature, Multiple Linear Regression, Turbine Wheelspace Temperature**

1. Introduction

Over the years, Nigeria has suffered perennial power problem. There is poor and epileptic power supply across Nigeria [1,2]. There is also problem of access to the national power grid [3,4]. As such, efforts are being made to boost the power supply by developing additional power plants at selected locations across Nigeria [5,6,7]. One of such power project is the gas power plant in Akwa Ibom State which is tied to the national grid [8,9,10].

While gas power plant is effective in generating electric power, the state of the gas turbine is crucial for reliable power output [11,12]. The operating status of the gas plant can be determined from the temperature readings taken at different parts of the gas plant [13,14]. In this work, the focus is on the turbine exhaust temperature and the turbine Wheelspace temperature [15,16]. There are acceptable temperature range for the exhaust temperature and the Wheelspace temperature. When the temperature exceeds any of the ranges, the gas plant will likely malfunction. As such, the operating values of turbine exhaust temperature and the turbine Wheelspace temperature can therefore be used to predict the need for maintenance of the turbine. Accordingly, in this work, two multiple linear regression (MLR) models are developed, one for predicting the turbine exhaust temperature and the other one for predicting the turbine Wheelspace temperature. The models are trained with data obtained from the case study gas power plant in Akwa Ibom State. The prediction performance of the models are assessed using five different metrics.

2. Methodology

The focus in this work is to use multiple linear regression to model and predict the power gas turbine exhaust and wheelspace temperatures which are essential for application in predictive maintenance framework. The study is a data-driven approach to model development. As such, the relevant dataset for the case study gas power is obtained and then applied in the model development. The research procedure is presented in Figure 1 and Figure 2. Specifically, according to the procedure presented in Figure 1, the MLR model is used to predict power gas turbine exhaust temperature and also power gas turbine wheelspace temperature.

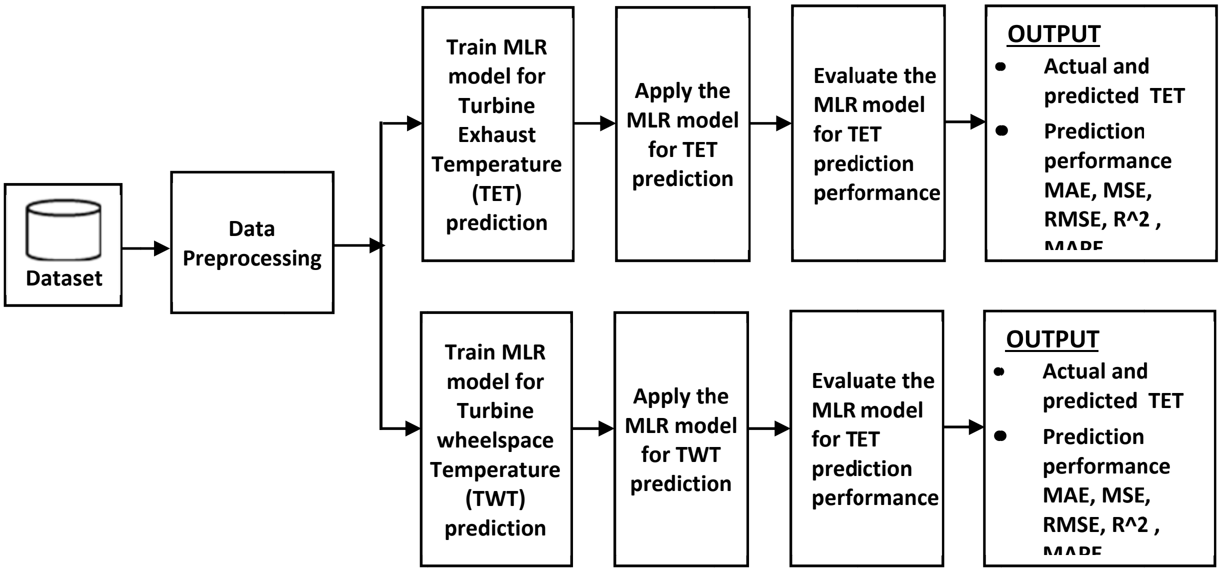

Figure 1 The research procedure showing the two temperatures being predicted using the MLR model

The cases study dataset from a gas power plant in Akwa Ibom State Nigeria has the following data columns, time of the day, power output of the turbine, the exhaust temperature and the turbine wheelspace temperature. The descriptive statistical analysis was carried out on the dataset using some online statistical tools. The missing data records and incomplete data records were identified and removed. The time data column was processed and the day and time components were identified and separated. The outlier analysis was also carried out followed by the data scaling. The outliers in the dataset were determined using the procedure in Algorithm I.

Afterwards, data spitting was done with 80 % reserved for training while 20% of the dataset was used for the model validation. The analytical expression for the MLR is given as;

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + . + \beta_n X_n + \in \quad (1)$$

Where

Model Symbol	Description
Y	Dependent variable
X_k	Independent variable
β_k	Regression coefficients for independent variable X_k
β_0	Intercept
$\in$	Error term

Furthermore, as presented in Table 1, the metrics used for the prediction performce evaluation include MAE, MSE, RMSE, R2 and MAPE.

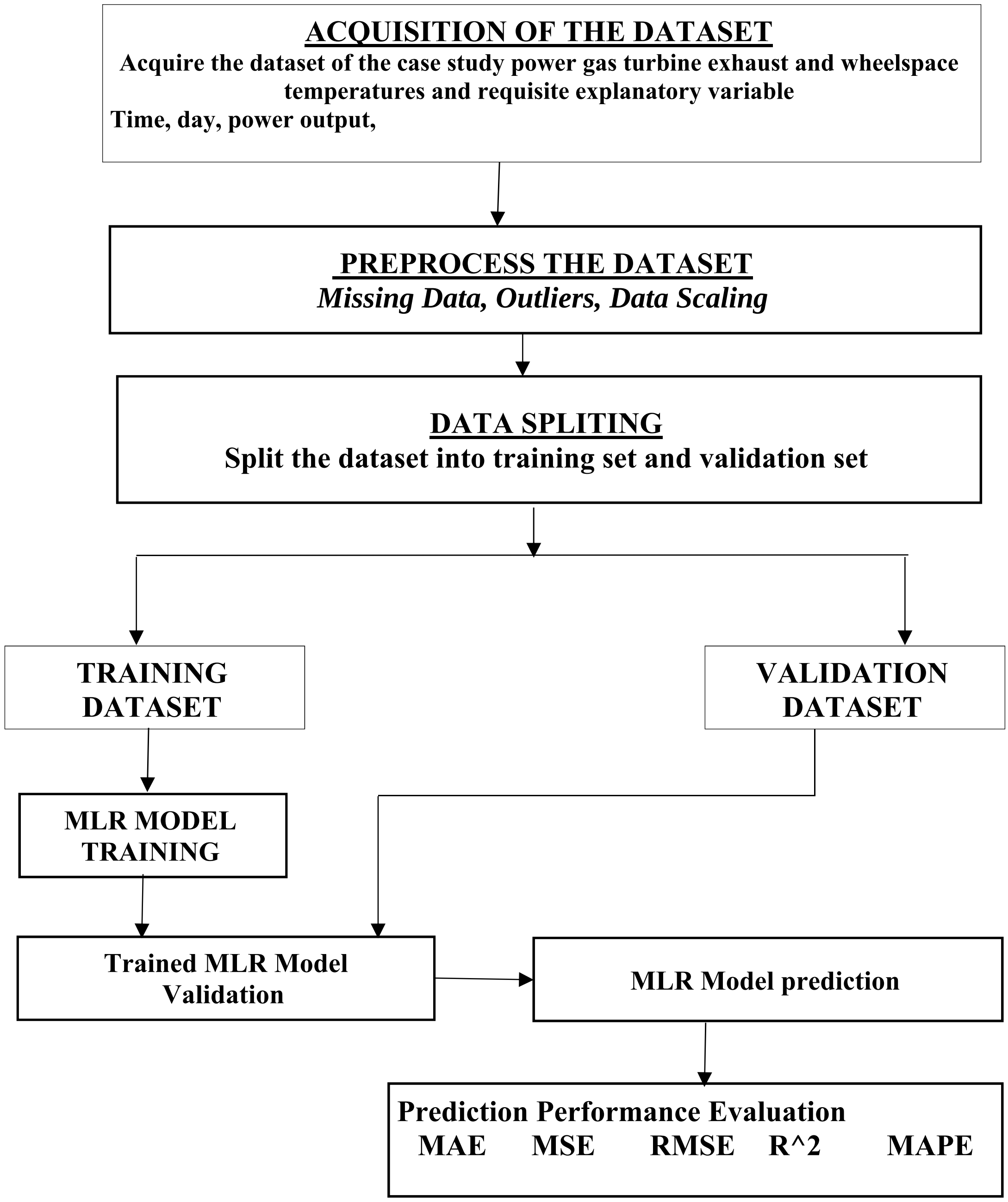

Figure 2 The procedure showing how the MLR model is trained and validated for the prediction of the temperatures

Algorithm I : The procedure for detection of outliers in the dataset

Step 1: Sort the dataset with n data points in ascending order

Step 2: Compute the First Quartile (Q1): (1/4) × (n + 1)

Step 3: Compute the Third Quartile (Q3): (3/4) × (n + 1)

Step 4: Compute the Interquartile Range: IQR = Q3 - Q1

Step 5: Compute the Lower Fence: Lower Fence = Q1 - (1.5 x IQR)

Step 6: Compute the Upper Fence: Upper Fence = Q3 + (1.5 x IQR)

Step 7: Find Outlier:

Step 7.1: Any data value below the lower fence are outliers (Lower fence outliers)

Step 7.2: Any data value above the upper fence are outliers. (Upper fence outliers)

Step 8: Output n, Lower fence outliers, Upper fence outliers

Table 1 The Prediction Performance Metrics Use For Evaluation of the Model

S/N	Metrics	Formula
1	Mean Absolute Error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$
2	Mean Squared Error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
3	Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
4	R2 (Coefficient of Determination)	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$
5	Mean Absolute Percentage Error (MAPE)	$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i - \hat{y}_i}{y_i}\right\rvert$

Where y_i is actual data, $\hat{y}_i$ is predicted data, and $\bar{y}$ is the mean of y_i

3. Results and discussion

3.1 Results of the descriptive statistical evaluation of the dataset

The results of the descriptive statistical evaluation of the dataset are presented in Table 2 and Table 3, while the correlational analysis results are presented in Table 4. In Table 2, the results show that there are up to 2004 records in the dataset but some variables have missing data whicj resulted in Exhaust temperature having 1986 data samples, Wheelspace temperature having 1991 data samples, Output Power having 1973 data samples, while Day, Time and Time in hour in a day have 2004 data samples) The data records with incomplete data items were removed and the statistical analysis of the resultant dataset is presented in table 3 which shows that all the variables have 1,973 data samples each. The correlation matrix results in Table 4 show that only the Wheelspace Temperature and the Exhaust Temperature have very strong correlation value above 0.5.

Table 2 The results of the descriptive statistical analysis for the original dataset

Groups	Exhaust temp (DEG F)	Wheelspace Temp 1 (DEG F)	Output Power (MW)	Day-Time	Day	Time (Hour in a day)
Number of observations	1,986	1,991	1,973	2,004	2,004	2,004
Number of missing values	18	13	31	0	0	0
Minimum	5.4	91	0	1	1	0
Maximum	954	1,288	378	86.9583	86	23
Range	948.6	1,197	378	85.9583	85	23
Mean (x̄)	440.5563	436.562	62.1369	43.835	43.3558	11.501
Sum	874,944.9	869,195	122,596.03	87,845.3333	86,885	23,048
Standard Deviation (S)	105.5371	149.2427	23.3695	25.0202	25.017	6.9627
Q1	373	388	42.4	21.8542	21	5
Median	425	419	64.5	43.4375	43	12
Q3	472	434	81.3	65.6042	65	18
Interquartile range	99	46	38.9	43.75	44	13

Table 3 The results of the descriptive statistical analysis for the dataset after all incomplete data records are removed

Groups	Exhaust Temp (Deg F)	Output Power (MW)	Wheelspace Temp 1 (DEG F)	Day-Time	Day	Time (Hour in a day)
Number of observations	1,973	1,973	1,973	1,973	1,973	1,973
Number of missing values	0	0	0	0	0	0
Minimum	5.4	0	226	1	1	0
Maximum	954	378	1,288	86.9583	86	23
Range	948.6	378	1,062	85.9583	85	23
Mean ($\bar{x}$)	442.006	62.1369	438.37	44.2156	43.738	11.4633
Standard Deviation (S)	103.8277	23.3695	148.3956	24.9885	24.9845	6.9485
Q1	373	42.4	389	22.2917	22	5
Median	426	64.5	419	44.0417	44	12
Q3	472	81.3	434	65.875	65	17
Interquartile range	99	38.9	45	43.5833	43	12

Table 4 The Correlation matrix (pearson) for the five variables contained in the dataset

	Exhaust Temp (Deg F)	Output Power (MW)	Wheelspace Temp $_1$ (DEG F)	Day	Time (Hour in a day)
Exhaust Temp (Deg F)	1	0.220043	0.890793	-0.217208	0.113201
Output Power (MW)	0.220043	1	-0.0996187	0.104097	0.22573
Wheelspace Temp $_1$ (DEG F)	0.890793	-0.0996187	1	-0.19552	0.0604525
Day	-0.217208	0.104097	-0.19552	1	0.00798158
Time (Hour in a day)	0.113201	0.22573	0.0604525	0.00798158	1

3.2 The results of outliers' determination

The results of outliers determination is presented for the Exhaust Temperature having 1,986 data samples (as shown in Table 2 where n = 1986 for the Exhaust Temperature). The details of the sample calculations for the outlier determination for the Exhaust Temperature is presented as follows:

Step 1: Sort the dataset with n data points in ascending order

Compute the First Quartile (Q1):

(1/4) × (n + 1)

Q1 position = (1/4) × (1986 + 1) = 496.75

Since the position is fractional, we average values at positions 496 and 497:

Q1 = (373 + 373) / 2 = 373

Q1 = 373

Compute the Third Quartile (Q3):

(3/4) × (n + 1)

Q3 position = (3/4) × (1986 + 1) = 1490.25

Since the position is fractional, we average values at positions 1490 and 1491:

Q3 = (472 + 472) / 2 = 472

Q3 = 472

Compute the Interquartile Range:

IQR = Q_3 - Q_1

IQR = 472 - 373

IQR = 99

Compute the Lower Fence:

Lower Fence = Q_1 - (1.5 x IQR)

Lower Fence = 373 - (1.5 x 99)

Lower Fence= 224.5

Compute the Upper Fence:

Upper Fence = Q_3 + (1.5 x IQR)

Upper Fence = 472 + (1.5 x 99)

Upper Fence= 620.5

Find Outlier:

Any numbers in the data that are below the lower fence are outliers.

Any numbers in the data that are above the upper fence are outliers.

The detailed results of the outlier determination for the Exhaust Temperature is presented in Figure 3 when the missing data records are included and in Figure 4 when the missing data records are not included. The results in Figure 3 showed that with the missing data records included, the Exhaust Temperature has 8 lower outliers and 71 upper outliers which gives a total of 79 outliers. On the other hand, the results in Figure 4 showed that with the missing data records excluded, the Exhaust Temperature has 2 lower outliers and 71 upper outliers which is a total of 73 outliers. The outliers associated with the Exhaust temperature are shown in the scatter plot of Figure 5 and the box and whisker plot of Figure 6.

Similarly, the results in Figure 7 showed that with the missing data records excluded, the Wheelspace Temperature has 5 lower outliers and 71 upper outliers which is a total of 76 outliers. The outliers associated with the Wheelspace temperature are shown in the scatter plot of Figure 8 and the box and whisker plot of Figure 9.

Tukey's Fences with k = 1.5			
Q1:	373.0000	Lower Fence:	224.5000
Q3:	472.0000	Upper Fence:	620.5000
IQR:	99.0000	Multiplier (k):	1.5000

Upper Outliers (Number of upper outliers =71)	Lower Outliers (Number of lower outliers =8)
791.0000, 795.0000, 813.0000, 863.0000, 864.0000, 866.0000, 867.0000, 869.0000, 871.0000, 872.0000, 873.0000, 874.0000, 875.0000, 875.0000, 878.0000, 878.0000, 881.0000, 881.0000, 881.0000, 881.0000, 882.0000, 882.0000, 883.0000, 883.0000, 883.0000, 883.0000, 884.0000, 884.0000, 885.0000, 887.0000, 887.0000, 890.0000, 891.0000, 892.0000, 893.0000, 893.0000, 893.0000, 894.0000, 894.0000, 894.0000, 895.0000, 897.0000, 899.0000, 899.0000, 900.0000, 900.0000, 901.0000, 903.0000, 904.0000, 905.0000, 909.0000, 909.0000, 910.0000, 910.0000, 911.0000, 911.0000, 916.0000, 918.0000, 919.0000, 920.0000, 921.0000, 921.0000, 922.0000, 924.0000, 925.0000, 929.0000, 931.0000, 933.0000, 941.0000, 950.0000, 954.0000	5.4000, 5.5000, 58.0000, 62.0000, 75.0000, 90.0000, 112.0000, 157.0000

Figure 3 The screenshot of the result of the outlier detection for the turbine exhaust temperature conducted using the original dataset

Tukey's Fences with k = 1.5			
Q1:	373.0000	Lower Fence:	224.5000
Q3:	472.0000	Upper Fence:	620.5000
IQR:	99.0000	Multiplier (k):	1.5000

Upper Outliers (Number of upper outliers =71)	Lower Outliers (Number of lower outliers =2)
791.0000, 795.0000, 813.0000, 863.0000, 864.0000, 866.0000, 867.0000, 869.0000, 871.0000, 872.0000, 873.0000, 874.0000, 875.0000, 875.0000, 878.0000, 878.0000, 881.0000, 881.0000, 881.0000, 881.0000, 882.0000, 882.0000, 883.0000, 883.0000, 883.0000, 883.0000, 884.0000, 884.0000, 885.0000, 887.0000, 887.0000, 890.0000, 891.0000, 892.0000, 893.0000, 893.0000, 893.0000, 894.0000, 894.0000, 894.0000, 895.0000, 897.0000, 899.0000, 899.0000, 900.0000, 900.0000, 901.0000, 903.0000, 904.0000, 905.0000, 909.0000, 909.0000, 910.0000, 910.0000, 911.0000, 911.0000, 916.0000, 918.0000, 919.0000, 920.0000, 921.0000, 921.0000, 922.0000, 924.0000, 925.0000, 929.0000, 931.0000, 933.0000, 941.0000, 950.0000, 954.0000	5.4000, 5.5000

Figure 4 The screenshot of the result of the outlier detection for the turbine exhaust temperature conducted after the records with missing data items were removed

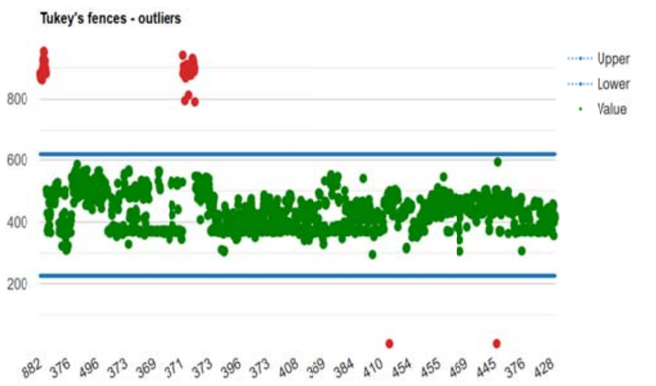

Figure 5 The scatter plot showing the outlier detection based on the turbine exhaust temperature

Figure 6 The box and whisker plot showing the outlier detection based on the turbine Exhaust temperature

Tukey's Fences with k = 1.5			
Q1:	389.0000	Lower Fence:	321.5000
Q3:	434.0000	Upper Fence:	501.5000
IQR:	45.0000	Multiplier (k):	1.5000

Upper Outliers (Number of upper outliers =71)	Lower Outliers (Number of lower outliers =5)
878.0000, 903.0000, 918.0000, 921.0000, 922.0000, 923.0000, 925.0000, 931.0000, 931.0000, 933.0000, 934.0000, 1101.0000, 1108.0000, 1200.0000, 1202.0000, 1202.0000, 1203.0000, 1203.0000, 1203.0000, 1204.0000, 1211.0000, 1211.0000, 1212.0000, 1214.0000, 1217.0000, 1217.0000, 1218.0000, 1220.0000, 1221.0000, 1222.0000, 1222.0000, 1222.0000, 1223.0000, 1225.0000, 1227.0000, 1229.0000, 1230.0000, 1230.0000, 1231.0000, 1233.0000, 1235.0000, 1235.0000, 1235.0000, 1236.0000, 1236.0000, 1237.0000, 1241.0000, 1241.0000, 1242.0000, 1242.0000, 1244.0000, 1245.0000, 1246.0000, 1250.0000, 1253.0000, 1255.0000, 1256.0000, 1256.0000, 1256.0000, 1258.0000, 1259.0000, 1260.0000, 1261.0000, 1262.0000, 1265.0000, 1271.0000, 1271.0000, 1271.0000, 1280.0000, 1281.0000, 1288.0000	226.0000, 271.0000, 301.0000, 305.0000, 321.0000

Figure 7 The screenshot of the result of the outlier detection for the turbine Wheelspace temperature conducted after the records with missing data items were removed

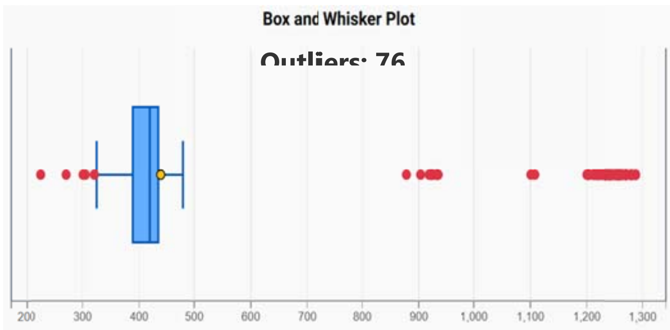

Figure 8 The box and whisker plot showing the outlier detection based on the turbine Wheelspace temperature

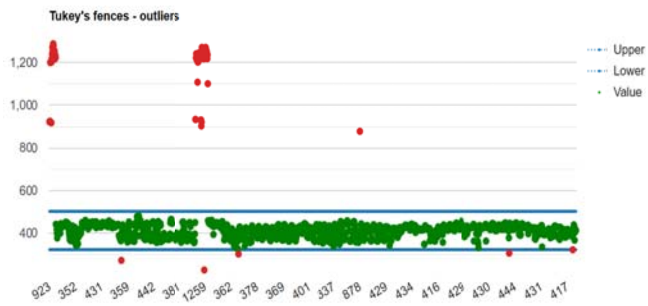

Figure 9 The scatter plot with fitted line for the ctual and the predicted turbine Wheelspace emperature

3.3 The results of the model prediction and erformance evaluation

The results of the test for significance of the xplanatory variables when all the explanatory ariables are considered in the MLR model training for ie turbine exhaust temperature are presented in able 5. In Table 5, the P-value for the Time variable is 0.0683114 which is above the significance level of 0.05 used for the confidence level analysis. Hence, the results showed that the Time variable is not significant in predicting the Exhaust Temperature and it is then dropped.

The results of the test for significance of the explanatory variables when only three of the variable (not including Time) are considered in the MLR model training are presented in Table 6. Based on the results presented in Table 6 the MLR model for the prediction of the Exhaust Temperature (not including Time) is expressed as shown in Equation 2.

Exhaust Temp (Deg F) = 88.836113 + 1.413253 Output Power (MW) + 0.635481 Wheelspace Temp 1 (DEG F) - 0.302274 Day (2)

The scatter plot with fitted line for the actual and the predicted turbine exhaust temperature is presented in Figure 10 while the prediction performance of the MLR model for the turbine exhaust temperature is presented in Table 7. The results show that the model has MAE of 13.49557, RMSE of 26.92566 and R-squared value of 0.932712 which show that 93.27 % of the variance in the Exhaust Temperature is explained by the explanatory variables in the MLR model in Equation 2.

Table 5 The results of the test for significance of the explanatory variables when all the explanatory variables are considered in the MLR model training for the turbine exhaust temperature

Independent variables	Coefficients	p-value
b	89.947367	1.11022e-16
Output Power (MW)	1.427525	1.11022e-16
Wheelspace Temp 1 (DEG F)	0.636285	-2.22045e-16
Day	-0.302274	4.44089e-16
Time (Hour in a day)	-0.205059	0.0683114

Table 6 The results of the test for significance of the explanatory variables when 3 out of the 4 explanatory variables are considered in the MLR model training for the turbine exhaust temperature

Independent variables	Coefficients	p-value
b	88.836113	0
Output Power (MW)	1.413253	0
Wheelspace Temp 1 (DEG F)	0.635481	0
Day	-0.302274	1.55431e-15

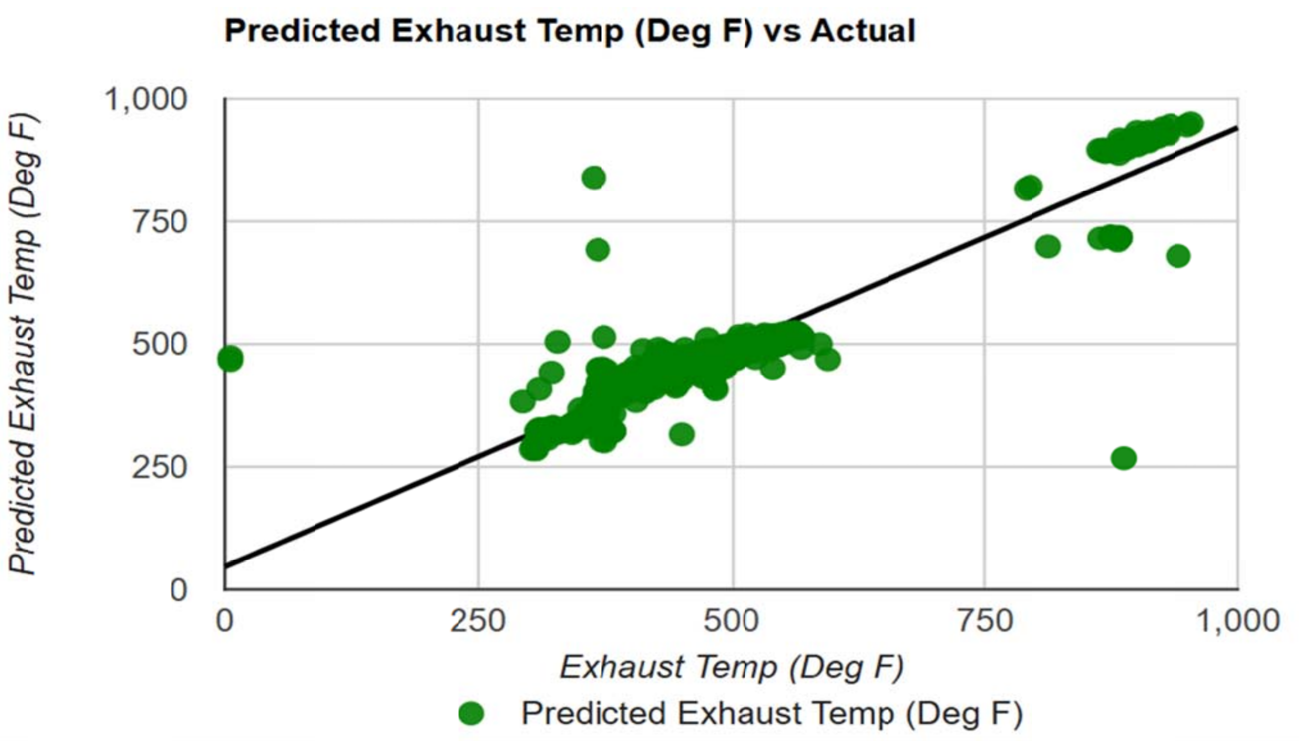

Figure 10 The scatter plot with fitted line for the actual and the predicted turbine exhaust temperature

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Table 7 The prediction performance of the MLR model for the turbine exhaust temperature

MAE	MSE	RMSE	R^2	MAPE
13.49557	724.991	26.92566	0.932712	9.89%

Similarly, the MLR model for the prediction of the Wheelspace Temperature (not including Time) is expressed as shown in Equation 3.

Wheelspace Temp 1 (DEG F) = -62.303503 - 2.02206 Output Power (MW) + 0.288834 Day + 1.388409 Exhaust Temp (Deg F) (3)

The scatter plot with fitted line for the actual and the predicted turbine Wheelspace temperature is presented in Figure 11 while the prediction performance of the MLR model for the Wheelspace temperature is presented in Table 8. The results show that the model has MAE of 25.56581, RMSE of 49.74893and R-squared value of 0.887554 which show that 88.76 % of the variance in the Wheelspace Temperature is explained by the explanatory variables in the MLR model in Equation 2.

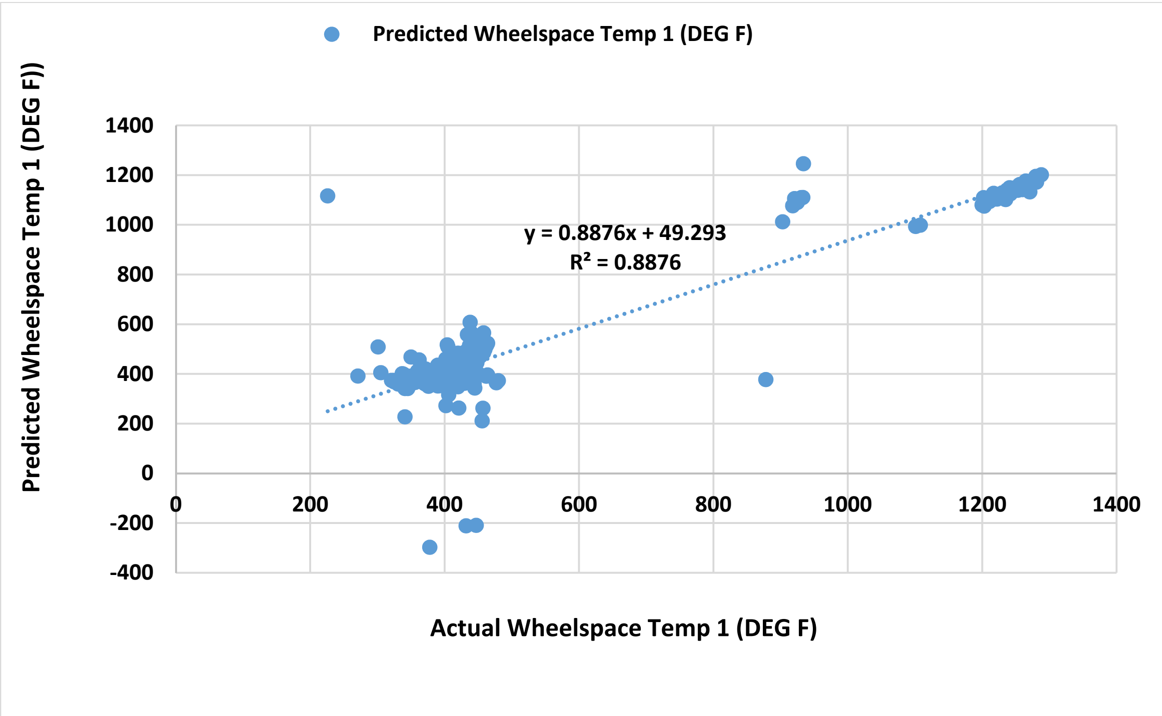

Figure 11 The scatter plot with fitted line for the actual and the predicted turbine Wheelspace temperature

Table 8 The prediction performance of the MLR model for the turbine Wheelspace temperature

MAE	MSE	RMSE	R^2	MAPE
25.56581	2474.956	49.74893	0.887554	5.67%

4. Conclusion

The model training and evaluation for prediction of power gas turbine exhaust temperature and the turbine Wheelspace temperature is presented. The Multiple Linear Regression (MLR) model is used. The dataset is obtained for a case study gas power plant in Akwa Ibom State Nigeria. The data is pre-processed to identify and handle missing data and outliers. Two MLR models were presented, the first MLR model is for the prediction of the power gas turbine exhaust temperature while the second MLR model is for the prediction of the power gas turbine Wheelspace temperature. The results showed that there are numerous outliers in the dataset and the MLR models have good prediction performance with R-squared value above 0.88 in both cases. The MLR models are expected to be employed in predictive maintenance framework which uses the predicted power gas turbine exhaust temperature and the turbine Wheelspace temperature to identify possible fault or abnormal state of the turbine and then trigger maintenance status for the turbine orperators.

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