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Modeling and Prediction of the Temperature Spread Variation for Evaluation of Gas Turbine Performance

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Abstract: ***This study presents modeling, analysis and prediction of the temperature spread variation for a 110 MW GT11N2-3VGV Alstom Gas Turbine at the Kpone Thermal Power Station (KTPS) for the purpose of optimised operation. The study focuses on the temperature spread variation around the mean point of the turbine section since uneven distribution of temperature around this section leads to severe deformation. A data-driven statistical analysis called Time Series Modeling was used as a tool for predicting the temperature spread variation of the gas turbine. Analysis of historical monitoring data of the industrial turbine informed the use of first order autoregressive model (AR (1)). The validity of the proposed autoregressive mode was tested using data covering three months logged from the Egatrol 8.0 software interface and the model was verified using residual analysis. The study revealed that the temperature spread at any instant follows an autoregression model of order one (1) with 95% confidence limits and an error of ±3.01. Hence, the AR (1) model can be used to predict the thermal health of the turbine as well as determine when maintenance should be conducted***.

Keywords: Gas Turbine, Temperature Spread, Autoregressive Model, Time Series.

1. Introduction

Safe, adequate, affordable and reliable supply of power is one of the critical factors for sustained economic growth in developing countries. Research has shown that economic growth and development have a strong correlation with electricity use [1]**.** This correlation implies a critical reliance on the availability of electricity for economic growth. Likewise the availability of electricity is dependent on the availability and reliability of generation, transmission and distribution infrastructure.

Since 1997 to date, the state-owned Volta River Authority (VRA) and other Independent Power producers (IPP's) have built a number of thermal power Plants that operate on Natural Gas, diesel fuel oil (DFO) and Light crude oil (LCO) fired thermal plants to meet peak power demands and to provide back up in the event of shortfalls in hydroelectric power. As result, there is need for Ghana's thermal power generation to be given critical attention for effective operation. Ghana currently has a gross installed generating capacity of 3,737 MW out of which 2,134.5 MW (representing 57.12%) is from thermal sources. Hydropower (1580 MW) and Solar PV power (22.5 MW) constitute 42.28 % and 0.60%, respectively [2]. The Volta River Authority (VRA) projects an annual demand growth rate of 200 MW of electric power; making the need for supply availability and reliability all the more heightened if Ghana's economic development trajectory is to be maintained. To meet this demand, Ghana can only rely on efficient thermal power generation as the nation's untapped hydro-power generation resources do not hold much promise [3].

Temperature spread variation may be used to determine the thermal health status of a gas turbine. Most temperature spreads are the result of combustion anomalies that can lead to tragic failures. High capacity gas turbines mostly employ multiple combustors, called '***can annular combustors***,' each of which produce high temperature gases that are directed to the first stage nozzles of the turbine section in a manner intended to generated torque. Most temperature spreads are the result of mechanical problems; typically, plugged fuel nozzle orifices, enlarged fuel nozzle orifices, fuel nozzle assembly problems, fuel flow divider defects (for liquid fuel fired turbines), and failed liquid fuel check valves. Detection of combustion chamber malfunction relies on comparisons of thermocouples located circumferentially at a convenient point in the hot gas path. The method usually recommended by engine manufacturers compare absolute values taking no account of any initial asymmetry due to manufacturing tolerances, thermocouple positioning or turbulence of the gas flow at the measurement point [4]. Currently, there is no model available for the monitoring of temperature spread variation in Gas turbine operation in Ghana.

The main aim of this work is to optimise the operation of the thermal power generation plant at the Kpone Thermal Plant Station (KTPS) through monitoring, modeling and prediction of the temperature spread around the mean point of the turbine section on the gas turbine train using the Time Series approach. This will also serve as a guide to enhance the effectiveness of maintenance works.

2. Description of equipment

Figure 1 shows a sectional view of the 110 MW capacity GT11N2-3VGV Alstom gas turbine at the Kpone Thermal Plant Station. Essential components of the plant set up include the thermal block, generator block, control valve block, auxiliary block, fuel oil / fuel gas block, NOx water block, air Intake system, exhaust system, electrical and control modules.

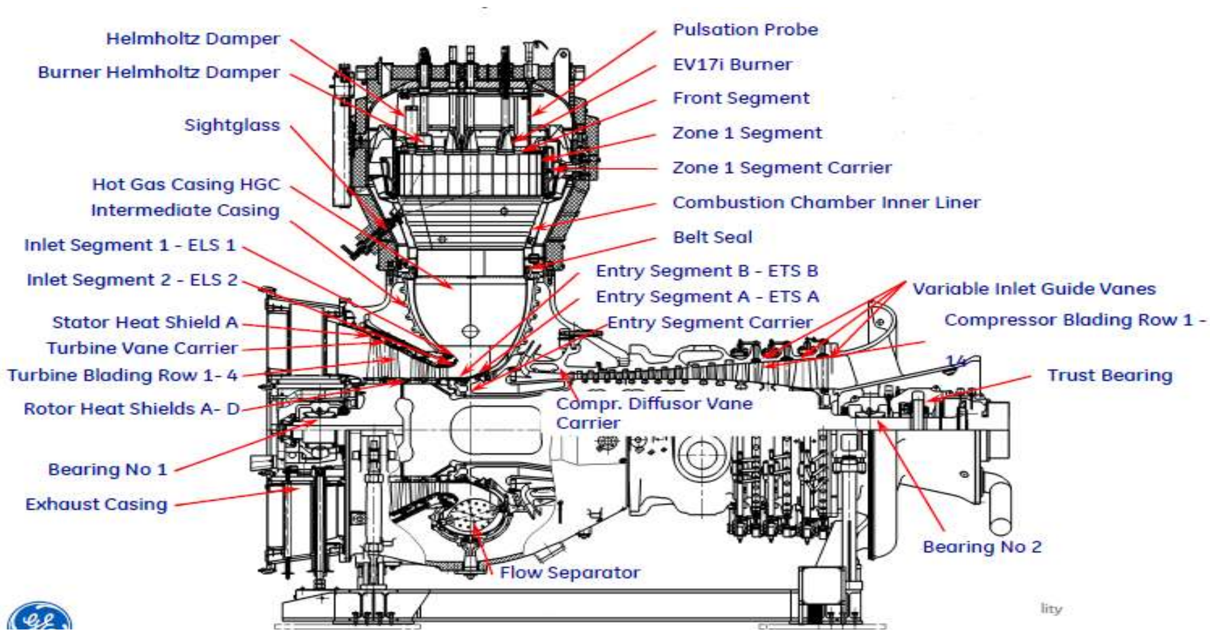

Figure 1: Sectional view of GT11N2-3VGV gas turbine

This model of the Alstom turbine comprises of fourteen (14) compressor stages, four (4) turbine stages and operates at a nominal speed of 3600 rpm with a frequency range of 50 to 60 Hz. The turbine is operated with a gear box to attain a frequency of 50 Hz. Table 1 shows pertinent technical performance data.

Table 1: Technical performance data sheet (At ISO conditions)

Parameter	Value
Fuel	Natural gas
Gross electrical output	113.6 MW
G Gross electrical efficiency	33.3%
Gross heat rate	10,811 kJ/kWh
Compressor pressure ratio	16.01:1
Exhaust gas flow	400 kg/s
Exhaust gas temperature	525 ^{o}C
NOx emissions (at 15% O_2)	< <25 vppm

Source: [5]

The Fuel / NOx water supply system is the source of fuel supply to the combustor for the combustion process in effective running of the Gas turbine. The standard operation of ALSTOM gas turbines is with gaseous fuel only. Fuel oil is the optional backup fuel. The fuel oil system supplies fuel oil to the burners of the gas turbine for combustion. At the defined gas turbine speed during operation with fuel oil, injection of NOx water is provided by the NOx water system to lower the emission levels of nitrous oxides (NOx) in the exhaust to prescribed levels and also for combustion stabilization, lance cleaning and purging of residual fuel oil from the fuel oil distribution system. The fuel oil system and its functional units increase and regulate the fuel oil pressure to control the flow rate to each lance for combustion. The fuel oil system supplies the EV burners with fuel oil for combustion for the following specified parameters: quality, pressure, temperature and flow rate.

Maximum temperature spread is defined as the proportional distribution of temperature around the mean point of the turbine section on the GT train. Too much deviation of this value from the mean point will heighten the tendency of deformation. Its relevance in effective gas turbine monitoring and operation is to inform the operator the degree of temperature received by the turbine blade and hardware (turbine inner shell) so that measures can be taken to avoid the occurrence of deformation hence, optimise the operation efficiency of the gas turbine.

3. Methodology

Temperature data measured at hourly intervals over a three months period was used for the analysis. However, a limited amount of data is shown in the analysis because of space restrictions. The type of model used was determined by plotting the spread temperature monitored at hourly intervals (Fig.2). The trend established in Fig. 2 indicates random behaviour hence, the study makes use of a stochastic model for data analysis.

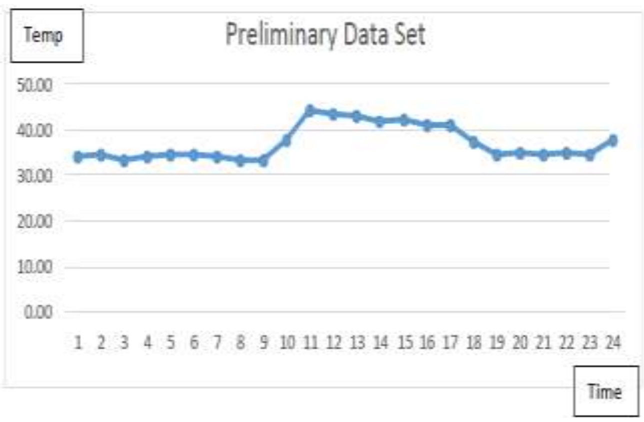

Figure 2: Time series Plot of Representative Temperature

Time Series Modeling and Analysis

The time series model is represented by

$$X_t = \Sigma\varphi_j X_{t-j} + a_t \qquad (1),$$

where φ_j are autoregressive parameters, a_t is the error associated with the observation, X_t and j = 1, 2, 3, 4, …n. These Autoregressive Models are shorthanded as **AR (n)** where n is the order of the model and n is how far back X_t depends on its past values.

Specifically;

AR (1) model represents the model: $X_t = \varphi_1 X_{t-1} + a_t$

AR (2) model represents the model: $X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + a_t$

AR (3) model represents the model: $X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \varphi_3 X_{t-3} + a_t$

Once the autoregressive parameters are determined, the model can be used to predict future values of X_t (that is X_{t+1}, X_{t+2}, X_{t+3}, ….. X_{t+j})

Estimation of Model Order and Parameters

The first order model (n=1) or AR(1) is the simplest model that recognizes the dependence of the current data on the immediate past data. To verify this dependence, a scatter plot of X_t versus X_{t-1} is made (see Fig. 3)

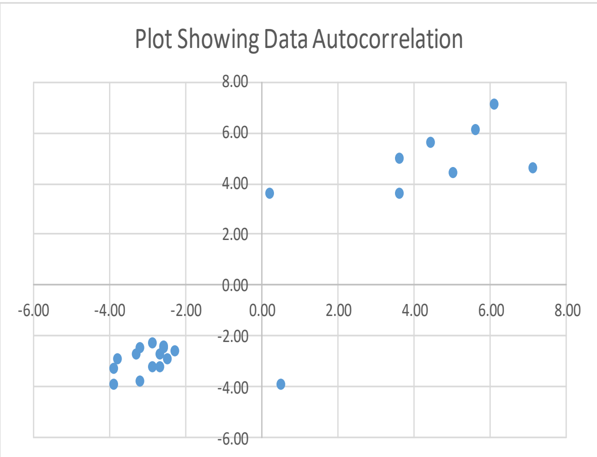

Figure 3: Scatter Plot of X_t versus X_{t-1} for Exploratory Temperature Spread Data

Figure 3 indicates linear dependence of successive data.

Therefore, the study would investigate the use of first order autoregressive model, AR (1) for analysis and prediction. The next step is to estimate the autoregressive parameter φ_1 and the probabilistic parameters that define the system. As with any modeling technique, the best set of parameters are those that minimize the sum of squares of the errors (residuals). Using this approach, the value of the first order autoregressive parameter φ_1 can be found as:

$$\varphi_1 = \Sigma X_t . X_{t-1} / \Sigma X^2_{\ t-1} \text{ from } t = 2 \text{ to } t = N.$$

For the best fit, the errors must have a mean of Zero and a variance of $\sigma_a^2 = (1/N)\ \Sigma a_t^2$.

4. Data Analysis and Discussions

Monitoring of the operation of the power plant is automated with a fully instrumented computerized system that runs on Egatrol 8. Parameters monitored include fuel/NOx water supply system, stator temperature, cold air temperature, hot air temperature, temperature spread, diesel fuel oil temperature, gas fuel flow, gas fuel temperature, temperature spread, lube system parameters and excitation system parameters. Table 2 shows part of the data used for the modeling procedure.

Table 2: Observed Temperature Spread Data

Day 1		Day 2		Day3		Day 4		Day 5		Day 6		Day 7	
Obs	Temp	Obs	Temp	Obs	Temp	Obs	Temp	Obs	Temp	Obs	Temp	Obs	Temp
1	29.5	25	33.6	49	43.2	73	43.6	97	35.5	121	39.8	145	36.5
2	29.7	26	34.2	50	43.4	74	43.1	98	35.1	122	36.0	146	36.7
3	28.8	27	34.7	51	42.5	75	44.3	99	35.1	123	35.7	147	35.5
4	39.5	28	34.7	52	41.5	76	42.4	100	35.0	124	36.1	148	36.0
5	28.9	29	34.1	53	42.1	77	42.5	101	35.9	125	35.9	149	36.6
6	29.6	30	33.5	54	41.0	78	43.2	102	36.2	126	36.1	150	36.4
7	39.7	31	33.5	55	42.3	79	43.3	103	35.2	127	36.2	151	36.2
8	39.7	32	42.0	56	35.8	80	41.5	104	35.1	128	36.2	152	36.4
9	41.9	33	44.5	57	35.4	81	43.5	105	34.8	129	35.8	153	36.3
10	41.9	34	43.5	58	35.5	82	35.1	106	34.3	130	36.4	154	36.9
11	41.9	35	43.0	59	35.2	83	35.7	107	34.9	131	36.3	155	36.6
12	41.9	36	41.8	60	35.3	84	35.2	108	35.4	132	36.8	156	36.5
13	40.2	37	42.4	61	35.2	85	35.2	109	36.0	133	36.9	157	36.9
14	40.2	38	41.0	62	34.8	86	35.9	110	36.7	134	36.6	158	36.2
15	40.2	39	41.0	63	35.0	87	34.5	111	36.8	135	36.4	159	36.6
16	40.2	40	35.0	64	34.5	88	35.0	112	36.1	136	36.9	160	43.3

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17	40.2	41	34.8	65	34.7	89	43.0	113	36.7	137	36.3	161	43.3
18	41.5	42	35.1	66	34.1	90	35.2	114	36.6	138	36.2	162	43.3
19	40.2	43	34.5	67	34.4	91	34.5	115	36.2	139	35.3	163	44.7
20	40.2	44	34.9	68	35.4	92	35.2	116	36.3	140	35.7	164	42.3
21	40.2	45	34.8	69	35.6	93	35.3	117	35.8	141	35.8	165	44.0
22	34.9	46	41.5	70	35.0	94	35.2	118	35.9	142	35.6	166	41.8
23	34.2	47	41.0	71	34.0	95	35.2	119	35.9	143	35.8	167	35.7
24	34.5	48	42.4	72	43.8	96	35.2	120	36.0	144	36.0	168	36.4

Fig. 4 shows a plot of observed data against time whereas Fig. 5 show the plot of model data against time. The model data used for plotting Fig. 5 was generated using the average ***average subtracted data*** defined as X_t = Observed Data – Data Average. It can be observed that both figures (Fig. 4 and Fig. 5) exhibit identical variation with time. Secondly, a closer observation of both scenarios show that Fig. 4 is centered around the mean value of the data while Fig. 5 is centered around Zero.

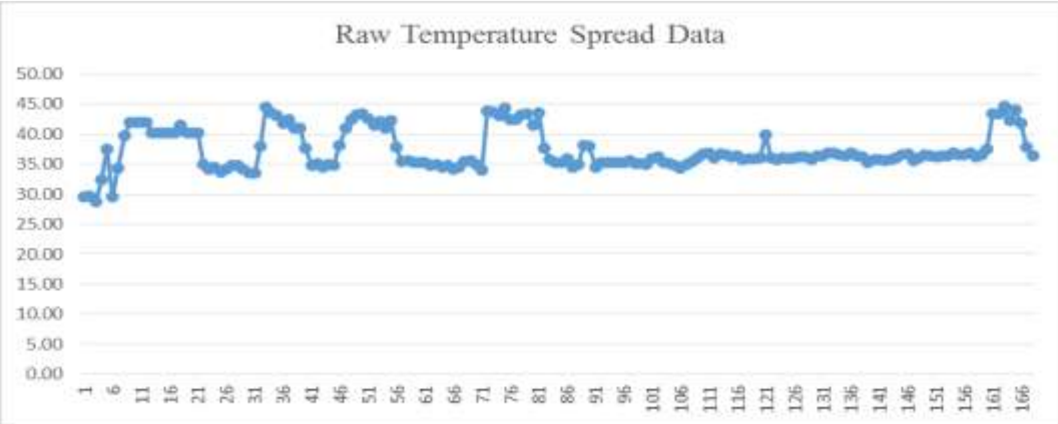

Figure 4: Spread Observed Data

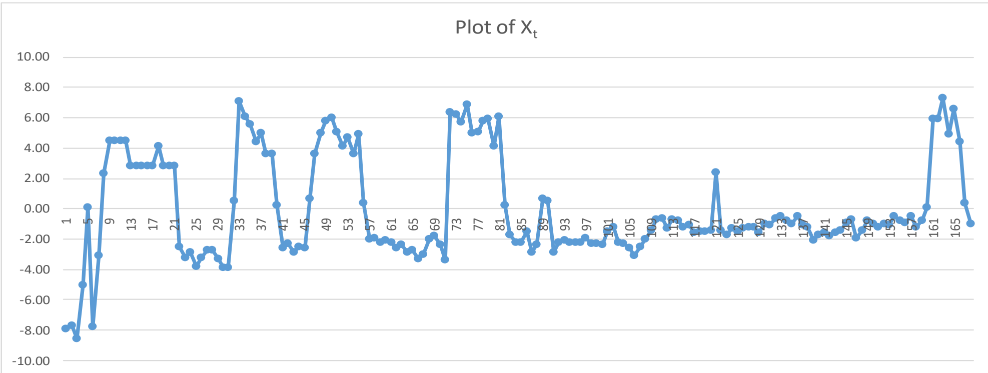

Figure 5: Temperature Spread variation of Model Data

In order to determine the validity of using an autoregressive model, a scatter plot of X_t versus X_{t-1} is generated as shown in Fig. 6.

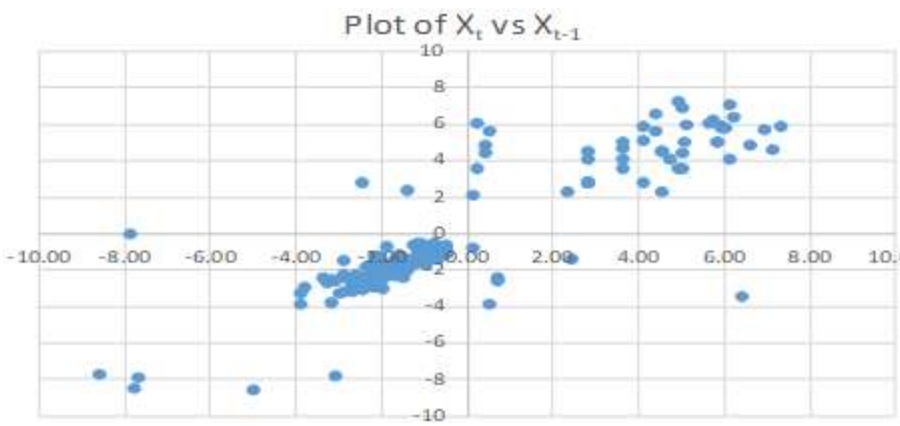

Figure 6: Scatter Plot of X_t versus X_{t-1}

It is revealing from Fig. 6 that the points are scattered around a straight line through the origin. The straight line trend shows that X_t is dependent on X_{t-1}. Using a simple regression method that minimizes the sum of squares of the errors, the autoregressive parameter φ is obtained to be 0.836. Therefore, temperature spread may be described by:

$$X_t = 0.836X_{t-1} + a_t \qquad (2)$$

The rather large value of φ indicates a strong dependence on relation between X_t and X_{t-1}.

Check for Model Adequacy

It was established that there is a strong dependence of X_t on X_{t-1}. However, there could be dependence of X_t on X_{t-2}, X_{t-3}, and so on leading to higher order AR (n) models. Thus, there is the need to check such dependence. Figure 8 shows a plot of X_t versus X_{t-2}. The data seems to be scattered and does not show the strong linear relationship as in Fig. 6. Therefore, there is no clear evidence that a higher order model is needed.

Figure 7 shows a plot of X_t versus X_{t-2}. The data seems to be scattered and does not show the strong linear relationship as in Figure 6 which shows the dependence of X_t on X_{t-1}. Therefore, there is no clear evidence that a higher order model is needed.

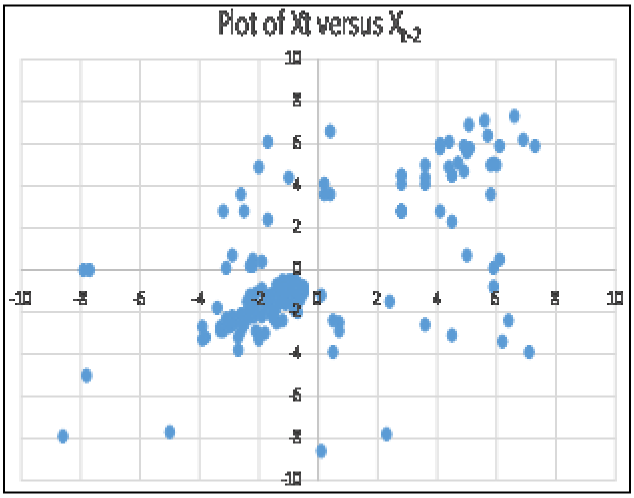

Figure 7: Scatter Plot of X_t versus X_{t-2}

Figure 8 shows the X_t data obtained from the observation with X_t generated from the model superimposed on it. The similarity of the two plots is one of the proofs of the adequacy of the AR(1) model to describe the system. Inspection of Figure 8 shows deviations of the data series from the model series. These deviations are the errors or residuals. The statistical nature of these errors allows us to estimate the confidence intervals of each measurement. For the model to be complete, the variance of the errors (a_t) is needed. The errors are assumed to be random with a mean value of Zero and a variance, $\sigma_a^2 = (1/N)\, \Sigma a_t^2$.

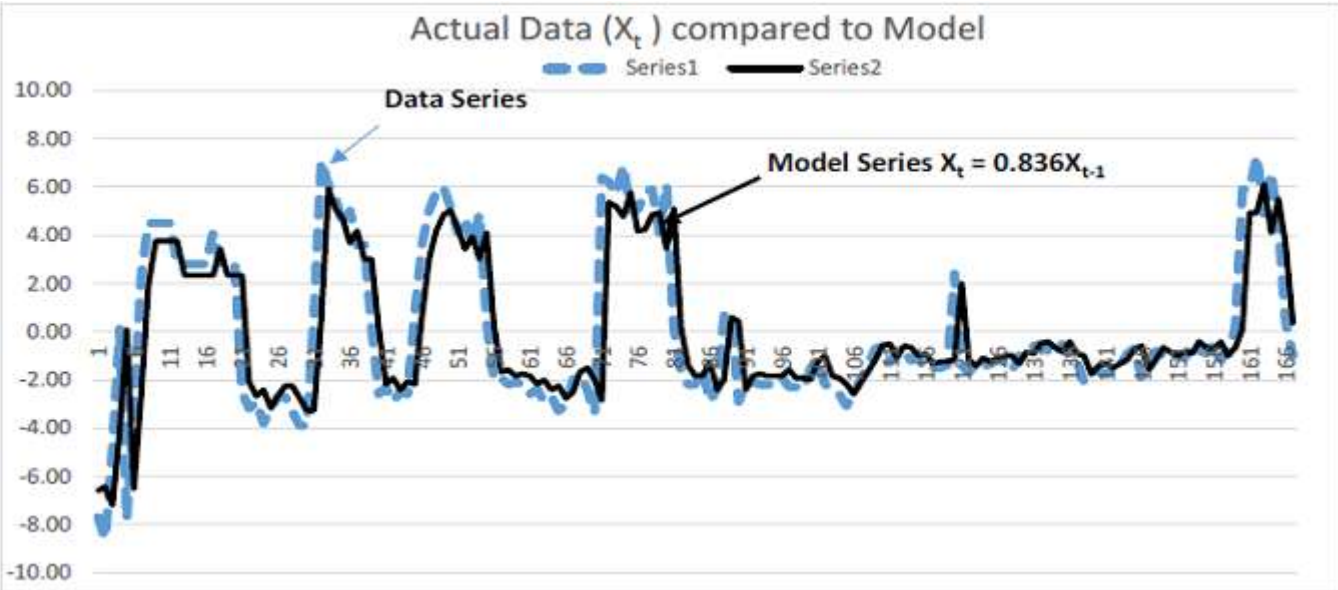

Figure 8: Comparison of the Data Series and the Model Series

The variance of the errors was obtained to be 2.36. Thus, the errors are Normally Independently Distributed with Mean of Zero and Variance of 2.36 (that is $a_t \sim NID\ (0, \sigma_a^2)$).Thus the complete statistical model for the prediction of the spread is:
Predicted model value

$$X_t = 0.836X_{t-1} + a_t \qquad (3)$$

and a_t = NID (0, 2.36)

Since the number of observations are statistically large, Z-Distribution is used to estimate the error at each observation. The error at the 95% Confidence is then $\mathbf{e_t = \pm 1.96 * \sqrt{2.36} = 3.01}$. Finally, the prediction of the observed value is: (X_t + Average) ± 3.01. Table 3 shows the observed values and the predicted values for a 24-hour period. Comparing observed values with predicted values, it is observed that the observed values fall within the 95% confidence limits of the predicted values. Hence, the prediction model is validated. The results of the study compares reasonably well with the findings of [6] irrespective of the slight difference in approah. [6] deployed a fusion approach based on fuzzy C-means (FCM) clustering algorithm and support vector machine (SVM) classification model to monitor and diagnose the exhaust gas temperature of a gas turbine. The historical monitoring data of EGT from an industrial gas turbine was analyzed and used to verify the performance of the fusion fault diagnosis approach. The study showed that the SVM multiclassification model can effectively diagnose the fault of gas turbine EGT with a 95% accuracy rate for the testing samples.

Table 3: Comparison of Observed Values and the Predicted Values

No.	Observed June 26,2016	Predicted Value (X_t+Average)	95% Confidence Limits of Predicted Values; (error = ±3.01)	Accuracy Y/N
1	40.5	-	-	-
2	38.5	40.1	37.09, 43.11	Y
3	38.0	38.5	35.49, 41.51	Y
4	38.0	38.0	34.99, 41.01	Y
5	39.0	38.0	34.99, 41.01	Y
6	39.9	38.9	35.89, 41.91	Y
7	39.0	39.6	36.59, 42.61	Y
8	37.6	38.9	35.89, 41.91	Y
9	37.6	37.7	34.69, 40.71	Y
10	39.3	37.7	34.69, 40.71	Y
11	37.1	39.1	36.09, 42.11	Y
12	37.7	37.3	34.29, 40.31	Y
13	36.5	37.8	34.79, 40.81	Y
14	36.1	39.1	36.09, 42.11	Y
15	37.1	36.5	34.09, 39.51	Y
16	39.9	37.3	34.29, 40.31	Y
17	36.9	39.6	36.59, 42.61	Y
18	38.9	37.1	34.09, 40.11	Y
19	39.7	38.8	35.79, 41.81	Y
20	38.1	39.5	36.49, 42.51	Y
21	38.7	38.1	35.09, 41.11	Y
22	37.1	38.6	35.59, 41.61	Y
23	37.4	37.3	34.29, 40.31	Y
24	39.5	37.5	34.49, 40.51	Y
Average	38.3			

5. Conclusions

The thermal power plant consists of several subsystems that must operate together to achieve the overall goal of producing power. The gas turbine is considered as a major component of the system. The main purpose of this work is to optimise the operation of the gas turbine by developing a model that can predict temperature spread variation. Considering the distribution characteristics of the gas turbine temperature spread and its effect on the thermal health condition of the gas turbine, an autoregressive model is proposed and successfully applied to an industrial gas turbine in this study. It can be concluded that an autoregressive model of order one, AR(1) describes the dynamics of the temperature spread variation at any time. Based on the results shown in table 5, it is demonstrated that the autoregressive model, AR(1) can effectively predict the temperature spread around the mean point of the turbine section within a margin of error of ± 3.01 with 95% confidence. Hence, the model has a great potential to improve the conduct of maintenance operations so far as the gas turbine used is concerned. It is worth noting that the scope of this work does not include exhaust gas conditions at the inlet of the first stage turbine. Therefore, more studies and improvement about the application of this approach are needed further.

6. Acknowledgments

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