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Gas Turbine Bearing Temperature Monitoring via Regression Modelling

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***Abstract**: This paper focuses on using Regression technique (MLR) towards finding solution to incidence of high compressor bearing temperature on one of the units at Geregu power plant in Ajaokuta, Nigeria. Monitoring of parameters related to the bearing temperature was carried out to find out causes for the high bearing temperature fault and came up with successful diagnosis by interrelating the gas turbine current lube oil test results of parameters like the kinematic viscosities, % concentration of additives and flash point with reference and standard VG46 lube oil data published in literature. Using statistical tools like the Pearson correlation and co-variant metrics for the five-years, the oil viscosities at 100^oC and 40^oC were selected as the input of the MLR model based on their Pearson coefficients of (-98.08%) and (-99.68%) respectively relative to the compressor bearing temperature. The MLR model for the bearing temperature prediction gave a root mean square error of 0.121 and coefficient of determination (R^2) of 99.71%. The model predicts that by the 2^{nd} quarter of 2025, the bearing temperature would have reached the alarm point (90^0C) from the current value of 85^0C and that by the 1^{st} quarter of 2027, the bearing temperature would have reached the trip point (120^0C). Conclusion reached is that a well formulated data driven model can reliably forecast bearing temperature and together with sensors aid in gas turbine condition monitoring. Likewise, it is concluded that shearing due to the consistent high temperature operation of the gas turbine lube oil is responsible for the depletion of the Zinc (-23.9%) and Magnesium(-26%) additives leading to the decay in the viscosity and consequent bearing temperature increment. Recommendation made is to either replenish oil with anti-wear additives or completely replace the oil to minimize the bearing wear rate and thus the bearing temperature.*

Keywords: Regression, gas turbine, lubricant, bearing temperature, RMSE.

1. INTRODUCTION

Gas turbines are essential in many industrial establishments be it for power generation, propulsion of aero planes, ships or trains. Gas turbines have a lot of accessories/auxiliaries ranging from Bearings, seals, couplings, bolts and others. In order to see out its design life cycle, the gas turbines especially industrial gas turbines which are relatively larger need stability and integrity. This stability and integrity is especially important for the rotating components such as the shaft which interlinks several components like the compressor, combustor, turbine and major auxiliaries like the generator. The shaft is a link where several sources of energy are transmitted from one source to another until the final conversion from mechanical to electrical output. To conveniently undertake its function, the shaft needs to be fully and properly supported on the bearings so as to prevent catastrophic damage to lives and equipment. Feroz and Jabri [1] reported that the optimum support and positioning needed by the rotating components is provided by the bearings in gas turbine and steam engines. Boyce [2], stated that when bearings are designed, long service life, high degree of reliability and efficiency are paramount .The likes of Nicholas [3], and Malcom and Leader [4] said that for the proper functioning of the bearings, factors like bearing speed, the bearing lubrication oil type and the oil viscosity at operating temperature need to be considered. Malcom and Leader [4], further mentioned that the most important aspects considered for health and longevity of bearings are installation, proper lubrication and the hydrodynamic load on the bearing surface.

In spite of several precautions taken by operators to ensure bearings keep performing their primary function of providing support and balance to the gas turbines, like every other equipment, component failure arises over time either due to the effect of operating conditions or other faults. The prominent bearing manufacturing company SKF in their publication [5] in 2017, reported that bearing failure could arise due to excessive heat, noise, vibration and shaft movement. SKF further stated that the above mentioned causes of bearing failure could originate because of high bearing speed, rubbing effect, contamination and bearing damage respectively. It is stated in [3] that many bearing instability problem is due to increase in the bearing clearance as a result of wear caused by oil contamination or because of repeated gas turbine start-ups. Malcom and Leader [4] also reported that bearing failures could be due to metal to metal contact from gas

turbine start-up, or from foreign materials in the lubricant, or as a result of fatigue damage, imbalance or because of excessive vibration. McCloskey [6] concluded that bearing failure is a leading contributor of gas turbine unavailability.
High bearing metal temperature is one of the most critical bearing faults as it could lead to tripping of the gas turbine or even component failure and subsequent loss of revenue. Totten [7] enumerated the cause of high bearing metal temperature to include high vibration amplitudes, high inlet and drain oil temperature, low oil film pressure. In the publication of SKF [5], it is reported that an increase in bearing temperature could occur due to excessively high operating speed, seal misalignment, large temperature difference between the shaft and the bearing housing or due to improper seal lubrication. According to [2], high bearing metal temperature could lead to creeping of the metal surface as a result of white metal softening and [6] reported that such astronomical bearing temperature increment could lead to deterioration of bearing physical properties and thus fatigue failure.

Feroz and Jabri [1] used Fish bone diagram for root cause analysis based on available data and historical trend to investigate the causes of high thrust bearing metal temperature in a gas turbine plant in Oman. Bore-scope inspection, X-ray diffraction, lube oil analysis, and the mean time between failures were utilized to classify the causes under design, material, installation and operations. The duo thus, concluded that high bearing temperature is caused by a multitude of factors ranging from the poor performance of lube oil cooler system to insufficient bearing clearance and particle accumulation in oil filters /scrubbers. Russo [8], stated that when the amount of heat conducted away from the bearing to the housing and the shaft during the conversion process of friction (from moving parts) to heat is low, then the non-equilibrium between the heats in different units is reflected by the high bearing temperature. The consistent increment of the bearing temperature for rotating equipment like the gas turbines will warrant measures like load reduction, to be able to maintain bearing temperature below the alarm point and such output reductions lead to massive revenue loss. Thus, together with parameters like vibration, bearing temperature monitoring is one of the most significant and important gas turbine non gas path parameter which needs to be constantly monitored to enhance revenue, equipment longevity and safety of manpower.

According to Matzan [9] in Noria corporation publication of 2007, vibration, acoustic and oil wear monitoring are given more priority compared to bearing metal temperature monitoring in spite of the huge implication of failure due to high bearing temperature. Almeida [10] stated that bearing temperature increment could be monitored through bearing wear and tear from friction and through the returning oil temperature from the bearings back to the sump tank. Generally, the traditional mode of monitoring bearing metal (Babbitt) temperature is via thermocouples installed at different locations within the Babbitt surface. Gokaltun [11] and Zhou [12] said that the installation of thermocouples within the bearing pads is mostly in line with API 670 specifications. The authors thus, postulated that the sensitivity of the thermocouples is highly dependent on the location they are installed. Zhou [12] further reported that Ettles et al, used thermocouples for polytetra Fluordethylene coated bearings (PTFE) and Babbit bearings by placing them below the Babbit/PTFE surface in order to measure the temperature around the area. Though the efficacy of the method was declared, the general complaint against it was that, it was slow to track gradual changes in bearing load and the speed; hence the sensitivity of the technique was reported to be relatively poor. considering it's high-power loss. Zhou [12] also reported that (Glavatskih, 2003) placed the thermocouple for the PTFE and Babbitt bearing below the bond line to measure the metal temperature. The technique was praised for its high sensitivity but was criticized for its inability to quickly detect sudden changes. Similarly, [12] measured fluid temperature through a hole in the pad surface, the technique was praised for its efficacy and high sensitivity but according to [12] the technique like the others before it was impeded by the slow tendency of fluid to track sudden changes despite being able to curb power loss. [12] gauged the fluid film temperature in a polyetheretherketone (PEEK) bearing by using sensor flush with pad surface to indicate bearing distress. The method was praised for tracking gradual changes of the bearing load and speed swiftly.

It can be concluded from literature, that the traditional techniques of obtaining the temperature of Babbit, PEEK or PTFE bearings; ranging from hole metal procedure to metal backing, fluid and fluid film hole are quite cumbersome and also the accuracy or sensitivity of the sensors is highly dependent on the sensor location, thus high vibration amplitude could result in sensor error and consistently cause false alarms, slow reaction times and slow tracking of fluid film changes in temperature. All these limitations could result in missing of important trackers to forewarn on approaching bearing failures incidents. To prevent bearing failure/damage, it is imperative to device other supplementary tools for bearing temperature monitoring. This can be achieved by designing a predictive model based on historical data and tied to several independent parameters which directly affect the bearing metal temperature. Such models will give prior warning and be able to pinpoint variables that are near out-of-range for correction in order to prevent instances where failures occur due to very slow response of equipment to gradual changes in parameters. This is particularly required to mitigate degradation rate which according to Matzan [9], is accelerated once bearings keep operating outside their normal/ideal temperature range. Models like the multi-linear regression (MLR) and Artificial neural networks (ANN) could come in handy to resolve such issues. Ozigis [13], reported that Karadas et al mentioned that both ANN and MLR have been found to be effective in analyzing time series data of power plants and can also perform well when exposed to random data. Thus, they could be used as handy tools in predicting tendencies for high bearing temperatures in gas turbine.

Wang and Chang [14] predicted the temperature rise of oil and air lubricated contact ball bearing using ANN models the objective was to provide an overview of temperature calculations of the bearings and to propose a new artificial intelligence-based prediction method (GA+ANN) for temperature rise forecasting. Conclusion reached was that the

ANN+GA model achieved shorter training time, higher accuracy and better stability compared to the ANN model. According to the authors, the ANN/GA model result also correlated more with the experimental data .The authors also declared that more than 92% of bearing temperature rise cases under varying conditions could be predicted using the ANN/GA model. Alias [15] used ANN model to predict temperature rise in generator transformer of a hydro-turbine, parameters like ambient temperature, power output and current were linked in weighted proportion to the temperature rise predictions that closely matched experimental results. Furthermore, Guangxi [16], reported that Astolfi et al., used a regression model based on ANN to predict wind turbine rotor bearing temperature and vibration amplitude with the inputs being wind turbine power output turbine external temperature and the wind speed. Again, the ANN model was found to have produced results very similar to field measurements. It is also reported by [16], that Abdusamad et al., used MLR model to analyze the temperature trend in wind turbine generator using power residual.

Computation prediction has also been used severally to monitor temperature profiles in bearings. Jeng and Huang [17] predicted the temperature rise of a ball bearing using a computer code that compares favourably with experimental data. In a similar trend, Laubichler [18] worked on data driven model for temperature monitoring of a sliding bearing in an internal combustion engine. Regression models like support vector, regression with Lasso boosting and without Lasso boosting were tried and the researcher concluded that the comparative studies of the models shows that the support vector regression model gave the best prediction based on the fact that it had the least root mean square error (RMSE). The authors also mentioned that the regression model combined with the heavy duty diesel engine thermocouple sensor provided a powerful tool for condition monitoring.

It can be seen that many of the works in literature are focused on the bearing temperature prediction in renewable energy sector be it hydro or wind energy. Similarly, a lot of work is also centred on temperature rise prediction of contact ball/roller bearings. The present work uniquely focused on extending bearing temperature prediction to gas turbine bearing using MLR, as there are scant research works in the area. Furthermore, the use of wide range of independent variables selected from different operating conditions of vibration and lubrication systems among others gives the work a unique feature. Thus, factors like the lube oil characteristics, the lube oil pump pressures, the lube oil cooler temperatures and bearing vibration are incorporated in the MLR model proposed in this work. Comparatively, ANN is basically better suited for interpolation between current values while for future or past data histories; the MLR is better as it can be used for extrapolatory applications.

The future prediction of the bearing metal temperature of GT13 gas power plant at Geregu in Ajaokuta Nigeria, has become necessary as the present value of the bearing Babbit metal temperature is inclining towards the alarm point set by the turbine manufacturers (Siemens). As suggested by Matzan [9], once the bearing temperatures are outside the ideal temperature range, they tend to degrade at an accelerated rate. Such situation will lead to loss of power, increase in cost of maintenance and frequent replacement of parts.

The main objective of the present work is to predict the future value of GT13 bearing temperature based on the historical values of some key independent variables related to the bearing temperature using multi-linear regression (MLR) modelling technique for the purpose of gas turbine condition monitoring.

1.1 Multi-Linear Regression Mode l (MLR)

Kanade [19], defined Linear Regression as an algorithm which provides linear relationship between independent variables and a dependent variable so as to predict the outcomes of future events. [19] also described linear regression as a statistical method widely used in data, science and machine learning for predictive analysis. [19] further gave the advantages of the technique as; easy interpretability, easy implementation, scalable and optimal for online settings.[20] defined linear regression as a procedure which estimates coefficients of linear equations involving one or more independent variable which best predicts the independent variable.[20] similarly stated that in the multiple linear regression model(MLR), Y has a normal distribution with mean giving as:

$$Y = \beta_0 + \beta_1 + X_1 + - - - + \beta_p X_p + \sigma(Y) \quad (1)$$

Where Y is the dependent variable or continuous response, $X_1, X_2, \cdots, X_p$ are the predicator variables (independent variables), $\sigma(Y)$ is the standard deviation and $\beta_1, \ldots, \beta_p$ are regression coefficients, must be estimated from the data sets.

The standard deviation gave σ is defined as the residual standard deviation estimated as;

$$\sigma_{residual} = \sqrt{\sum \frac{(residuals)^2}{n(p+1)}} \quad (2)$$

Where n(p+1) represents the number of degrees of freedom (df). The (p+1) parameters, according to [20] are estimated.
The features of regression model suggest that the variables to be predicted be continuous with similar spread across range, have no multi-collinearity and have normality of residuals. Prashnat [21], mentioned that the MLR is the extension of ordinary least square regression and that the polynomial regression type is a variant of MLR model where the best fit line is a curve rather than a straight line. Other extension of polynomial regression according to [22] is the rational regression function which is a ratio of two polynomials.

2. MATERIALS AND METHOD

2.1 Case Study (GT13 Compressor End Journal Bearing Temperature – at Geregu Power Plant, Nigeria)

This research is aimed at investigating the future value of the GT13 bearing Babbitt metal temperature at Geregu power V94.2 Gas turbine in Ajaokuta, Kogi state of Nigeria, based on the present values of some vital independent variables which directly relate to the bearing metal temperature. The investigated bearing is situated at the compressor section of the gas turbine engine. This particular bearing has consistently experienced rising temperature and the temperature is currently about 5% away from the alarm point specified by Siemens. The bearing pad Babbit material is made from Bronze. (Siemens, v94.2 Geregu manual, 2006). The Babbit metal temperature resistance is about 120 $^{o}C^{o}$ to 130 ^{o}C [3,23] and it has a surface friction coefficient of between 0.08 - 0.3 [24]. The Bronze Babbitt also has a linear expansivity of $1.8 \times 10^{-5} \frac{m}{m\,^{o}C}$. Operational speed of the gas turbine rotor is 3,000 revolutions per minute. The life span expectation of the bearing is approximately between 4 to 5 years (Siemens v 94.2 Geregu manual, 2006). Figure1 is a schematic of the GT13 lubrication system with the compressor bearing on the two sides of the compressor, label number 2.

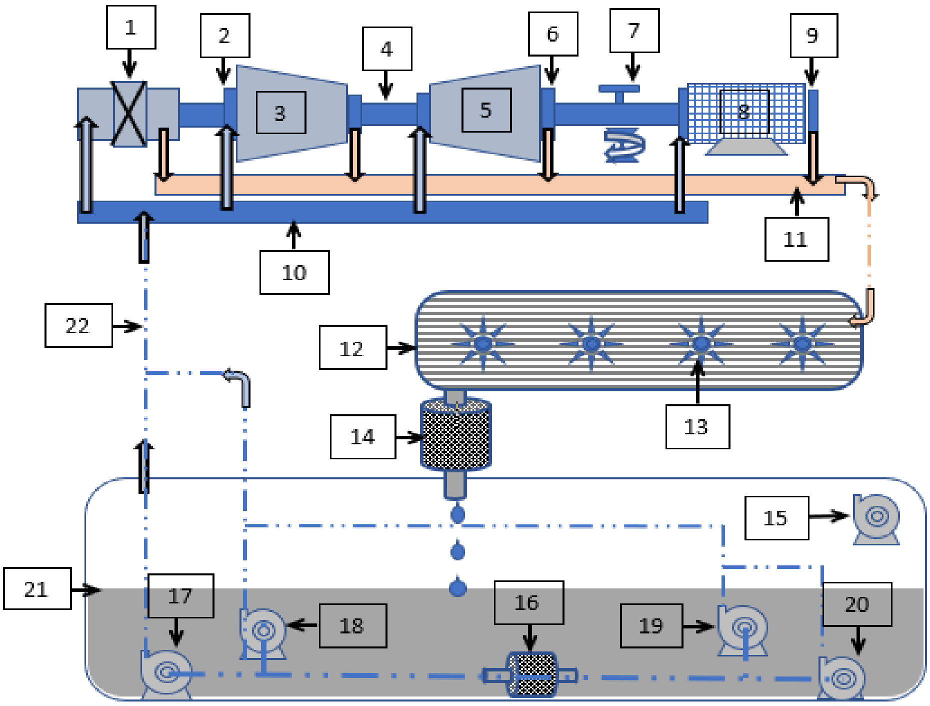

Figure1: Modified schematic diagram of Geregu V94.2 gas turbine bearing lubrication system (Geregu power plc, 2022).

Table 1.0: Gas turbine lubrication system part list

S/N	Part Description	S/N	Part Description
1	Thrust and journal bearing	12	Return oil cooling unit
2	Journal bearing	13	Return oil cooling fans
3	Compressor	14	Return oil filter
4	Main Shaft	15	Lube tank mist extraction pump
5	Turbine	16	Oil supply filter
6	Journal bearing	17	Main supply pump
7	Wheel with turning gear	18	Stand-by pump
8	Generator	19	Last resort pump
9	Journal bearing	20	Lift pump
10	Oil supply header	21	Lube tank
11	Oil return header	22	Supply line

From Figure 1, the GT lube oil/bearing lubrication system shows that the lube oil pumps push out the oil from the tank through the filters to the bearings .The oil then extracts heat from the bearings and moves through piping arrangements to the cooling systems(fans) where heat is extracted from the hot oil to the atmosphere(heat exchange).The oil then travels back to the lube oil tank and the process is repeated continuously .So from the bearing lubrication procedure, the parameters which will directly have a leverage on the bearing temperature include; the pump discharge pressure, the filter differential pressure, the cooler inlet and outlet temperatures, the bearing feed pressure and the lubrication oil characteristics(Viscosity, flash point, wear metal concentration, acid number and oil water content among others). Vibration will also be considered as one of the factors that affect the bearing temperature as suggested by [1, 2, 5]. The other parameters the cooler temperatures, filter differentials were selected based on the lubrication system-bearing interchange procedure and the work of [1]. The lube oil characteristics were selected based on their significance to the lube oil quality as reported by [25 - 31]. Bearing and seal clearance as well as shaft misalignment reported by [1, 2] were not considered because of the fact that these parameters mostly become crucial when a major overhaul or inspection which warrants the change or re-installation of bearings, seals or realignment of components has been undertaken. Similarly, parameters like bearing over speed/excessive loading pinpointed out by [32 - 33] were not considered because even at low bearing speed, the bearing temperature depreciated only marginally.

2.2 Statistical Tools

1) Correlation coefficient: Correlation coefficient is the level of linear association between the dependent and independent variables. The Pearson correlation coefficient is measured on a scale that varies from -1 to +1. Thus, 100% correlation between the two variables is either +1(positive) when one increases as the other increases, or -1 (negative) when one increases and the other decreases. Also two variables which have small or no linear correlation could have a strong nonlinear correlation. Thus, finding out the linear correlation before fitting a model is a useful tool in identifying the kind of relationships between dependent and independent variables.
The equation used for computation of the variables correlation coefficient with the output is given as [34];

$$r = \frac{n(\sum XY) - (\sum X)(\sum Y)}{\sqrt{[n\sum X^2 - (\sum X)^2([n\sum Y^2 - (\sum Y)^2}} \quad (3)$$

Where r is the correlation coefficient, n is the number of observations and X and Y are the variables.

2)Variable covariance: According to [35], Covariance determines the directional relationship between two independent variables. A positive covariance between two variables mean they behave exactly the same. As such, when one increases the other also increases while a negative covariance is denoted by an inverse relationship between the two independent variables. The eequation used for computation of independent variables covariance is given as **[**36].

$$\mathrm{Cov}\ (x, y) = \sum\left(\frac{(X_i - \bar{X}) * (Y_i - \bar{Y})}{(N-1)}\right) \quad (4)$$

Where X_i is a **d**ata variable of x, Y_i is a data variable of y, $\bar{X}$ is the mean value of x data, $\bar{Y}$ is the mean value of y data and N is the number of data set variables.

2.3 Data Set Collection and Model Formulation

Data set from around March 2017 to early 2023 formed the basis of the historical data used in the research. The values for the cooler outlet and inlet temperatures, bearing feed pressure, lube oil system filter pressure differentials, the main lube oil pump discharge pressure were all taken about twice (2) a year around the time lube oil sampling was undertaken in the plant which is every six (6) months on the average, representing about 4320 operating hours of the turbine. The maximum bearing temperatures obtained on the days of the lube oil sampling were used as the output variable of the model. The aforementioned dataset were all obtained about the time the average modal bearing metal temperature was observed. Most of the data were obtained from the HMI in the control panel where large historical data can be accessed. Before the MLR model was developed, all the independent variables were subjected to correlation and covariant relationship to ascertain the kind of interaction each parameter has with the output and between themselves.

2.4 The performance Evaluation Criteria for The MLR Model

In this paper, two performance indicators; root mean square error (RMSE) and coefficient of determination (R^2) were the criteria utilized to establish the accuracy of the regression models used for forecasting. The (RMSE) is the difference between the predicted and experimental values. Thus, the lower the RMSE the more accurate is the model evaluated. The coefficient of determination (R^2) measures the variance which is interpreted by the model and has a value from 0 – 1. The prediction accuracy by the model is said to be high when R^2 tend towards 1 and the reverse is the case when it tends towards Zero.

3. RESULTS AND DISCUSSIONS

3.1 Result

Table 2: Lubrication oil test result for unit 13 at Geregu Power Plc (2017-2023) (0EOH-43200EOH)

Month/ Year	Iron	Copper	Lead	Total acid number	Viscosity at 40 °C	Viscosity at 100 °C	Chromium	Nickel	Magnesium	Zinc	Flash point
Mar. 2023	0.23	0.31	0.67	0.08	31.6	5.1	1.40	1.83	0.6	0.7	215
Sep. 2022	0.22	0.27	0.50	0.10	31.63	5.2	1.19	1.76	0.67	0.68	220
Mar. 2022	0.22	0.25	0.21	0.017	31.71	5.4	1.2	1.54	0.66	0.76	230
Sep. 2021	0.20	0.22	0.05	0.08	38.85	5.7	1.15	1.08	0.62	0.78	216
Sep. 2020	0.20	0.24	0.31	0.08	43.9	6.6	1.5	1.62	0.78	0.74	215
Mar. 2020	0.20	0.20	0.33	0.08	45.0	6.65	1.7	1.5	0.76	0.82	216
Sep. 2019	0.17	0.20	0.4	0.08	44.5	6.6	1.14	1.0	0.70	0.90	217
Mar. 2019	0.18	0.20	0.14	0.08	46.0	6.7	1.05	1.4	0.80	0.89	215
Sep. 2018	0.15	0.16	0.23	0.08	45.0	6.65	1.6	1.55	0.75	0.90	216
Mar. 2018	0.14	0.21	0.27	0.08	44.5	6.65	0.95	1.32	0.85	0.93	217
Sep. 2017	0.15	0.14	0.35	0.08	44.5	6.65	1.1	1.10	0.85	0.91	217
Mar. 2017	0.14	0.11	0.11	0.08	44.5	6.65	1.22	1.45	0.84	0.95	217

Table 3: HMI result for unit 13 at Geregu Power Plc (2017-2023) (0EOH-43200EOH)

Year	Main pump	Bearing feed pressure	Filter differential pressure	Cooler inlet temperature number	Cooler outlet temperature 40 °C	Turbine vibration	Bearing temperature
Mar. 2023	6.40	2.62	0.05	64	34.5	4.36	85.0
Sep. 2022	6.60	2.55	0.07	62	35.0	4.18	84.5
Mar. 2022	6.35	2.54	0.03	66	34.0	4.05	84.5
Sep. 2021	6.40	2.60	0.11	63	35.0	3.94	83.5
Sep. 2020	6.70	2.70	0.02	61	34.0	4.50	80.5
Mar. 2020	6.70	2.70	0.06	61	34.0	4.22	80.4
Sep. 2019	6.60	2.60	0.12	65	35.0	4.85	80.5
Mar. 2019	6.60	2.60	0.08	65	35.0	3.60	80.5
Sep. 2018	6.50	2.80	0.08	60	34.0	4.40	80.4
Mar. 2018	6.50	2.80	0.07	60	34.0	5.02	80.5
Sep. 2017	6.80	2.70	0.05	62	33.0	4.15	80.5
Mar. 2017	6.80	2.70	0.09	62	33.0	3.75	80.5

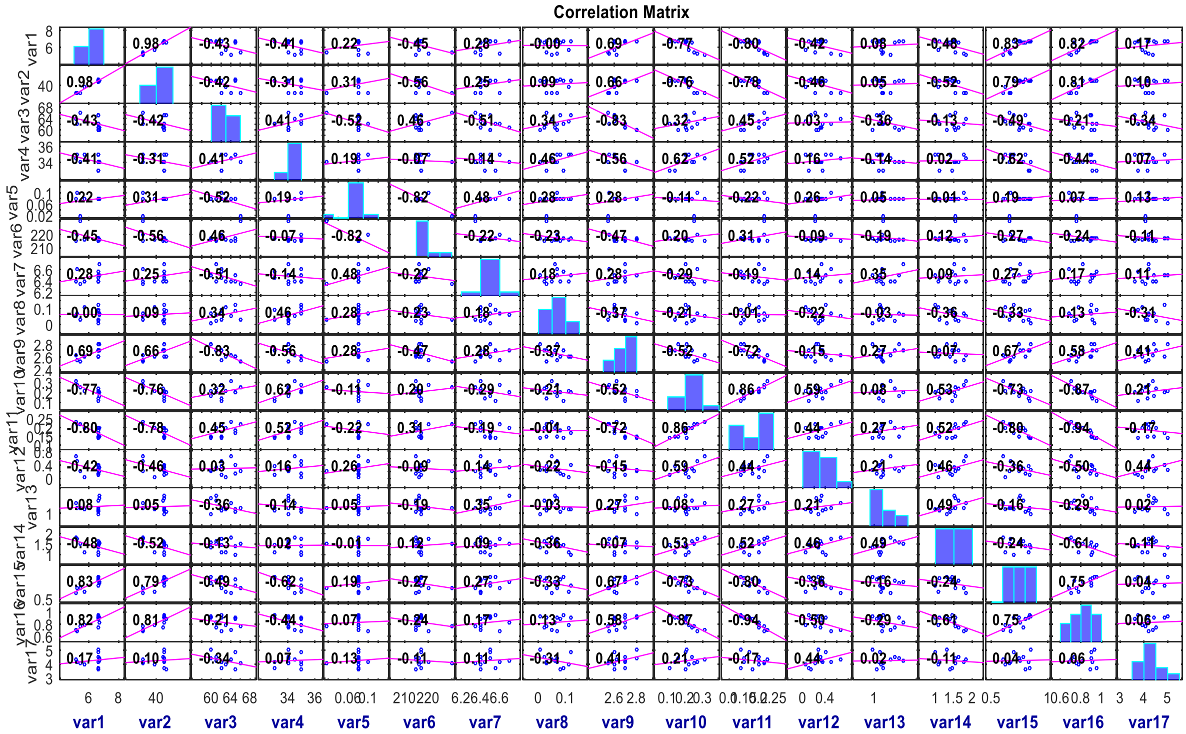

Figure 2: Covariance matrix of independent Variables.
__Note:__ **var1**- Visc_100, **var2**-Visc_40, **var3**:Coolerinlet_ temp., **var4**:Cooleroutlet_temp, **var5**:TAN, **var6**:Flashpoint, **var7**:Mainpumppressure, **var8**:Filterdifferential_pressure, **var9**:Bearingfeed_pressure, **var10**:Copper, **var11**:Iron, **var12**:Lead, **var13**:Chromium, **var14**:Nickel, **var15**:Magnesium, **var16**:Zinc, **var17**-Vibration

Table4: Pearson correlation coefficient result of each variable with the output (Bearing temperature)

S/N	Parameters	Value
1	Kinematic Viscosity at 100°C	-0.9968
2	Kinematic Viscosity at 40°C	-0.9808
3	Acid number	-0.2793
4	Flash point Temperature	0.4873
5	Filter differential pressure	0.0064
6	Main pump pressure	-0.3046
7	Turbine Vibration	-0.1755
8	Bearing feed pressure	-0.6842
9	Cooler outlet temperature	0.3919
10	Cooler inlet temperature	0.44475
11	Magnesium content	-0.8428
12	Zinc content	-0.7961
13	Lead content	0.3773
14	Copper content	0.7190
15	Chromium content	-0.0807
16	Nickel content	0.4426
17	Iron content	0.7884

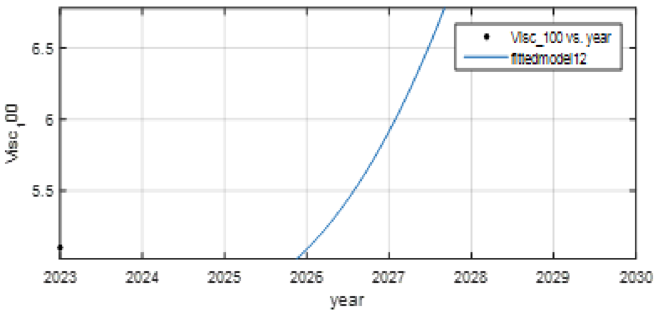

Figure 3: 3rd Order polynomial regression model for predicting future values of viscosity at 100°C.

1) *Solution to Objective function*: $f(x) = p_1 * x^3 + p_2 * x^2 + p_3 * x + p$
where x is normalized by mean 2020 and standard deviation 2.015.Coefficients (with 95% confidence bounds):
p1 = 0.1341 (-0.07203, 0.3402)
p2 = -0.3288 (-0.5045, -0.153)
p3 = -0.7381 (-1.1, -0.3763)
p4 = 6.495 (6.292, 6.697)

2) *Goodness of Fit:* SSE: 0.3212
R-square: 0.9321
Adjusted R-square: 0.9066 RMSE: 0.2004

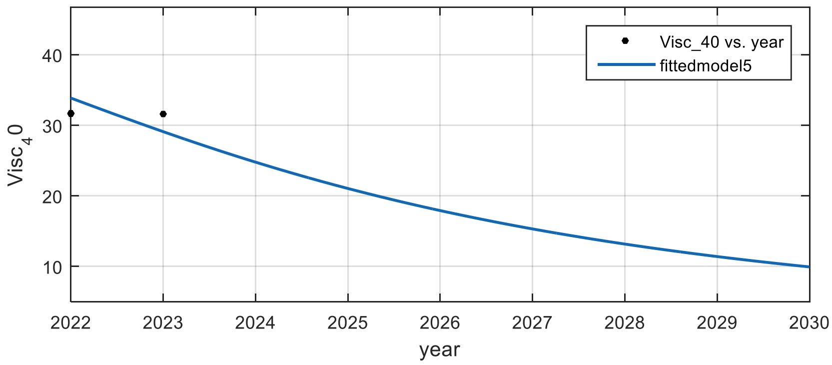

Figure 4: Rational(denominator,Numerator)regression model for prediction of future values of viscosity at 40°C

3) *Solution to Objective function:* f(x) = (p1) / (x^2 + q1*x + q2)
where x is normalized by mean 2020 and standard deviation 2. 015.Coefficients (with 95% confidence bounds):
p1 = 424.6 (257, 592.2)
q1 = 1.322 (0.7672, 1.876)
q2 = 9.667 (5.588, 13.74)

4) *Goodness of fit:* SSE: 26.25
R-square: 0.9312
Adjusted R-square: 0.9159
RMSE: 1.708

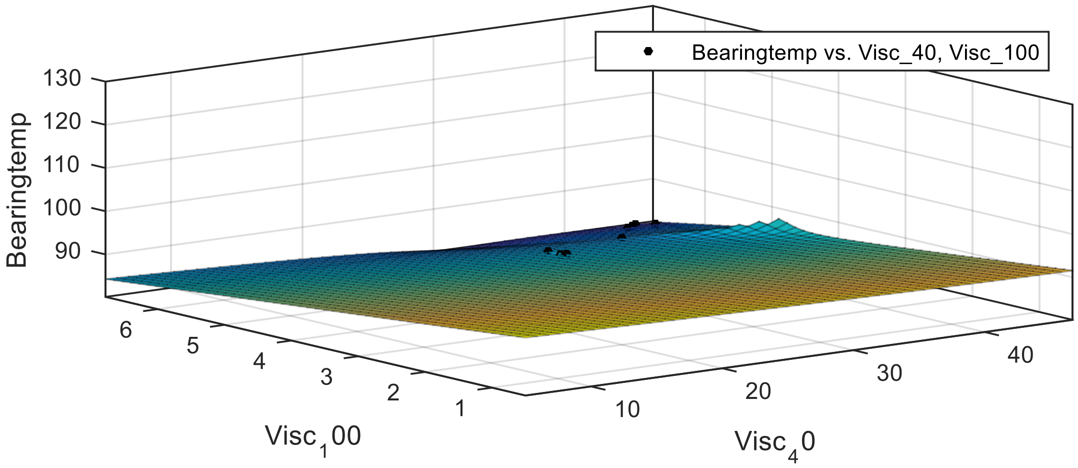

Figure 5: Loess regression model for prediction of future values of bearing metal temperature

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5) *Locally weighted smoothing linear regression*: f(x,y) = lowess (linear) smoothing regression computed from p where x is normalized by mean 40.97 and sandard deviation 5.889,
y is normalized by mean 6.217 and sandard deviation 0.6555.
Coefficients: p = coefficient structure

6) *Goodness of fit:*
SSE: 0.1211
R-square: 0.9971
Adjusted R-square: 0.996
RMSE: 0.1231

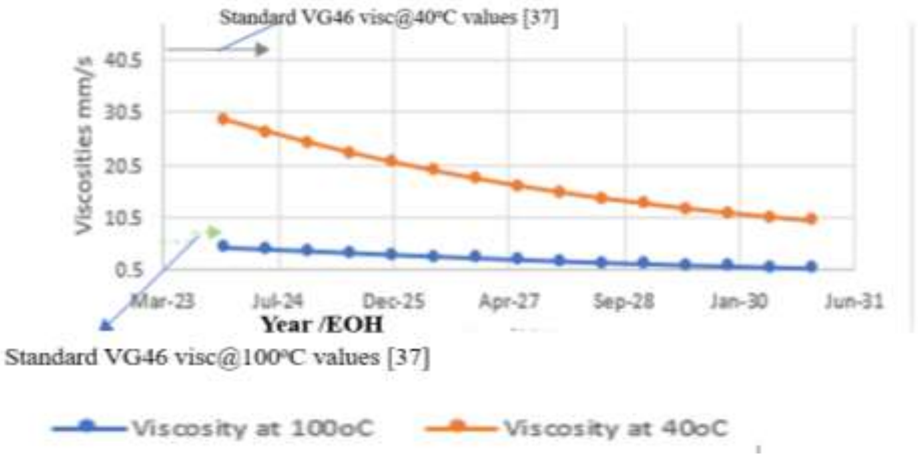

Figure 6: Viscosity at 100^{o}C and 40^{o}C predictions by the polynomial and rational regression models

Figure 7: Bearing temperature prediction by the Loess (MLR) regression model.

3.2 Discussion

The Pearson coefficient result reveals that the oil viscosity(at 100^{o}C and 40 ^{o}C) together with the lube oil Zinc concentration, Magnesium Concentration and the oil pump feed pressure had the highest linear correlation with the bearing metal temperature through the 5-6year duration.(March 2017 - March 2023). In essence, it means that the strong correlation between the Five(5) independent variables and the dependent variable(bearing temperature) is inverse in nature.i.e.it entails that when the values of the Five(5) variables are low, the turbine metal bearing temperature increases, this can be viewed fromTable4. Likewise from Figure 2, it can be observed that the co-variant relationship among the aforementioned variables is very strong compared to their relationship with the other independent variables. This strong co-variant relationship is a pointer indicating that an increase or decrease in the value of one of the variables simultaneously affects the other two variables in like manner. Though the degree it affects a particular variable varies. For example, an increment in the value of the viscosity at 100 ^{o}C leads to a concurrent increase in the value of viscosity at 40 ^{o}C in almost equal % but the % increase in the bearing feed pump pressure` will be less due to its degree of co-variance with the other two viscosity variables. This very strong co-variance between the two viscosities and also their high Pearson correlation coefficient with the bearing temperature was the platform on which the two viscosities were selected as the inputs to the multi linear regression (MLR) model. Similarly judging from the prediction by the polynomial and rational type regression models, it is observed that if the rate of decay in kinematic viscosities between 2022 and 2023 at both 40 and 100 ^{o}C is sustained, then by the 2nd quarter of 2025 the lube oil viscosity at the two temperatures would have deteriorated by at least another 30%. Comparing the forecasted viscosity figures with standard VG46 lube oil viscosities at 40 and 100 ^{o}C, (as viewed in Fig.6),it means that by the 2nd Quarter of 2025,viscosities at 40 and 100 ^{o}C must have deviated from standard oil values by 54% and 47% respectively. Likewise, if the trend between 2022 and 2023 is maintained, then the prediction by the MLR model using the future forecasted values for the two(2) viscosities as input is that by the 2nd quarter of 2025 the metal bearing temperature would have risen by at least 18%.

Also, from Figure 2, it is ascertained that the co-variance between Iron and copper content in oil is strong and that the two metals have an inverse relationship with the viscosity at both temperatures. This is not surprising because it means that as the viscosity of the oil decreases, the wearing level of the metals in the oil increases. Authors such as [28-30] reported that the wearing of these metals (Iron and Copper) together with metals like Lead and Tin is a reflection of bearing wear. The types of metal worn mostly depend on their composition in the bearing metal (Babbitt) material. And since this wear metals concentration in the oil is inversely related to the oil viscosities, it means that they are directly related linearly to the bearing metal temperature. So as the wearing rate increases, so does the bearing temperature .So it is very critical to design a condition monitoring tool for a critical parameter like the bearing temperature .The MLR model could also provide a prognosis based on the trending of the independent variables. Results also indicate the high accuracy of the models prediction based on the high values of R^2 (Coefficient of determination) and low values of RMSE (Root mean square error).

4. CONCLUSION

A multi-linear regression model that utilizes key inputs operation to predict the future values of the bearing metal temperature and simultaneously monitors the values of the independent parameters is developed. Thus, the future behaviour of the bearing system can be known to a reasonable accuracy using the present values of the input and output parameters. The model was typically applied on the current Geregu power plant in Ajaokuta, Nigeria and a predicted results shows that by the 2nd quarter of 2025, the oil viscosity at 40 and 100 ^{0}C would have decayed by 34% and 34.8% relative to 2022 values, respectively and that the bearing temperature at this period would have reached the alarm point of 90 ^{0}C from the current value of 85 ^{0}C, as shown in Figure 7. The MLR model further predicted that by the 1st quarter of 2027, viscosity values at 40 and 100 ^{0}C would have decayed by 52% and 54% respectively and that the GT13 bearing metal would have reached the trip-off point of 120 ^{0}C as specified by the manufacturers.

The resulting RMSE and R^2 values from the statistical analysis of viscosities against temperature are respectively 0.708 and 0.931 at 40 ^{o}C, and 0.2004 and 0.932 respectively at at100 ^{o}C. The values RMSE and R^2 for bearing metal temperatures are respectively 0.1211 and 0.9971 which are good indications of high accuracy of the models. The lubricating oil total acid number (TAN) and flash point remained relatively stable across the 5+ years, it can thus be concluded that shearing due to the consistent high temperature operation of the lube oil is most likely responsible for the depletion of oil additives such as Zinc and Magnesium additives which dropped by 23.9% and 26% respectively after 47,520 equivalent operating hours (EOH) leading to the decay in the viscosity. The Magnesium elemental additive decreased by more than the 25% limit earmarked by ASTM D4378 and D5185`[38] for precautionary action to be undertaken ,while both additives depreciated by more than the $\pm$ 20% of new oil concentration for Zinc, Calcium and phosphorus suggested by Ngele et al., (2013) as reported by [39].

The conclusion that shearing is responsible for the decay in viscosity is based on the parameter trends and indicators which conform with assertions made by [40-43]. The shearing effect on the oil is even more visible at 100 ^{0}C which is approximately the operating temperature range of the oil. This fact is also reflected in the relationship between the bearing temperature and the viscosity at 100 ^{0}C which gave the highest Pearson coefficient correlation scores (-0.9968).

Likewise, it is concluded that the strong inverse/negative correlation between the viscosities, bearing feed pump pressure, Zinc and Magnesium additive concentrations with the metal wear rate is responsible for the high bearing metal temperature and as such, a way has to be found to boost the viscosity and the oil film pressure either by replenishing oil with anti-wear additives like Zinc dialkyldithiphosphate or completely replacing the oil to minimize the bearing wear rate and consequently the bearing metal temperature.

Hence, through careful monitoring of key independent parameters using such models and taking prompt action when values of the parameters deviate alarmingly, catastrophic failures could be curtailed.

5. RECOMENDATION

In reality, the low value or lack of relationship between many of the independent variables with the bearing metal temperature might not be true because the low value of interrelationship just reflects low linear correlation between the dependent and independent variables whereas the non-linear relationship between the two might be high because in the actual real life scenario, a very high viscosity will also lead to high bearing metal temperature since the high oil viscosity will cause the demand for more pumping power and hence film pressure, but because the viscosity of the oil is high, the pump will struggle and subsequently less oil will be sent to the bearings which will definitely cause bearing temperature inflation. Also, massive increment in additive level over new oil values (not just drop in additive level as reflected in the work) is a sign of high wearing as cited by Bertinato [39] and it could also trigger bearing metal temperature increment .This real life scenario is almost the opposite of the linear correlation results. So for a more practicable and accurate result that will encompass both the linear and non-linear aspects of a problem, it is recommended that a model like the auto-regressive or Regression-ANN model should be used .

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REFERENCES

[1] Feroz, S. & Jabri, A.F. (2017). Investigation of Thrust Bearing High Temperature in Gas Turbine. International Journal of Renewable Energy and its Commercialization, IJREC, 3(1), 1–13. pp(1)

[2] Boyce, M. (2002). Gas turbine Engineering Handbook. 2nd ed. Gulf professional Publishing Company, an imprint of Butterworth-Heinemann

[3] Nicholas, C.J. (2012). Tribology handbook, Chapter 44 - Journal bearings. https://www.researchgate.net/ publication/ 322332531. Pp(1-2)

[4] Malcom, E. & Leader, P.E. (2016). Understanding journal bearings, Applied Machinery Dynamics, Co. Durago, Colorado.pp(11)

[5] SKF. (2017). Bearing damage and Failure Analysis. Skf.com https://www.skf.com › binaries › pub12 ›Images

[6] McCloskey, T.H. (1995). Trouble Shooting Bearing and Lube Oil System Problems, Proceeding of 24th turbo-machinery symposium https://core.ac.uk>download>pdf .pp(1)

[7] Totten, G.E. (2006). Handbook of Lubrication and Tribology: Volume I Application and Maintenance, 2nd ed. Boca Raton, CRC Press, Taylor & Francis.pp(8-9)

[8] Russo, S. (2019). On failure Modes and Design of Multi-bolted FRP Plate in Structural Joints - Composite Structures 218, (27-38). doi.org/10.1016/j.compstruct.2011.03.048

[9] Matzan, E. (2007). Detecting Bearing Failure. Machinery Lubrication. https://www.machinerylubrication.com/Read/1041/detecting-bearing-failure

[10] Almeida. (2017). https://www.quora.comhttps:/What-are-the-methods-to-measure-temperatures-at-bearings-of-turbines-other-rotating-equipments-in-power-plants

[11] Gokaltun, S., Fabijonas, B. & Rodzwic, R.C. (2021). Condition Monitoring of PEEK Bearing using Temperature Measurements, 20th Prime Workshop, High Performance Materials for Journal and Thrust Bearings.pp(10)

[12] Zhou, J. (2016). Temperature Monitoring of PEEK Bearings, 71st STLE Annual Meeting and Exhibition Las Vegas, USA.pp(15)

[13] Ozigis, I. I., Adeyemi, R.A., Odanachi, P.A. & Oodo, S.A. (2021). Performance Evaluation of Kianji Hydro-electric Power Plant using Artificial Neural Network and Multi Linear Regression, Journal of Energy and water resources 6(2), 231-241.pp(3)

[14] Wang, B. & Chang, X. (2019). Temperature Rise in Oil and Air Lubricated Angular Ball Bearing using ANN, 12(3). https://doi.org/10.2174/22127961.pp(1)

[15] Alias, A.M. (2013). Neural Network Based Temperature Rise Prediction in Bearing of Generator Transformer ISSN 2278-8875 12(1).pp(2-3)

[16] Guangxi, Y., Chengqing, Y. & Yu, B. (2021). Wind Turbine Bearing Temperature Forecasting using a New Data-Driven Ensemble Approach. Machines 2021, 9(11), 248; https://doi.org/10.3390/machines9110248 .pp(2)

[17] Jeng, Y.R. & Huang, P.Y. (2003). Predictions of Temperature Rise for Ball Bearings. Tribology Transactions 46(1), 49-56. DOI:10.1080/10402000308982599.pp(1)

[18] Laubichler, C., Kiesling, C., Marques da Silva, M., Wimmer, A. & Hager, G. (2022). Data-Driven Sliding Bearing Temperature Model for Condition Monitoring in Internal Combustion Engines. Lubricants, 10, 103. https://doi.org/10.3390/lubricants10050103.pp(16)

[19] Kanade, V. (2023). Linear Regression, http://spiceworks.com/tech/artificial-intelligence/articles//what-is-linear-regression

[20] Alexopoulous, E.C. (2010). Introduction to Multi-variate Regression Analysis. Hippokratia. 2010. Dec:14 (Suppl1), 23-28. PmciD:pmc3049417/pmd:21487487.
[21] Prashnat, S. (2022). https://www.analyticsvidhya.com/blog/2022/01/different-types-of-regression-models/
[22] Kumar, S. (2017). https://blog.revolutionanalytics.com/2017/04/fitting-rational-functions-with-lm.html
[23] Waukesha Bearings. https://www.waukbearing.com/products/babbitt-bearings..html#:~:text=Typical
[24] https://www.nationalbronze.com/pdfs/Selectingbearingmaterials.pdf.
Ozigis, I.I., Oche, J.I.O. & Lawal, N.M. (2021). Locomotive engines and future of railway automotive power in Africa: A review. Nigerian journal of technology July, 2021,.40(4).pp660-673.248; https://dx.doi.org/10.4314/njt.v40i4.13.pp(5)
[26] Kamal, G. (2013). In-service Condition Monitoring of Turbine Oils. Presented at 2nd Middle East Turbomachinery Symposium (2013), Doha, Qatar, 5-15. https://turbolab.tamu.edu/wp-content/uploads/2018/08/METS2Tutorial8.pdf.
[27] Doyle,D.(2017). Turbine oil analysis oil analysis E source oil fuel and coolant analysis. eSource https://www.alsglobal.com/en/News-and-publications/2022/06/esource-102-turbine-oil-analysis
[28] Magaroni, D. (2002). The Role of Lubricant Condition Monitoring in Maintenance Programmes https://www.lube-media.com/wp-content/uploads/2017/11/Lube-Tech024
[29] Langfill, Q. & Haselbach, L. (2016). Assessment of Lube Oil Management and Self Cleaning Oil Filter Feasibility in WSF Vessels-Final Report. (Washington State Department Of Transport). Pp:29-68 . https://depts.washington.edu/trac/bulkdisk/pdf/859.1.pdf
[30] Evans, J.A. (2010). Where does all that metal come from? 42, 1-6. https://wearcheck.com/resources/techdoc/WZA047.pdf.
[31] Lucas, M. & Anderson, D.P. (1997). Lubricant Analysis for Gas Turbine Condition Monitoring. Journal of Engineering for Gas Turbine and Power, 119(4), 863-869. Pp(4-7)
[32] Sh, J. & Mao, H. (2011). Investigation of high speed rolling bearing temperature rise with oil-air lubrication journal of tribology .133(2)DOI:10.1115/1.4003501 .pp(1)
[33] Ma, X., ,Zhang, M., Yang, F., & Xue, Y. (2023). Analysis of circulation characteristics and fault balance of high speed rolling bearing under oil-air lubrication.11(3):136. DOI:10.3390/lubricants11030136.pp(1)
[34] Srivastava, H .S. & Patel, P. (2022). Radar remote sensing of soil moisture Science Direct_https://www.sciencedirect.com › topics › correlation-coef.
[35] Thakur, M. (2023). Covariance Formulae. https://www.educba.com/covariance-formula/
[36] Hayes, A. (2022). https://www.investopedia.com/terms/c/covariance.asp
[37] Ansaldo, E. (2016). Turbine Oil Specifications. https://b2b.lukoil-shop.kz/upload/iblock/435/4350618d322cf17df1b1dda87f2269df.pdf. Pp(3)
[38] MOBIL (2016). Laboratory tests for steam and gas turbines ‘’https://mobilserv.mobil.com/pdfs/steam-and-gas-turbines-laboratory-tests.pdf.
[39] Bertinato, R., Freidderich, L.P., Bariccati R. & Souza, S.N. (2017). Analysis of Lubricant Oil Contamination and Degradation and Wear of a Biogas Fed Otto Cycle Engine, Maringa, 39(4), 409-416. https://www.researchgate.net/publication/320095283_. Pp(6)
[40] Mills, A. & Gadelovits, S. (2019). Oil system health management for aerospace gasturbines University of Sheffield
[41] Noria corporation. Lubricant additives-A practical guide https://www.machinerylubrication.com/Read/31107/oil-lubricant-additives.
[42] Mobil Technical Training Guide. (2009). Turbine Lube Oil Condition Monitoring https://www.academia.edu/38430610/Tt_turbine_oil_condition_monitoring_training_guide
[43] Russo, R. (2015). The Importance of Shear Stability in High Viscosity Oils https://club.mobilindustrial.com/lube_talk/b/product_and_application_expertise/posts/the-importance-of-shear-stability-in-high-viscosity-oils.