DEVELOPMENT OF A STATISTICAL MODEL TO PREDICT THE EFFECTS OF FAILURE AND PRODUCTION RATES ON ELECTRICAL ENERGY CONSUMPTION OF A LUBRICATING OIL INDUSTRY.

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Abstract

This work presents formulation of linear regression model for the effect of energy consumption and production rates on the breakdowns of Lubcon oil production line. The model validation confirmed the existence of statistical relationships between breakdowns and energy consumption and production rates. Applying data collected from the Lubcon oil industry, R^2 value of 98.6% was obtained for Lubcon oil production line model; thus, indicating that about 98.6% of the variation in electrical energy consumption could be explained by breakdowns and production rates, thus reducing the probability of consuming excess energy due to unplanned breakdowns in the production line to the barest minimum. The multiple linear regression models obtained by using the control and dependent variables give good estimation. The regression model also showed that given the failure (breakdowns) and production rates, the expected electrical energy consumption can be determined, thus, enabling the maintenance personnel to significantly monitor and reduce energy consumption in the lubricating oil production line.

Key words: Production rate, Energy consumption rate, equipment breakdowns, maintenance quality

1.0 Introduction

In Manufacturing companies, and process plants within them, can define their strategies and competitive priorities on different key performance indicators for their production systems: flexibility, productivity, quality, but also safety, environmental protection, and energy efficiency. Maintenance is fundamental in assuring the availability and reliability of production facilities; thus, if Companies design proper maintenance policies which are a set of rules describing the triggering mechanism for the different maintenance actions, they could more easily reach their productivity goals and guarantee plants efficiency. Complex process plants contain several major-energy consuming equipment, and thus offer multiple opportunities for energy saving, that was linked to a significant boost to the overall industrial productivity, as demonstrated by the review of more than 70 industrial case studies (Micaela et al., 2018). To gain the above discussed benefits, most of all for plants where the energy efficiency policy is still under development, it is important to define a prioritization criterion for the multiple energy efficiency measures that could be identified, leading to a maximization of the implemented measures efficacy (Micaela et al., 2018).

Maintenance can be defined as a set of activities aimed at retaining or restoring to the functional state of any technical system to achieve its maximum working life. Traditionally, maintenance has been considered as a necessary evil, but in fact it is a profit center rather than just unpredictable and unavoidable expense (Al-Najjar et al., 2004). Effective maintenance policies, such as Condition Based Maintenance (CBM), can significantly reduce failure rate which resulting in considerable savings of money, time and company's reputation in the market (Karanovi et al., 2018).

Engine lubrication is the process or technique to reduce wear of one or both surfaces in close proximity. Lubrication can also describe the phenomenon such reduction of wear occurs without human intervention. Adequate lubrication allows smooth continuous operation of equipment with only mild wear and without excessive stresses. When lubrication breaks down, metal or other components can rub destructively over each other causing destructive damage, heat and failure. Lubrication with a lubricating oil focuses on the key principle: building an oil film between two mating surfaces that move relative to each other, to separate the surfaces and prevent them from touching. Achieving this goal reduces friction and can help prevent wear caused by direct surface-to-surface contacts. Selecting the right lubricants is critical to preventing surface-to-surface contact.

According to Alev et al. (2013) it was stated that lubricant consumption has great importance in the sustainability assessment of machining processes. Huge amounts of cutting fluids consumption disposal costs were recorded in many countries. The lubricants mixtures benefit from properties of various lubricants They are useful lubricants that can give best protection to the engine and reducing wear and friction generated from sliding between two contact surface when engine in started condition (Alev et al., 2013).

Lubricants are categorized according to their application area. Regarding this, there are many types of lubricants. Automotive lubricants and industrial lubricants are the most general categories. The industrial lubricants can be classified as industrial gear oils, hydraulic lubricants, turbine and compressor oils, heat transfer oils, metalworking fluids, etc. All these lubricants are characterized by their viscosity, viscosity index, colour, acidity, lubricant, detergent and dispersant properties, thermal and oxidative stability, hydrolytic stability, foaming characteristics, anti-corrosion properties, anti-wear and extreme pressure properties, and carbon residue leaving tendencies regarding the processes in which they are involved in reality, lubricants that are employed in most applications are fully formulated containing several additives.

According to Djurdjanovica et al. (2003), implementing a proper maintenance activity can save a company up to 20% due to the resulting smaller production losses, improved product quality, etc. There have been three industrial revolutions in the past 200 years, driven by mechanisation, electrical power, and information technology (Deloitte, 2015; Drath & Horch, 2014; Kagermann et al., 2013). Now a fourth industrial revolution is expected as a result of the recent technological advancements in the Internet of Things (IoT), the Internet of Services (IoS) and Cyber Physical Systems (CPS). The fourth industrial revolution is characterised by the vertical integration of systems at different hierarchical levels of the value creation chain and the business process as well as by the horizontal integration of several value networks within and across the factory and end- to- end engineering integration (Park, 2016; Thoben et al., 2017).

As such, innovative maintenance paradigms, techniques, tools and systems are necessary in order to fulfil the demands of future industries, as well as, to benefit from the technological advances, which serve as enablers to solve the problems faced by industry (Bokrantz, 2017). With the digital trend in the recent industrial concepts, such as Industry, Smart Factories, Industrial Internet, etc., several maintenance terminologies are proposed to explain maintenance in digitalised industry, such as Prognostic and health management (PHM), Maintenance 4.0 and Smart Maintenance (Bokrantz *et al*., 2019). For example, PHM is described as a group of technologies and strategies to promote diagnostic, prognostic and maintenance of a product, machine or process (Qiao and Weiss, 2016; Ayad, Terrissa and Zerhouni, 2018). Maintenance 4.0 is developed to fulfil the demands of Industry 4.0 with an emphasis on maintenance aspects involving data collection, analysis, decision making and visualisation of assets (Kans, Galar and Thaduri, 2016). Smart Maintenance is defined by Bokrantz *et al*., (2019) as "an organisational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies". It is characterised by data-driven decision-making, human capital resource, internal integration and external integration. To engineer such maintenance solutions, it is essential to determine their tasks and features. Several researchers discussed maintenance tasks for digitalized maintenance (DM) (Labib 2006; Lee *et al*., 2011; Al Najjar and Algabroun, 2018).

Captions Statistical methods such as cluster analysis, pattern recognition, design of experiments, factor analysis, and regression analysis are some of the statistical techniques which enable one to analyze the experimental data and build empirical models to obtain the most accurate representation of physical situations (Kumar and Singh, 2012). In this work, regression modeling was adopted as a modeling technique. There are a number of variables controllable to varying degrees which affect the quality of equipment maintenance. These variables, such as equipment breakdowns (failure rates), production rate and poor maintenance culture play significant role in determining the degree of electrical energy consumption and should be controlled throughout the lubricating oil production process (Olorunnishola and Omojogberun, 2019).

Therefore, the focus of this paper is to present a regression model that predicts the effect of failure and production rates on electrical energy consumption in a lubricating oil production line. This work will provide input data for reducing energy consumption along the lubricating oil production line through identifying, validating, and controlling statistically significant control factors (i.e. failure rate, production rate and maintenance quality) that can influence energy consuption along the lubricating oil production line.

2.0 METHODOLOGY

In achieving the specific objectives of this paper, a careful review of the existing problems that associated with energy consumption in the lubricating oil industry and identification of problem and possible solution. Data was collected from a lubricating oil industry (Lubcon oil as a case study), data are the basic input to any decision-making process in a business for establishment of a model formulation for calculating and analyzing the data to generate a statistical model for the oil production line.

2.1 DATA COLLECTION

Data is a collection of fact, figures, objects, symbols and events gathered from different source. Organization collects data to make better decisions in terms of management, and to Developed an interface provide strong problem solver in forecasting future repair, predictive maintenance, reduction of friction and increasing equipment availability or life spend. Data used in this research work was collected from Lubcon Oil Industry, Ilorin, Kwara state, Nigeria from 2018 to 2020.

2.1.1 DATA PRESENTATION

The data as collected from Lubcon Oil Industry Ilorin is as presented below;

Table 1: Lubcon oil production line data

EEC	PR	FR
69.0	58045.0	25.0
55.7	45109.0	38.0
63.0	54060.0	29.0
44.0	29550.0	51.0
71.3	60000.0	20.0
67.7	57442.0	26.0
77.5	69226.0	13.0
42.1	27940.0	54.0
56.1	45923.0	38.0
68.7	58000.0	24.0
77.0	69030.0	13.0
51.2	40770.0	43.0
74.6	64230.0	17.0
38.4	18020.0	66.0
59.4	48550.0	34.0
70.5	60520.0	20.0
80.7	70000.0	10.0
70.8	59480.0	21.0
44.9	30240.0	50.0
60.0	49930.0	33.0
67.9	57770.0	26.0
68.4	58000.0	25.0
67.0	56900.0	27.0
58.5	47880.0	35.0
70.2	59100.0	22.0
49.7	38940.0	44.0
69.3	60030.0	20.0

Source: Lubcon Oil annual report, 2018 to 2020.

2.2 Model Formulation

Based on the selected variables and model assumptions, the following multiple linear regression model was formulated for a lubricating oil production line.

Model**:** for a lubricating oil production line.

$$Exp(EEC_{Lo}/FR, PR) = b_{oLo} + b_{1Lo}FR + \rightleftarrows b_{2Lo}PR \qquad \text{...Eqn. 1}$$

Where:

$Exp(EEC_{Lo}/FR, PR)$ is the expected value of electrical energy consumption in kW/l given the independent variables FR and PR, b_o is intercept of *model*, b_1 is regression coefficient associated with failure rate of the model,b_2 is regression coefficient associated with production rate of the model.

2.2.1 Hypothesis 1: Testing Model Validity

Model I hypothesis: for a lubricating oil production line:

$$H_0 : \beta_{jesw} = 0, \; j = 1, 2, 3$$
$$If \; H_0 \; is \; rejected, then \; H_1 : at \; least \; one \; \beta_{jesw} \neq 0 \qquad \text{…Eqn. 2}$$

2.2.2 Hypothesis II: Individual Testing of Coefficients of the Multiple Linear Regression Model.

Hypothesis II for any independent variable is as presented in equation 3.

$$H_0 : \beta_{1-3} = 0 vs H_1 : \beta_{1-3} \neq 0 for\ the\ model \qquad \text{…Eqn. 3}$$

The null hypothesis assumed that there was no statistically significant relationship between electrical energy consumption and any of the independent variables (failure and production rates).

3.0 MODELS ANALYSES AND DISCUSSION

3.1.1 Using SPSS (version 16.0)

SPSS was used to analyse the data obtained in Tables 1 and results are as shown in Table 2.

Table 2: Model summary for lubcon oil production line

		ANOVA			COLLINEARITY DIAGNOSTICS					RESIDUALS	
Parameter	**Value**	**Parameter**	**Sum of squares**	**Parameter**	**Condition index**	**Coefficients**	**Durbin watson**	**T-Statistic**	**Parameter**	**Mean (μ)**	**Standard Deviation (σ)**
R^2	0.986	Regression	3431.251	Constant (b_{0Lo})	1.00	49.728	1.806	2.868	Standard Predicted value	0	1
Adjusted R^2	0.985										
F-Statistic	859.583	Residual	47.901	FR (b_{1Lo})	3.565	-0.373		2.212	Standard Residual	0	0.961
Significance of F-statistic	0.00	-	-	PR (b_{2Lo})	134.06	0.0001		-1.800	-	-	-

Scatter diagram shown in Figure 1 was plotted which clearly indicates the validity of initial selection of variables. The model summary shown in Table 2, gave a computed value for the R^2 as 0.986, thus indicating that the regression was significant as about 98.6 % of the variation in breakdowns could be accounted for by the control variables. The *ANOVA* analysis in the regression result, shown in Table 1, gave a computed value for the *F*-statistic as 859.583 while the corresponding table value of 3.98 at 0.05 level of significance (q) and (2,35) degrees of freedom showed that the multiple linear regression models was significant and valid (*Neave, 1978*). Also, large regression sum of squares (3431.251) in comparison to the residual sum of squares (47.901) indicated that the model accounts for most of variation in the dependent variable. The coefficients b_0, b_1 and b_2 shown in Table 2 are 49.728, -0.373, and 0.0001 respectively; and the results of the *t*- test indicated that regression coefficients b_1, b_2 were statistically significant and not equal to zero (as given by hypothesis ii) at 0.025 level of significance and 35 degrees of freedom (table t-value=$t_{0.025}$, 35 = 2.201) (*Neave, 1978*). Therefore, the regression equation of breakdowns of lubricating oil production line in hours. can be given by equation 4. It should be noted that the assumptions made were valid for this model with respect to multi co-linearity and residuals' distribution. As seen from Table 2, the condition indexes values of 3.565 and 134.06 are for FR and PR respectively. To test for the autocorrelation in the residual, the calculated Durbin-Watson statistic is used to compare with the table DW value. Table 2 gave the calculated DW statistic as 1.806 while the table values of dl = 1.240 and du = 1.556 Since K = 2 variables and n = 27 respondents, the model at five percent level of significance is free from autocorrelation of the residual.

Finally, as it might appear to be a misleading result, the coefficient of failure rate was negative, implying that as failure rate decreases, energy consumption rate decreases. For steady energy consumption per month, reducing amount of failure would necessarily improve energy consumption by decreasing kWh/l, and thus, a negative coefficient in the energy consumption equation.

$$Exp(EEC_{Lo} / FR, PR) = 49.728 - 0.373FR + 0.0001PR \quad \text{...Eqn. 4}$$

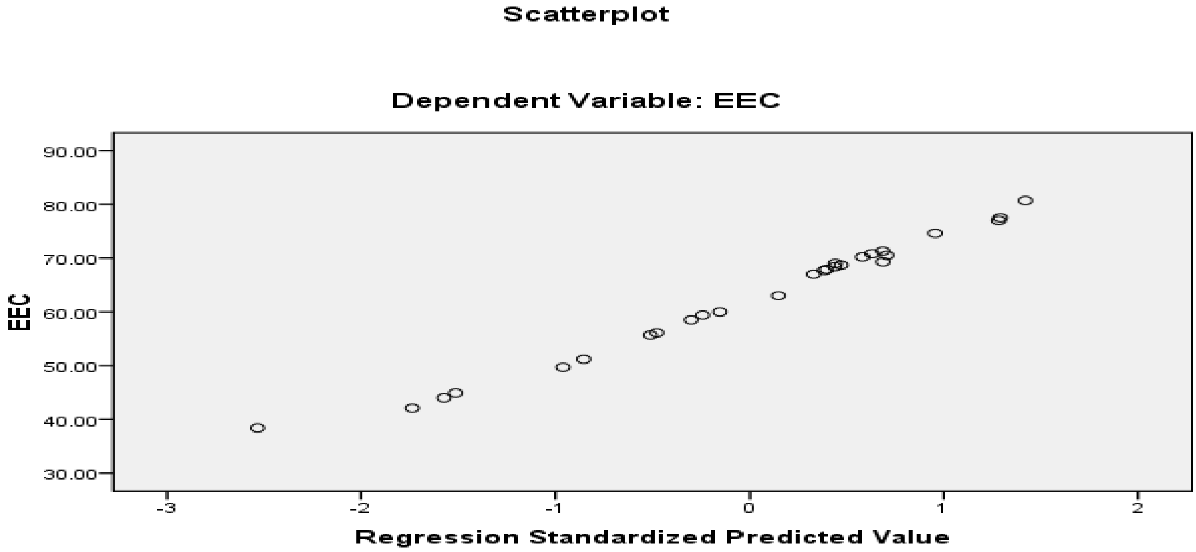

Figure 1: Scatter plot for lubcon oil production line

Conclusion

The regression model developed in this paper can effectively predict the expected values of breakdowns based on energy consumption and production rate. The results obtained using electrical energy consumption (as dependent variable), failure and production rates (as independent variables) and multiple linear regression models give good estimation (R^2 as 0.9898). Results show that this technique easily captures the intricate relationship between various process parameters and can be readily integrated into existing manufacturing environment (Kumar and Singh, 2012). The results further established a significant relationship between electrical energy consumption, failure and production rates of the Lubcon oil production line, thus, call for additional efforts for integrating this model (method for ensuring conformance to a standard maintenance culture) inside the production facility such as quality maintenance control and production management. The model will enable equipment maintenance personnel to significantly monitor and reduce breakdowns in the lubricating oil production line.

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