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Regular Research Manuscript

Employment of Intelligent Predictive Maintenance on Thermal Power Plant Component Parts Taking Condenser Vacuum as a Case Study

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ABSTRACT

This work proposes deployment of machine learning in the maintenance of individual constituent parts of steam power plant assemblages. With the condenser vacuum of a steam turbine (in a six-turbine plant assemblage) taken as a case study, information on the past operating parameters of the selected plant component was used to forecast its future working condition. Based on Exponential Gaussian Process of Regression, a model was developed, trained using the diachronic operational data, and employed in determining the future. A quantitative evaluation was employed to provide the distribution of the test values of the data about the lines of regression, as well as to measure the prediction accuracy of the model. The results show MAE and RMSE values are 6.1602 and 7.9286 respectively during the training; while for the prediction, the values are 92.6544 and 92.7235 respectively. It is concluded that modern power plants with myriads of instrumentation and data acquisition mechanisms can leverage on the approach of this study to model and plan the maintenance scheme that best suits and fits individual component units of power plants, since understanding of the anticipatory values of operational parameters helps to determine the likelihood of components failures.

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INTRODUCTION

Breakdown of national electric grids has been a frequent occurrence in most developing nation and thus the challenge of delivering electricity reliably to end-users appears insurmountable in the countries. Impacts of epileptic supply of electric power keep hitting hard on human welfares and national economies. In a recent study, ESI Africa (2021) revealed that fewer than 43% of African populace enjoy reliable electric utility services because consumers connected to power grids are plagued by lengthy durations of fluctuations in voltage profiles and incessant power supply failures. Nigeria despite being the largest economy in the continent (Reuters, 2022), with huge and consistent investment on its electric power industry (Ajewole *et al.*, 2021a), also wrestles with grid collapse at rapid sequences.

On the Nigerian grid system, 4 incidents of collapse were recorded within the first two trimester of the year 2021, while 5 cases occurred during the first four months of the year 2022 (Udegbunam, 2021; Udegbunam, 2022). The most recent grid collapse in the country was experienced on 14th March 2022 and it resulted in prolonged hours of outage that threw not fewer than 117 million people (Reuters, 2022) out of the over 200 million population of the country (NPC, 2021) into darkness, in several cities and towns across the franchise zones of the power distribution business, including Lagos which is a city-state that is the commercial hub of the nation and Abuja a modern city that is the political capital of the Nigerian federation (Jeremiah, 2022). It is on record that Nigeria's power sector, which its privatization commenced in 1999 and completed in 2013, recorded about 130 incidents of grid collapse between the first eight years of the unbundling (2013 – 2020), more than 200 times in the last nine years (The Conversation, 2022), and the failures keep counting (Jeremiah, 2022; Vanguard News Nigeria, 2021).

Causes of the re-occurring failures on the Nigerian grid has been partly attributed to improper functioning of the system's archaic infrastructures for power generation (Ajewole *et al.*, 2021a), transmission (Ajewole *et al.*, 2021b) and distribution (Ajewole *et al.*, 2019) due to poor facility maintenance culture, as recently made known by the nation's Minister of Power (Udegbunam, 2022). Another factor that is prominently affecting the grid is low water levels at the hydropower plants during dry seasons. Likewise, shortage of gas supply to thermal plants, as a result of gas pipeline vandalism and complications in gas supply chain (The Conversation, 2022), is a bane to the reliability of the grid. Structure of the energy market that currently obtains in the Nigerian electricity value-chain is another issue, for being partly oligopolistic (in the upstream) and partly monopolistic-tending hybrid (in the downstream).

The entire grid system was grievously affected by the March 14th crash. According to Addeh *et al.* (2022), the total crash was due to loss of the active generation plants one after the other. Of the 24 plants that were earlier active on the grid prior to the crash, 19 were producing at 3,867 MW peak as at 06:00 hour of the day. Generation began to reduce gradually by 10:00 hour as six of the plant went down at a very rapid succession, leaving just 13; and by 10:40 hour, the grid crashed to zero. While other factors mitigating against the grid are also regarded crucial, functionality of the generation plants is particularly of special concern as at present, due to the cases of extensive power outage that their occurrences have been blamed wholly on the operational problems faced by the plants that accounts for the largest portion of the electricity generation in the country (Udegbunam, 2021).

While heavy investments on power supply facilities is continually recorded, it has been reported that the Generation Companies (GenCos) are of the view that the current status of the Nigerian electricity market does not encourage investing to boost up power plants capacities or licensing additional power generation businesses because such moves tend to create greater risks in terms of facility breakdown and cost implications of maintenance and repairs of plant infrastructures (Vanguard News Nigeria, 2021). Therefore, a better option to grid expansion is to give attention to effective overhauling and maintenance practices, so that the existing plants can generate at their current maximum installation capacities uninterruptedly. Going by this submission would thus requires the Nigerian power industry diving deep into modern technology for plant maintenance. Thus, an inevitable requirement of the sector is regular appraisal of the performances of power systems for problems identification and solutions provision. More so, power systems nowadays are heavily automated networks, thus making the systems prone to more severe breakdowns occasioned by natural disasters as well as required and unrequired human interventions. Meanwhile, the maintenance service industry in Nigeria, particularly in the electric utility sector, is cumbered with issues bothering on poor maintenance skills, lack of industry-specific maintenance management model and non-availability of efficient maintenance technologies (Madueme, 2002).

In the efforts to attain high level of reliability and availability in power supply, the maintenance measures that have been conventionally used by Nigerian GenCos are the conventional: preventive (Oyedepo and Fagbenle, 2011), reactive (Mobley, 2002) and predictive (Tiddens, 2018) strategies. According to Brahm de Jong (2015), deterioration occurs most frequently when machines are not recognized as a consideration for preventative maintenance due to usage patterns and frequency. Therefore, early detection of machine breakdowns will lessen the negative influence on a manufacturing company's operating efficiency (Ahmad *et al.*, 2018). But in the traditional manufacturing system, identifying important failures and studying their relationships with other process factors is difficult and so application of modern technology to maintenance process becomes germane.

Over the years, some Nigerian GenCos have strived to perfect the art of preventive maintenance with occasional breakdown maintenance. This technique is majorly based on rule of thumb for smooth operation of plant, unlike predictive technique that is wholly data-based. The approach is characterized with fast-fix culture that lacked adequate planning and time management, thus maintenance becomes either inadequate or difficult. However, for the rising demand in availability and reliability of power plants in the constantly changing national population and economy, a better approach to power plant maintenance strategy is necessitated. The concept that is used to optimize asset maintenance programs by using data-driven strategies to predict asset breakdown is known as predictive maintenance (Meyer zu Wickern, 2019). Predictive maintenance approach deploys the actual operational condition of plant equipment and systems to optimize plant performance. Tiddens (2018) described that in predictive technique, real operational state of essential plant systems is obtained using the most prudent tools: vibration monitoring, thermography, tribology, *etc*; and the needed maintenance tasks are scheduled premised on the data. Thus, predictive maintenance, being data-based, lends itself to the manipulations of Artificial Intelligence (AI) technique, which is the science and engineering of creating intelligent devices, particularly intelligent computer programming. According to Tyagi (2020), one of the major branches of AI is machine learning (ML). In ML, machines automatically learn from their operations and refine themselves to produce better results (Pedamkar, 2022).

While the use of AI in power plant maintenance is beginning to take foothold, there has been a number of studies on the deployment of the technique in predictive maintenance applications in different environmental installations generally. In the literature abounds the applications of ML in facilities other than power systems (Bahri *et al.*, 2009; Brahm de Jong, 2015; Bayoumi and McCaslin, 2017; Vuyyuru, 2018; Ahmad *et al.*, 2018; Li *et al.*, 2019; Pai *et al.*, 2019; Long *et al.*, 2020; Niyonambaza *et al.*, 2020; Girit *et al.*, 2021; Miao, 2021; Li *et al.*, 2021; Wei *et al.*, 2021). In similarly vein, Hua *et al.* (2020), Olesen and Shaker (2020) and Yang *et al.* (2020) are instances of several cases of deploying ML in power systems infrastructures other than thermal generating plants.

In Hua *et al.* (2020), a maintenance and operation optimization method to tackle the challenges associated with traditional photovoltaic (PV) power plant maintenance and the convergence speed and optimization ability were considerably improved by defining an appropriate fitness function using the ML method. The technology optimally automated and reliably overridden typical PV plant operation and maintenance dispatching activities. The solution outperformed the traditional way when applied to many PV plants, multiple maintainers, multipoint departure, variable dispatching conditions, and cost considerations. Olesen and Shaker (2020) investigated the practicality of using various predictive maintenance strategies for pump systems and power plants. Prognostics and health management models, machine learning models and the neural network models considering data types such as vibration, temperature, pressure, mass flow, oil flow, exhaust vacuum, full load power, current and humidity were examined. Appropriateness of various predictive analytics algorithms, such as kernel extreme learning machine, time delay neural network, autoregressive integrated moving average among others, were also investigated for the analysis of various process parameters. More domain specific researches to cater to unique cases was advocated. Authors in Yang *et al.* (2020) researched flaws on a distribution network using the golden search technique. A fault area search was performed, which was optimized using minimum fault reactance. Based on the importance of distributed energy resource supply on fault point current in distribution networks, an improved trapezoidal iteration approach for load flow analysis and fault current calculation were provided. Validation was performed using the IEEE 34-Node test feeder and the results of the simulation showed the method was suitable for fault location in distribution networks with many distributed generators, and the method could accurately locate active distribution network faults in a variety of situations.

Thermal power plant maintenance based on ML approach, has been attempted by some authors. Pamungkas *et al.* (2018) adopted a preventative maintenance method at the Nagan Raya Steam Power Plant to improve the performance reliability of crucial boiler components. The authors predicted time-based preventive maintenance on the dependability value of important boiler components to improve future reliability. In order to reduce future failures, the evaluation and performance improvement in terms of reliability were also decided. Every activity performed on the boiler prior to a breakdown was counted as preventive maintenance and the findings revealed an increase in reliability. The ML methods, as well as first principle models were used in Asnes *et al.* (2018) to develop the Hymatek Controls Condition Monitoring System (HCMS), which was deployed as a cloud solution to analyse continuous streams of real-time data from a power plant. The result of the analysis was then used as input for the determination and development of the optimal maintenance plan for the power plant. The study also confirmed that application of predictive models to early warning sign detection systems and lifecycle analysis is a feasible area of research. The use of data analysis to design a fault diagnostic and optimization system to enhance power plant efficiency through optimal design criteria was proposed by Saraswathi and Deivasigamni (2019). These authors applied Vander Monde Matrix and K-Means to optimize for some beyond-the-surface operation data that were extracted and present in machine readable form. The submission by Li *et al.* (2019) advised on the need for predictive analytics in the control of reheat systems in power plants. The need for exact reheat steam temperature regulation necessitates a comparison of past control loop data to previous unit performance, which was fed into the limited predictive control algorithm. MATLAB simulation was used to determine the steady-state values of control quantities in the reheat steam temperature control system under various scenarios. Input and output steady-state values of the loop and steady-state time were analyzed, while the reference values and governing law of the control quantities, as well as the precise constraint range of the systems control quantities, were provided. This provided reference data and a theoretical foundation for field adjustments of the reheat steam temperature management system in power plants, therefore increasing the safety and the effectiveness of the system.

Application of intelligent predictive approach is proposed in this present study as the most appropriate maintenance technique for use in the generation sub-system of the Nigerian electricity industry. Availability and reliability of demand in the Nigerian electricity market is a keen pointer to the fact that the maintenance strategy and approach of key power plant assets must be data driven rather than by the rule of thumb. Use of running-hours dependent maintenance practices does not guarantee lack of breakdowns between major inspections. The multilevel structured preventive maintenance strategy has been observed to be insufficient to prevent some catastrophic failures such as boiler explosion, turbine mass loss, generator explosion, *et cetera*. Therefore, there is the need for a more realistic approach which will look into every-time operating conditions of the plants. Such approach will help both the maintenance administrators and planners to determine daily activities while not negatively impacting on the plant reliability.

In the approach of this study, available power plant operational data would be used to predict, by ML, the future failure time of a plant asset, so that just-in-time strategy for power maintenance could be applied to avoid failures. Thus, prediction of failures of a component unit of a steam thermal plant is carried out in the study, based on the data of selected operational parameters of the component. The operational data was employed to analyse the trend of the operation of the unit. This article is structure as follows: Section 2 gives the materials and method of the study; and the results obtained from the analyses of the data are presented and discussed in Section 3; while in Section 4 the conclusion drawn from the study is highlighted alongside with suggestions and recommendations.

METHODS AND MATERIALS

Description of the study area

The three main tasks involved in this investigation are: selected operational data of the studied component of the steam power plant was gathered; operational trend of the unit was modelled using ML modelling approach; and the developed models were appraised (trained, validated and tested) using true values of the operational data. Information on the operating parameters of the condenser vacuum, which is an important component of the steam turbine, was used to determine the future working condition of the component. On MATLAB simulation platform, a forecasting model was created based on Exponential Gaussian Process of Regression (EGPR) and following been trained and validated with the historical operational data, the model was then used to predict the future operating condition of the component. Also, the ability of the developed tool to correctly predict other items that were not used in the training was measured through quantitative analysis using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), by which the distribution of the test values about the line of regression was obtained.

Egbin Power Plant Plc, which is situated in the south-western part of Nigeria, began operation in 1985 and still running to date. As shown in Figure 1, the plant is situated on the bank of a lagoon that serves as a constant source of cooling water. Choice of the plant for study was premised on the fact that it is the largest power generation plant in the country. According to Ajewole *et al.* (2021a), the plant has total installed capacity of 1,320 MW, consisting of six generating units with each having 220 MW maximum capacity rating. Each unit consists of a hydrogen-cooled power generator with auto synchronization and voltage management, an extraction steam turbine with automatic run-up and supervision, and a steam generator with reheat and superheat cycles. The feed water cycle includes a steam surface condenser with air ejectors, tube cleaning equipment, two 100% condensate extraction pumps, two 50% condensate polishers, two 100% condensate booster pumps, three 50% duty electric boiler feed-pumps, a feed heating train of three low-pressure heaters, one deaerator, and two high-pressure heaters.

Figure 1: Aerial view of Egbin power plant (Partners, 2018).

The steam flow process in each of the generating unit of the plant is depicted in Figure 2. During operation, combustion air is supplied by two 50% duty forced draft fans and the units receive fuel from shared handling systems. Six intermediate storage tanks are used to deliver the fuel oil from the four main storage tanks to the units. Before being distributed to the units, natural gas is supplied via a high-pressure gas pipe and has its pressure decreased. Both fuel oil and natural gas can be used at full load by the units. In the event that natural gas is not available for burner start-up, liquefied petroleum gas (LPG) is available from storage to allow operation with oil. A typical water treatment plant provides the water needed to make up for losses caused by blowdown, vents, and drains. Six deep wells or a succession of them provide access to raw water. A circulating water system, a closed-circuit cooling water system, and a common services cooling water system all provide cooling water. The turbine surface condenser and the heat exchangers in the closed-circuit cooling system use cooling water that is drawn from the lagoon via the circulating water system. The steam generator and turbine auxiliaries are serviced by the closed-circuit cooling system. Each unit comes with two circulating water (CW) pumps that are rated for 50% duty.

Operational Modes of the Candidate Plant Component

The plant component studied in this work is the Condenser Vacuum. In a condensing turbine, shown in Figure 3, water is used to convert steam to liquid. The volume ratio of water and steam is 1:1600, which means steam is condensed to a size of 1/1600 times its original size. The vacuum inside the condenser is created by this massive drop in volume. More gas will be drawn in to be cooled as a result of the partial vacuum. Therefore, vacuum must be maintained at all times to ensure proper and continuous steam flow to the condensers and more work can be extracted from the steam at the low pressure (LP) turbine.

LP turbines rely heavily on the condenser parameters of steam turbines. An improper management of the parameters may be catastrophic to the prime mover. The near-absolute vacuum value is required in the condenser to reduce backpressure at the LP turbines due to poor rate of steam condensation. For normal operation, the condenser vacuum is around 4 kPa to 8 kPa (cued from the Operation Manual), which is extremely close to ideal vacuum. If the vacuum rises to around 23 kPa during operation, the generator output would be limited, and in severe circumstances the unit will trip off. Effect of inadequate vacuum on the generating equipment is determined by the turbine operation mode. The three principal operation modes in use are coordinate control mode (CCM), turbine master mode (TMM), and boiler master mode (BMM).

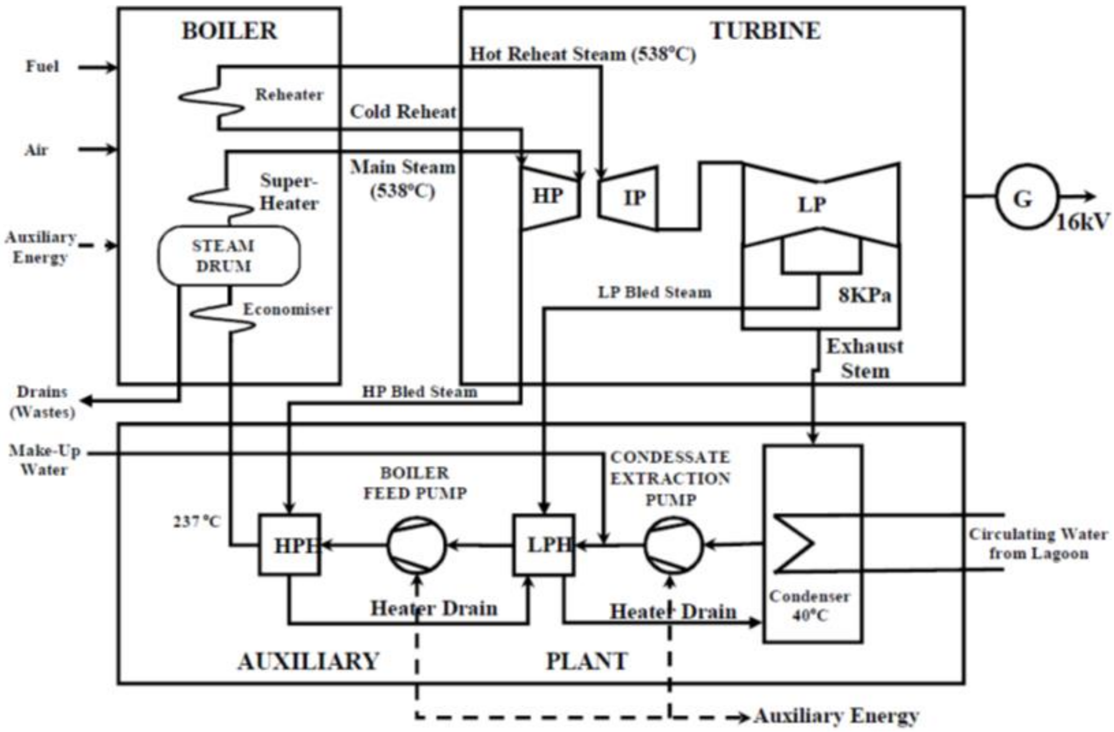

Figure 2: Steam flow process in Egbin power plant (Kukwa, 2014).

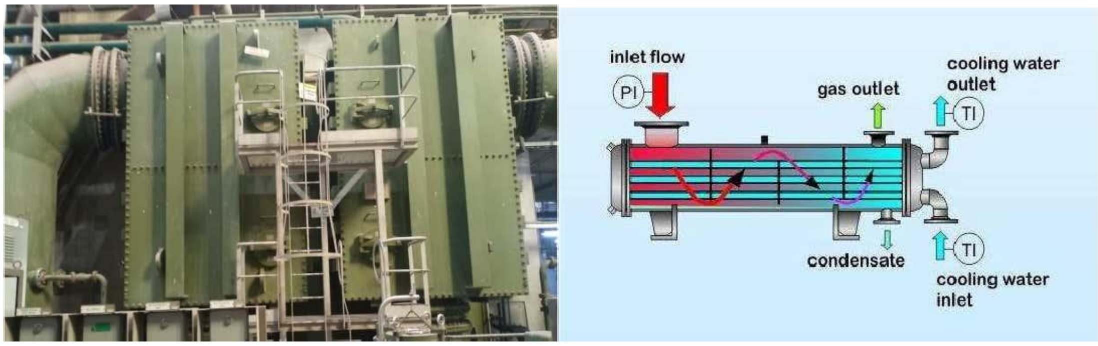

Figure 3: Condenser front view and operation (Abisoye, 2021; Bolaji and Emeka, 2014).

Data Collection and Description

Over the years, multilevel preventive maintenance scheme has been relied upon for the management of the plant and its components. However, deployment of predictive maintenance that anchors on historical operational data is beginning to gain acceptance (Pamungkas *et al.*, 2021). The data required for this study was obtained as the steam turbine was carefully examined and the relevant data picked to give the desired outcome for proper planning through parameters forecasting. Gathering the data was through access to the Daily Generation Report (DGR) of the plant, which contains daily operational information and parameter trends. Also, there was an access to the plant design alarm points, which is used as the set point for failure (target point). The obtained data is a two-hourly record of the condenser vacuum pressure in relation to the generator load, over a period of three months (March, April and May 2020). An online monitoring recorder that is connected to the condenser, with a vacuum pressure transmitter, serves as the sensing device for the data logging purpose.

Model Development, Training and Testing

According to Zhang *et al.* (2018) and Alghamdi *et al.* (2020), the EGPR is a method of statistical inference that uses a Gaussian process to model a given set of data. It is described as (Zhang *et al*., 2018):

$$k(x_i, x_j \mid \theta) = \sigma_f{}^2 \exp\left(-\frac{r}{\sigma_l}\right) \tag{1}$$

where

$$r = \sqrt{(x_i - x_j)^T (x_i - x_j)} \tag{2}$$

While k represents the similarity between two data points x_i and x_j, θ is a parameter used to adjust the similarity between the two data points. The term σ_f^2 is the variance of the function, which is used to measure the uncertainty of the data points. The parameter σ_l is the standard deviation between the two data points. The Euclidean distance between the two data points is represented by r, which is calculated by taking the square root of the difference between the two data points.

As Figure 4 shows, the ML model was fed with two inputs: electrical load in MW and vacuum pressure in mmHg; while there are 15 neurons in the hidden layer of the model. Training of the model was done using Levenberg–Marquardt algorithm. The data was split into training dataset and test dataset. While the training dataset was used in supervised learning of the model and comprised of 70% of the total data, the 15% validation dataset was , while the 15% test dataset was used to examine the ability of the model to predict the future correctly. For model evaluation, MAE and RMSE were employed to assess the distribution of the values around the selected line of regression. The evaluation indices are given in Ajewole *et al.* (2021c) as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - x_i| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)} \quad (4)$$

where y_i and x_i are the observed values and the predicted values, respectively; while n represents the number of data.

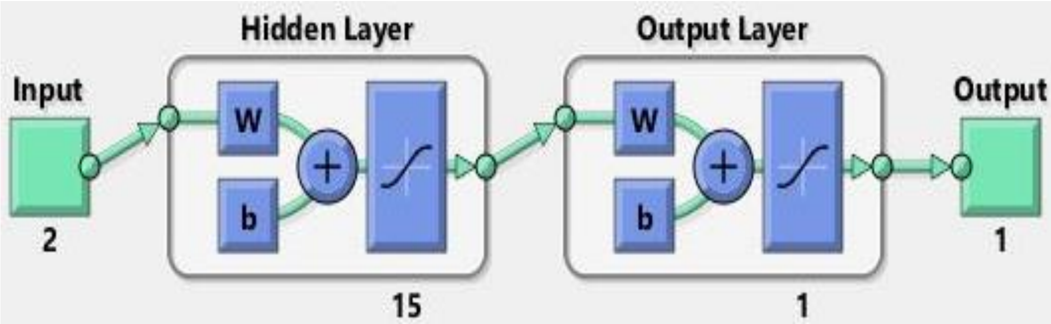

Figure 4: ML model.

RESULTS AND DISCUSSIONS

The regression plots of the algorithm are presented in Figure 5, with each of the plots having the output against the target. The closer the target to the output, the better the regression plots. Likewise, the more the regression value is close to 1, the better. The output value represents the equation of a straight line, in which the coefficient of the target is the gradient and the constant value is the intercept on output axis. Also, the more the slope is to unity and the intercept to zero, the better the regression plot. Using the algorithms, four different plots: training, validation, test, and the all plots; are produced. The figure shows that the algorithm was well trained with regression value of 0.54512, and performed well during validation and testing, as each has a regression value of 0.60805 and 0.55151, respectively. The all plot gives the overall performance with a value of 0.56034.

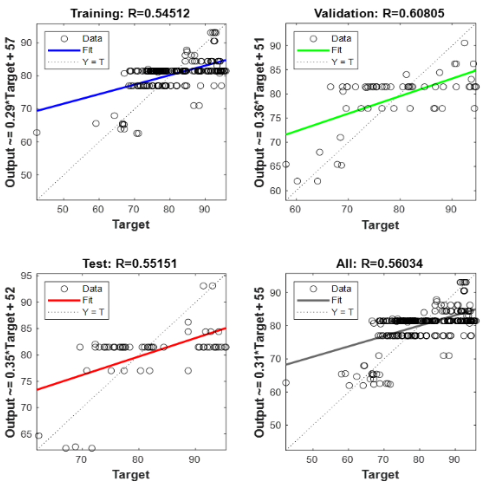

Figure 5: Regression plots.

Figure 6 presents the behaviour of the model during the training process and the figure shows that the model performed well during the session. The error values that compares the target data and the output pressures are almost zero, ranging between 0 and –10; indicating that the target data and the output pressures are very close to each other. The model was thus used for prediction and illustrated by Figure 7 is the performance of the model during the prediction session. The prediction errors ranged between 0 and 10 in the process, but are largely zero. From the quantitative evaluation that measured the prediction accuracy of the model, it was obtained that MAE and RMSE values are 6.1602 and 7.9286 respectively during the training; while at the prediction, the respective values are 92.6544 and 92.7235.

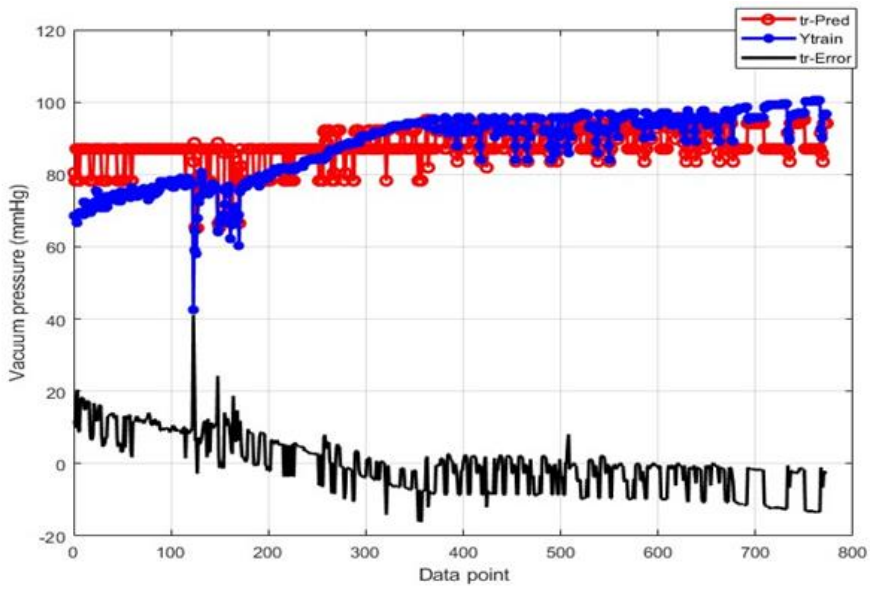

Figure 6: Model behaviour during training.

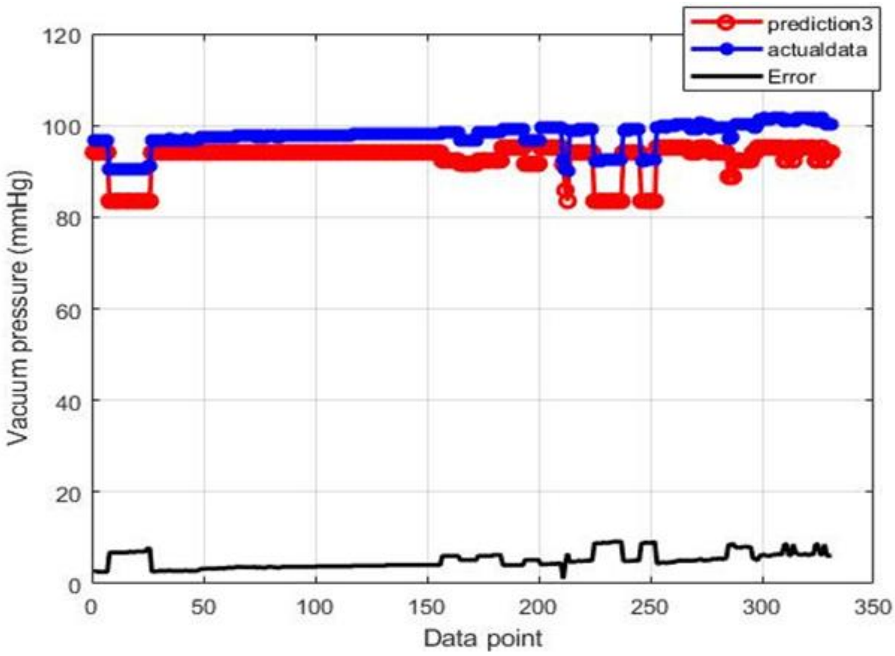

Figure 7: Model behaviour during prediction.

With a proper model used, a good understanding of anticipatory values helps to determine the likelihood of failure. Pre-empting failures could be achieved when the predictions are compared with the vacuum pressure's safety threshold of 23kPa (172.5mmHg) as specific to the plant unit investigated in this study. Thus, the use of predictive techniques to obtain operational parameters can help to plan better for the maintenance of the plant component.

CONCLUSION

National economies across the globe are greatly influenced by availability and reliability of electric power supply. Therefore, maintenance planning and execution is highly paramount to the sustenance of power generation plants in particular and grid systems in general. Scheduled and detailed maintenance is important for the life span of the power plant infrastructures. By the application of artificial intelligence techniques to predict likelihood and timing of failure occurrence, maintenance planning schedule can be determined more accurately. This approach brings about predictive maintenance that could enhance the overall goal of making power systems efficient.

Machine learning approach to the maintenance of thermal power plant turbine vacuum is examined in this study, as against the traditional breakdown approach in maintenance scheduling. Using a thermal power plant component part as a case study, prediction of the operational parameters, which is a factor of plant performance and maintenance, was carried out in this investigative study using data on the turbine vacuum condenser fouling. Outcome of this study shows the strategy as highly effective and describes the data analysing and predicting method as a way to improve maintenance planning.

With the current situation of the Nigerian electricity industry, the drive for modernisation and systems sustainability depends on how best the financially huge power supply infrastructure does not cripple due to poor maintenance. Therefore, efforts should be made to incorporate internet-of-things into power system infrastructures, as this will help to gather data that could be used to monitor degradation, as well as to plan maintenance that can prolong the life of electric utility asset, which is hugely financed by foreign loans. To this, end data management and machine learning techniques should be adopted as tools to leveraged on for the sustainability in the Nigerian electricity industry.

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