

# APPLICATION OF MACHINE LEARNING TO PREDICTION OF TURBINE ROTOR VIBRATION IN STEAM POWER PLANT

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## Article History

Received:  
January 20, 2023

Received in revised form:  
August 20, 2023

Accepted:  
August 20, 2023

Published Online:  
December 15, 2023

## Abstract

Presented in this study is a predictive approach to the maintenance of turbine rotors in thermal power plants. Using a supervised machine learning technique, a model that could predict future vibrations was developed on the MATLAB simulation platform. Historical data on the vibration symptoms of the turbine-generator couple in a generating unit of a steam power plant were employed on the model to predict the future technical condition of the plant component after the model has already been trained with a portion of the turbine-generator section's operational data. Distribution of the test values of the data about the lines of regression was obtained by quantitative analysis; likewise, the model's ability to correctly predict items that were not used in the training process was also measured. Performance evaluation of the model shows mean square error and mean absolute error of 0.000013691 and 0.0025, respectively at training; 0.000078253 and 0.0030, respectively at validation; as well as 0.0011 and 0.0037 respectively at testing. Future maintenance needs of the turbine rotor can thus be determined by comparing predictions with the vibration safety threshold of the rotor. Operators of modern power plants can leverage the approach of this study to model and plan maintenance schemes that best suit individual units of power plants, rather than premising maintenance of plant components on the rule of thumb.

Keywords: turbine rotor; machine learning; power plant; predictive maintenance; electricity generation

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## 1.0 INTRODUCTION

Utility-size electric power is conventionally generated from hydrocarbons, hydrodynamics, and radioactivity. While thermal power plants depend on hydrocarbon-rich fossil fuels for electricity generation, the inherent energy of dammed volume of water is converted to electric power by hydropower plants, and nuclear power plants depend on reactions from bombardments among radioisotope nuclei as the energy source for the generation of electricity. Steam power plants are designed for electric power generation, heat energy production for industrial purposes, and water desalination for domestic uses. According to the 2013 World Energy Statistics, the annual generation of electricity from all sources was 22,126 TWh in 2011 with 68% of this being fossil-fueled [1]. The steam power plant is fossil-(coal, oil, or gas) based and runs through traditional and sophisticated technologies. A typical steam power plant comprises of boiler, turbine, generator, and other accessorial equipment; with the prime mover steam-driven. The boiler heats water to create steam at high temperature and pressure, then the turbine transforms the generated heat energy into mechanical energy as the turbine rotors are rotated by the steam to drive the electric generator that produces the electricity, and the steam condenses into a condenser that recycles the water for re-heating against process repeats [2]. Thus, the most critical and hazardous equipment in the plant is the turbine [3].

A major cause of the steam turbine fault is the failure of the turbine rotor blades. The convoluted-shaped rotor blades undergo severe dynamic and thermal loadings as they rotate at high speeds, interacting with the erosive environment [4]. These operating conditions expose blades to many vibration excitation mechanisms and make the

vibration measurement process of blades a highly complex task. Symptoms that are functions of vibrations are the most important for assessing the technical condition of rotating machines like the turbine rotor. The absolute vibration spectra, relative vibration vectors, and time evolution of spectral components are essential kinds of vibration symptoms for diagnosing the Steam turbine rotor [5]. Therefore, proper monitoring of the vibration of the steam turbine rotor is vital to maintain the efficient operation of any steam turbine power plant.

There have been studies on the use of vibration symptoms for diagnostic assessment of the technical condition of rotating machines or components. Vibration signal analysis for rotating shafts and rolling element bearings that were placed under various load and operating conditions has been experimentally investigated [6]. Through a data logging device with an Ethernet connection to a computer, the study monitored, measured, and evaluated vibration signals processed in both time and frequency domains. Satisfactory results were obtained from the experimentation as the analysis of the vibrations enabled the prediction of the progress of fatigue failures in the components. In addition to time domain and frequency domain analysis methods, root mean square (RMS) analysis has also been employed in determining defects in ball bearings. In an experimental test conducted on six sets of bearings by [7], an FFT analyzer was used to measure vibration to show the baseline performance of a suitable bearing. The study revealed that the results of the experiment could be used to determine the type and size of bearing damage as the severity of vibration in defective bearings was indicated by the time domain analysis, while prediction of defects was made possible by the frequency domain analysis.

The vibration analysis approach to the identification of potential progressing faults in components of power plants, other than the turbine, has been investigated. Authors in [8] examined upgrading the efficiency and the reliability of the Rankine cycle at a steam power plant through simulation in Aspen's Hyprotech and Systems (HYSYS). Based on the outcome of the study, modification of the plant, depending on heat loss reduction from the condenser, was proposed. For a comparative analysis of steam gas-fired and combined-cycle power plants that were operated under different load conditions; exergy, combined pinch-exergy, and exergoeconomic methods were applied by in [9] using a simulator developed from the thermodynamic modeling of the plants that was designed to mimic the cycle behavior for diverse operating conditions with very minimal error. With the software model refined using data obtained from the plants' performance tests, the exergy of the flows is calculated following the thermodynamic simulation. In [10], energy and exergy analysis of the regeneration Rankine cycle, covering fuel, furnace boiler, regenerative heat equipment, boiler drum, turbine, and condenser, was carried out. The study shows that while the whole plant has energy and exergy cycle efficiencies of 29.1% and 51.2% respectively, the turbine's energy and exergy efficiencies are 69% and 58%, respectively. Using TN8000 steam turbine vibration analysis software, [11], analyzed the vibration test signal of a 600 MW steam turbine unit of a power plant. Steam flow mechanism of excitation through vibration fault and fault-sensitive parameters were analyzed and measures for reducing unit vibration were proposed. It was found that the vibration caused by the vapor stream excitation occurs in the high-pressure rotor steam inlet end and was concluded that problems could be identified early. [12] enunciated extensively the losses in steam turbines that tend to decrease the efficiency and work output of a turbine. The turbine rotor is identified as one of the individual components whose inefficient functioning decimates the overall cycle inefficiency.

Monitoring turbine conditions using vibration data has been a way of maintaining the turbine component of power plants. Authors in [13] adopted a strategic way of monitoring gas turbine engine conditions using vibration data, wherein wavelet transform implementation was examined to get features from vibration signals that describe the non-stationary parts. The high dimensionality of the elements was addressed by compressing them using the kernel principal component analysis so that more meaningful lower-dimensional features could be used to train pattern recognition algorithms and, for feature discrimination, a novelty detection scheme that depends on one-class support vector machine (OCSVM) algorithm was selected for investigation. The developed strategy for condition monitoring was employed for detecting excessive vibration levels that could lead to engine component failure and its performance on vibration data from an experimental gas turbine engine operating under different conditions was demonstrated. Obtained results indicate that the detection scheme achieved satisfactory validation accuracy through the appropriate selection of parameters.

Nowadays, predictive maintenance over corrective and preventive care is rising across the globe as it is becoming the most economically effective. However, predictive maintenance of critical machines with high unit cost and severe consequences of a potential failure, such as the steam power plant turbine, depends on reliable condition assessment procedures. The technical condition assessment of the steam turbines depends on specific, measurable physical properties that are sources of diagnostic symptoms [14]. [15] set up an intelligent monitoring system for predictive wind turbine monitoring, performance assessment, and fault diagnosis. The study adopted logistic regression (LR) in assessing the performance condition of the bearing; autoregressive moving average (ARMA) in predicting the bearing's future variation trend; and in classifying and diagnosing the possible fault of the turbine bearing, support vector machine (SVM) was deployed. It was concluded that intelligent monitoring systems can achieve real-time vibration monitoring, current performance assessment, future performance trend prediction, and possible fault classification for wind turbine bearings.

A study presented in [16] is on the diagnosis of rotary machine failures using machine learning (ML). Proposed in the study is the use of support vector machine (SVM) algorithm on experimental data gathered from a rotary machine model of a rigid-shaft rotor and flexible bearings, to proffer fault diagnosis of rotational unbalance in

the rotor of the machine. In a similar vein, the deployment of ML in power plant maintenance is beginning to take a foothold [17-20].

The turbine rotor is a highly essential component of the steam power plant. Failures of this component could be extremely exorbitant to fix or repair and possibly have huge consequential revenue losses if electricity is not generated. For an uninterrupted generation of power, therefore, safety assurance and improved reliability of turbines are necessary. In ensuring improved operations, preventive and corrective maintenance measures have been deployed. However, for better optimization of rotor performance, a shift from the conventional maintenance approach to an ML-based predictive method is important. In this present study, therefore, a predictive approach that anchors on vibration levels monitoring and the use of ML is proposed for turbine rotor maintenance. The structuring of this paper is as follows: in the second section is presented the materials and method of the study, while the results obtained from the analyses of the experimental data are presented and discussed in the third section, and the conclusion drawn from the study is highlighted in the fourth section.

## 2.0 METHODOLOGY

Development, training, and performance validation of a steam turbine rotor vibration prediction model is the main task of this study. Historical data on selected operational parameters of the steam power plant under study was collected and an ML model that can predict future parameters for turbine rotor vibration was developed on the simulation platform of MATLAB using a supervised ML technique (deep neural network). The ML technique was used to evaluate the model, which can be adapted for daily decision-making based on historical data of the turbine rotor vibration, and this was followed by an appraisal of the model's predictions with the actual values based on past operational logs.

### 2.1 Description of the Case Study Power Plant

Data for this study was obtained from Egbin Thermal Plant, which has an installed capacity of 1,320 MW. Located in the coastal area of the southwestern part of Nigeria, the power station is a gas-fired plant with six 220MW independent boiler-turbine units that can also run on high-power fuel oil (HPFO). Each of the units operates a closed system that is based on a reheat-regenerative Rankine cycle with high intermediate low-pressure impulse reaction turbine design and hydrogen-cooled generators where electric power is wheeled out at the cheapest rate within optimal levels of efficiency and global standards in health safety and environment (HSE) compliance [21].

The choice of the plant for the study was premised on the fact that it is the largest power-generating station in Nigeria. Despite consistent and huge investments in its electric power industry [22-24], Nigeria has always wrestled with grid collapse at rapid sequences. More than 200 incidents of collapse have been recorded on the Nigerian national grid in the last nine years [25] and the failures keep counting [26, 27]. The crashes were due to a number of reasons, including rotor failures. According to [28], the relatively recent total crash of the grid on 24<sup>th</sup> March 2022 was due to the loss of the active generation plants one after the other due to rotor vibrations. Despite this menace, the Generation Companies (GenCos) in Nigeria do not encourage further investment along the path of boosting power plant capacities or licensing additional power generation businesses [27]. The option favoured by GenCos is giving attention to effective maintenance practices. Hence, the need to deploy ML in power-generating plant maintenance in the country.

### 2.2 Experimental Design and Data Preparation

The procedure of this study followed data gathering, data cleaning, data analysis, model development, and model validation. Two-hourly data on the operation processes of the steam turbine, covering from mid-day of 1<sup>st</sup> January 2021 to 24<sup>th</sup> March 2021, was obtained from the plant. It must be noted that in the plant section under study, there are three different shafts: high/intermediate pressure turbine rotor shaft, low-pressure turbine rotor shaft, and generator rotor shaft; with the three coupled together to form one piece. Therefore, comprised in the obtained data are ten attributes/parameters of the coupling: generated active- and reactive powers, generator's rotor- and stator temperatures, Bearing-1 and Bearing-2 (on high/intermediate pressure turbine rotor shaft) vibrations, Bearing-3 and Bearing-4 (on low-pressure turbine rotor shaft) vibrations, as well as Bearing-5 and Bearing-6 (on generator rotor shaft) vibrations. The vibrations are measurements of the linear displacements of the shafts along the  $x$ -axis. As specific to the rotor under study here, the vibration data is recorded in millimeters and the vibration safety threshold of the turbine rotor is 0.25 mm (250  $\mu$ m).

Following the acquisition, the data was cleaned. The cleaning up (or filtering) was achieved using averaging principle method, where the above value and the value in between were added and divided. This was done to remove space in the acquired data. For the large data, correlative analysis was carried out to know the relationship between the examined parameters and other parameters of the plant with a 0.5 boundary limit. Each of the ten attributes has 988 datapoints, but this study used 900. By convention, the data was split into a training dataset (70%) used to teach the created ML mode, a validation dataset (15%) used to qualify the performance of the model, and a test dataset (15%) used for the actual prediction.

### 2.3 Development of Deep Neural Network Model

A code was created to perform all the activities of model development and validation. The model was developed using a deep neural network (DNN) with Levenberg-Marquardt algorithm. DNN describes artificial neural network (ANN) that has multiple hidden layers between the input and the output layers. DNN easily extracts features of various levels of abstraction and so learns more complex patterns.

#### 2.3.1 Multi-layer perceptron (MLP)

Of the major types of DNN: multi-layer perceptron (MLP), convolution neural network (CNN), and recurrent neural network (RNN); MLP is adopted in this study being the simplest kind of feed-forward ANN that generates a set of outputs from a set of inputs [29, 30]. MLP is a fully connected multi-layer ANN that trains by learning the relationship between linear and non-linear data. It has several layers of input nodes connected as a directed graph between the input and output layers and applies back-propagation for training the network. It is a deep learning method that is used for supervised learning format. Neural Network (NN) is generally expressed as [29]:

$$Y = X^T \cdot W \tag{1}$$

Where  $Y$  is the target/output,  $X$  is the input and  $W$  is the weight

Figure 1 shows the topology of the DNN employed as the network model. The architecture has nine inputs, two hidden layers, and one output. Both the first and second hidden layers have fifteen neurons each, with tangent-hyperbolic as their activation function. Also, the output layer has purelin as its activation function. During training, the network error was optimized by setting the values of weight,  $w$ , and biased,  $b$ , via back-propagation.

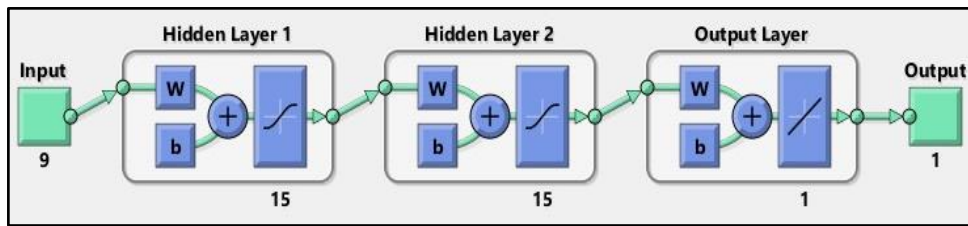


Figure 1. Developed DNN network topology

The neural network model used in this study is a supervised learning technique, which has an input and a target for model development as shown in Figure 2(a). Nine of the attributes of the rotor were the inputs; while a parameter, vibration 6, was the target because it is the most severe vibration that quickly leads to rotor failure. After the model has been developed, it could be used for prediction using different inputs as shown in Figure 2(b). In this study, the predicted parameter is vibration 6.

#### Weight Optimization

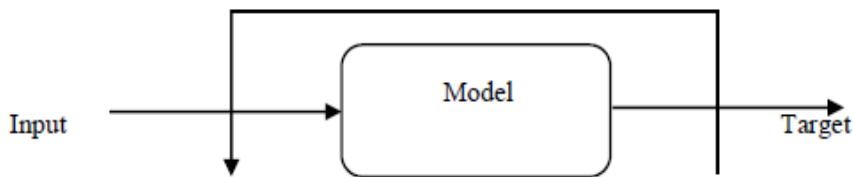


Figure 2(a). Training process

#### Weight Optimization

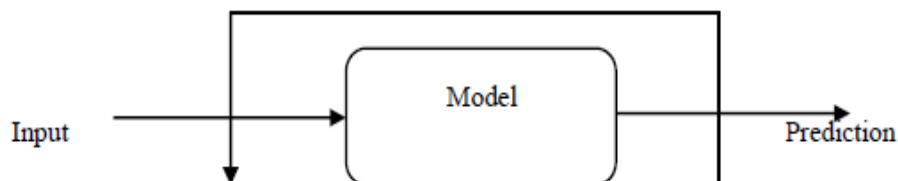


Figure 2(b). Prediction process

### 2.3.2 MLP learning procedure

MLP learning follows the following important procedures.

- Step 1: Forward propagation – data propagation from the input layer to the output
- Step 2: Error calculation based on the output – the difference between the predicted and known outcome
- Step 3: Error back-propagation – obtain the derivative of the error, with respect to each weight in the network and update model
- Step 4: Repeat steps 1-3 over multiple epochs to learn ideal weights
- Step 5: Take the output via a threshold function to obtain the predicted class labels

### 2.3.3 MLP forward propagation

In the first step, calculate the activation unit  $a_1(h)$  of the hidden layer.

$$Z_1(h) = a_0(in)w_{0,1}(h) + a_1(in)w_{1,1}(h) + \dots + a_i(in)w_{k,1}(h) \quad (2)$$

$$a_1(h) = \phi(Z_1(h)) \quad (3)$$

The activation unit is the result of applying an activation function  $\phi$  to the  $z$  value. It must be differentiable to be able to learn weights using gradient descent. The activation function  $\phi$  is often the sigmoid (logistic) function.

$$\phi(z) = \frac{1}{1+e^{-z}} \quad (4)$$

It allows the nonlinearity needed to solve complex problems like image processing. The activation of the hidden layer is represented as:

$$\begin{aligned} z(h) &= a(in).W(h) \\ a(h) &= \end{aligned} \quad (5)$$

For the output layer;

$$\begin{aligned} Z(out) &= A(h).W(out) \\ A(out) &= \end{aligned} \quad (6)$$

Where;

- $a_i(in)$  is the  $i$ th value in the input layer
- $a_i(h)$  is the  $i$ th unit in the hidden layer
- $a_i(out)$  is the  $i$ th unit in the output layer
- $a_0(in)$  is the bias unit with the corresponding weight  $w_0$
- $w_{k,j}(i)$  is the weight coefficient from layer  $I$  to layer  $i+1$

## 2.4 Model Performance and Data Analysis

In determining the model performance to predict the desired output, three statistical parameters: mean square error (MSE) and mean absolute error (MAE); were employed. The statistical parameters are expressed as [29, 30]:

$$MSE = \frac{\sum_{i=1}^n (O_i - P_i)^2}{n} \quad (7)$$

$$MAE = \frac{\sum_{i=1}^n |O_i - P_i|}{n} \quad (8)$$

Where  $n$  represents the number of data,  $O_i$  stands for the observed values, and  $P_i$  is the predicted value.

### 3.0 RESULTS AND DISCUSSION

As shown in figure 3, the best validation performance of the neural network model is  $2.7877 \times 10^{-5}$  at epoch 10. This good validation value implied the model could be deployed for the proposed prediction.

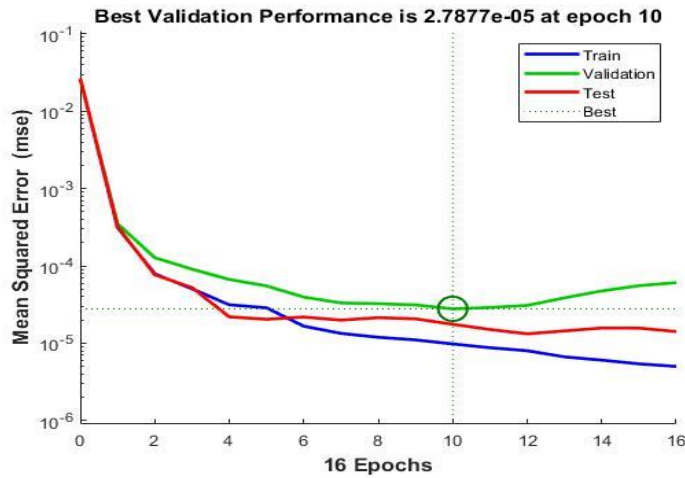


Figure 3. Best validation performance of the neural network model

Regression analysis of the model is presented in figure 4 that comprises of four different charts: training, validation, test and all; with each having output plotted against target. Conventionally, the closer the target to the output, the better the regression plot. While the output represents the equation of a straight line, the coefficient of the target is the gradient and the constant value is the intercept on the output axis. The closer the target is to the output, the more the slope is to unity and the intercept is to zero, then the more the regression value approaches 1; and the better the regression plots. As obtained from the figure, the regression values for training, validation, test, and all are 0.99647, 0.98148, 0.93149, and 0.98825, respectively. The figure is thus a good indication that the network performed well.

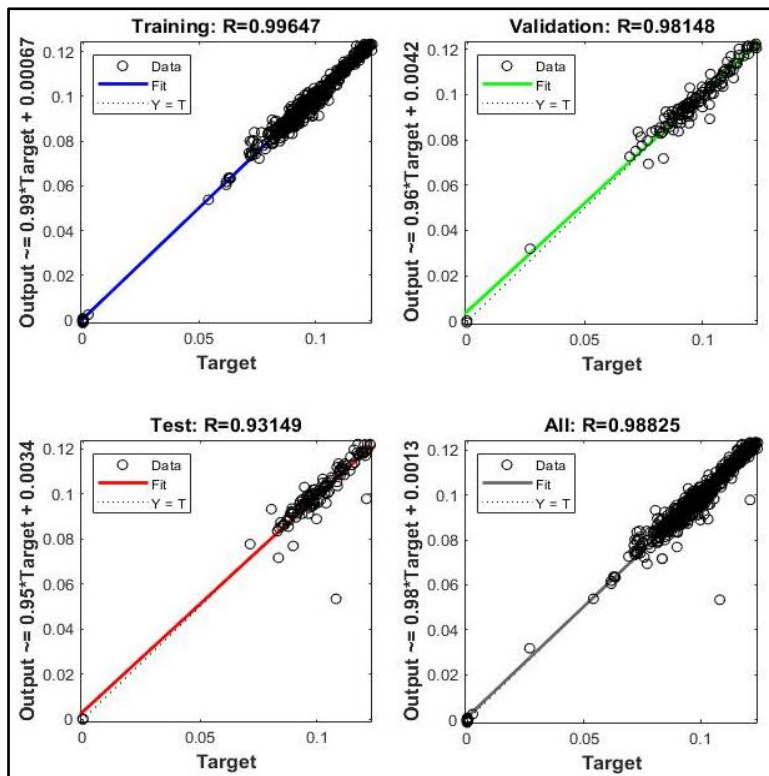


Figure 4. Regression plots of the DNN

The behaviour of the network during training is presented in Figure 5, which shows target data, output vibration, and errors. The training took a period of 3 s and the error-values are mostly around zero as the target data and

the output vibration are very close to each other. These indicate that the model did well during the training process. Figures 6 and 7, on the other hand, presents the performance of the model during validation and testing, respectively. The figures show that the errors are largely zero.

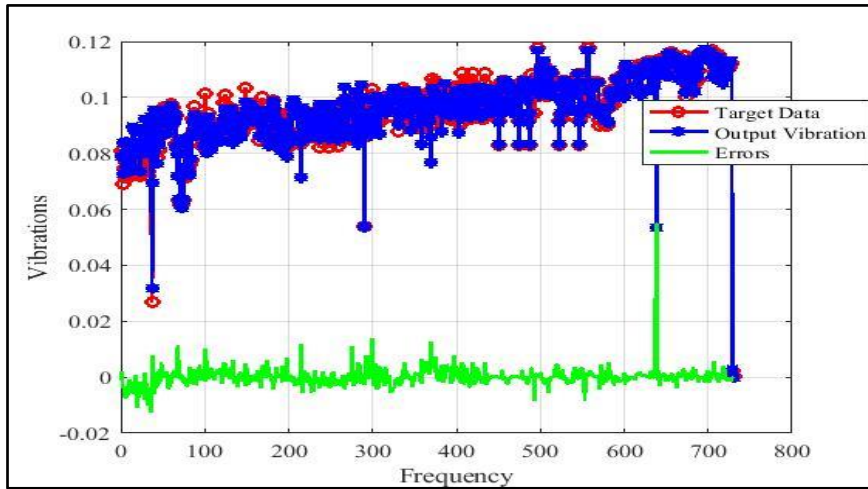


Figure 5. Performance of the DNNmodel during training

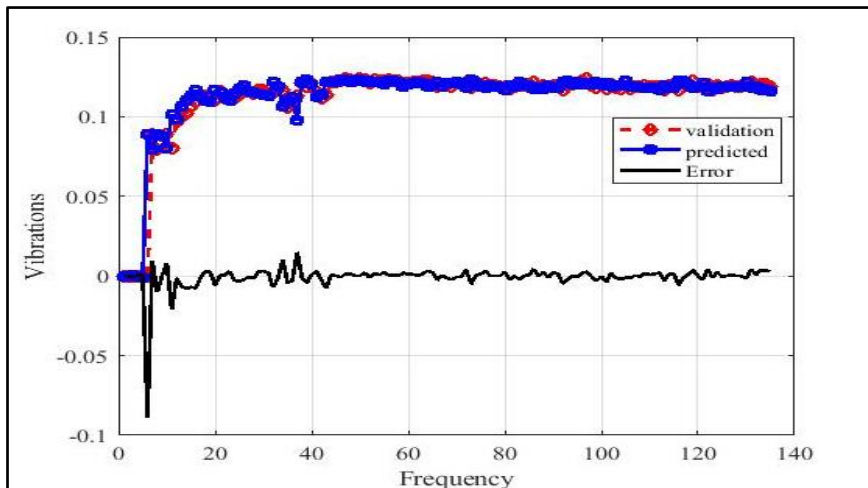


Figure 6. Performance of the DNNmodel during validation

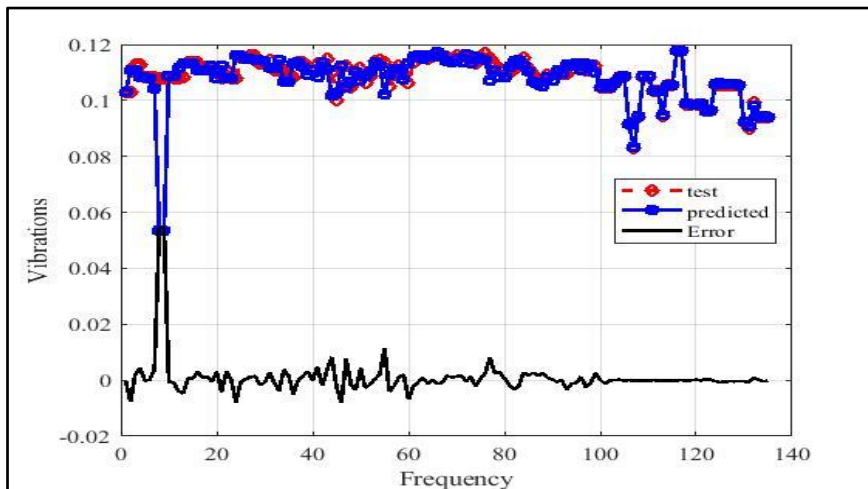


Figure 7. Performance of the DNNmodel during testing

The Prediction Model was evaluated for performance using mean square error (MSE) and mean absolute error (MAE). The values of the performance are shown in Table 1. The training performance values are usually more than the forecast evaluation because the result was exposed to the network during training. However, the result was not shown to

the model during prediction.

**Table 1.** The training performance

	MSE	MAE
<b>Training</b>	0.000013691	0.0025
<b>Validation</b>	0.000078253	0.0030
<b>Prediction</b>	0.0011	0.0037

From the forecasted operating condition of the turbine rotor, the inevitability and timing of future failure can be determined beforehand by comparing the predictions with the vibration safety threshold of the turbine rotor, which is 250  $\mu\text{m}$ .

#### 4.0 CONCLUSION

In ensuring better optimization of electric power plants, a paradigm shift in the plant maintenance culture has become inevitable. The need to change from the conventional approach to the machine learning-based predictive method in the maintenance of plant components has become important and thus a predictive approach that anchors on vibration levels monitoring is in this study proposed for turbine rotor maintenance. With historical operational data on rotor vibrations deployed on a machine-learning model, the future operating condition of the component was predicted. Inevitability and timing of failure are determined beforehand by comparing the predictions with the vibration safety threshold of the rotor. It is more economical to shut down the plant (or its component) for maintenance purposes than have it breakdown to call for repairs. Modern power plants with myriads of instrumentation and data acquisition mechanisms can leverage the approach of this study to model and plan the maintenance scheme that best suits and fits individual units of the plant, rather than premising maintenance on the rule-of-thumb.

#### Acknowledgements

There was no funding received for this work.

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