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Establishment of Machine Signature for Pulverizing Machine

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Abstract: Production activities suffered setbacks due to incessant machine breakdown caused by an incipient fault that occurred without prior notification has become worrisome to industrialists or machine users and brought delay to production and products optimization processes. Hence, the need to establish machine signature as a means of assisting plant operators to optimally maintain such machines. Therefore, this paperwork focuses on the establishment of a signature for a developed plantain flour pulverizing machine. In carrying out this research, the pulverizing machine condition data was retrieved under two conditions, namely without degradation; and with imposed degradation at different loading capacities using a data logger to monitor in real-time responses of the machine to operating conditions such as temperature, vibration, and sound. Retrieved data was analyzed using signal analyzer 8.0 in MATLAB software and signal analyzer in Origin software where the signature of pulverizing machine was established under different conditions. A regression model was established for the pulverizing machine using the aforementioned stated conditions. A logarithm function trend describes the operation characteristic note of the machine. Validation of this trend was done, and the result showed that pulverizing machine signature without degradation and imposed degradation have a distinct characteristic. Thus, the study outcome forms the basis for developing a predictive maintenance system for the pulverizing machine which distinguishes it as a novel tool for predictive maintenance and condition monitoring of machinery in the industry.

Keywords: Machine signature, pulverizing machine, maintenance.

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1. Introduction

The industrial production process is often disrupted by the intermittent machines/machinery breakdown caused by improper maintenance and upkeep. In recent times, the demand and competition in the market on machine reliability and maintainability which is transforming maintenance methods in use in terms of flexibility, cost, machine downtime, and operator idle time, is on the upward trend (Jardine et al., 2006; Rosin and Temperini, 2010). Machine components are made from diverse mechanical engineering materials with different failure rates. These components are subjected to diverse degrees of stresses generated from the machine making machine component failure inevitable, hence the need for regular maintenance.

Pulverizing machine is a value addition machine mostly used in the tropical region of the world to add value to agrarian produce for the purpose of increasing the economic value of the farm produces. The pulverizing machine of Fig. 1 is a locally fabricated machine made from stainless steel for converting different dried food items such as plantain, cassava, maize etcetera into the production of flour. It consists of the structural base, bottom casing, top casing (pulverizing chamber), transmission shaft, hammers, hammer hangers, screen (particle sieve), transmission bearings, pulleys, toothed V-belt, electric motor (5 hp), inlet hopper, inlet regulatory device, pillow bearings, belt cover, bolts and nuts (Olutomilola et al., 2021). Pulverizing machine comprises one central shaft from which four rigid shafts carrying a series of exchangeable hammers have their attachment and enclosure within a metallic casing. The dried food items are crushed by the repeated hammer impacts, collisions with the walls of the grinding chamber as well as particle-on-particles impacts. A mesh is attached to the bottom of the mill, which separates coarse materials by allowing the properly sized materials to pass through as finished products.

In developing countries where the gross domestic product (GDP) is quite low and the need to salvage this challenge calls for the setup of small or medium enterprising and modular industries to alleviate unemployment. For sustainable practice, smooth running, and encouragement of these modular industries, there is a need to provide a veritable maintenance upkeep plan for most of the locally produced pulverizing machines.

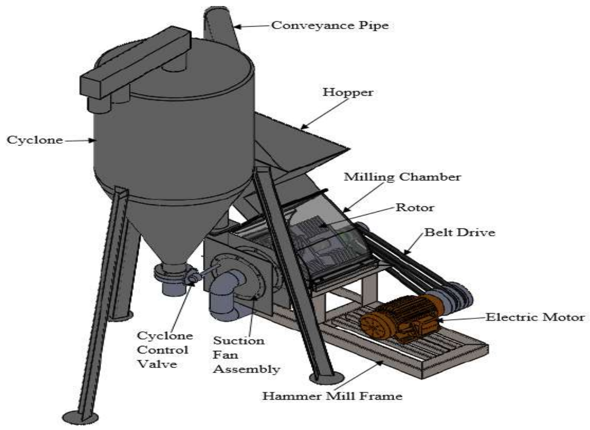


Fig. 1. The 3D view of locally developed pulverizing machine

2. Literature Review

Machine diagnostic and prognostic have proved to be a possible solution to ensure early faults tracing and aid necessary action to prevent and minimize machine downtime, the advancement of technology has made machine diagnostic and prognostic easier and faster (Mulchandani et al., 2008). This method uses a machine signature to predict the possible failure time of the component (Madhav et al., 2014). Machine signature designates the signal patterns which characterize the state or condition of a system from which the signals are acquired. Several methods have been applied by different researchers to develop machine signatures and predict the remaining useful life (RUL) of machine components. Adeyeri (2018), used machine history and its present data through monitoring as a tool for detecting faults. Also, Adebena and Jae-Cheon, (2020) posited that a monitoring program is said to be a function of set parameters that were put in place at a predefined set range to provide signals or alerts whenever there is an incipient fault on the machine system.

Al-Raheem et al., (2007) proposed a method for which bearing fault could be identified using autocorrelation of wavelet de-noised vibration signal through a wavelet base function derived from the bearing impulse response. The wavelet parameters are improved by maximizing the kurtosis criteria to generate wavelet base function with a high resemblance of impulses created by bearing defects that lead to an increase in the amount of the wavelet coefficients connected to the fault impulses and improve the fault detection process. Findings show the effectiveness of the proposed technique to reveal the bearing fault impulses and periodicity for both simulated and real rolling bearing vibration signals. Aherwar (2012), presented a review of diagnostic approaches that had been found successful in rotating machinery applications, fault detection, and identification techniques based on vibration analysis. Boskoski et al. (2017) also proposed a model using the data recorded from the deployment of inexpensive sensors for the determination of signatures for a shot blasting machine signatures. The model developed employed the use of vibrational patterns, utilizing the connection between the abrasive wear in the rotor and blades.

Wang et al. (2017) proposed a hybrid prognostics approach for RUL prediction and, therefore, the signature of rolling element bearings by degradation data of bearings which sparsely represents the use of relevance vector machine regressions with different kernel parameters and exponential degradation models and the Fréchet distance for the estimation of RUL. The proposed approach appraised the vibration data from accelerated degradation tests of rolling element bearings and the public PRONOSTIA bearing datasets. Wang et al., (2020) proposed RUL prediction based on an improved Temporal Convolution Network (TCN) for nuclear power plant valves.

Adeyeri (2016) proposed an agent-based preventive maintenance algorithm for the upkeep of a hammer mill, however, this proposition is meant to keep the operator informed whenever there is a hitch with the machine. But the present work will both describes the operation characteristics and keep operators informed on the initiation of incipient fault. Presently, research in maintenance engineering is drifting towards the use of digital technology for the determination of useful life and end of life of equipment for industrialists to be up to date with their facilities and machines. Yao et al. (2021), Li et al. (2019), and Wu et al. (2021) utilized a convolution neural network, diagnostic and prognostic tools, and classification regression method respectively to determine the health status and remaining useful life of machines at both dynamic and static states. In the same vein, Schwendemann et al. (2021) made an encompassing survey on the application of machine learning techniques for the monitoring of bearings in grinding machines.

Thus, the work reported in this manuscript makes use of machine signature analysis of pulverizing machine data retrieved using supervised learning tools. Data is/are retrieved from critical parts (bearings and milling chamber) of the pulverizing machine at various operating conditions and capacities. After which, the data is/are trained, modeled, verified, and validated to predict the machine characteristics using MATLAB software.

Machine signature and RUL determination are salient factors in the maintainability and reliability of industrial machines. Therefore, for any investor to invest in any machine, there is a need for the installation Engineer and or service personnel to have an idea of the performance characteristics or signature of the machine from point of installation and know what will become of it at a further period of time as its being used. Therefore, the present work presents a sustainable real-time maintenance practice which in turn will help in maintaining zero downtime of the machine thereby avoiding incessant breakdown and machine failure. Consequently, it will reduce power wastage as malfunctioning parts will be exposed at an early stage thereby assuring the good quality of products at all times and a reduced production cost.

3. Methodology

The experimental setup required for acquisition and retrieval, and the model training are being discussed in this section.

3.1. Experimental Data Acquisition Setup

With the experimental setup of Fig. 2, the experimentation was conducted through the running of the pulverizing machine without degradation conditions and with imposed degradation. Table 1 illustrates machine conditions designed for the experimental models operated under the following experimental tasks: Running of the test at no load, running of the test at 25% of full load capacity, and running of the test at 75% of full load capacity.

Temperature (thermocouple type k of max 6675), acoustic sensor max 4466, and accelerometer mpu 6050 were mounted on critical parts of the pulverizing machine as shown in Fig. 3. These sensors were attached to a Wi-Fi-enabled data logger which was set at 60 seconds intervals to monitor machine conditions as shown in Fig. 3. The module automatically creates data entry as a log in three datasets for temperature, vibration, and sound reading respectively. The data logged was retrieved via a wireless system unit where online monitoring and analysis are carried out.

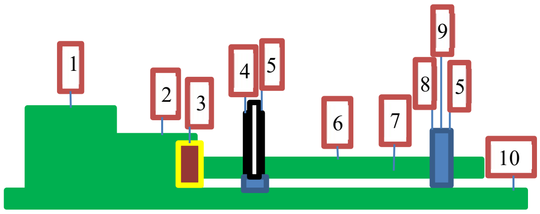
Table 1. Experimental model without degradation and with imposed degradation

Machine condition	Operation activity/description
Without degradation	Running of test at different load capacities
With degradation imposition - Belt failure, Foreign object in the bearing and Worn damping material	Running of test at different loads with: i. Belt failure ii. Foreign object in the bearing iii. Worn damping material iv. Belt failure and Foreign object in the bearing v. Belt failure and worn damping material vi. Foreign object in the bearing and worn damping material vii. Belt failure, foreign object in the bearing and worn damping material

3.2 Model Training, Validation and Testing

A signal analyzer (signal processing toolbox 8.2) and neural network time series 12.1 application in MATLAB was deployed for the training of the model. The retrieved pulverizing machine condition dataset was divided into three sets of which its algorithm experimental procedures are as shown in the flowchart of Fig. 4.

Pulverizing machine condition data builds up the machine learning algorithm which corresponds to an expected output. The model evaluates the data repeatedly to learn more about the data's behavior and then adjusts itself to serve its intended purpose. This takes 60% of the retrieved pulverizing machine condition. During training, data validation infuses new data into the model. Validation data provides the first test against new data set, this allows evaluation of how well the model makes predictions based on the new data. 20% of the retrieved machine condition data was deployed for validation.



Legend: 1- cyclone; 2- hopper; 3-milling chamber; 4, 7- accelerometers; 5- acoustic sensor max 4466; 6- shaft; 9- electric motor; 8- thermocouple; 10- installation platform;

Fig. 2. Block diagram of experimental setup showing sensors postion

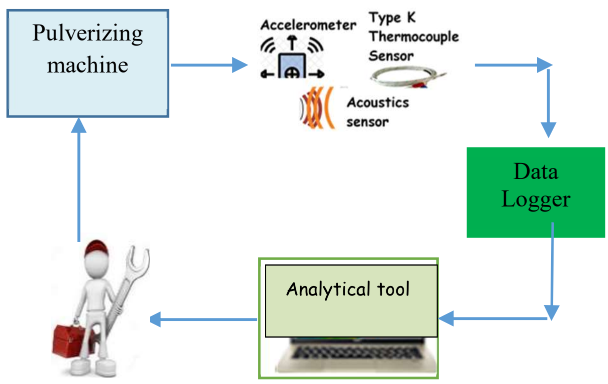


Fig. 3. Schematic diagram of experimental setup for data capturing

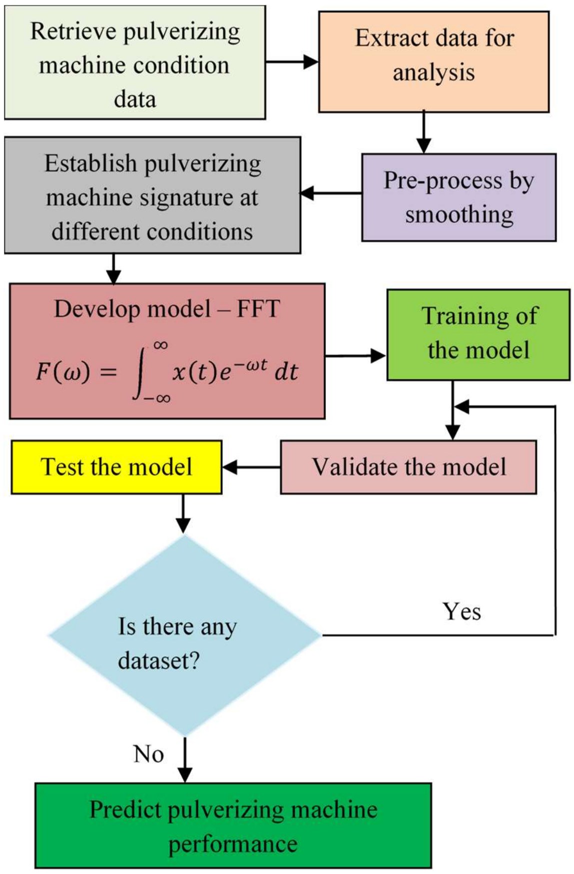


Fig. 4. Analytical flow chart on the retrieved machine data

After the model was built, testing data was deployed to validate that it could make accurate predictions. Test data provides a final check of the new dataset to confirm that the model was trained effectively for prediction. 20% of retrieved data was used for testing purposes. The neural network time series was set up and trained. Vibration data from monitored pulverizing machine condition without degradation was set as a target while vibration data from monitored pulverizing machine condition with imposed degradation was set as output. The Neural network was trained (data were presented to the network during training, and the network adjusted according to its error), validated (this tool was used to measure network generalization, and to halt training when generalization stops improving), and tested (these have no effect on training and so provide an independent measure of network performance during and after training). The total training steps were 256 steps (50%), 20% were used for validation and 30% were used to test the network. The remaining useful life was predicted using the nonlinear input-output and the trained network was validated using nonlinear autoregressive with external inputs of Eq. (1) and Eq. (2) (Raturi and Sargsyan, (2018); MATLAB (2018a)).

$$y(t) = f\big(x(t-1), \ldots\ldots, x(t-d)\big) \quad (1)$$

$$y(t) = f(x(t-1),\ x(t-d), y(t-1), \ldots, y(t-d) \quad (2)$$

Where x is the vibration response, t is time factor and d is the past values of series $x(t)$.

Spectrum analysis tool Fast Fourier Transform (FFT) was used to transform vibration signal from the time domain to the frequency domain. Hence, gives us the frequency spectrum that includes all the signal's fundamental frequency and its harmonics that could be reprocessed further to predict RUL. The equations for the Fast Fourier Transform (FFT) to move from the time domain to the frequency domain, as well as the mean square error, are as expressed in Eq. (3) and Eq. (4) (MATLAB 2018a).

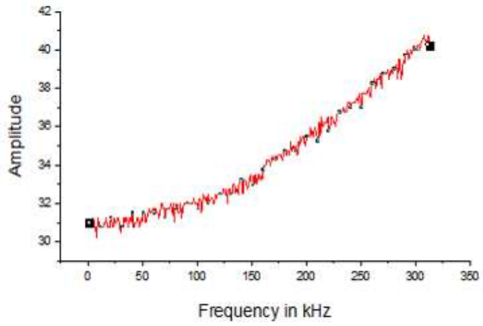
$$F(\omega) = \int_{-\infty}^{\infty} x(t)e^{-\omega t}\, dt \quad (3)$$

$$MSE = \frac{1}{n}\sum_{i-1}^{n} h_i^2 \quad (4)$$

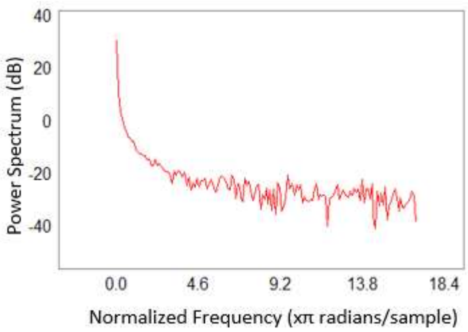
Where $x(t)$ is the time domain response of the pulverizing machine, $F(\omega)$ is Fourier Transform of $x(t)$, h_i is the difference between estimated RUL and predicted RUL, and n is current sample.

4. Results and Discussion

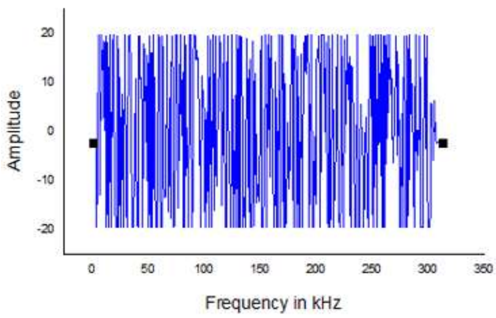
This section discusses the outcome of the experimental setup and the possible responses of the pulverizing machine as observed when in use under both degraded and degraded



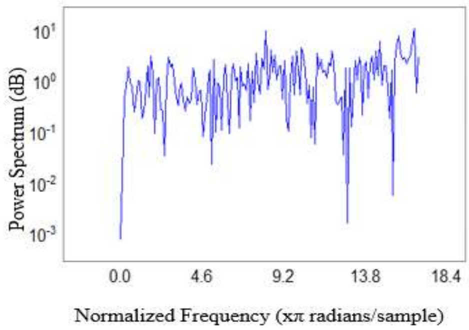
a1: Temperature response in time domain



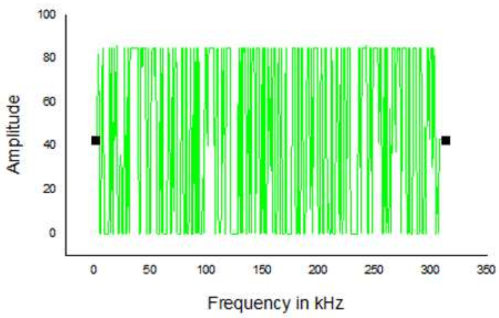
a2: Temperature response in frequency domain



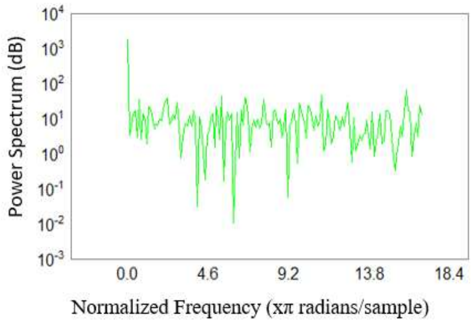
b1: Vibration response in time domain



b2: Vibration response in frequency domain



c1: Sound response in time domain



c2: Sound response in frequency domain

Fig. 5. Pulverizing machine signature without degradation at no load state

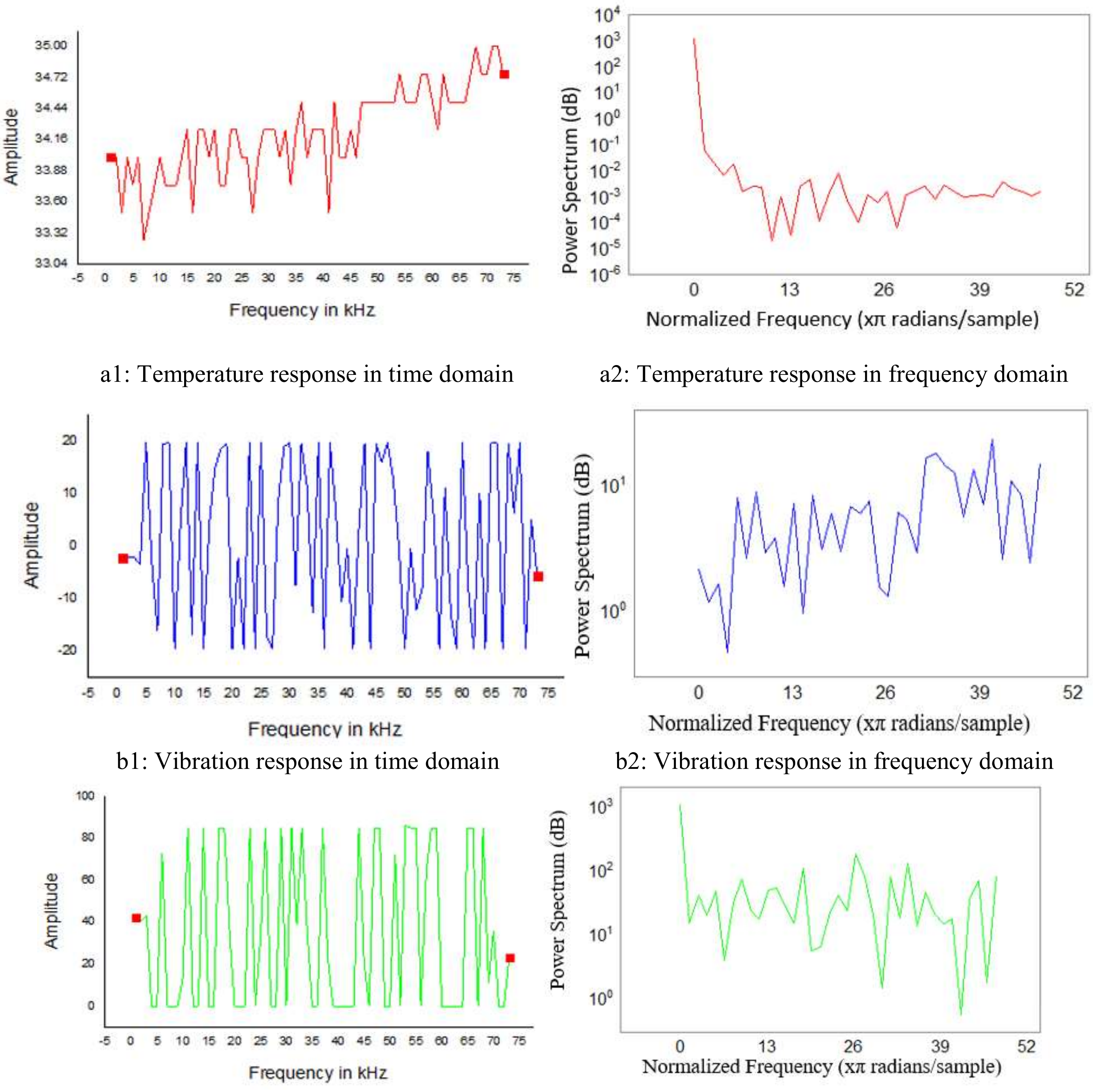
4.1 Establishment of Pulverizing Machine Signature without Degradation at Both No Load and Loaded State

Fig. 5 and Fig. 6 describe the machine signature relative to temperature, vibration, and sound responses of pulverizing machine conditions under "without degradation" at no load and loaded state. Here, time-domain i.e., Fig. 5 (a1, b1, and c1) depicts the characteristic of the pulverizing machine's response to temperature, vibration, and sound respectively as retrieved from the experimental task. Also, Fig. 5 (a2, b2, and c2) describes the behavior of the signal spectral received from temperature, vibration, and sound sensors respectively. Conversely, Fig. 6. (a1, b1, and c1) represents the characteristic of the pulverizing machine's response to temperature, vibration, and sound respectively as retrieved from the experimental task. Fig. 6 (a2, b2, and c2) portrays the behavior of the signal spectral received from temperature, vibration, and sound sensors respectively.

Results showed that pulverizing machine signature at no load when the machine was being operated without degradation has a uniform spectral in respect of vibration and sound (both vibration and sound portray a fairly uniform distribution of energy level in their spectral) while machine response to a temperature slightly increase due to hitting of the hammer while the pulverizing machine runs at no load. The amplitude of machine response to vibration has an amplitude of 35 Hz and that of sound response was 80 Hz in the time domain as shown in Fig. 5. When pulverizing machine was loaded without degradation, the resulting machine signature showed that machine response to temperature has a slight increase in temperature energy level and machine response to vibration and sound range were 40 Hz and 75 Hz respectively as described in Fig. 6.

4.2. Comparison of Pulverizing Machine Responses at No Load with No Degradation and Under Imposed Degradation

Fig. 7 shows the extract of the vibration trend of the pulverizing machine both without degradation and with imposed degradation at no load capacity. Observation at the instant of the 100th cycle position of the operation time shows that the vibration amplitude under without degradation condition is lower than the vibration amplitude (20 Hz) of the imposed degradation. This implies that once failure is initiated, the machine's response to the vibration effect will become more pronounced.



a1: Temperature response in time domain

a2: Temperature response in frequency domain

b1: Vibration response in time domain

b2: Vibration response in frequency domain

c1: Sound response in time domain

c2: Sound response in frequency domain

Fig. 6. Pulverizing machine signature without degradation under loaded state

For further clarity on the machine responses, the machine was operated at both 25% and 75% operating capacity, the observed features of the vibration trend of the pulverizing machine under "without degradation at 25% and 75% load capacities are as shown in Fig. 8. The observation at the instant of the 100th cycle position of the operation time shows that the vibration amplitude of the 25% load capacity is lower than the vibration amplitude (20 Hz) of the 75% load capacity without degradation. This implies that an increase in the load capacity of the machine has a pronounced vibration effect.

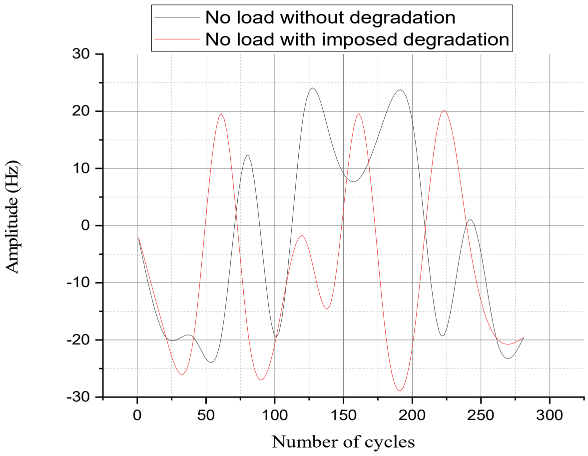


Fig. 7. Machine response comparison based on vibration at no load under without degradation and with imposed degradation

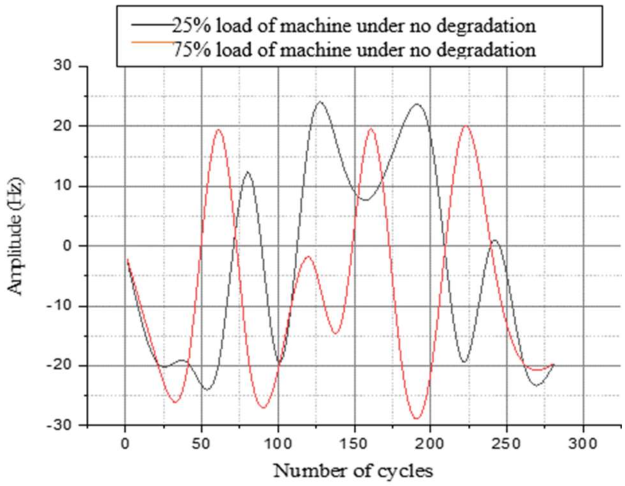


Fig. 8. Comparison of machine response to vibration at 25% and 75% load capacity under without degradation

4.3. Comparison of Machine Response at 25% and 75% load capacity under imposed degradation

Fig. 9 shows the extract of the vibration trend of the pulverizing machine at imposed degradation of 25% and 75% load capacities. Observation at the instant of the 100th cycle position of the operation time shows that the vibration amplitude of the 25% load capacity is lower than the vibration amplitude (21 Hz) of the 75% load capacity under imposed degradation. This implies that an increase in load capacity under imposed degradation of the machine also has a pronounced vibration effect.

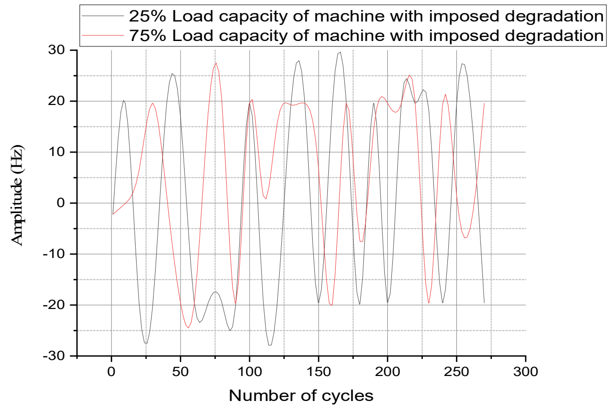


Fig. 9. Comparison of machine response to vibration at 25% and 75% load capacity for machine conditions with imposed degradation

4.4. Comparison of Machine Response at 25% without Degradation and with imposed Degradation

Similarly, Fig. 10 shows the extract of the vibration trend of the pulverizing machine at 25% load capacity without degradation and with imposed degradation. Observation at the instant of the 100^{th} cycle position of the operation time shows that the vibration amplitude under without degradation is lower than the vibration amplitude (20 Hz) of under imposed degradation. This implies that once failure is initiated at 25% load capacity under the two stated conditions earlier, the machine's response to the vibration effect will become more pronounced.

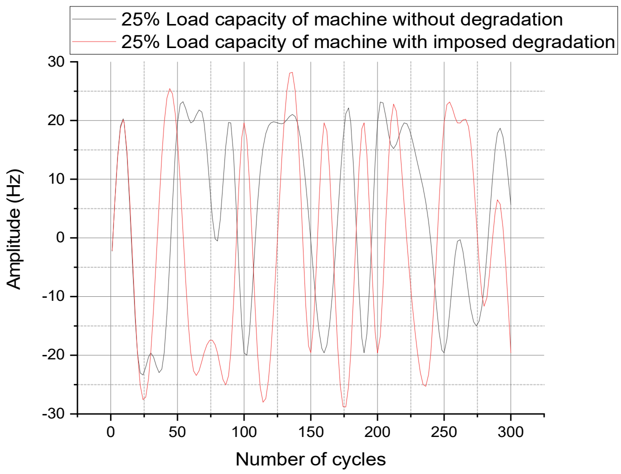


Fig. 10. Comparison of machine response to vibration at 25% under without degradation and with imposed degradation

4.5. Comparison of Machine Response at 75% under without Degradation and with Imposed degradation

Similarly, Fig. 11 shows the extract of the vibration trend of the pulverizing machine at 75% load capacity without degradation and with imposed degradation. Observation at the instant of the 100th cycle position of the operation time shows that the vibration amplitude under without degradation is lower than the vibration amplitude (20 Hz) of under imposed degradation. This implies that once failure is initiated at 75% load capacity under the two stated conditions earlier, the machine's response to the vibration effect will become more pronounced.

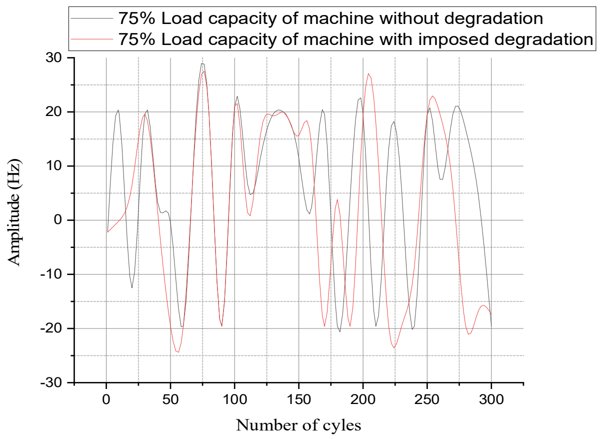


Fig. 11. Comparison of machine response to vibration at 75% under without degradation and with imposed degradation

4.6. Regression Model for Pulverizing Machine at Loaded State

The regression model showing the relationship of the three variables is presented in Fig. 12. The optimized model equations through the regression approach for the three variables in R^2 closer to unity (1) are as shown in Eq. (5), (6), and (7), where $\boldsymbol{y_T}, \boldsymbol{y_V},$ and $\boldsymbol{y_S}$ are the machine output signature of the pulverizing machine with respect to temperature, vibration, and sound, respectively. In reality, this unity was not achieved, however, these show that pulverizing machine response to temperature has a logarithm equation with R-squared of 0.686 as shown in Eq. (5). Machine responses to vibration effect also take a logarithm relationship having an R-squared of 0.001 as depicted in Eq. (6) while machine responses to sound have a linear relationship with an R-squared of 0.072 as depicted in Eq (7).

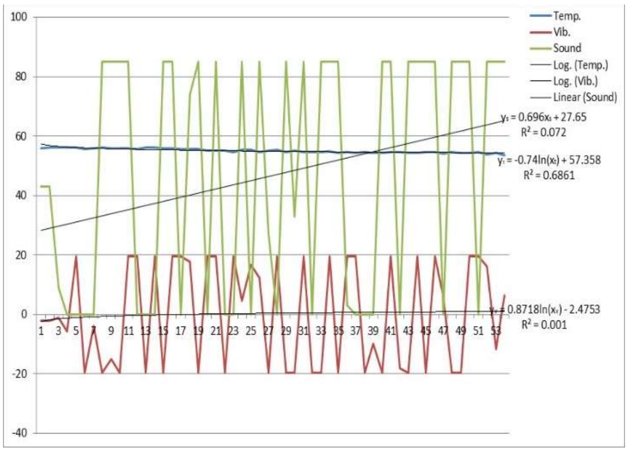


Fig. 12. Regression model of machine signature at loaded state

$$\boldsymbol{y_T = -0.74\ln(x_t) + 57.35;\ R^2 = 0.686} \tag{5}$$

$$\boldsymbol{y_V = 0.871\ln(x_v) - 2.475;\ R^2 = 0.001} \tag{6}$$

$$\boldsymbol{y_S = 0.696(x_s) + 27.65;\quad R^2 = 0.072} \tag{7}$$

4.7. Neural Network Training Performance of Pulverizing Machine at Loaded State

Fig. 13 and Fig. 14 presented the Mean Squared Error (MSE) and R^2 for the training, validation, and test respectively. For the training test data, the R^2 value is 0.68325, the R^2 value of 0.53635 is derived for the testing data, while the R^2 value after validation and the total set are 0.49746 and 0.63521 respectively. It is expected for the data to converge, to achieve this, early stopping was imposed using a neural network, and the point of convergence of the mean square error was found to be at epoch 9 in 15 cycles data training set with validation performance of 609.4814. At epoch 15, which is 6 error repetitions after the best validation, the analysis stopped. The test and validation curves showed there is no overfitting. The training path curve reduces more than the other curves, thus, indicating that the learning data is better than the others. For a better description of the signature, an error histogram showing the residuals of the targets and output is depicted in Fig. 15. The error histogram showed the outliers between -3.701 and 3.677.

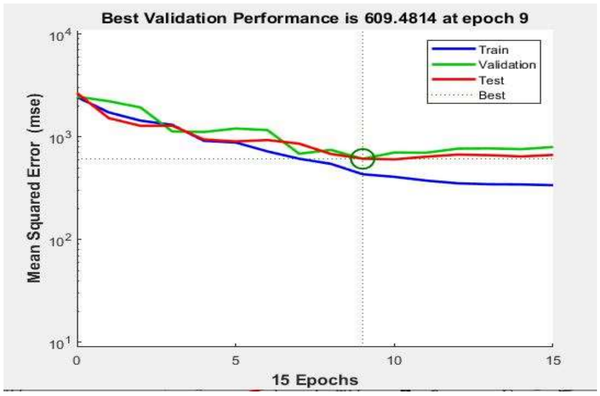


Fig. 13. Neural network training performance for 15 epochs

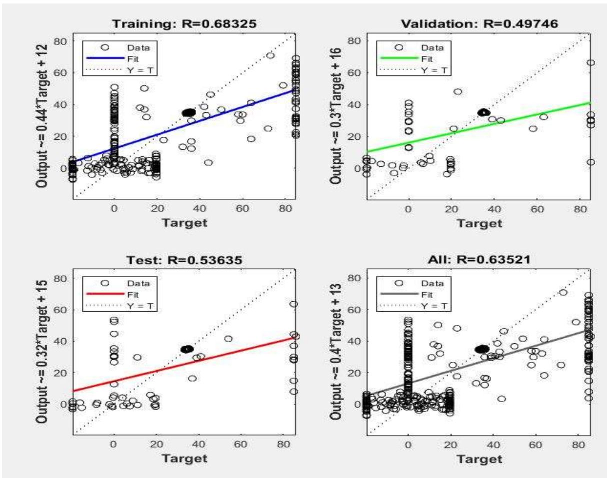


Fig. 14. Data training performance

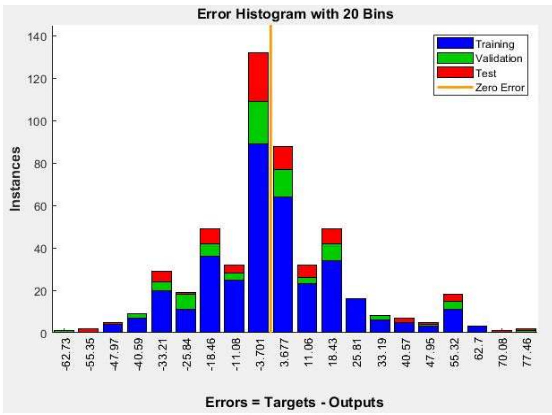


Fig. 15. Error histogram

5. Conclusion

The machine's signature was established for a locally developed pulverizing machine for the plantain flour production plant. The pulverizing machine condition was monitored using a data logger at one-minute set intervals. The data logger was deployed to monitor the temperature, vibration, and sound responses of the pulverizing machine simultaneously. The experimental setup was implemented based on the architecture and real-time monitoring showcased in the experimental model. The pulverizing machine signature in response to the three operating conditions was analyzed in both the time domain and frequency domain using the signal analyzer 8.0 toolbox. Inferences from results show that responses of the machine to temperature, vibration, and sound have a varying signature with the operating load of the machine under imposed degradation.

The pulverizing machine signature without degradation and imposed degradation have distinct characteristics. The energy level of vibration spectral increased due to wear of machine (imposed degradation) while sound reduced slightly as a result of hammers not clicking against one another without degradation imposition. Machine characteristic differs at each operating condition (temperature, vibration, and sound) and each loading state (no-load and loaded state). Thus, this established signature could be used by maintenance engineers and manufacturers to form a reference guide for the formulation of a maintenance plan and the upkeep of the pulverizing machine for sustainable production activities.

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