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Early Warning Detection for Pulverizer Abnormalities Unit 2 Suralaya PGU 1 × 400 MW with Noise Spectrum Analysis*

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Abstrak

Anomali pada pulverizer/mill di pembangkit listrik tenaga batu bara (PLTU) dapat mempengaruhi tingkat keandalan perusahaan secara signifikan. Artikel ini memperkenalkan sistem peringatan dini untuk mendeteksi anomali pada pulverizer/mill, khususnya di PT PLN Indonesia Power Suralaya PGU Unit 2 1x400 MW. Data akustik dari pulverizer 2E di Unit 2 PT PLN Indonesia Power Suralaya PGU dikumpulkan antara September 2022 dan September 2023. Dataset ini diperoleh melalui perangkat perekam dan kemudian diproses serta divisualisasikan menggunakan MATLAB dengan menetapkan nilai ambang batas atas dan bawah berdasarkan data yang tercatat selama periode ketika pulverizer tidak beroperasi dan ketika pulverizer menunjukkan pola suara abnormal. Artikel ini mengungkapkan korelasi antara peningkatan anomali suara dan jam operasional kumulatif dari pulverizer. Hasil penelitian menunjukkan bahwa seiring dengan bertambahnya jam operasional pulverizer, getaran semakin sering terjadi. Artikel ini memperkenalkan pendekatan baru dalam pemeliharaan pulverizer/mill, yang sebelumnya berbasis pemeliharaan interval setiap 3000 jam operasional pulverizer, menjadi strategi berbasis grafik waktu nyata menggunakan data yang diproses dengan MATLAB. Pendekatan ini mengusulkan peningkatan komprehensif dalam strategi pemeliharaan pulverizer di pembangkit listrik tenaga batu bara.

Kata kunci : pemantauan kondisi, pulverizer, MATLAB, spektrum suara.

Abstract

The coal pulverizer/mill abnormalities in coal power plants significantly affect the corporation’s reliability level. This paper introduces an early warning system for detecting pulverizer/mill abnormalities, specifically in PT PLN Indonesia Power's Suralaya PGU Unit 2 1x400 MW. Acoustic data from pulverizer 2E in Unit 2 of PT PLN Indonesia Power's Suralaya PGU were collected between September 2022 and September 2023. This dataset was acquired through recording devices and subsequently processed and visualized using MATLAB with the establishment of upper and lower threshold values based on recorded data during periods when the pulverizer is inoperative and when the pulverizer exhibits abnormal sound patterns. This paper reveals a correlation between increased sound abnormalities and the cumulative operational hours of the pulverizer. The results underscore that as the pulverizer operational hours accumulate, vibrations become more occurred. This paper introduces a novel approach to pulverizer/mill maintenance from the conventional strategy of interval-based maintenance every 3000 operating hours of the pulverizer, to a real- time graph-based strategy using data processed with MATLAB. This approach proposes a comprehensive enhancement of maintenance strategy within coal power plant pulverizers.

Keywords: condition monitoring, pulverizer, MATLAB, sound spectrum.

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1. INTRODUCTION

The pulverizers/mills play a critical role in coal- fired power plants by grinding coal into fine particles for combustion (Agrawal *et al*, 2015). The efficient operation of these systems is essential for power generation plant (Agrawal *et al*, 2015). The continuous output of the pulverizer is determined by the amount of coal fed into the pulverizer (Agrawal *et al*, 2015). The primary air flow transports the pulverized coal through the pulverizer, dries the coal for optimum combustion, and maintains coal circulation within the pulverizer. A change in primary air flow for a constant fuel input will produce a transitory change in the pulverized coal flow from he pulverizer until equilibrium conditions are again established. Primary air flow to the pulverizer is regulated by a damper in the primary air duct and the damper is controlled to maintain a preset fuel/air relationship dependent on pulverizer loading. A gravimetric belt feeder is used to regulate the raw coal flow to the pulverizer. The control system regulates the primary air damper and feeder to adjust the pulverizer output to meet load demand. Raw coal from the feeder is fed through a downspout in the centre of the pulverizer and flows radially outward due to centrifugal force where it is pulverized between the rollers and grinding ring segments. The mechanism of the particle size reduction is typically particle-to-particle attrition within the material layer interposed between the grinding ring segments and the rotating roller elements. This type of grinding mechanism produces low wear rates on the grinding elements.

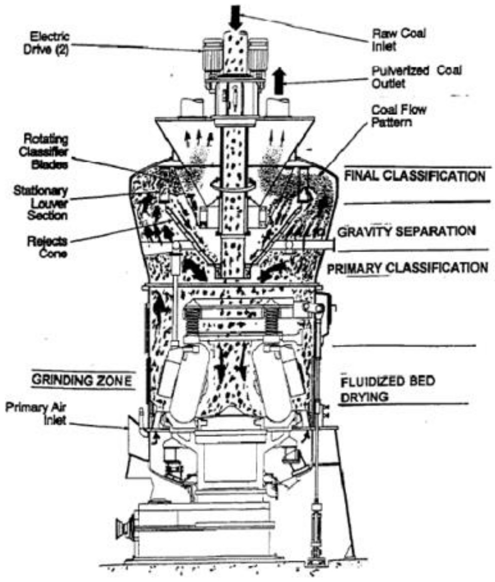

Figure 1. B&W MBS Pulverizer of PT PLN Indonesia Power Suralaya PGU Unit 2E

Table 1. Specification Pulverizer Mill Unit 2 PT PLN Indonesia Suralaya PGU

Character	Specification
type	B&W Roll Wheel Pulverizer
rated speed	985 rpm reduced to 23,5 rpm
power motor drive	522 kW/3,3 kV/158 A/ 50 Hz
voltage	6 kV
noise	Above 90dbA
area of primary chamber	9520 m^2
capacity	67.495 kg/hr, coal moisture 28,3%
coal fineness	70% through 200 mesh
	29% through 100 mesh
	1% through <50 mesh

Any deviations from normal operation of pulverizer can lead to reduced efficiency and potential breakdowns. Traditional diagnostic methods often rely on vibration analysis, which may not be sufficient to capture complex sound anomalies within the system. Modern diagnostic method develops more effective and efficient technique called predictive maintenance techniques to help evaluate the condition of in-service equipment. This strategy offers cost savings over routine or time-based preventive maintenance, because only when warranted are tasks performed. It is therefore considered to be condition-based maintenance carried out as indicated by an item's deterioration status estimates. Data Driven of predictive maintenance is very useful and effective as it helps in reducing the downtime of the pulverizer and optimize spare parts inventory. Preventive maintenance plays an important role in maximizing the equipment lifetime.

The coal pulverizer/mill is an essential component facilitating the use of coal efficiently in power generation. Found at the beginning of the process in the coalfired power plant, the pulverizer crushes the coal into a fine powder in order to be burned efficiently in the furnace.

According to a recent EEI survey, coal pulverizer operation has a major impact on the availability of large coal fired steam generators. The significance of lost generation due to the pulverizer has been cited by Southern Company System (Venkatesh *et al*, 2020) The pulverizer was ranked sixth in terms of lost generation causes in 1976 for the 78 units in the System. Four percent of the total generation losses were pulverizer related. Since the EEI data bank does not include outage causes of pulverizer failures, there existed a definite need for detailed information about the major causes of pulverizer outages and the limitations imposed on a boiler by poor performance. It was the goal of this study to provide this information and to identify the major problems of coal pulverization.

Careful monitoring of the pulverizer/mill must be done and when the machines do breakdown unexpectedly, it will cause massive loss to the company such as decrease the reliability level of the coal plant manufacture, in this case PT PLN Indonesia Power (Zhang *et al*, 2006) This can be prevented by diagnosing the machine to determine the fault or potential fault such as imbalance, wear, misalignment, defective bearing, friction whirl, and cracking teeth in gearing (Hershey, 2021), (Gulati *et al*, 2021). Several available diagnosis methods have been applied over the years including oil analysis, vibration signal analysis, particle analysis, corrosion monitoring, acoustic signal analysis, and wear debris analysis (Gulati *et al*, 2021), (Szolc, 2011). Among these analyses, acoustic and vibration signal analysis emerge as popular choices because many faults can be identified without stopping the machine or tearing the machine down. +e changes of these signals often indicate the presence of a fault. Acoustic analysis has the advantages of short analysis time, high recognition efficiency, and non- destructive testing. However, it is very challenging to properly capture the acoustic signals due to several factors such as environmental conditions, different parameter of recording software, and reflected acoustic signals (Zhang *et al*, 2006). Vibration signals analysis also has some advantages and disadvantages. Real-time machine monitoring can be achieved using vibration analysis and there are many well-developed signal processing techniques that can be applied. The limitations of vibration analysis are noise contamination and proper mounting position of the vibration sensors (Hershey, 2021). Another technique that can be used for machine monitoring and diagnosis is thermal imaging analysis. In this analysis, an infrared camera is usually used to detect many electrical faults in the machine based on the thermal anomalies. +e thermal images obtained are useful in detecting and locating the machine's faults. However, this technique is expensive and requires a longer time to process the thermal images compared to processing the acoustic and vibration signals. Vibration analysis is considered as the best method in determining the machine condition (Gulati *et al*,, 2021). According to Saucedo- Dorantes et al. (Szolc, 2011), the percentage of fault diagnosis techniques conducted with the means of vibration analysis exceeds 82%. Machines are mostly made up of moving parts that generate unwanted vibration and with vibration analysis, and a decision on whether the machine can continue to operate or needs to be shut down and repaired can be made.

The machine's condition can be determined by the vibration amplitude and frequency, as both can reveal the severity and source of the machine problem, respectively (Ghazali *et al*, 2021). At first, without the help of vibration equipment, machine conditions can still be diagnosed with a human brain of trained personnel coupled with the senses of touch and hearing which acts as a vibration analyser. However, human perception is somewhat limited, and it is impossible to detect problems that are beyond the capability of human senses of touch and hearing. when, vibration analysis was based on a real-time spectral analyser and now it can be categorized into time, frequency, and time-frequency domain (Chini *et al*, 2005). Time and frequency domain analysis analyses the time series of data with respect to time and frequency, respectively. Time frequency domain analysis used both time and frequency domains at the same time. Vibration analysis for most machine monitoring and diagnosis can be divided into lowspeed and high-speed machines. Because currently there is no universally accepted speed range to differentiate both types of machines, machines with rotating speeds up to 600 rpm such as wind turbines and paper mills are considered low- speed machines. According to Kim et al. (Manish *el al*, 2017), low- speed machines can be very time-consuming and more difficult to monitor compared to high-speed machines as the rotating elements and the fault is typically low unless the fault has reached above the background noise level. Vibration monitoring of low-speed machines is highly associated with low- speed bearing in ensuring the reliability of the machine. A simulation of the fault detection based on monitoring vibration can be prepared in MATLAB. Data of recording pulverizer/mill 2E unit

2 of PT PLN Indonesia Power Suralaya PGU recorded and collected, then with MATLAB, data processed into a readable Figure. This paper presents a correlation between sound abnormalities of pulverizer and duration of the pulverizer running/running's hour.

2. NOISE DETECTION

Audio signals are composed of multiple single- frequency sound waves. When these waves are recorded, only the amplitudes captured. The amplitudes Figures do not give much information about the signal. Thus, a mathematical technique, Fourier Transformation is used to decompose the signal into its constituent frequencies (Manish *el al*, 2017). This new Figure represents the amplitude of every frequency present in the signal.

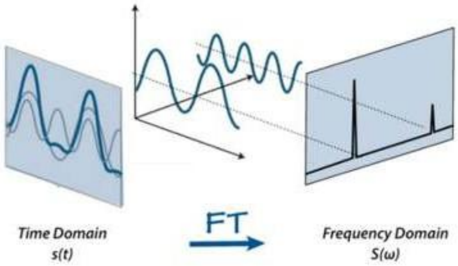

Figure 2. Time domain Figure vs frequency domain Figure (Hamomd, 2018)

The vibration analysis for machine monitoring and diagnosis typically consists of three main steps, which are data acquisition, signal processing, and fault recognition. To date, there are lots of techniques and instruments used in each of the aforementioned steps, and choosing the right ones might be quite challenging. This is because each method and instrument have its characteristics, advantages, and disadvantages. These methods can be divided into two main groups which are model- based and data driven methods. Model-based methods require an analytical model of the system whereas data-driven methods do not need any assumption about the system's model. In data-driven methods, advanced signal processing techniques are applied. Because it is very difficult to model a faulty system, data-driven methods are widely applied in machine diagnosis and monitoring compared to model-based methods. Thus, the main contribution of this article is the review of various data-driven vibration analysis techniques and instruments used for monitoring and diagnosing the machines

Chini, 2015 (Gulati *et al*, 2021) detects cavitation in centrifugal pump using noise spectrum. Chini (Gulati *et al*, 2021) presents a new approach for monitoring cavitation based on the noise measurement spectrum and analysis. Noise is measured using a microphone and a P.C. equipped with soundcard and Matlab6.1 uses Fast Fourier Transform to change the domain from time to frequency. It has been found that the sound pressure level at some frequencies can be used as a primary monitoring feature to detect the onset of the cavitation and to quantify the severity of the cavitation.

Viswakarma, 2017 (Szolc, 2011) review of some vibration feature extraction methods applied to different types of rotating machines. Vibration analysis techniques for a variety of rotating machines is presented by grouped in three categories, time domain, frequency domain and time-frequency domain. Time domain vibration signals have some limitations for detecting early fault generation (Szolc, 2011). So the research has been conducted for increasing sensitivity of statistical

parameters. Filter based methods such as modulation are being used effectively which separate fault signals from unwanted signals such as noise. Frequency domain features are generally more effective in detecting faults as compared to time domain features (Szolc, 2011). Time frequency domain features are useful in diagnosis of non-stationary vibration signals. The research is being conducted to increase the order of transformation parameters. Time frequency techniques are also being researched for analysing vibration signals for specific applications.

Aherwar, 2015 (Ghazali *et al*, 2021), discussed a variety of vibration analysis approaches in diagnosing the rotating machinery including the AI methods. It concludes that gearbox vibration signals are usually periodic and noisy. Time-frequency domain average technique successfully removes the noise from the signal and captures the dynamics of one period of the signals (Ghazali *et al*, 2021). Time domain techniques for vibration signal analysis as waveform generation, indices (RMS value, peak level value and crest factor) and overall vibration level do not provide any diagnostic information, but may have limited application in fault detection in simple safety critical accessory components. The statistical moment as kurtosis is capable to identify the fault condition but skewness trend has not shown any effective fault categorisation ability in this present gear fault condition.

Audio segmentation and sound event detection have similar goals—to detect acoustic classes and their respective boundaries within an audio stream. They provide information regarding the content of audio and the temporal occurrences of audio events. It is helpful for indexing audio archives, target-based distribution of media, and as a pre-processing step for speech recognition. In addition, detecting audio events in real-time is beneficial for self-driving automobiles, surveillance, bioacoustics monitoring, and intelligent remixing (Agrawal *et al*, 2015).

This paper proposes the application of filter band and Short-Time Fourier Transform (STFT) to separate sound sources of noise spectrum of vibration from a mixture of audio signal and create distinct sound profiles for analysis.

3. METHODOLOGY

A. Data Collection

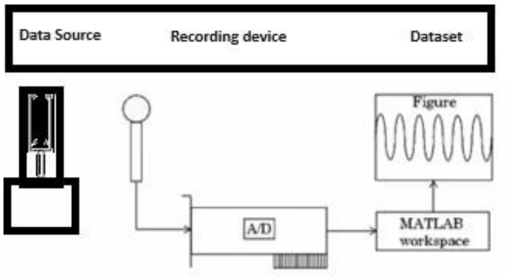

Figure 3. Flow diagram data collection


Figure 4. Location noise data recording pulverizer/mill 2E

Data of sound pulverizer/mill 2E unit 2 PT Indonesia Power Suralaya PGU collected between September 2022 – September 2023. Sensor device used is android phone POCO X3 NFT, sound card used is live android v8 using built-in software of android device 'PEREKAM', MATLAB used is MATLAB R2022. The sampling point of recording is located at upper pyrite box system the west side.

B. Predictive Maintenance Workflow

Algorithm development starts with data that describes pulverizer/mill system in a range of healthy and faulty conditions. The raw data is preprocessed to bring it to a form from which desired extract condition indicators. These are features that help distinguish healthy conditions from faulty. In this paper, it can use the extracted features to train a machine learning model that can:

1. Detect anomalies
2. Classify different types of faults
3. Estimate the remaining useful life (RUL) of your machine

Finally, the paper purpose the algorithm and integrate it into pulverizer/mill systems for machine monitoring and maintenance at PT PLN Indonesia Power Suralaya PGU.

Figure 5. Flowchart predictive maintenance using MATLAB

C. Preprocessing Data

The methodology for analysing pulverizer/mill vibrations and generating vibration signals with MATLAB. Below are outlines the procedures within MATLAB:

1. Data collection. The first step of the methodology involved the collection of recording data from the pulverizer.
2. Noise removal. Prior to analysis, the collected data underwent a preprocessing stage to eliminate undesired noise. This critical step employed MATLAB's filter function to enhance the clarity and accuracy of the analysis.
3. Fast Fourier Transform. Subsequently, the FFT function in MATLAB was applied to the preprocessed data. This step allowed for the conversion of the data from the time domain to the frequency domain, providing valuable insights into the frequency components of the signal.

4. Spectrogram Analysis. The next step of analysis entailed the generation of a spectrogram on a decibel (dB) scale. In this step, MATLAB facilitating the visualization of time-dependent variations in the frequency of data.
5. Ball Pass Frequency Outer Calculation. The dataset, now processed and refined, was subjected to further analysis to calculate vibration signals. This involved the application of MATLAB's Ball Pass Frequency Outer function. This step allowed for the extraction of key information regarding the pulverizer vibrations.
6. Envelope Spectrum. Following the calculation of vibration signals, the envelope spectrum was derived using envelope function with MATLAB. This critical step was executed to capture amplitude modulations present in the data.
7. Graphical Representation. To present the results effectively, the data was translated into graphical form. Specifically, the collected data was represented by a yellow line, data falling below the defined limit was indicated by a blue line, and data exceeding the limit was depicted by a red line. This visual representation facilitated the identification of abnormal vibration patterns of the pulverizer.

D. Under and Upper Limit Data

In the period of September 2022-September 2023, there are times, the pulverizer/mill 2E not operating same as mill 2A, 2B, 2C, 2D, and pulverizer mill unit 3, unit 4, and unit 1.

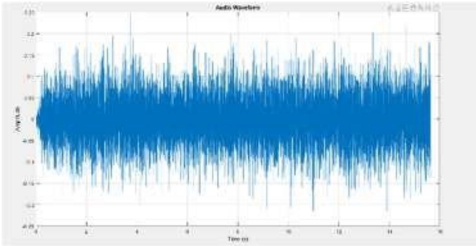

Figure 6. Waveform of pulverizer mill 2E when not operating

Figure 6 above is typical waveform of pulverizer mill 2E when not operating, this waveform indicates no vibration happens inside and around pulverizer/mill because the pulverizer/mill not operating and environment around it also did not have vibration because no other pulverizer/mill operating

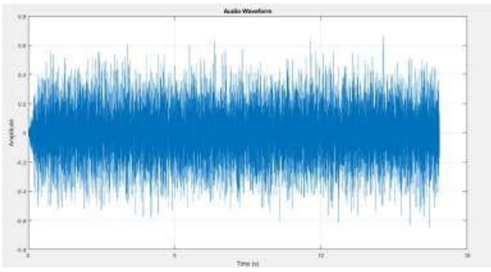

Figure 7. Waveform of pulverizer mill 2E when operating from off condition indicates a vibration signal

Figure 7 above is typical waveform of vibration of pulverizer/mill 2E, the data obtained for 10 second duration when pulverizer/mill 2E operating from off condition. The process of mill/pulverizer start could happen high vibration because there are no materials grinds inside of the pulverizer/mill.

4. RESULT

A. Dataset Description

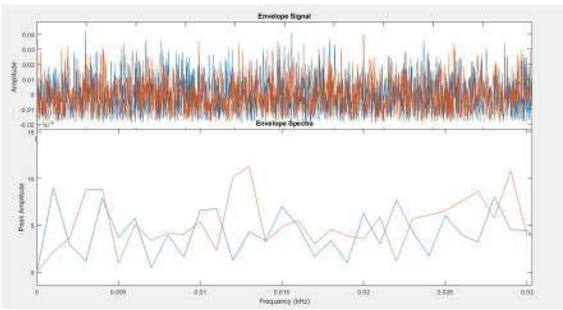

Figure 8. Comparison of pulverizer/mill from off operation (blue line) and data from pulverizer/mill that indicates have a vibration signal (red line)

Figure 8 above are the figure of pulverizer/mill compare to data from pulverizer/mill off operation and data from pulverizer/mill that indicates have a vibration signal

Figure 8 can be used as an indicator to indicates vibration signal in form of a blue area and red area from pulverizer/mill 2E that operates at PT PLN Indonesia Power Suralaya PGU.

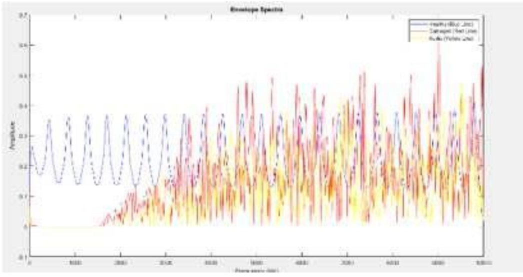

Figure 9. Comparison of pulverizer/mill from off operation (blue line) and data from pulverizer/mill that indicates have a vibration signal (red line) with input signal from data collected September 23th 2023 (yellow line)

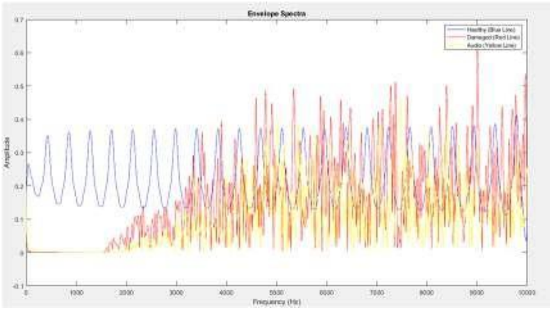

Figure 10. Comparison of pulverizer/mill from off operation (blue line) and data from pulverizer/mill that indicates have a vibration signal (red line) with input signal from data collected September 24th 2023 (yellow line)

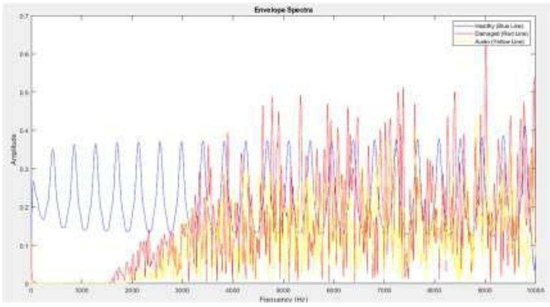

Figure 11. Comparison of pulverizer/mill from off operation (blue line) and data from pulverizer/mill that indicates have a vibration signal (red line) with input signal from data collected September 29th 2023 (yellow line)

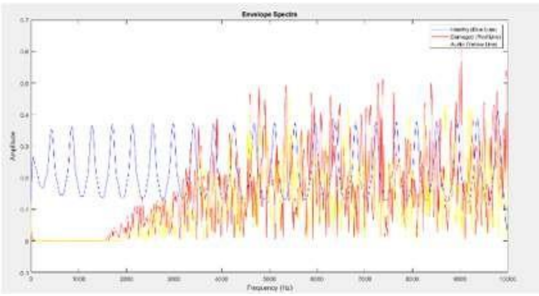

Figure 12. Comparison of pulverizer/mill from off operation (blue line) and data from pulverizer/mill that indicates have a vibration signal (red line) with input signal from data collected October 1st 2023 (yellow line)

B. Abnormality Detection Performance

In this paper, daily sound recordings of Pulverizer 2E were collected and analysed using MATLAB software on desktop computer to identify vibrations and sound abnormalities. The results indicate a strong association between the cumulative operational hours of the pulverizer and the emergence of vibrations. As operational hours accumulate, the amplitude and frequency of vibrations increase. This is manifested in the form of sound abnormalities. The real-time data analysis conducted using MATLAB proved effective in identifying these vibrations promptly, thereby validating the viability of a real-time maintenance strategy.

The key insight derived from this study is the inadequacy of traditional interval-based maintenance, which occurs every 3000 operating hours. By employing real-time data analysis, we can proactively detect and address issues as they arise, optimizing the maintenance approach for coal power plant pulverizers.

This study proposes a comprehensive enhancement of maintenance strategies within coal power plants. The implications of adopting real-time data analysis are significant, as it leads to improved reliability and performance of pulverizer systems. This approach minimizes operational downtime and aligns maintenance efforts with the actual operational state of the machinery.

The data from Figure 9 show the pulverizer/mill operates normally and have still range of the vibration signal (red area). While the data from Figure 10 show the pulverizer/mil operates normally but the data from the pulverizer/mill operates normally shows in yellow area almost enveloping of red area (the data that have vibration signal). The data from Figure 12 have indicator running hours of total running time 19801 hours. The data from Figure 9 have indicator running hours of total running time 19584 hours. This shows the correlation of the running hours of the pulverizer mill affect the vibration of the operates/mill.

In summary, the findings of this research advocate for the implementation of a real-time graph-based maintenance strategy, facilitated by MATLAB, to address the challenges associated with maintaining pulverizers in coal power plants. This shift in strategy holds the potential to transform maintenance practices and enhance the overall efficiency and operational reliability of coal power plants

Tabel 2. History of running hours pulverizer 2e

Date	Running Hours	tal Running Hours
23-09-2023	906	19584
25-09-2023	954	19640
27-09-2023	1010	19696
01-10-2023	1115	19801

5. DISCUSSION

Figure 13. Maintenance strategy for pulverizer mill unit 2E PT PLN Indonesia Power PGU Suralaya

This paper purpose a new approach strategy for maintaining pulverizer mill unit 2E PT PLN Indonesia Power Suralaya PGU, the old one give a scheduled for 3000 hours of running hours pulverizer to maintenance pulverizer mill, and this paper purpose to scheduled for duration as long as the data of spectrogram give an vibration signal from the collected data. So, it does not always count at 3000 hours of running hours pulverizer to maintenance of pulverizer mill unit 2E PT PLN Indonesia Power PGU Suralaya. With this new approach, it gives an advantage such as:

1. Better sparepart management
2. Better reliability level of power plant management
3. Longer lifetime of pulverizer/mill

6. CONCLUSION

This paper purpose a new maintenance strategy based on data collected from pulverizer mill 2E replacing the old method that always maintenance based of 3000 running hours pulverizer/mill. With this new method it will give better downtime, better reliability, more efficiency of managing the sparepart and longer lifetime of pulverizer/mill

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8. REFERENCES

V. Agrawal, B.K. Panigrahi, P.M.V. Subbarao, "Review of control and fault diagnosis methods applied to coal mills", Journal of Process Control, Volume 32, Pages 138-153, 2015. https://doi.org/10.1016/j.jprocont.2015.04.00

Venkatesh, Satvik & Moffat, David & Miranda, Eduardo, "You Only Hear Once: a Yolo- like Algorithm for Audio Segmentation and Sound Event Detection", Applied Sciences, 12, 2022. 3293. 10.3390/app12073293.

Zhang, George & Thulen, Paul, "Coal Pulverizer Monitoring and Analysis: A Case Study. American Society of Mechanical Engineers", Power Division (Publication) PWR., 2006. 10.1115/POWER2006-88095.

Hershey, S.; Ellis, D.P.; Fonseca, E.; Jansen, A.; Liu, C.; Moore, R.C., "Plakal, M. The benefit of temporally-strong labels in audio event classification", In Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Toronto, ON, Canada, 6–11 June 2021; pp. 366–370

Gulati, Karan & Basandrai, Keshav & Tiwari, Shubham & Kamat, Pooja & Dr, Kumar, "Predictive maintenance of bearing machinery using simulation- a bibliometric study", 2021.

Szolc, Tomasz & Jankowski, Łukasz & Pochanke, Andrzej & Michajłow, Maciej, "Vibration control of the coal pulverizer geared drive system using linear actuators with the magneto- rheological fluid, 2011.

Ghazali, Mohamad & Rahiman, Wan, "Vibration Analysis for Machine Monitoring and Diagnosis: A Systematic Review", Shock and Vibration. 2021. 1-25. 10.1155/2021/9469318.

Chini, Farshid & Rahimzadeh, Hassan & Bahrami, Mohsen, "Cavitation Detection of a Centrifugal Pump Using Noise Spectrum", 2005. 10.1115/DETC2005-84363.

Manish Vishwakarma, Rajesh Purohit, V. Harshlata, P. Rajput, "Vibration Analysis & Condition Monitoring for Rotating Machines: A Review, Materials Today", Proceedings, Volume 4, Issue 2, Part A, 2017, Pages 2659-2664, ISSN2214-7853, 10.1016/j.matpr.2017.02.140.

Hamomd, O, "Compound Fault Diagnosis of Centrifugal Pumps Using Vibration Analysis Techniques", The University of Huddersfield, School of Computing and Engineering, 2018.