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Predictive maintenance of mobile mining machinery: A case study for dumpers

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Abstract

The health of mobile mining machinery is critical to the achieve effectiveness and efficiency in mining production. However, the performance of mobile mining machinery, such as dumpers, is influenced by factors such as the operational environment, machine reliability, maintenance regime, human factor, etc., that lead to the downtime of dumpers. These downtimes have significant consequences on the overall equipment effectiveness (OEE) and lead to decreased capacity, increased maintenance costs and reduces availability. The enablement of prognostics and health management (PHM) can contribute to improve the OEE in mining production.

Conventionally, the existing solutions focus mostly on the reliability and maintainability analysis of dumpers using failure data, maintenance data, operation data etc. Though several existing methods utilize condition monitoring techniques, there is less focus on monitoring the engine vibration and impact the health of the driver. In addition, the existing solutions are not real-time, scalable, or offline-based. Hence, the objective of this paper is to develop a concept for the enablement of PHM for the engine and driver comfort of dumpers. Furthermore, a cloud-based solution for condition monitoring of dumpers has been designed and developed. The solution can be used to assess the engine vibrations and seat vibrations and to estimate the remaining useful life (RUL) of the selected features using standards. The cloud-based architecture is implemented on the AI Factory platform that enable PHM for the improvement of OEE. This platform also facilitates the enablement of a digital twin for components and systems within dumpers or other mobile mining machinery.

Keywords: predictive maintenance, digital twin, dumpers, condition assessment, remaining useful life estimation

1. Introduction

Dumpers are critical for production in mining operations due to their capability to transport large quantities of mining materials over long distances. Dumpers are operated in heavy loads, rugged terrain, and harsh environmental conditions that are common in mining operations. Maintenance is essential for dumpers in mining operations to ensure their safe and efficient operation, maximize their lifespan, and minimize the risk of costly breakdowns and downtime to operate in these harsh conditions.

Maintenance of dumpers is necessary to prevent and detect issues before they lead to major breakdowns, reduce the likelihood of accidents, and optimize the performance of the equipment (Kumar, U. and Klefsjö 1992, 217-224). Condition monitoring (CM) and prognostics and health management (PHM) play a crucial role in maximizing overall equipment effectiveness (OEE) within the mining industry (Kumar, R. and Kumar 2004, 299-307).

Mining companies can reduce the likelihood of equipment failures and the associated costs of repairs and replacement, minimize unplanned downtime, and extend the equipment lifespan. Technology can facilitate CM and PHM of dumpers for real-time assessment of mining machinery to make immediate decisions.

Usually, PHM has prevalent in several industries, however, it is quite nascent in the mining industry which is of high relevance. In addition, the cloud-based platform is also needed for remote monitoring and maintenance of the fleet. There are several researchers carried out PM of mining machinery (Martins and Soofastaei 2020a, 149-168; Castilla et al. 2018, 663-668; Taghizadeh Vahed et al. 2019a, 1242-1246; Dong, Mingyue, and Guoying 2017, 885-889; Guerra Vallejos et al. 2021; Marino et al. ; Żak, Wyłomańska, and Zimroz 2019, 449-458; Taghizadeh Vahed et al. 2019b, 1242-1246; Rihi et al. 2022, 2483-2492; Martins and Soofastaei 2020b, 149-168; Kruczek et al. 2019, 459-470) but only a few studies on cloud implementation for dumper, (Kruczek et al. 2019, 459-470; Jakobsson 2022; Michalak et al. 2019, 471-480). Hence, the purpose of this paper is to propose a concept for the enablement of PHM for the engine and driver comfort of dumpers. This concept has been implemented on the AI Factory platform (Karim et al. 2021, 1160-1167; Karim, Galar, and Kumar 2023). The scope of the work is carried out on an Indian open pit mine and limitations for CAT dumpers and period of measurement from Jan to July.

2. Methodology

2.1. *Selection of case study*

The data acquisition from the dumpers is carried out at the Sonepur Bazari Coal Mine which is in the Eastern Part of Raniganj Coalfields in the district of Burdwan, West Bengal. The haul roads are vital for dispatching the coal from the extraction face to the dump and coal handling plants. The performance depends on the quality and dimension of the haul roads. The selected dumper is CAT-777D with 100T capacity.

2.1.1. *Specifications and requirements*

The detailed requirements and specifications need to be identified for getting relevant industrial context and benefit for the research study. From the selected mine, the main requirements are:

- Real-time monitoring of the dumper's health.
- Analysis for forecasting of RUL.
- Optimizing the maintenance decisions for effective asset management
- Realtime cloud-based platform for data to decision making.

2.2. *AI Factory platform*

To enable PHM, an integrated cloud-based platform is needed, leveraging AI and digitalization. The cloud-based architecture is envisioned implemented on the AI Factory platform. AIF for Mining (AIF/M) intends to provide capabilities such as acquisition, integration, transformation, and processing of mining vehicle-related data across endpoints, e.g., industries, operators, and authorities. AIF/M architecture is built on coupled storage and computing services, see Figure 1.

AIF/M is to enable a DT approach for PHM through an integrated platform and toolkit for fact-based decision-making. AIF/M's technology platform is a service-oriented end-to-end scalable environment for enabling capabilities for information logistics, including (but not limited to) e.g., service data acquisition (data filtering, data quality, data transformation), data integration, cybersecurity, and data processing/analytics, and a visualization. These services can be utilized to support e.g., diagnostics, CM, PHM and assessment, risk management, asset management, etc.

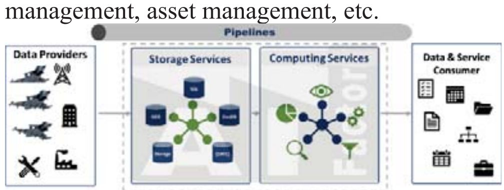


Figure 1 AIF/M's conceptual architecture

2.3. *PHM Methodology*

The process workflow is developed based on the AIF platform with functionalities related to PHM for dumpers as shown in Figure 2. The detailed description of the steps is mentioned below:

2.3.1. *Data acquisition*

Sensors equipped on the dumpers will gather real-time data. This data includes prime engine conditions, axle load and vibration. axle bearing temperature, vehicle ride quality and tire conditions. Data acquisition was carried out for four months each 30 mins per day. In addition to the online monitoring data, operational data such as the loading capacity of dumpers, breakdown data of dumpers and maintenance data are recorded in parallel through the web-based client. The placement of sensors is an important component of any condition monitoring since sensors are positioned where the most information about any equipment can be collected. Accelerometer sensors should be located close to the rotating and vibrating parts of the machine so that the signal they gather accurately reflects the state of the machine. The engine is the heart of the vehicle, it will be one of the primary sources of vibration. However, through the wheel, suspension, and frame, road vibration travels to the seat. The schematic diagram of the dumper and placement of sensors is shown below in Figure 3.

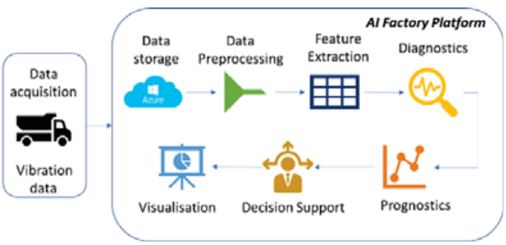


Figure 2 PHM methodology for dumpers

2.3.2.Data storage

The data generated from LabVIEW is stored on the Azure cloud server using mobile data. Traditionally, this data is stored in Azure blob storage from all vibrations acquired from sensors.

2.3.3.Data preprocessing

The data preprocessing step needs to be performed to conduct data quality and data cleaning. Some of the measurement campaigns need to be removed because it doesn't have the expected acceleration value from the sensors. Data analysis, data preprocessing and feature extraction will be performed on the data. The algorithms and code are analyzed on a cloud-based platform where feature extraction is performed on the server.

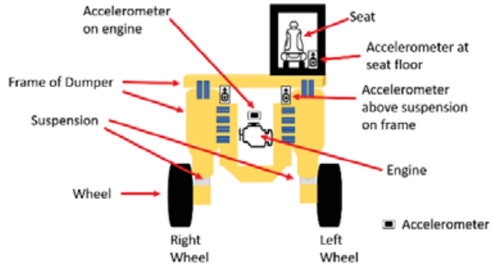


Figure 3 Schematic diagram for mining dumper with accelerometer position

2.3.4.Feature extraction

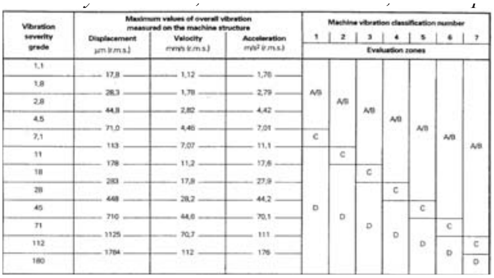
Two types of analysis are performed from the vibration signals acquired from dumpers: engine vibration analysis for detecting the severity of the engine and seat vibration analysis for detecting the comfort level of the driver.

2.3.4.1.*Engine vibration*

ISO 10816-6 standard (ISO 2015)is chosen to predict the severity of the engine vibration. The thresholds from the standard to predict severity is shown in Figure 4. Hence, to determine the health of the engine, velocity and displacement signals need to be extracted from the raw measurement of acceleration. The selected engine is class 6. However, it is necessary to perform a band-pass filter from 2 Hz to 1000 Hz because the functional part of the engine vibration resides within the frequency range. The band-pass filters need to be applied when transforming from acceleration to velocity and velocity to displacement.

2.3.4.2.*Seat comfort*

ISO 2631-1 standard (ISO 2011) is selected to predict the whole-body vibration from the dumper. The classification is shown in Figure 5. The web-based client extracts these features from the monitored KPIs and depicts the existing condition of the dumpers using visualization charts (using Power BI). For safe and secure operation, respective authentication details will be provided so that only the people who have access to the website can be able to see and visualize the KPIs of dumpers. In addition, a preliminary analysis of historic breakdown data is also to be shown in the web-based client. The position measurement data will be positioned from the exposure duration and the amount of weighted acceleration experienced by the driver.



Vibration severity grade	Maximum values of overall vibration measured on the machine structure: Displacement µm (r.m.s.)	Velocity mm/s (r.m.s.)	Acceleration m/s² (r.m.s.)	Machine vibration classification number / Evaluation zones: 1	2	3	4	5	6	7
1,1				A/B	A/B	A/B	A/B	A/B	A/B	A/B
	17,8	1,12	1,78							
1,8				A/B	A/B	A/B	A/B	A/B	A/B	A/B
	28,3	1,78	2,79							
2,8				A/B	A/B	A/B	A/B	A/B	A/B	A/B
	44,8	2,82	4,42							
4,5				A/B	A/B	A/B	A/B	A/B	A/B	A/B
	71,0	4,46	7,01							
7,1				C	A/B	A/B	A/B	A/B	A/B	A/B
	113	7,07	11,1							
11				D	C	A/B	A/B	A/B	A/B	A/B
	178	11,2	17,8							
18				D	D	C	A/B	A/B	A/B	A/B
	283	17,8	27,9							
28				D	D	D	C	A/B	A/B	A/B
	448	28,2	44,2							
45				D	D	D	D	C	A/B	A/B
	710	44,6	70,1							
71				D	D	D	D	D	C	A/B
	1125	70,7	111							
112				D	D	D	D	D	D	C
	1784	112	178							
180				D	D	D	D	D	D	D

Figure 4 Thresholds for severity estimation of the engine from ISO 10816-6

2.3.5. Diagnostics

From analyzing the condition monitoring data, the detection of faults will be identified by using an expert's judgement and the data by considering predefined thresholds from the standards (Kępski and Barszcz 2012, 25-30). This fault detection needs to be investigated with breakdown data of dumpers (Papic et al. 2016a, 283-299) for safety (Papic et al. 2016b, 485-496).

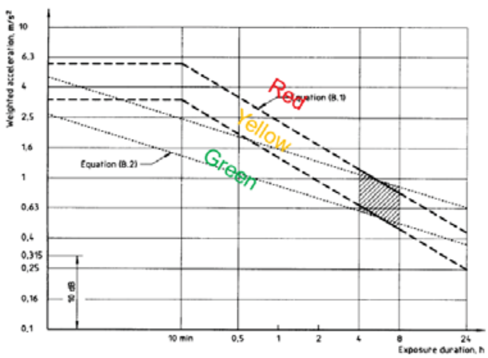


Figure 5 Health guidance caution zones (Green: No effects, Yellow: Caution for potential health, and Red: Health risks are likely)

2.3.6. Prognostics

By applying data-driven predictive models to gathered data, the best model will be selected based on performance metrics and appropriately, the future condition of the KPIs will be determined (Wen et al. 2022, 110276). To predict the RUL of the dumper, thresholds will be defined and selected such that the estimated parameter values of KPIs will determine the time taken to reach the specific thresholds.

2.3.7. Maintenance decision support

Based on the estimated time intervals of KPIs, suitable PM actions will be suggested for future time so that the overall availability can be increased based on context (Galar et al. 2015, 137-150).

2.3.8. Visualisation

The users will have access to PowerBI which is a visualization tool. The platform is built on the Azure platform. The user can access without login or with login using the credentials. The web-based access to the PowerBI of the platform enables the user to interact with various data related to history, CM data, and predictions based on the prescribed threshold limits.

3. Results and analysis

3.1. Data acquisition

Data acquired from the installed sensors acquired from locations as depicted in Figure 3 are stored in an Azure blob storage platform.

3.2. Data storage

A snapshot of the vibration signal from the seat floor and the engine is shown in Figure 7.

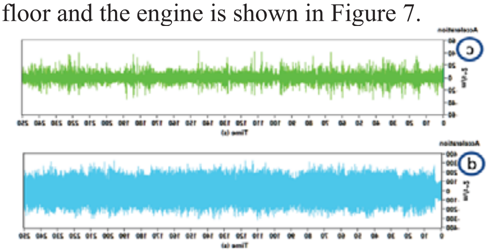


Figure 6 Vibration data from an accelerometer on dumper 2182 (a) seat floor, and (b) engine

3.3. Data preprocessing

The measured dumpers undergo several operations such as loading, unloading, idle state, stops, etc. Hence, it is necessary to detect and remove unwanted states to detect and predict the actual vibration (Figure 7).

3.4. Feature extraction

The conventional feature extraction is carried out from the vibration signals for each measurement campaign as shown in Figure 8.

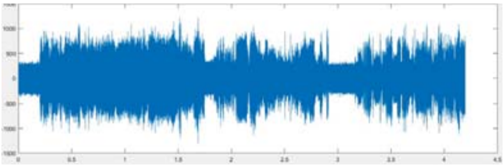


Figure 7 Preprocessed data from engine vibration

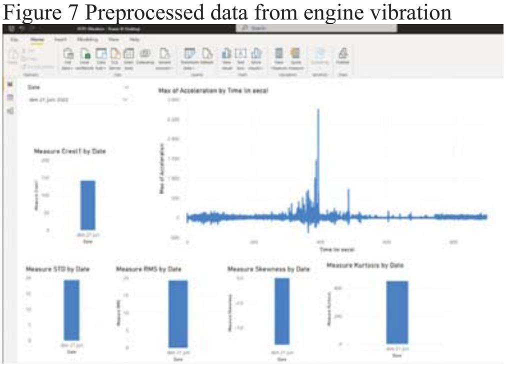


Figure 8 Feature extraction from seat vibration

3.4.1.Engine vibration

To determine the health of the engine, velocity and displacement signals need to be extracted from the raw measurement of acceleration. The selected engine is class 6. However, it is necessary to perform a band-pass filter from 2 Hz to 1000 Hz because the functional part of the engine vibration resides within the frequency range. The band-pass filters need to be applied when transforming from acceleration to velocity and velocity to displacement. The filtered signals for measurement campaigns are visualized in Power BI as shown in Figure 9.

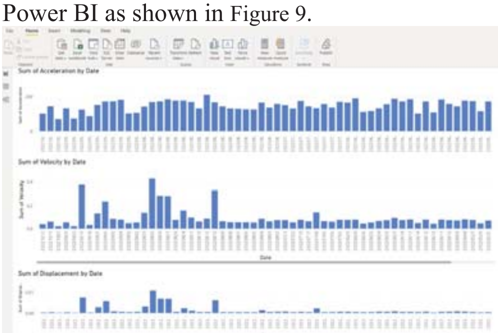


Figure 9 Engine features for health assessment

3.4.2.Seat comfort

The whole-body vibration will also be assessed by the max composite weight, fourth power vibration dose, maximum transient vibration and whole-body vibration as shown in Figure 10.

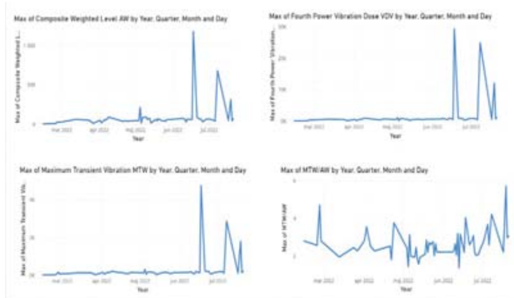


Figure 10 Feature extraction from the ISO 2631-1

3.5.Diagnostics

There exist some anomalies in the features that are extracted from the raw signals. These anomalous features can be occurred due to incorrect sensor acquisition, mishandling of the dumpers at the site, potholes on road, or any other unknown reasons. These deviations occurred due to the above reasons are reflected in Figure 11 for engine vibration and Figure 12 for seat vibration.

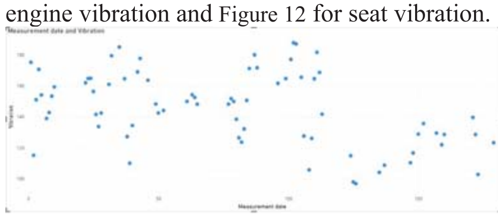


Figure 11 Deviations on engine vibration, X-axis is measurement data, and the Y-axis is acceleration.

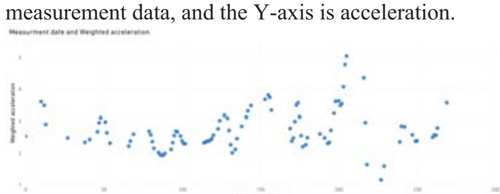


Figure 12 Deviations on weighted acceleration, X-axis is measurement data, and the Y-axis is acceleration

3.6.Prognostics

3.6.1.Prediction of engine health

Based on the thresholds defined, the acceleration, velocity, and displacement are calculated and identified as the severity criteria. However, the assumption laid out here is that the vibration experienced by the engine accumulates to all conditions. Even though, based on the velocity, speed can be extracted, the total load experienced by the engine depends on road conditions, weather, driving behaviour, and position of the dumper. The health can be classified from the standard shown below in Figure 13. It was reported from the data set that 14% of data points are classified as C and 86% of data points are classified as D (Figure 14).

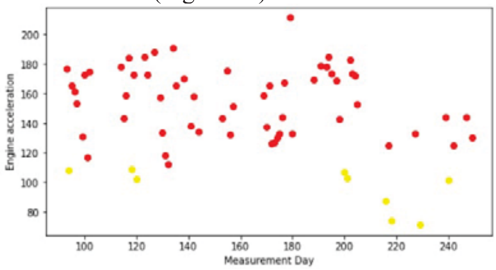


Figure 13 Prediction of health from engine vibration (Yellow: Unsatisfactory for long-term operation, Red: Sufficient severity to cause damage to the machine)

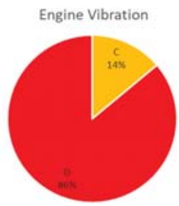


Figure 14 Pie chart of health categorization

3.6.2.RUL prediction of engine vibration

Since the measured data is uneven across each measurement campaign, the total vibration experienced also varies. In addition, as was reported in previous sections, the vibration also depends on location, road conditions, weather, driving behaviour, and speed of the dumpers. Cleaning and anomaly detection was performed on the data set using spline methods, and the filtered data along with various time series and algorithms are developed shown in Figure 15. In addition, exponential smoothing algorithms are developed as shown in Figure 16.

3.6.3.Prediction of the health of seat comfort

Similarly, based on the thresholds defined in Figure 5, the acceleration, velocity, and displacement are calculated and identified the severity criteria. However, the assumption is that the vibration experienced by the seat floor accumulates to all conditions. Even though, based on the velocity, speed can be extracted, the total load experienced by the seat floor depends on road conditions, weather, driving behaviour, and position of the dumper. The health can be classified as shown in Figure 17.

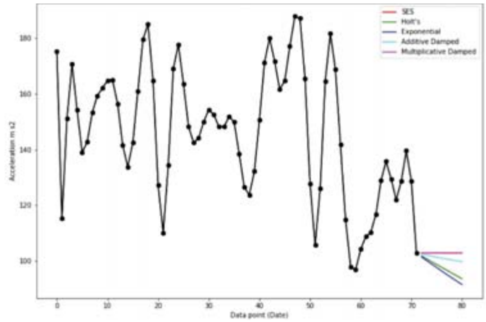


Figure 15 RUL prediction of the engine using trend algorithms, the X-axis is measurement data, and the Y-axis is acceleration.

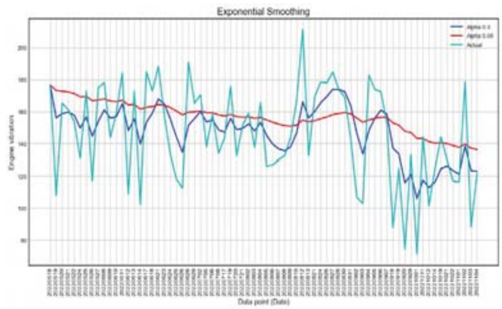


Figure 16 RUL prediction of the engine using exponential smoothing.

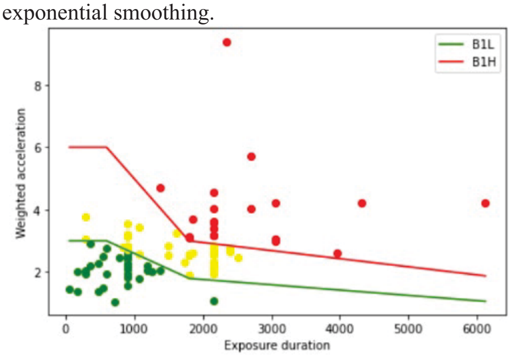


Figure 17 Prediction of health from seat vibration (Green: No effects, Yellow: Caution for potential health, and Red: Health risks are likely)

It was reported from the data set that 41% of data points are categorized as green, 36% of data points are categorized as a warning, and 23% of data points are categorized as red as shown in Figure 18. However, the whole-body vibration was assumed that the engine does not correlate with the engine.

3.6.4.RUL Prediction of seat comfort

Since the measured data is uneven across each measurement campaign, the total vibration experienced also varies. In addition, as was reported in previous sections, the vibration also depends on location, road conditions, weather, driving behaviour, and speed of the dumpers. Cleaning and anomaly detection was performed on the data set using spline methods, and the filtered data along with various time series and algorithms are developed shown in Figure 19. In addition, exponential smoothing algorithms are developed as shown in Figure 20.

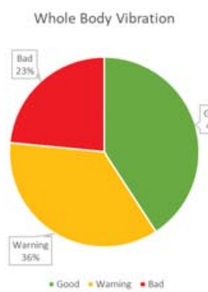


Figure 18 Pie chart of seat vibration

3.7.Maintenance decision support

From the analysis of the seat vibration, it was concluded that more analysis needs to be performed to check the driving behaviour to make sure that the dumpers can be the better condition. Additional data preprocessing and cleaning are required for a better assessment of the vibration observed by the driver. From the analysis, it was concluded that the dumper is not in a better condition and hence, condition monitoring techniques need to be implemented for better assessment of health. This dumper operation has an impact on availability that leads to a reduction of OEE. Hence, a more proactive maintenance strategy needs to be implemented in terms of inspecting and carrying out preventive maintenance actions.

4. Discussion

To exploit the best out of technology, it is necessary to understand the challenges that are faced by the mining industries. Hence, this research initiates from the industrial problems and requirements of dumper's performance. The data that are being generated are not quality enough to develop RUL because for several reasons such as driving behaviour, road conditions, weather conditions, vehicle prior history of failures and maintenance, and operating conditions.

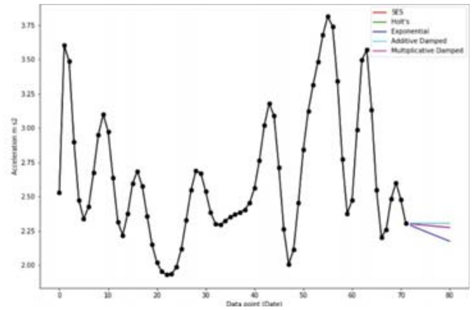


Figure 19 RUL prediction of the seat using trend algorithms, the X-axis is measurement data, and the Y-axis is acceleration.

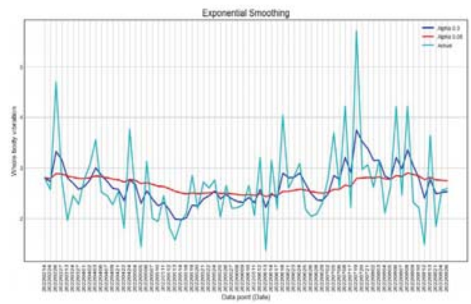


Figure 20 RUL prediction of the seat using exponential smoothing.

Hence, the developed models are not accurate enough to predict RUL since there is no trend in the data and there are several anomalies in the data that need further processing. Hence, this study concludes that additional information is needed to identify the root cause of failures and entirely data-driven doesn't provide the overall picture of the health of dumpers. In addition, a complete platform is required for the implementation of data-decision for the real-time monitoring and assessment of mobile mining machinery. This platform enables mining companies to remotely monitor KPIs. This platform also facilitates the enablement of a digital twin for components and systems within dumpers or other mobile mining machinery for improving OEE.

5. Conclusion

The real-time condition monitoring for predictive maintenance of dumpers within the mining industry has several benefits such as reduced breakdowns, reduced total cost, improved culture for maintenance, and improve OEE. However, there are still several challenges that need to be addressed such as the initial cost of installation for predictive maintenance, technological challenges, gathering the right kind of information, and interpretation of results. The case study implemented in this paper can also be extended to better maintenance management of other fleets of vehicles such as trains, buses, trucks, etc.

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References

Castilla, Javier, Juan C. Fortes, J. M. Dávila, Sergio Melgar, and Aguasanta Sarmiento. 2018. "Predictive Maintenance of Mining Machinery Based on Vibrational Analysis." *International Multidisciplinary Scientific GeoConference: SGEM* 18 (1.3): 663-668.

Dong, Li, Ren Mingyue, and Meng Guoying. 2017. "Application of Internet of Things Technology on Predictive Maintenance System of Coal Equipment." *Procedia Engineering* 174: 885-889.

Galar, Diego, Adithya Thaduri, Marcantonio Catelani, and Lorenzo Ciani. 2015. "Context Awareness for Maintenance Decision Making: A Diagnosis and Prognosis Approach." *Measurement* 67: 137-150.

Guerra Vallejos, Ernesto, Francisco Pastene, Aníbal S. Morales Montecinos, Luciano Radrigán, and Pablo Aqueveque. 2021. "Data-Driven Condition Monitoring of Mining Mobile Machinery in Non-Stationary Operations using Wireless Accelerometer Sensor Modules."

ISO. 2015. *BS ISO 10816-6:1995+A1:2015: Mechanical Vibration. Evaluation of Machine Vibration by Measurements on Non-Rotating Parts* British Standards Institute.

ISO. 2011. *BS ISO 2631-1:1997: Mechanical Vibration and Shock. Evaluation of Human Exposure to Whole-Body Vibration* British Standards Institute.

Jakobsson, Erik. 2022. "Condition Monitoring in Mobile Mining Machinery.". doi:10.3384/9789179292997.

Karim, Ramin, Pierre Dersin, Diego Galar, Uday Kumar, and Håkan Jarl. 2021. "AI Factory--A Framework for Digital Asset Management."Research Publishing Services, .

Karim, Ramin, Diego Galar, and Uday Kumar. 2023. *AI Factory: Theories, Applications and Case Studies* CRC Press.

Kępski, Paweł and Tomasz Barszcz. 2012. "Validation of Vibration Signals for Diagnostics of Mining Machinery." *Diagnostyka* (4 (64): 25-30.

Kruczek, P., N. Gomolla, J. Hebda-Sobkowicz, A. Michalak, P. Śliwiński, J. Wodecki, P. Stefaniak, A. Wyłomańska, and R. Zimroz. 2019. "Predictive Maintenance of Mining Machines using Advanced Data Analysis System Based on the Cloud Technology."Springer, .

Kumar, Rajesh and Uday Kumar. 2004. "Service Delivery Strategy: Trends in Mining Industries." *International Journal of Surface Mining, Reclamation and Environment* 18 (4): 299-307.

Kumar, Uday and Bengt Klefsjö. 1992. "Reliability Analysis of Hydraulic Systems of LHD Machines using the Power Law Process Model." *Reliability Engineering & System Safety* 35 (3): 217-224.

Marino, Laís, Jánes Landre Jr, Cádmo Augusto Rodrigues Dias, and Bernardo Rocha. "Challenges and Cases of Artificial Intelligence Applied to Assist Predictive Maintenance in the Industry, Respectively in the Mining Sector." .

Martins, Paulo and Ali Soofastaei. 2020a. "Predictive Maintenance of Mining Machines Applying Advanced Data Analysis." In *Data Analytics Applied to the Mining Industry*, 149-168: CRC Press.

Martins, Paulo and Ali Soofastaei. 2020b. "Predictive Maintenance of Mining Machines Applying Advanced Data Analysis." In *Data Analytics Applied to the Mining Industry*, 149-168: CRC Press.

Michalak, Anna, P. Śliwiński, Tomasz Kaniewski, Jacek Wodecki, Paweł Stefaniak, A. Wyłomańska, and Radosław Zimroz. 2019. "Condition Monitoring for LHD Machines Operating in Underground Mine—Analysis of Long-Term Diagnostic Data."Springer, .

Papic, Ljubisa, Srdja Kovacevic, Diego Galar, and Adithya Thaduri. 2016a. "Investigation of Causes of Mining Machines Maintenance Problems."Springer, .

Papic, Ljubisa, Srdja Kovacevic, Diego Galar, and Adithya Thaduri. 2016b. "Safety Analysis of Mining Machines Specific Maintenance Operations."Springer,

Rihi, Ayoub, Salah Baïna, Fatima-zahra Mhada, Essaid Elbachari, Hicham Tagemouati, Mhamed Guerboub, and Intissar Benzakour. 2022. "Predictive Maintenance in Mining Industry: Grinding Mill Case Study." *Procedia Computer Science* 207: 2483-2492.

Taghizadeh Vahed, Amir, Behzad Ghodrati, Nuray Demirel, and Morteza Hosseini Yazdi. 2019a. "Predictive Maintenance of Mining Machinery using Machine Learning Approaches."Research Publishing Services, .

Taghizadeh Vahed, Amir, Behzad Ghodrati, Nuray Demirel, and Morteza Hosseini Yazdi. 2019b. "Predictive Maintenance of Mining Machinery using Machine Learning Approaches."Research Publishing Services, .

Wen, Yuxin, Md Fashiar Rahman, Honglun Xu, and Tzu-Liang Bill Tseng. 2022. "Recent Advances and Trends of Predictive Maintenance from Data-Driven Machine Prognostics Perspective." *Measurement* 187: 110276.

Żak, G., A. Wyłomańska, and R. Zimroz. 2019. "Predictive Maintenance of Mining Machines—Problem of Non-Gaussian Noise."Springer, .