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Optimizing Condition Based Maintenance for Assessing Failure Indicators in Heavy Equipment Components

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ABSTRACT– The coal industry remains attractive business, making heavy equipment quite essential for efficient coal mining operations. Effective maintenance of this equipment is crucial for maintaining performance, as breakdowns and component failures can lead to significant losses and disrupt mining activities. To mitigate these risks, this study focuses on optimizing Condition-Based Maintenance (CBM) to better identify and reduce component failures. To optimize CBM, especially in assessing component health, an index has been developed to represent component condition. Fifteen parameters are used to determine the health of Komatsu HD785-7 engine components. Each parameter plays a distinct role and carries a different weight in identifying failure indicators for the components. The determination of these weights requires operational analysis approach to achieve optimal values. The index used to represent engine component health is called the Condition Monitoring Index (CMI). Through rigorous monitoring and evaluation, the incidence of unscheduled overhauls can be significantly reduced. The CMI can serve as a guide for determining subsequent proactive maintenance actions. Continuous monitoring and evaluation are essential for detecting early engine component failures.

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Introduction

Coal remains an essential global energy commodity, vital to various industries due to its cost-effectiveness and abundant supply, with major consumers like China and India. Despite global shifts towards renewable energy, coal's affordability and availability keep it in demand. Indonesia, a leading producer and exporter of coal, plays a significant role in the international market with its vast reserves and advancing infrastructure. The Indonesian government aims to increase production to 710 million tons in 2024, which is up from 694.5 million tons in 2023 [1], reinforcing its commitment to bolstering its global position and meeting both domestic and international energy needs.

One of the largest coal contractors in Indonesia faced a similar challenge of increasing production targets, which required maintaining the physical availability of heavy equipment. However, the contractor encountered significant issues with unscheduled overhauls, experiencing a 52% rate in 2023, primarily due to frequent component failures in the HD785-7 units that make up 17.5% of their fleet. Engine components, being the most costly, contributed to 54% of these overhauls, driving up maintenance costs. Effective maintenance management, including proactive condition monitoring and timely failure detection, is essential for reducing downtime, improving operational efficiency, and ensuring equipment availability to meet production targets.

Literature Review

A. Condition Based Maintenance

Heavy equipment maintenance involves regular inspections, lubrication, cleaning, component replacements, and minor repairs to ensure proper functioning and early detection of issues. These proactive measures help prevent serious problems and maintain equipment availability [2]. As maintenance practices evolve, they enhance efficiency and effectiveness, leading to reduced costs and minimized operational downtime [3].

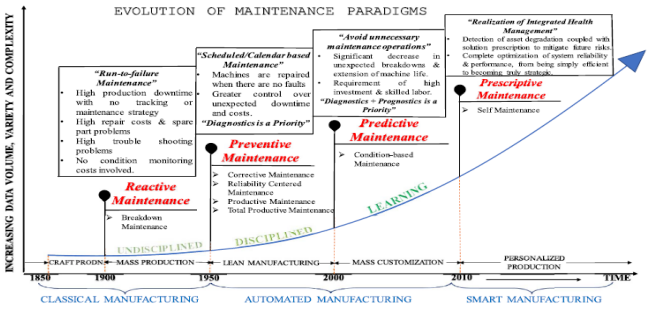


Figure 1. Evolution of Maintenance Paradigms [4]

The evolution of maintenance models in Fig.1, aligned with advancements in time and technology, leads to improved asset performance in terms of availability and reliability. Different type of maintenance is explained in Fig.2. The progression from reactive, preventive, and predictive

maintenance to prescriptive maintenance demonstrates an increase in maintenance quality through ongoing learning.

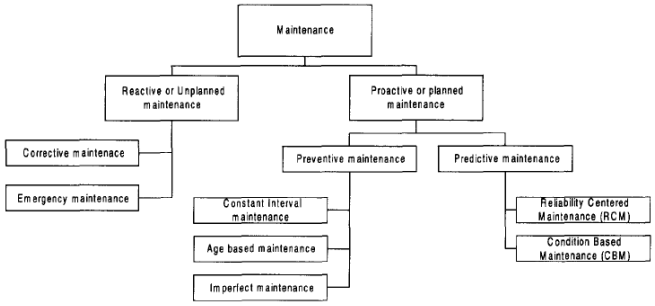


Figure 2. Taxonomy of maintenance philosophies [5]

Condition-Based Maintenance (CBM) determines maintenance actions based on actual asset conditions rather than a fixed schedule. It uses monitoring and data analysis to predict maintenance needs and address potential failures timely, reducing costs and optimizing equipment availability. CBM relies on condition monitoring data, such as oil analysis, machine inspections, and electronic data from the equipment units [6].

B. Komatsu HD785-7

The Komatsu HD785-7 is a robust dump truck designed for coal mining, featuring a 91-ton payload capacity and its specification is shown in Fig.3. It is equipped with a powerful Komatsu SAA12V140E-3 engine, a 12-cylinder turbocharged and aftercooled system with a 30.48-liter displacement, delivering 1,200 horsepower and 5,920 Nm of torque. This engine uses direct injection with electronic control for efficient combustion, and includes a High Pressure Common Rail injection system and an air-to-air aftercooler, meeting EPA Tier 2 emissions standards. With its advanced engine and transmission system, the HD785-7 ensures efficient hauling of overburden and mined coal, making it well-suited for demanding mining conditions.



Figure 3. Information about the HD785-7 [7]

C. Failure Indicator

Failure indicators are critical signs that can suggest a potential failure in a system or heavy equipment components, making their identification and understanding vital for preventing unplanned damage and maintaining optimal performance. Meticulously monitoring these indicators plays a significant role in implementing effective maintenance strategies, ensuring the continued efficient and safe operation of machinery. Comprehensive assessments of failure indicators are crucial for mitigating the risk of unexpected failures, with the development of failure models providing a solid foundation for identifying these indicators. The PF (potential failure) graph as shown in Fig.4 is a valuable tool in maintenance management, used to identify and visualize potential failures within a system or component. It illustrates the results of condition monitoring, where "Potential failure" marks the onset of early signs of damage or performance degradation, and "P-F Interval" indicates when the component can still operate but no longer meets expected performance levels. In condition-based monitoring (CBM), the PF graph aids in pinpointing the optimal time for maintenance before functional failure occurs, ultimately enhancing maintenance management practices.

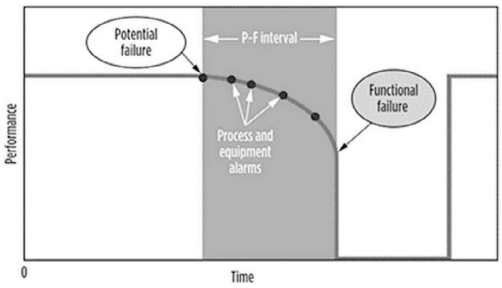


Figure 4. Potential Failure Graph [8]

Methodology

This study employs the DMAIC method (Define, Measure, Analyze, Improve, Control) as shown in Fig.5 and utilizes descriptive analysis and case studies focused on specific heavy equipment. The research begins by identifying the problems occurring in the equipment, followed by a literature review related to the issue, data collection and the application of descriptive analysis to the gathered data.

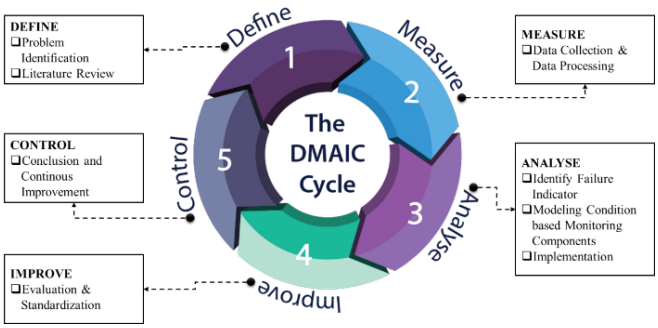


Figure 5. The DMAIC cycle in this research

In the define stage, the study focuses on understanding the problem of unscheduled breakdown overhauls, linking it to relevant literature. During the Measure stage, data related to component failures are dissected to provide critical inputs for analysis. The Analyze stage involves assessing failure indicators through data analysis and condition monitoring modeling, with the goal of determining the optimal timing for preparing replacement of component failure. The Improve stage focuses on implementing the developed condition monitoring model, including evaluation and standardization, while the Control stage ensures the effectiveness of the model through evaluation, drawing conclusions, and promoting continuous improvement.

A. Collecting Data

In the Measure stage, data collection encompasses three key areas: VHMS (Vehicle Health Monitoring System) data, which provides information about the machine's operating condition for health examination [9]; oil analysis data; and machine inspection data. This data is gathered during Periodical Service (PS), which is a fundamental and mandatory maintenance activity necessary to continuously maintain equipment performance equipment [10]. Improvements have been made in the process of collection VHMS data as shown in Fig.6, transitioning from manual downloading to an automated process, enhancing efficiency and accuracy.

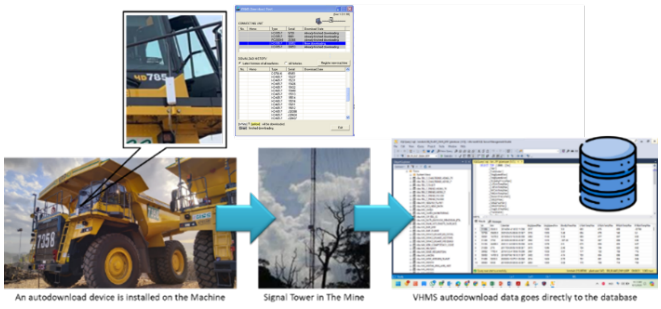


Figure 6. The VHMS autodownload data will go directly into the database

Any piece of equipment with a lubricating system is a potential candidate for oil analysis [11]. This process as shown in Fig.7 begins with sample collection, followed by analysis using a microlab, which generates detailed results. These results are then entered into a database for further evaluation.

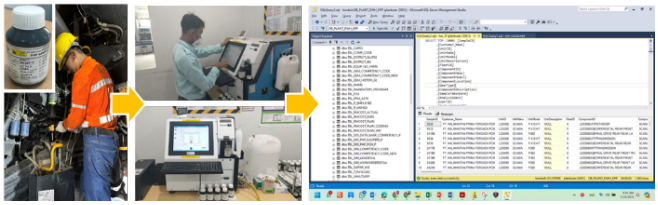


Figure 7. Analysis process of lubricants at FOWA Lab

Machine inspection data is also crucial, serving as validation for the VHMS data; any deviations detected through inspections are carefully analyzed [12]. This process as shown in Fig.8 has been further improved by adopting a digital form for machine inspections, moving towards a paperless system that streamlines data recording and enhances overall data management.

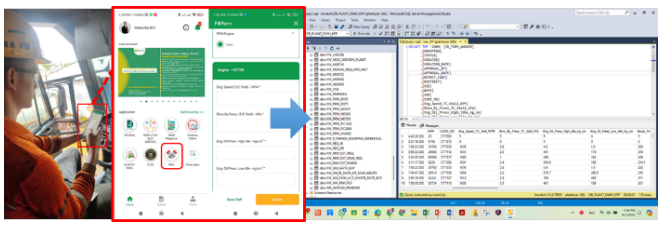


Figure 8. Mechanics fill out the digital form, and the data is directly entered into the database

B. FGD with Maintenance Experts

The analysis of failure indicators for the HD785-7 leverages the expertise of heavy equipment maintenance professionals with over 25 years of experience. This process integrates historical data with a comprehensive understanding of operational conditions and component performance. To assess component health, the Condition Monitoring Index (CMI) is used. Key parameters for the CMI are established through focus group discussions with these experts. The CMI, derived from Vehicle Health Monitoring System (VHMS) data and oil analysis act as an early indicator of component health, enabling proactive maintenance to prevent major failures. This approach improves equipment reliability and availability, reduces downtime, and minimizes unexpected repair costs [13]. CMI is expressed as a percentage, with higher values indicating better engine condition. It is validated against standard machine data and the Komatsu Oil and Wear Analysis (KOWA) guideline. Fifteen parameters as shown in Table 1, sourced from VHMS and oil analysis, are used to determine engine component health based on expert analysis and discussions.

Table 1, Parameters for Condition Monitoring Index (CMI)

No.	Engine Parameter	Unit	Data Source
1	Blow By P Max	kPa	VHMS
2	Engine Oil P Lo Min	MPa	VHMS
3	Cool T Max	Deg C	VHMS
4	Boost P Max	kPa	VHMS
5	EGT LF	Deg C	VHMS
6	EGT LR	Deg C	VHMS
7	EGT RF	Deg C	VHMS
8	EGT RR	Deg C	VHMS
9	Fe	Ppm	Oil Analysis
10	Cu	Ppm	Oil Analysis
11	Al	Ppm	Oil Analysis
12	Si	Ppm	Oil Analysis
13	Na	Ppm	Oil Analysis
14	Pb	Ppm	Oil Analysis
15	Soot	Ppm	Oil Analysis

C. Determination of Weight Scale for CMI Parameters in Engine Components

To construct the Condition Monitoring Index (CMI) for assessing engine component health, an operational analysis method is employed. Since not all parameters can be weighted equally, the Solver feature in Microsoft Excel is used to determine the optimal values for 15 predefined parameters, which collectively contribute 100% to the assessment. Constraints based on failure data and expert discussions are applied to these parameters to reflect their varying importance in evaluating engine health. Using Solver, the optimal value (maximum or minimum) for a formula in a single cell, known as the objective cell, can be found while considering constraints or limitations on the values of other formula cells in the worksheet [14].

Once constraints are established, the data is used to identify failure indicators by combining failure analysis results with expert knowledge. These constraints form a solid foundation for evaluation and monitoring and they are defined using mathematical logic. Constraints are then utilized to limit the values that the Solver can use within a

specific model [15], ensuring that the optimization process adheres to the predefined criteria. The constraint criteria from the expert analysis are:

1) The weight scale for the failure indicators (Coolant Temperature Max and Engine Oil Pressure Low Min) should be the same.
2) Two parameters (Coolant Temperature Max and Engine Oil Pressure Low Min) that are significant to engine failure must be given greater weight compared to other parameters.
3) The Blow By Pressure Max parameter must be higher than the Boost Pressure Max parameter.
4) The Boost Pressure Max parameter must be higher than the EGT (Exhaust Gas Temperature) parameter.
5) The Exhaust Gas Temperature parameters (RF, RR, LF, LR) must have equal weights.
6) The parameters for wear metal oil analysis, Fe and Cu, have equal weight and are greater than Al and Pb.
7) The parameters for wear metal oil analysis, Pb and Al, have greater weight compared to the contaminant parameters, Si and Na.
8) The contaminant parameters in oil analysis, Si and Na, have equal weight and are greater than the Soot parameter.
9) The soot parameter must be greater than 0.

The determination of mathematical logic helps in setting the constraints for the Solver. Then, Solver will perform iterations to find the appropriate weight scale that meets the established constraints.

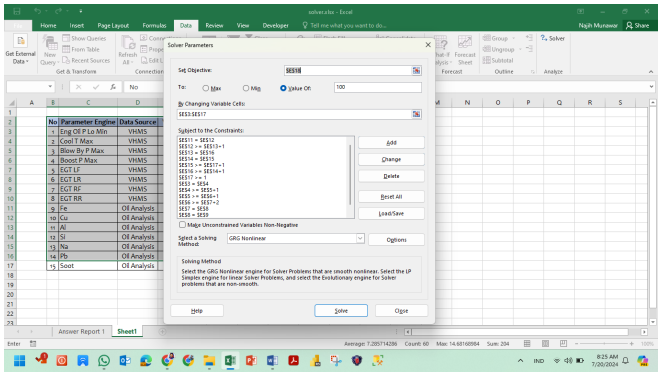


Figure 9. Translation of constraint to solver parameter in Excel

After running Solver iterations in Excel, the weights for each parameter were determined as shown in Fig.9. These weights are crucial for calculating the Condition Monitoring Index (CMI), ensuring accurate representation of each parameter's influence. The CMI, computed using these weights, provides a comprehensive assessment of equipment condition, helping predict potential failures and optimize maintenance strategies.

Implementation and Results

The result of the weighting determined through operational analysis is shown in Table 2. The 15 parameters for the Condition Monitoring Index (CMI) are crucial for evaluating engine health. These parameters are vital for setting warning thresholds that act as early indicators of potential engine failures. By establishing these thresholds, the CMI effectively highlights issues before they escalate into significant problems, allowing for timely maintenance and preventing more severe failures.

Table 2, Weight Scale for Condition Monitoring Index (CMI)

No.	Engine Parameter	Data Source	Weight Scale (%)
1	Blow By P Max	VHMS	14.68
2	Engine Oil P Lo Min	VHMS	14.68
3	Cool T Max	VHMS	8.51
4	Boost P Max	VHMS	7.51
5	EGT LF	VHMS	3.64
6	EGT LR	VHMS	3.64
7	EGT RF	VHMS	3.64
8	EGT RR	VHMS	3.64
9	Fe	Oil Analysis	8.37
10	Cu	Oil Analysis	8.37
11	Al	Oil Analysis	6.37
12	Si	Oil Analysis	6.37
13	Na	Oil Analysis	4.79
14	Pb	Oil Analysis	4.79
15	Soot	Oil Analysis	1.0

Condition-Based Maintenance (CBM) should provide early warnings as soon as failures begin [16]. Implementing these warning standards enables proactive management of engine health, helping maintenance teams address potential issues before they cause significant disruptions. This approach is crucial for maintaining optimal engine performance and reducing the risk of unexpected failures.

The data collected from VHMS, oil analysis, and machine inspections will be integrated into the SQL Server. A dedicated data warehouse will be created to optimize data storage and management. This will facilitate accurate analysis and decision-making. To visualize the data, a dashboard will be developed using Microsoft Power BI as shown in Fig.10, enabling comprehensive and understandable presentation of the analyzed information. This setup aims to enhance operational efficiency and strategic decision-making.

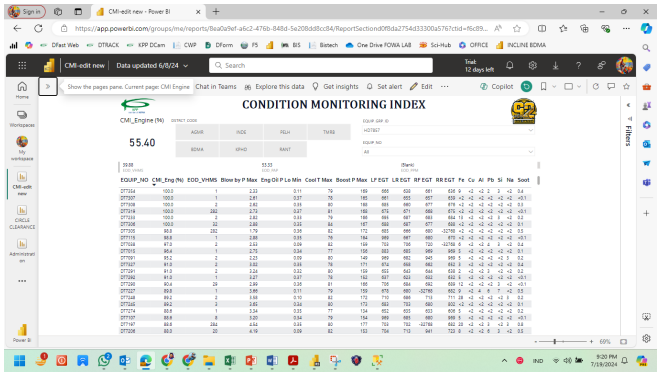


Figure 10. Condition Monitoring Index web version using Power BI

The CMI dashboard enables the technical expert team to monitor conditions in real time, prioritize units needing attention, and prevent unscheduled breakdowns and premature engine replacements. By analyzing the Condition Monitoring Index values, deviations are identified, and units

requiring follow-up are determined. Issues are then validated with the Plant Engineer on-site, and deviations lead to Task Force Team (TFT) meetings to discuss and implement corrective measures, enhancing operational response. If further investigation is necessary, the expert team conducts site visits to resolve deviations, often revealing lapses or oversights in maintenance practices. These evaluations help uncover root causes, implement corrective actions, and prevent future issues, thereby improving overall maintenance effectiveness. Two of the most important aspects of maintenance are procedural adherence and discipline [17], as they ensure that each step is carried out correctly and consistently, leading to more reliable results and long-term equipment performance.

The Condition Monitoring Index (CMI) supports proactive maintenance by identifying deviations. To manage these effectively, CMI values must be standardized into cautionary or critical levels as shown in Fig.11, each requiring specific follow-up actions.

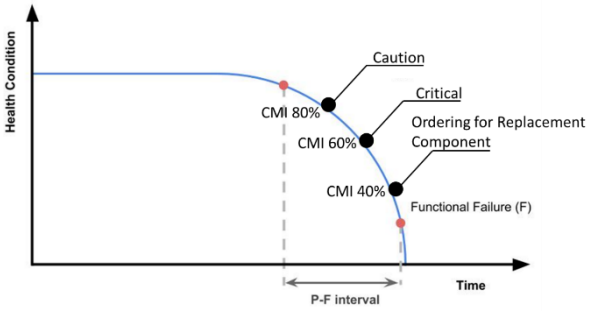


Figure 11. CMI Grading and its Categories

Based on the established grading, the necessary follow-up actions for maintenance are also determined as explained in Table 3.

Table 3, Follow Up for Maintenance Actions

No.	CMI Grading	Category	Follow Up Maintenance Actions
1	80% < x	Normal	Continue and maintain condition monitoring.
2	60% < x < 80%	Caution	Validate the data with the PM Clinic and the Task Force Team (TFT) in collaboration with expert teams.
3	40% < x < 60%	Critical	The expert team will follow up with the unit at the job site. All involved parties (factory, distributor, and maintenance team) will come together to conduct a more in-depth inspection of the unit.
4	x < 40%	Stop	Stop the operation and prepare for component replacement. Ordering the component will take time for the new part to arrive at the job site.

After implementing the recommendations, an evaluation of unscheduled breakdowns for the Komatsu HD785-7 was conducted using the Condition Monitoring Index dashboard and a proactive maintenance approach. The results showed a 45% reduction in unscheduled overhauls, demonstrating the effectiveness of the condition monitoring system and proactive maintenance strategy. Addressing remaining issues will be crucial for further refinement and continued performance improvement.

Conclusions and Recomendations

A. Conclusions

Based on the data analysis and research results conducted, several conclusions can be drawn, including:

- In this case, the indicators that most significantly affect engine failure in the Komatsu HD785-7 are "minimum engine oil pressure" and "maximum coolant temperature."
- The condition monitoring index values can be used to determine the priority scale for addressing deviations occurring in the Komatsu HD785-7 engine, making the maintenance process more effective.
- By evaluating failure indicators on the Komatsu HD785-7 engine, it is possible to reduce the frequency of unscheduled breakdown component replacements.
- The condition monitoring index can be easily and quickly accessed by relevant personnel through both computers and mobile devices, facilitating faster information delivery and enhancing the synergy for a more effective maintenance process.
- With grading in the Condition Monitoring Index (CMI), it becomes easier to determine the health level of engine components and assess their failures. Follow-up maintenance can also be better planned.

B. Recommendations

- Monitoring and evaluating the Condition Monitoring Index (CMI) must be conducted rigorously to reduce the risk of failure in the Komatsu HD785-7 engine.
- The development of the Condition Monitoring Index (CMI) should not be limited to the engine components of the Komatsu HD785-7 alone. As part of continuous improvement, the CMI should also be able to cover other components and various types of units.
- For future research, there is potential for further development, including:
  - Adding analysis using machine learning to predict component failure times.
  - Implementing a warning alert system to ensure that information is accessible to all relevant parties.
  - The Condition Monitoring Index (CMI), which indicates the health of engine components, should be linked to the prompt preparation of replacement components when the CMI shows poor condition.
  - To better identify failure indicators, additional parameters are needed that can more clearly indicate abnormalities in moving components by incorporating vibration sensors to enhance the assessment.

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