Multi Sensor-Based Failure Diagnosis using the Mahalanobis Taguchi System

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Abstract. Heavy equipment in the mining industry is an essential instrument in achieving the company's production targets. But on the other hand, heavy equipment is complicated and expensive equipment. These problems can be overcome by leasing the equipment to an external agent. In the lease contract between the lessee and lessor, it is discussed about the maintenance strategy of the equipment that will be rented by the lessee. This research presents a real-time monitoring scheme based on multi-sensor data installed on the machine. Case studies from this research were carried out on excavator units in heavy equipment rental companies. The Mahalanobis Taguchi System (MTS) method is used to handle multi-sensor data. Multi-sensor data is grouped into normal condition groups and abnormal condition groups. The variables used to monitor excavator conditions include vibration, pressure and temperature sensors. Based on the results of the calculation of the excavator threshold conditions using the Mahalanobis Distance (MD) measurement technique, the threshold of normal conditions is (-2.137 to 4.121). In contrast, in abnormal accumulator conditions (4,331 to 39,458), pump failure (40,956 to 138,048), valve failure (2708,104 to 3404,187) and the threshold in the condition of the cooler failure is (10736.160 to 11434.151). This research shows that the MD-based CBM scheme produced can detect, identify, and isolate the failure of excavator components under study.

Keywords: Condition Based Maintenance. Mahalanobis Distance, Mahalanobis Taguchi System, Leasing Equipment

1. Introduction

In the mining industry, heavy equipment such as excavators is used to load and transport mining material from the mining site to the processing unit. Heavy equipment plays an essential role in achieving the company's production targets. When the device is deteriorating due to its age and usage, an effective way to deal with the incident is to carry out maintenance activities. However, heavy equipment such as excavators is complicated and expensive equipment. The best economical way to overcome this is by leasing equipment to an external agent [1].

Leasing is a cooperation contract between the lessee (lessee) using the equipment owned by the lessor (owner), both of which are separate parties. The lessee routinely pays a certain amount of fees to the lessor [2]. In the lease contract between the lessee and lessor, it is discussed about the maintenance
policy for the equipment to be rented by the lessee. This is done so that the lessor can ensure that they guarantee the satisfaction and reliability of the equipment during the rental period.

In general, there are two types of maintenance policies that can be carried out during the contract period, namely Corrective Maintenance (CM) and Preventive Maintenance (PM). CM measures are used to correct equipment failures and return them to operational conditions. While PM is a policy that is more directed to actions to maintain the functional state of equipment in avoiding failure [3]. But lately construction companies, aerospace and automotive are in a trend to develop their company's ability to use the Condition Based Maintenance (CBM) strategy as an effort to meet the demands of their customers [4].

Condition Based Maintenance (CBM) is a maintenance measure carried out following the current status of the equipment. Compared with other maintenance strategies, CBM is considered more effective in overcoming the advantages or disadvantages of the amount of maintenance. If the CBM program is implemented correctly, it is possible for the company to significantly reduce maintenance costs by reducing the amount of maintenance activity. CBM activities consist of diagnostic and prognostic processes. The diagnostic itself consists of detection, isolation, and identification of failures, whereas prognostic is a prediction activity before the failure occurs [5]. The success of implementing CBM depends very much on the company's ability to extract information from a data set that comes from monitoring the condition of the equipment.

Some methods that have been used as tools in implementing CBM include Principal Component Analysis (PCA) and Fuzzy C-Means (FCM) in their research entitled "Application of PCA method and FCM clustering to the fault diagnosis of excavator's hydraulic system" PCA and FCM used as a fault diagnostic approach to improve the reliability of excavator hydraulic systems. FCM clustering is done as a failure classifier to determine failure testing. Fault diagnostics using PCA and FCM have proven to be feasible and effective on excavator hydraulic systems. [6]. Furthermore, other multivariate methods are also used by Yang, et al. [7] in his research entitled "The use of the Mahalanobis-Taguchi System to improve flip-chip bumping height inspection efficiency" overcomes the problem of bumps height inspection efficiency. The Mahalanobis - Taguchi System (MTS) method is used to reduce the number of bump height measurements while maintaining inspection with a high degree of accuracy. Successfully reduced the number of bump height inspections significantly from 10 to 6, and the inspection time could be reduced by 40%. Then Felix et al. [4] have researched excavators to improve the hydraulic performance of excavators through monitoring contamination of hydraulic oil. The study assessed the suitability of particle contamination sensors in carrying out diagnostic and prognostic requirements in implementing CBM. While the research of Soylemezoglu et al. [8] relates to the implementation of MTS based on prognostic decision making for the failure of centrifugal pumps. The main objective of the study is to apply the concept of the MTS model to demonstrate its prognostic ability to detect pump failures and determine or predict pump failure times. This study uses the mean (mean) and three times the standard deviation approach to determine the threshold for each failure condition studied. Helwig et al. [9] also re-used the Multivariate Statistics technique, namely Linear Discriminant Analysis (LDA), which is combined with Mahalanobis distance clustering in hydraulic system monitoring. The purpose of this study is to develop and evaluate a systematic approach to automating the hydraulic system condition monitoring system by analyzing various failure scenarios obtained from experiments on hydraulic systems. The results of the study conclude that the method chosen has proven suitable for detecting different types of errors that show typical symptoms at a predetermined scale. Recent research on the application of CBM in the concept of leasing was carried out by Zhang et al. [10] on this study regarding the satisfaction of lessees and the optimal CBM policy for leasing systems. The purpose of this research is to develop CBM policies for leasing systems, model lessee satisfaction, and make decision models that take into account the total benefits of the leasing system. The conclusion obtained is the CBM policy developed shows that the policy can increase the total lessor profit. In their research conducted a discrete CBM monitoring based on the implementation of inspections expressed by the deterioration rate (Ω) for each time epoch (tk) which then resulted in an Optimal maintenance policy that minimizes cost of maintenance from Preventive
activities Maintenance (PM) and Corrective Maintenance (CM) after increasing revenue (revenue) and total profit.

Based on various explanations about previous studies, the author will raise several research gaps. The gaps are the use of the Mahalanobis Taguchi System (MTS) to handle the extensive multi-sensor data set in applying CBM in heavy equipment leasing companies. Then in this study, the CBM strategy is based on multi-sensor data installed in the equipment or other words, monitoring is carried out continuously or in real-time. So that applying CBM will make it easier for the lessor to monitor and control the tools that are being used by the lessee during the contract period.

Case Study of this research itself was conducted at PT X, which is a company engaged in heavy equipment leasing. The type of heavy equipment that will be examined in this study is the excavator unit. This is based on the availability of multi-sensor data which is only available in the group. In this study, the application of the condition-based maintenance strategy was applied with the Mahalanobis Taguchi System approach to the excavator hydraulic system at PT X. The choice of the hydraulic system as the object of this study was based on the results of research conducted by Kamil and Ulka [3], which obtained results that the hydraulic system excavators are a vital component of excavator shutdown.

2. Methods
This research was conducted at PT X, which is a company engaged in heavy equipment leasing. The heavy equipment unit, which is the object of this research is the excavator unit. The components studied in excavators are hydraulic pumps, accumulators, valves and coolers from the excavator hydraulic system. Multi-sensor data in this study were collected into normal condition data group and abnormal condition data group. An explanation of each of the data conditions is as follows:

| Condition            | Information                                                                 |
|----------------------|-----------------------------------------------------------------------------|
| Normal               | Multi-sensor data in normal conditions is collected when the excavator is in its operating condition. |
| Failure of Pump      | Multi-sensor data on this condition is collected when a hydraulic pump fails or performance decreases, which can be caused by a leak in the hydraulic pump. This condition is characterized by a decrease in the pressure flow in the hydraulic system. |
| Failure of Accumulator| Multi-sensor data on this condition is collected when the hydraulic accumulator is experiencing a failure which is characterized by a decrease in pressure and the emergence of excessive vibration in the hydraulic system. |
| Failure of Relief Valve| Multi-sensor data on this condition is collected when the excavator hydraulic valve experiences lag or malfunction, causing an increase in fluid pressure in the hydraulic system. |
| Failure of hydraulic cooler| Multi-sensor data on this condition is collected when the hydraulic cooler fails or decreases performance which is marked by an increase in temperature in the hydraulic system. |

The variables in this study consisted of 4 sensor units .the sensor is vibration, temperature, pressure 1, and pressure 2. The following is an explanation of the units and supporting information of the sensors used.

| Code | Sensor Type | Unit | Information                                                                 |
|------|-------------|------|-----------------------------------------------------------------------------|
| X1   | Vibration   | mm/s | This component is located in the hydraulic pump casing section.              |
| X2   | Temperature | °C   | This component is located in the hydraulic oil tank section                   |
| X3   | Pressure1   | Bar  | This component is located on the boom cylinder.                              |
| X4   | Pressure2   | Bar  | This component is located on the travel motor.                               |
After the data collection process is complete, the next data will be processed using the MTS method. The stages in MTS consist of the following 4 stages [8]:

2.1. Construction of Mahalanobis Space (MS)
The first stage in this process is the transformation of data with z-scores. This process is done because there is variability in the unit of data set that will be processed. The details of this process are as follows:

1) Calculate the mean ($\bar{X}$) of each variable (sensor) on normal data

$$\bar{X}_i = \frac{\sum_{j=1}^{N} X_{ij}}{N}, \quad i = 1, 2, ..., p$$

Where:

- $X_{ij}$ = $i$th variable in the $j$th observation
- $N$ = Number of observations
- $p$ = Number of variables

2) Calculate the standard deviation ($\sigma X_i$) on each variable (sensor) from normal data

$$\sigma X_i = \sqrt{\frac{\sum_{j=1}^{N} (X_{ij} - \bar{X}_i)^2}{N-1}}, \quad i = 1, 2, ..., p$$

3) Furthermore, the transformation of data from each variable (i) on observation to (j) by making a $Z_{ij}$ matrix with the following equation:

$$Z_{ij} = \frac{X_{ij} - \bar{X}_i}{\sigma X_i}, \quad i = 1, 2, ..., p, \quad j = 1, 2, ..., N$$

4) Then the next step is to verify the average and standard deviations of $Z_{ij}$ after transforming the data, the average value must be 0:

$$\bar{Z}_i = \frac{\sum_{j=1}^{N} Z_{ij}}{N} = 0, \quad i = 1, 2, ..., p$$

and the standard deviation ($\sigma Z_i$) must be 1.

$$\sigma Z_i = \sqrt{\frac{\sum_{j=1}^{N} (Z_{ij} - \bar{Z}_i)^2}{N-1}} = 1, \quad i = 1, 2, ..., p$$

Where:

- $\bar{Z}_i$ = Mean of the $i$th variable transformation
- $\sigma Z_i$ = Standard deviation of the $i$th variable transformation

5) Make a transpose matrix ($Z_{ij}^T$)

6) Calculates the C correlation matrix from $Z_{ij}$.

$$C = \begin{bmatrix}
1 & r_{12} & \cdots & r_{1p} \\
 r_{21} & 1 & \cdots & r_{2p} \\
 \vdots & \vdots & \ddots & \vdots \\
 r_{p1} & r_{p2} & \cdots & 1
\end{bmatrix}$$

with $r_{ij}$

$$r_{ij} = \frac{\sum_{m=1}^{N}(Z_{im}Z_{jm})}{N-1}, \quad i, m = 1, 2, ..., p$$

7) Calculates the inverse of the correlation matrix ($C^{-1}$).

After obtaining the correlation matrix the inverse matrix calculation is then performed with the following formula [2]:

$$C^{-1} = \begin{bmatrix}
a_{11} & a_{12} & \cdots & a_{1p} \\
a_{21} & 1 & \cdots & a_{2p} \\
 \vdots & \vdots & \ddots & \vdots \\
a_{p1} & a_{p2} & \cdots & 1
\end{bmatrix}^{-1} = \begin{bmatrix}
1 & r_{12} & \cdots & r_{1p} \\
r_{21} & 1 & \cdots & r_{2p} \\
\vdots & \vdots & \ddots & \vdots \\
 r_{p1} & r_{p2} & \cdots & 1
\end{bmatrix}^{-1}$$
8) The last step is to calculate the Mahalanobis Distance \( (MD_j) \).

\[
MD_j = \frac{1}{p} Z_i^T C^{-1} Z_{ij}
\]

(9)

### 2.2. Validation of Mahalanobis Space (MS)

This stage begins by calculating the abnormal MD of the components of the cooler, valve, pump and accumulator based on sensors Pressure 1, Pressure 2, Temperature, and Vibration. The calculation of abnormal MD uses the mean, standard deviation and correlation matrix of the normal MD calculation in the previous stage. Furthermore, after an abnormal MD value is obtained, validation is performed between normal MD and every abnormal MD. The requirements for normal and abnormal MD distances must exceed more than 1. If the abnormal MD scale does not reach a value greater than 1 than the normal MD, then a new variable will be added.

### 2.3. Optimization of Mahalanobis Space (MS)

This stage purpose of selecting the critical variables used in monitoring for each condition (normal, cooler failure, valve failure, pump failure, and accumulator failure) using the Taguchi orthogonal array (OA) and signal to noise ratio (SNR). On OA calculations process there are 2 level numbers, namely numbers 1 and 2, where level 1 is inclusion means that the variable is included in the MD calculation process, and level 2 is exclusion means that the variable is not included in the MD calculation process while an empty column means no there is a variable placement in that column. This study will use the L8 array (27) to accommodate the variables studied. The calculation process for this array is counted eight times, with a combination of existing variable levels and the SNR type used is larger-the-better. This type of SNR is calculated by the following equation \[8\]:

\[
\eta_q = -10 \log \left( \frac{1}{p} \sum_{j=1}^{p} \frac{1}{MD_j} \right)
\]

(10)

Where:

\( \eta_q \) = Signal-to-noise ratio for the \( q \)th run of the orthogonal array (OA)

Furthermore, the average is calculated for each variable based on the variable level. As well as the difference calculated, using the following equation \[8\]:

\[
\text{Gain} = (\text{Average}. \text{SNR})_{\text{Level}-1} - (\text{Average}. \text{SNR})_{\text{Level}-2}
\]

(11)

Semakin tinggi nilai perbedaan, semakin besar pengaruh variabel-variabel ini pada objek. Begitu pula sebaliknya, semakin kecil perbedaan nilainya, semakin rendah dampak variabel-variabel ini pada objek. Sekalipun nilai selisihnya <0, dapat dikatakan bahwa variabel tersebut tidak mempengaruhi tujuan sehingga dapat dihilangkan untuk pemantauan kondisi lebih lanjut.

### 2.4. Failure diagnosis with variables selected based on criteria for classification determined by the threshold

This stage begins with the creation of the MD-Based Diagnostic Scheme. Monitoring data is then performed, where the data will be used to monitor the movement of MD values using MS that has been formed. If MD is from data monitor > T, where T is the threshold of the most expensive distance from normal conditions, then it can be concluded that the status of the tool is displaying abnormal behaviour, and appropriate corrective action is needed. And if MD < T, the condition of the equipment is normal.
3. Result and Discussion

3.1. The results of MD Calculation from normal condition data

Table 3. MD transformation and calculation for normal data

| Observation | Sensor Data | Transformation Data | MD normal condition |
|-------------|-------------|---------------------|---------------------|
|             | X1          | X2                  | X3                  | X4                  | Z1    | Z2    | Z3    | Z4    |
| 1           | 0.562       | 35.582              | 147.450             | 147.340             | 0.311 | 0.488 | -0.092| -0.428| 0.292 |
| 2           | 0.557       | 35.500              | 146.960             | 147.170             | 0.107 | -0.028| -1.355| -0.944| 0.640 |
| 3           | 0.555       | 35.422              | 147.880             | 147.990             | 0.025 | -0.519| 1.017 | 1.546 | 0.968 |
| …          | …           | …                   | …                   | …                   | …     | …     | …     | …     | …     |
| 120         | 0.591       | 35.574              | 146.990             | 147.170             | 1.499 | 0.438 | -1.278| -0.944| 1.012 |

\[
\bar{X}_1 = \frac{66.528}{120} = 0.554 \quad \text{and} \quad \sigma_{X_1} = \sqrt{\frac{0.071}{120-1}} = 0.024
\]

Based on the results of the normal and abnormal MD calculations in Table 2, the result is that the distance between normal and abnormal MD conditions has been > 1, so that the MS is validated and can proceed to the next stage.

Table 4. Validation of normal MD data vs. abnormal cooler data, relief valve, pump and accumulator

| Observation | MD Of Normal Condition | Value MD of a failure condition |
|-------------|------------------------|--------------------------------|
|             | Cooler                 | Valve                          | Pump                           | Accumulator                          |
| 1           | 0.292                  | 8578.906                       | 2324.393                      | 72.208                               | 16.851 |
| 2           | 0.640                  | 8558.780                       | 2173.396                      | 77.128                               | 13.353 |
| 3           | 0.968                  | 8505.433                       | 2380.389                      | 70.673                               | 15.358 |
| …          | …                      | …                               | …                             | …                                    | …     |
| 120         | 1.012                  | 8234.223                       | 2368.699                      | 66.002                               | 13.622 |

Based on the results of verification of the success of the effects of normal data transformation using equations (4) and (5), can be seen that the results of the transformation have addressed the correct results, it is based on the average for all variables has a value of 0 and the standard deviation has also been valued at 1.

3.2. The results of the MS validation process

After obtaining MD on normal condition data, then MD is calculated for abnormal condition data by using mean, standard deviation and correlation matrix from normal MD calculations.

Table 5. The threshold for each condition

| Condition                | Mean   | Std. Deviation | Minimum | Threshold (T) | Maximum |
|--------------------------|--------|----------------|---------|---------------|---------|
| Normal                   | 0.992  | 1.043          | -2.137  | 4.121         |         |
| Failure of Accumulator   | 17.106 | 4.202          | 4.499   | 29.713        |         |
| Failure of Pump          | 67.543 | 12.104         | 31.231  | 103.855       |         |
| Failure of Relief Valve  | 2292.756 | 86.955      | 2031.890 | 2553.622     |         |
| Failure of hydraulic cooler | 8314.401 | 87.127   | 8053.019 | 8575.782     |         |
3.3. The results of the Variable Optimization process

| Condition                  | Variable (Sensor) |
|----------------------------|-------------------|
|                            | X1  | X2  | X3  | X4  |
| Failure of Accumulator     | √   | x   | √   | √   |
| Failure of Pump            | √   | x   | √   | √   |
| Failure of Relief Valve    | x   | √   | √   | √   |
| Failure of hydraulic cooler| x   | √   | √   | √   |

Where (√) is the selected variable and (x) is a variable that is not used in monitoring the condition of the equipment. Selected variables will be used in monitoring and diagnosing the condition of the excavator using the scheme created in section 3.4.

3.4. Failure Diagnosis Scheme

This study presents an MD-based failure monitoring scheme for excavator components. Failure detection is the first step in the diagnosis, which indicates the occurrence of errors in the system being monitored or monitored. In this study, MD-based data clustering techniques are used to classify excavator failure data to different failure groups.

In this study, it does not enter into the scope of determining optimal policies for the maintenance of leasing equipment systems but focuses on determining narrative maintenance policies in the application of CBM strategies in heavy equipment leasing companies using MTS. The narrative maintenance policy produced in this study is in the form of an MD threshold-based monitoring scheme using multi-sensor data. The proposed CBM Scheme begins by inputting monitoring data and setting \( T = 60 \) minutes. The error detection process starts when the average MD monitoring \( (\mu_{MD}) \) exceeds \( T_1 \) (threshold from normal conditions). However, if \( \mu_{MD} \) is less than \( T_1 \), the monitoring process is continued with the addition of testing data by setting \( T = T + 60 \) minutes. After the detection process is complete then proceed with the excavator failure identification process, the type of failure is determined by filtering the type of failure based on the threshold value of the \( T_{accumulator} \), \( T_{pompa} \), \( T_{Valve} \), and \( T_{cooler} \) after the identification process is complete then proceed with the process of isolating the failure which will then proceed with the determination of the policy maintenance tools based on the type of failure studied.

4. Conclusion

In this research, a diagnostic condition monitoring scheme is presented using the Mahalanobis Taguchi System method. The proposed scheme is based on the Mahalanobis distance threshold. The conclusion of the proposed approach can be summarized as follows:

1) The threshold of normal conditions is (-2.137 to 4.121) while in abnormal accumulator conditions (4.331 to 39.458), pump failure (40.956 to 138.048), valve failure (2708.104 to 3404.187) and the threshold in the condition cooler failure is (10736.160 to 11434.151).
2) The built scheme has succeeded in distinguishing normal and abnormal conditions from the excavator components under study.
3) The future of research can develop a multi-sensor data-based CBM monitoring scheme in heavy equipment leasing companies by focusing on heavy equipment components that have a series circuit system.
Enter monitoring data
Transformation Data
Enter Threshold based on MD (Tnormal, Tvalve, Tpump, Taccumulator, and Tcooler)

Set T=1
Calculate MD value from Monitoring Data
Calculate MD mean from monitoring data (µMD)

Set T=T+1

IF µMD > Tnormal
THEN Failure Detection
ELSE
IF µMD < Tacc
THEN Failure of Accumulator
ELSE
IF µMD ≥ Tpump
THEN Failure of Pump
ELSE
IF µMD < TValve
THEN Failure of Relief Valve
ELSE
IF µMD < Tcooler
THEN Failure of hydraulic cooler
ELSE YES
END IF
END IF
END IF
END IF
END IF

Failure Diagnoses scheme

Figure 1. Failure Diagnosis scheme

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