Predictive Maintenance of Heavy Equipment in Indonesia Leading Heavy Equipment Company

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Abstract*—The use of heavy equipment in a production process, especially coal mining, is very dominant and is the main work tool. Therefore, the productivity of mining is very dependent on the performance of the heavy equipment used. In maintaining the performance of today's machines, it is not enough only with preventive and corrective maintenance, but also with predictive maintenance (PdM). Through PdM, it is expected that heavy equipment performance can be maintained properly because it can reduce the unscheduled breakdowns. PdM in this research aims to help prioritize heavy equipment routine service management, so that more urgent heavy equipment conditions will get priority for maintenance first so as to prevent unscheduled breakdowns compared to current service management which still uses time based as the only maintenance priority tool. PdM will focus on finding warnings and indicators that can be used to determine the remaining useful life (RUL) of engine components by using data from telemetry, oil analysis, historical component lifetime and other maintenance data. In this research, we get the predictive maintenance results in the form of 2 types of warnings and also the RUL prediction with a mean absolute error of 91 hours compared to the actual RUL.

Keywords*—coal mining, heavy equipment, predictive maintenance, early warning, monitoring system.

I. Introduction

For mining industry in Indonesia, especially coal mining, productivity from heavy equipment and operators is the most important thing. One of the factors that is very instrumental in determining productivity in the coal mining industry itself, among others, is the readiness of heavy equipment to always operate. The obstacle that often occurs is the heavy equipment is not always ready to operate and often damage is sudden or unexpected. This unscheduled breakdown itself is very closely related to the operation of the unit and the maintenance program of the unit itself. In this research, we will focus on how to reduce unscheduled breakdown caused by the process/maintenance program of the unit itself.

Before we further talk about unscheduled breakdowns, we should look at the big picture of maintenance management of heavy equipment so that ultimately it can cause unscheduled breakdowns. By improving maintenance management of heavy equipment, it is expected to reduce the possibility of unscheduled breakdown itself. Maintenance management to reduce the occurrence of unscheduled breakdowns can run effectively if the condition-based maintenance (CBM) process and also predictive maintenance (PdM) type have been able to be carried out by the maintenance team. If both types of maintenance (CBM & PdM) cannot be done, it is very difficult to be able to change/prevent unscheduled breakdowns from heavy equipment as shown in Fig. 1.

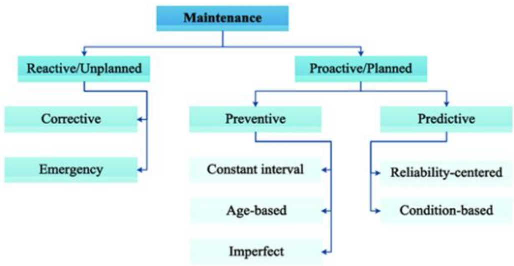

Fig. 1. Heavy equipment maintenance management type [1]

II. RESEARCH METHODS

In this research, we defined Predictive Maintenance (PdM) according to Kange and Lundell [2] as "Condition based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item". We will use historical data to get the trends of a system's behaviour in relation to predicting the time when the component will breakdown or fail. After we can get the failure trend, then the time of failure also can be predicted and also will be assign for a new preventive maintenance activity to be scheduled. Based on our definition above, a visual inspection can also be one of PdM technique that predictions are bases upon. As already mention earlier, we see this PdM as an advancement or upgrade from previous maintenance type that we already implemented, which is CBM. Because of that, we can't clasified PdM as a replacement of others maintenace types. The basic maintenance type will not completely eliminated because of implementation of PdM, but that will be complementary one and the other. If we can have an effective PdM and CBM, we can reduce the composition of PvM and corrective maintenance. PdM technique is a combination of a technology, mathematic and human skill. The making process of PdM analytic is by using all the data currently owned and also the performance units of the past as well as all the trouble records that have occurred before, then all the data is linked to the right maintenance activities and the most cost optimal for execution time. The study starts by determining the problems, and then searching for literature that is related to the research, data gathering, and finally implementing descriptive analysis method to all the data that will be used for analysis. Before inputing the data for descriptive analysis, the data and parameters are first prepared using the DMAIC framework [3].

A. Failure Analysis with manual pattern

Failure analysis is carried out using descriptive analysis method by monitoring the main parameters of the VHMS as a summary of the subject matter expert since the engine component is installed in the PC2000-8 excavator until the engine is removed from the excavator due to failure. The data used in the failure analysis are :

1. Telemetry / sensor data derived from VHMS [4]
2. Maintenance data in the form of historical component replacement.
3. Parameter limit from Komatsu Shop Manual Hydraulic Excavator PC2000-8

Failure analysis is carried out first by taking a sample of the PC2000-8 engine that is in the FMC contract, so that the completeness of the data and analysis can be carried out by the UT Subject Matter Expert team. Details of the dataset from the EX1701 engine as Table 1 below :

TABEL I
DETAIL DATASET OF ENGINE EX1701

Subject	Description
Code Unit	EX1701
SN Unit	20030
Customer	Pama Persada Nusantara
Unit	FMC
Component	Engine (Reman)
Install HM	11600
Remove HM	27335
Lifetime	15735
Replacement Status	Unschedule
Replacement Number	2

Details of the value limits of the main VHMS parameters that will be analyzed in order to provide a warning can be seen in the Table 2 below :

TABEL II
DETAIL STANDARD LIMIT OF ENGINE EX1701

NO	SUBJECT	UOM	BottomCriticalValue	BottomCautionValue	TopCautionValue	TopCriticalValue
1	E.Oil P.H_Min	kg/cm2	2,1	2,5		
2	EOil Pre.MAX	kg/cm2	2	3		
3	Boost Press Max	mmHg	750	850		
4	Eng.Oil Tmp.MAX	degC			110	120
5	E.Oil P.L_Min	kg/cm2	0,5	0,7		
6	Eng.Speed(Max)	rpm			2400	2500
7	BlowbyPress Max	mmH2O			600	720
8	Cool Temp.MAX	degC			85	95
9	FanPumpF P.Max	kg/cm2	125	150	200	225
10	FanPumpR P.Max	kg/cm2	125	150	200	225

After all the datasets needed for the EX1701 engine unit are available, then a descriptive analysis is carried out by making a scatter plot graph for each of the main VHMS parameters mentioned above. The scatter plot made consists of the x-axis and the y-axis, where the x-axis is for the hour meter (HM) of the unit and the y-axis is for the actual number of each of these VHMS parameters.

Maximum boost pressure is one of the main parameters that must be measured, where measurements are made based on the maximum boost pressure found on the inside of the turbocharger for a span of every 20 hours, according to the data transmission schedule from VHMS. Measurements are made using the mmHg unit and in ideal conditions it must be above the minimum limit based on data from the SMEs which is at 750 mmHg.

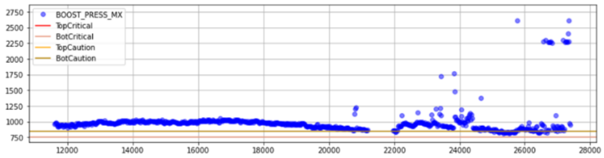

Fig. 2. Boost press Max vs SMR of engine EX1701

Fig 2 is showing failure analysis that occurred in the maximum boost pressure parameter began to occur after the engine operated for 9.217 HM, that is by recording a value of more than 1200 mmHg compared to the average value since starting operation of 952 mmHg (an increase of about 26%. Then, from SMR 20.817 to engine failure at SMR 27.335, there were 22 abnormal boost pressures with a value between 1.200 – 2.610 mmHg (an increase of about 26-174%).

TABEL III
SUMMARY OF ABNORMAL BOOST PRESSURE DATA FROM ENGINE EX1701

No.	Code Unit	SMR	RUL	Boost	Mean	Diff	%Tage
1	EX1701	20.817	6.518	1.200	953	247	26%
2	EX1701	20.837	6.498	1.230	953	277	29%
3	EX1701	23.284	4.052	1.208	953	255	27%
4	EX1701	23.404	3.931	1.215	953	262	28%
5	EX1701	23.424	3.911	1.725	953	772	81%
6	EX1701	23.825	3.510	1.770	953	817	86%
7	EX1701	23.845	3.490	1.478	953	525	55%
8	EX1701	24.647	2.688	1.373	953	420	44%
9	EX1701	25.771	1.564	2.610	953	1.657	174%
10	EX1701	26.574	761	2.273	953	1.320	139%
11	EX1701	26.634	701	2.295	953	1.342	141%
12	EX1701	26.734	601	2.265	953	1.312	138%
13	EX1701	26.755	581	2.265	953	1.312	138%
14	EX1701	26.775	561	2.265	953	1.312	138%
15	EX1701	26.795	541	2.280	953	1.327	139%
16	EX1701	26.835	500	2.258	953	1.305	137%
17	EX1701	27.176	160	2.295	953	1.342	141%
18	EX1701	27.236	99	2.265	953	1.312	138%
19	EX1701	27.256	79	2.280	953	1.327	139%
20	EX1701	27.276	59	2.273	953	1.320	139%
21	EX1701	27.296	39	2.265	953	1.312	138%
22	EX1701	27.316	19	2.408	953	1.455	153%

From the data Table 3, we can analyze that the increase in the value of boost pressure is directly proportional to the lifetime of the engine component. The higher the abnormal value of boost pressure, the closer to the end of the engine component's life.

From Fig. 3 below, we can see that the maximum pressure boost parameter can be used as an indication of the estimated age of engine components, especially for engines whose life will end in the next 6,000 HM. The maximum boost pressure parameter value with a range of 1.200 – 2.000 mmHg can provide estimation information that the engine life will end in another 2.500 – 6.500 HM. As for the maximum boost pressure value with a range above 2.000 mmHg, it can provide estimation information that the engine life will end in less than 2.500 HM again.

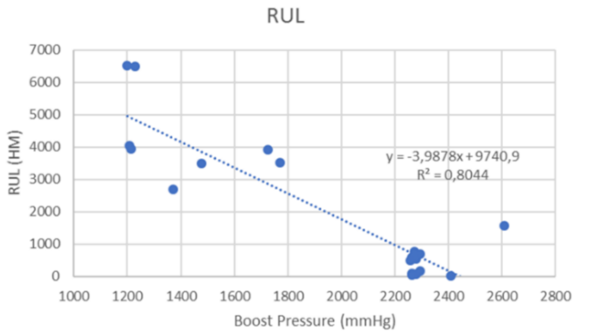

Fig. 3. Abnormal boost pressure vs RUL of engine EX1701

In addition, we can also look at the trendline and equation to determine the estimated engine life/remaining useful life (RUL) based on the maximum boost pressure parameter.

$$RUL\ (hours) = (-3{,}9878\ x\ boost\ pressure) +\ 9740{,}9\ ;$$
$$applied\ only\ when\ boost\ pressure\ abnormality\ is\ more\ than\ 1200\ mmHg$$

After the boost pressure maximum, we also see the maximum engine coolant temperature, where the measurement is made based on the maximum temperature of the engine coolant fluid in a span of every 20 hours, according to the data transmission schedule from VHMS. Measurements are made using units of degrees Celsius and in ideal conditions it must be below the maximum limit based on data from the SMEs which is at 95 degrees Celsius.

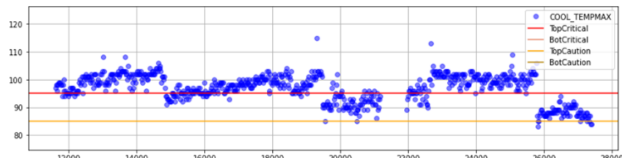

Fig. 4. Cool temp Max. vs SMR of engine EX1701

From the Fig. 4, the maximum engine coolant temperature parameter above, it can be concluded that the parameter has experienced an abnormality, even not long after the engine is installed in the unit. Engine coolant temperature throughout its life operates in a value range of 90-105 degrees Celsius. In addition, there is also a missing value because the data from the sensor does not transmit in the SMR 21.200 – 21.900 range. Failure analysis that occurred at the maximum coolant temperature parameter began to show abnormalities since the engine component was first installed on SMR 11.600 and continued until SMR 19.473 then continued again from SMR 22.621 to SMR 25.771 so that from the total lifetime of the engine component of 15.735 hours meters, the component has an abnormality in the coolant parameter, a maximum temperature of 70% of the total operating lifetime of the engine component (11.024 hours meter). Based on the failure analysis of the coolant temperature maximum parameter. As an individual this parameter can be used to see whether the engine component is operating in its ideal condition or not, but it cannot determine how much the maximum coolant temperature parameter has an effect on engine life.

Another parameter that we see is front side fan pump pressure, where measurements are made based on the maximum temperature of the engine oil in a span of every 20 hours, according to the data transmission schedule from VHMS. Measurements are made using units of kg/cm^2 and in ideal conditions it must be between the minimum and maximum limit ranges, based on data from SMEs it is 125 – 225 kg/cm^2.

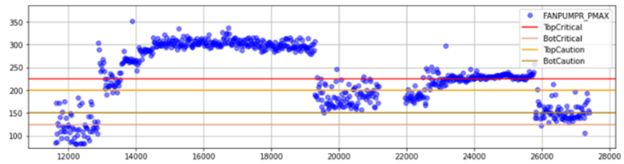

Fig. 5. Rear fan pump pressure vs SMR of engine EX1701

From Fig. 5 the rear side fan pump pressure parameter above, it can be concluded that this parameter has an abnormality tendency in the SMR 13,000 - 19,000 range because the fan pump pressure is above the maximum limit, in addition, there is also a missing value because the data from the sensor does not transmit in the SMR 21.200 – 21.900 range. Failure analysis that occurred on the rear fan pump pressure parameter began to show abnormalities since the engine component was installed on the SMR 11.600. From there, it can be seen that at the beginning the engine component operates up to SMR 12.849, the rear fan pump pressure tends to work under pressure below the minimum pressure limit, ideally at 125 kg/cm^2 and then since SMR 12.889 shows a different phenomenon, this time the rear fan pump pressure works over pressure above the maximum pressure limit, ideally at 225 kg/cm^2 up to SMR 19.273, after which the rear fan pump pressure operates within its ideal limits up to SMR 22.481. Only then at SMR 22.481 – 25.771 again experienced over pressure and returned to operating within its ideal limit until the component failed at SMR 27.335, so it can be concluded that the component has an abnormality in the rear fan pump pressure parameter of 69% of the total operating lifetime of the engine component (10.924 hours meters). Based on the failure analysis of the rear fan pump pressure parameters discussed earlier, the rear fan pump pressure parameter has the same analysis results as the maximum coolant temperature parameter, i.e. as an individual this parameter can be used to see whether the engine component is operating in its ideal condition or not, but cannot determine how much the rear fan pressure parameter has an influence on engine life.

B. Failure Analysis with data analytic software

Data analysis for RUL calculations using data analytic software starting from the preparation of the dataset. The dataset to be used is the same dataset as the dataset that has been used in the previous manual analysis, so there is not much data processing to start with. Data processing will be carried out based on iteration to get better accuracy results when the dataset is processed by data analytic software.

The details process of data forming to create the dataset along with the amount of each data and also the joint key can be seen in Fig. 6 below:

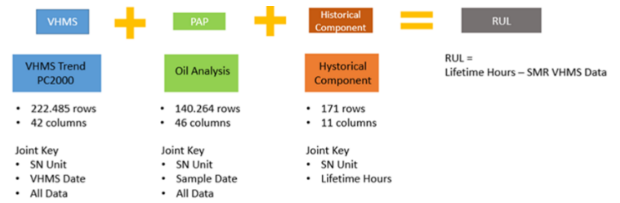

Fig. 6. RUL dataset structure

After getting a dataset that is ready to be used as input in machine learning software, then we make 4 models to experiment with the Orange Data Mining software, namely: Model A, Model B, Model C and Model D (see Fig. 7).

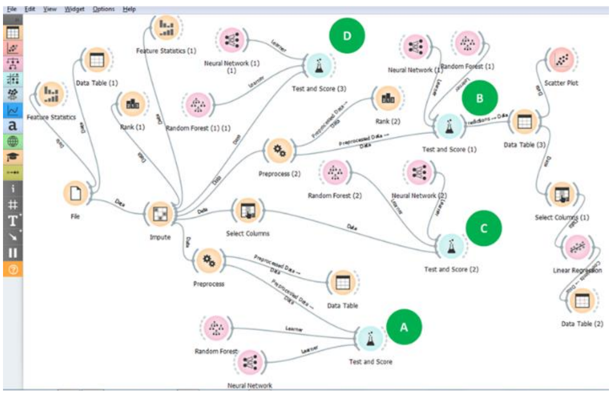

Fig. 7 RUL dataset structure

The results of calculating the RUL for the four models using the Orange software can be seen in Table 4 below:

TABEL IV
RUL CALCULATION RESULT FROM ORANGE

SUBJECT	MODEL A		MODEL B		MODEL C		MODEL D	
	Random Forest	Neural Network	Random Forest	Neural Network	Random Forest	Neural Network	Random Forest	Neural Network
MAE	699,899	N/A	427,434	454,548	407,945	390,021	426,109	430,846
RMSE	1.413,400	N/A	936,330	816,499	915,999	721,658	934,452	778,752
R2	0,939	N/A	0,973	0,980	0,974	0,984	0,973	0,981

Looking at the Table 4 above, there still a way to increase the accuracy of the predictions of model A and model C, several improvements need to be made, including: first is more experiment with the use of other algorithms, outside the Random Forest and Neural Network. Second, experiment with making changes and several alternative combinations of preprocess features, such as normalize to interval, select relevant feature, or by using other features such as rank, select column, etc. Third, experiment by doing on the dataset, by looking at the results of the accuracy of the previous predictions, where the inaccurate details of the dataset are separated and a separate model is made separately from the dataset whose results are good enough, so as not to reduce the total value of the predicted results.

III. RESULTS AND DISCUSSIONS

Continuing the failure analysis on the Komatsu PC2000-8 engine code unit EX1701 in the previous chapter II, then based on the results of the failure analysis and failure indicator on the EX1701 engine, a data analysis will be performed on all available failure data. From the 3 failure indicator parameters obtained above, we will analyze all 17 cases of engine premature lifetime (unschedule replacement), did the engine have the same failure indicator and warning that can be used as a predictive tool for estimating when the engine's life will end (RUL).

A. Data Analysis Implementation

Data analysis will be carried out for all 17 cases of unscheduled engine component replacements (USC), including the replacement of the engine component on the EX1701 unit discussed in the chapter 2 above. Data analysis has been carried out for 17 engine units that have unschedule component replacement to see the abnormality and critical warning from the total 10 parameter. The results of the critical warning can be seen in Table 5 and Table 6 below:

TABEL V
CRITICAL WARNING FOR ENGINE PC2000-8 (PARAMETER 1-6)

NO	MODEL	CN	REPL NUM	LIFETIME	E.Oil P.H_Min	EOil Pre. MAX	Boost Press Max	Eng.Oil Tmp. MAX	E.Oil P.L_Min	Eng.Speed (Max)
1	PC2000-8	EX1701	2	15.735	57	0	22	0	0	0
2	PC2000-8	EX1701	3	1.949	33	0	2	0	0	0
3	PC2000-8	EX1705	1	14.743	28	0	0	2	0	0
4	PC2000-8	EX1705	3	7.380	1	0	6	0	0	0
5	PC2000-8	EX011	1	13.505	126	0	0	0	0	0
6	PC2000-8	EX1722	1	13.569	149	0	1	1	1	0
7	PC2000-8	EX1724	2	14.580	1	0	0	0	0	0
8	PC2000-8	EX1730	1	2.326	9	0	0	0	0	0
9	PC2000-8	EX1734	1	660	8	0	0	0	0	0
10	PC2000-8	EX1734	2	12.189	17	0	0	0	0	0
11	PC2000-8	EX1734	4	15.052	5	0	2	0	0	0
12	PC2000-8	EX1734	5	1.066	1	0	0	0	0	0
13	PC2000-8	EX1734	6	5.564	4	0	0	0	0	0
14	PC2000-8	EX1751	1	15.768	4	0	0	0	0	0
15	PC2000-8	EX1758	2	22.883	3	0	7	0	1	0
16	PC2000-8	EX1765	1	23.808	93	0	7	0	3	0
17	PC2000-8	EX276	2	9.173	1	0	0	0	0	0
TOTAL					540	0	47	3	5	0

From Table 5 above, there are 6 parameters that are analyzed for critical warnings generated from all 17 units of the PC2000-8 engine component and a total of 595 warnings are obtained over the specified critical limit, that are only generated by 4 parameters. The 2 parameters that do not provide a warning for the 17 engine component units are engine oil pressure maximum parameter and engine speed maximum parameter.

From Table 6 above, there are the next 4 parameters that are analyzed for critical warnings generated from all 17 units of the PC2000-8 engine component and a total of 6281 warnings are obtained over the specified critical limit. It can also be seen from the 4 parameters above, it turns out that more than 80% of the warning is generated from 3 parameters, namely maximum coolant temperature, front fan pump pressure and rear fan pump pressure. Meanwhile, the parameter that gives the most warnings is the rear fan pump pressure parameter. So, for this critical warning, we can conclude some of the results of the analysis as follows:

1. The amount of warning data obtained varies greatly. To be able to perform the analysis properly and to get a conclusion, a large amount of data is required. One unit that has quite a lot of data is the replacement of the second engine unit EX1701, so in addition to getting a warning, it can also provide an estimate of the RUL prediction from the maximum pressure boost parameter..
2. From the 10 parameters that were analyzed on a total of 17 PC2000-8 engine units, there were 2 parameters that did not provide critical warning information, namely engine oil pressure maximum and engine speed maximum.
3. All units can provide critical warning information during operation and before failure.

TABEL VI
CRITICAL WARNING FOR ENGINE PC2000-8 (PARAMETER 7-10)

NO	MODEL	CN	REPL NUM	LIFETIME	BlowbyPress Max	Cool Temp. MAX	FanPumpF P.Max		FanPumpR P.Max	
							Below Limit	Above Limit	Below Limit	Above Limit
1	PC2000-8	EX1701	2	15.735	99	498	40	4	48	422
2	PC2000-8	EX1701	3	1.949	0	0	0	9	9	0
3	PC2000-8	EX1705	1	14.743	31	111	41	12	177	1
4	PC2000-8	EX1705	3	7.380	13	5	23	20	16	144
5	PC2000-8	EX011	1	13.505	21	31	123	81	273	2
6	PC2000-8	EX1722	1	13.569	7	80	120	6	280	4
7	PC2000-8	EX1724	2	14.580	31	60	0	338	30	290
8	PC2000-8	EX1730	1	2.326	1	0	44	1	71	0
9	PC2000-8	EX1734	1	660	13	0	1	0	6	0
10	PC2000-8	EX1734	2	12.189	28	1	19	11	128	0
11	PC2000-8	EX1734	4	15.052	40	94	106	25	223	5
12	PC2000-8	EX1734	5	1.066	0	2	0	25	0	41
13	PC2000-8	EX1734	6	5.564	7	3	0	46	107	3
14	PC2000-8	EX1751	1	15.768	64	0	6	46	246	67
15	PC2000-8	EX1758	2	22.883	22	99	0	129	32	29
16	PC2000-8	EX1765	1	23.808	46	154	0	225	180	25
17	PC2000-8	EX276	2	9.173	10	2	0	143	7	198
TOTAL					**433**	**1140**	**523**	**1121**	**1833**	**1231**

4. The amount of warning data obtained varies greatly. To be able to perform the analysis properly and to get a conclusion, a large amount of data is required. One unit that has quite a lot of data is the replacement of the second engine unit EX1701, so in addition to getting a warning, it can also provide an estimate of the RUL prediction from the maximum pressure boost parameter..
5. From the 10 parameters that were analyzed on a total of 17 PC2000-8 engine units, there were 2 parameters that did not provide critical warning information, namely engine oil pressure maximum and engine speed maximum.
6. All units can provide critical warning information during operation and before failure.

We also found the same way for the caution warning and The detailed summary of each warning and parameter can be seen in the Table 7.

So that from the total analysis carried out on the 17 unit of PC2000-8 engine components, there were 20,026 warnings during the engine operation which would help prioritize the service work of the more critical engines.

TABEL VII
CRITICAL WARNING FOR ENGINE PC2000-8 (PARAMETER 7-10)

Warning	E.Oil P.H_Min	EOil Pre. MAX	Boost Press	Eng.Oil Tmp.	E.Oil P.L_Min	Eng.Speed (Max)
Caution	2021	0	0	522	0	0
Critical	540	0	47	3	5	0
Total	**2561**	**0**	**47**	**525**	**5**	**0**

Warning	BlowbyPress Max	Cool Temp. MAX	FanPumpF P.Max		FanPumpR P.Max	
			Below Limit	Above Limit	Below Limit	Above Limit
Caution	88	4386	1961	742	2996	434
Critical	433	1140	523	1121	1833	1231
Total	**521**	**5526**	**2484**	**1863**	**4829**	**1665**

B. Data Analysis Implementation with data analytic software

The results of further analysis of the results of the RUL prediction using the full dataset show that there is an increase in the error of the RUL prediction which is closer to the time the component fails, so that the total prediction result is not optimal. Therefore, to improve the results of the RUL prediction, experiments were carried out by separating the dataset based on RUL below 1000 HM and RUL above 1000 HM. The results of the best RUL predictions that can be obtained currently consist of 3 pieces of dataset as follows:

1. Dual modeling by dividing the dataset, between datasets that have an RUL below 1000 hourmeter (HM) and datasets that have an RUL of more than 1000 HM. This dual modeling RUL Prediction succeeded in making predictions for RUL <1000HM with MAE 62.703 and prediction for RUL> 1000HM with MAE 85.045 using the AdaBoost algorithm and preprocess using the C model.
2. Single modeling using the full period RUL dataset Prediction is successful in making predictions with MAE 91,469 using the AdaBoost algorithm and preprocessing using the C model.

The detail experiment result with different dataset can be seen in Table 8.

TABLE VIII
RUL CALCULATION RESULT WITH ADABOOST ALGORITHM

SUBJECT	MODEL C - AdaBoost			REMARKS
	< 1000 HM	> 1000 HM	Full Data	
MAE	62,585	82,202	91,204	Diff 3-7 days only
R2	0,916	0,996	0,995	

C. Failure Analysis using Automation

As for the failure analysis process, it requires assistance from an automation process using an application/program that can speed up the process compared to manual analysis. This is mainly due the analysis process of creating alerts or notifications as an early warning involves quite a lot of parameters; the number of units and the daily transmit data interval. This makes manual analysis carried out individually will be less effective, because it requires a long time and also a lot of new data results transmits piled up and queued for analysis.

Based on the results of discussions with the subject matter expert team, one of them is the site technical engineer who carries out manual failure analysis on a daily basis. It can be concluded that the hopes and objectives of the automation process and system development that must be carried out are as follows :

1. Access to performance monitoring dashboard and parameters for all monitored machines, so that it can be seen in one place, one system, and one dashboard.
2. Automatic alerts and notifications will make it easier for site technical engineers to receive information on abnormalities quicker, so that they can immediately follow up on these abnormalities.

Details of the process flow can be seen in Fig. 8 below.

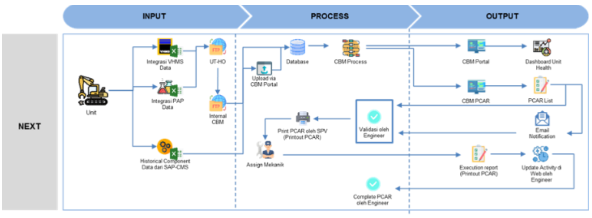

Fig. 8. Concept of failure analysis & data flow with automation in CBM

The aim of this automation system is that site technical engineers can facilitate the data collection process and can focus on the validation process, analysis and follow-up actions.

D. Monitoring System for unit health condition

In accordance with the requirements and objectives of the monitoring system as described in sub-chapter C above. The monitoring system requires a system consisting of a web application, email notification, application interface, and a business intelligence dashboard in order to provide early warnings on the data flow that is processed by the application. The monitoring system solution can be broadly divided as follows (Fig. 9):

1. Condition Based Monitoring (CBM) Portal – National condition dashboard & unit condition detail, that can display jobsite/branch conditions based on the number and movement of abnormalities on population units in the area and also displays detailed performance conditions for the machine consisting of abnormality parameters, and unit performance indicator (PA & MTBF).
2. Preventive and Correction Action Report (PCAR) Portal – Web application for detail analysis and follow up action, especially related to parameters experiencing these abnormalities. The functionalities of the PCAR portal are first, can display a dashboard for all PCARs that have been formed automatically, along with all progress status for each PCAR based on their respective areas and units. Second, automatically creates notification (warning) and PCAR for each parameter that exceeds the predetermined limits based on factory standards. Third, doing follow up actions; starting from analysis; recommendation of detailed actions that must be taken, so that monitoring can be done until the PCAR is closed, all in one portal.
3. Automatic Email Notification, The notification email is sent by the PCAR portal system directly to the email address of the registered team to give an early and proactive warning.

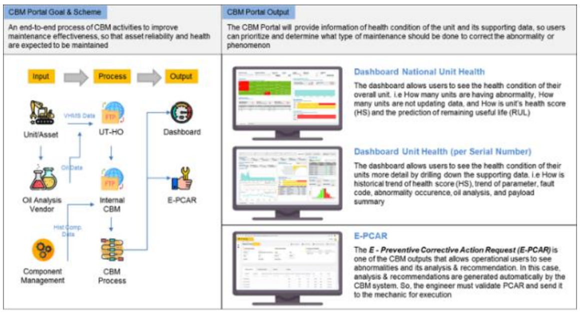

Fig. 9. Predictive maintenance analysis tools through CBM portal

IV. CONCLUSIONS

A. Conclusions

Based on the analysis, several conclusions can be obtained, including :

1. Predicting the estimated remaining useful life (RUL) of engine can be obtain through manual analysis from maximum boost pressure parameter and through data analytic software. RUL from boost pressure parameter will use the following equation :
   RUL (hours) = (-3,9878 x boost pressure) + 9740,9
2. The critical and caution warning obtained from the parameters can be used as early warnings that there are problems with the engine component based on the standard limits given by the factory.
3. Warning and prediction of RUL estimation can be used to provide prioritization tool for heavy equipment that must be prioritized for service to prevent unscheduled breakdown or premature failure to the engine components.
4. Monitoring system application can be used by UT site technical engineers and maintenance teams to prioritize units for faster and enable more accurate service schedule (improve analysis lead time from 8–10 days to 2–3 days with PCAR Portal).

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