The Combination of Reliability and Predictive Tools to Determine Ship Engine Performance based on Condition Monitoring

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Abstract. The evolution of maintenance has experienced developments in the fourth generation since the beginning of 2000 to the present. The fourth generation is the latest generation that focuses on condition-based maintenance, condition monitoring and failure eliminations. The maintenance strategy in the fourth generation aims to reduce the failure rate of an equipment by reducing the probability, based on preventive and predictive approaches. In this research, a maintenance approach was carried out by predicting the results of condition monitoring on ship engine to ensure performance. The concept developed is to use a combination of reliability tools for criticality assessment and predictive tools to determine diagnostic assessments. Reliability tool for criticality assessment is the Failure Mode and Effect Criticality Analysis (FMECA) based on the fuzzy logic approach. FMECA's bottom-up approach is intended to explore failure modes that provide potential failure in the main engine system. The fuzzy logic theory added to FMECA accommodates uncertainty due to obscure information as well as subjective preference elements that are used in the assessment of failure modes. The predictive assessment process uses the Multilayer Perceptron (MLP) approach using the Artificial Neural Network (ANN) method. ANN has advantages for self-learning, adaptivity, fault tolerance, nonlinearity, and advancement in input to an output mapping. The results of the current diagnostic assessment indicate the condition of the main engine is still normal. However, the trending of exhaust gas temperature prediction shows an increase, combustion and compression pressure which shows a decrease need to be prepared for determining the inspection/survey schedule. In this research, predictive assessment using an Artificial Neural Network based on Multilayer Perceptron (MLP) has been validated with an error of less than 5%.

1. Introduction

A diesel engine is a type of internal combustion engine in which the fuel is ignited by a compressed high temperature. Diesel engines are widely used as prime mover on a ship [1]. To fulfill the work of diesel engine on ship, there are several systems that must be considered, such as: the fuel system, the lubricating system, the cooling system, and the starting and compressed air system. These systems affect the performance of the diesel engine operations on the ship [2]. The engine maker also provides

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Fig. 1: Schematic diagram of a diesel engine system.}
\end{figure}
a manual troubleshooting book which is a general technical guide that can be used by crew of ship when operating or repairing an engine if there is a breakdown. Each type of diesel engine has different types of failure characteristics depending on the fabrication and operation [3].

The maintenance strategy has reached the era of the fourth generation. The failure pattern of the fourth generation equipment is statistically 89% associated with random failure, so predictive maintenance is very important [4]. When predictive maintenance is applied to all equipment in the entire system, it will certainly be very uneconomical. So there needs to be a scientific method for determining maintenance priorities that determine which equipment is required for predictive maintenance activities. Maintenance strategies that lead to predictive maintenance have also been implemented by several classification societies, such as the Lloyd Register, Nippon Kaiji Kyokai (NK), DNV-GL, and the American Bureau of Shipping [5-7].

The concept of maintenance using criticality assessment has been widely used by researchers to determine the level of risk and maintenance action such as those carried out by Liu [8], Adumene and Islam [9] [10], Baynal [11], Yazdi [12] and Siswantoro [13]. Its criticality is based on several approaches such as probabilistic risk assessment, decision making, and fuzzy [14] [15]. Meanwhile, the concept of condition monitoring has been carried out by monitoring the condition monitoring data on bearings and gearboxes [16] [17]. The concept of criticality assessment and condition monitoring carried out by previous researchers is not an integrated unit, which stops at one assessment in the form of only criticality or condition monitoring. So that there is still a gap where an integrated method is needed to perform criticality assessment and utilize condition monitoring data to diagnose equipment/main engine performance [18].

This urgency requires a solution in the form of an integrated method. Hybrid Predictive Method (HPM) accommodates the determination of priority maintenance with a criticality assessment approach to determine predictive assessment priorities. The proposed Hybrid Predictive Method (HPM) concept combines reliability tools and predictive / forecasting tools. Reliability tools for criticality assessment are Failure Mode and Effect Criticality Analysis (FMECA) based on the fuzzy logic approach. FMECA's bottom-up approach is intended to explore failure modes that provide potential failure in the main engine system. The analysis is then carried out to determine the criticality level of the equipment. Fuzzy logic theory added to FMECA accommodates uncertainty due to obscure information and subjective preference elements used in the assessment of failure modes that occur [19-21].

The predictive assessment process uses the Multilayer Perceptron (MLP) approach with the Artificial Neural Network (ANN) method. ANN has advantages for self-learning, adaptivity, fault tolerance, nonlinearity, and advancement in input to an output mapping [22]. The Multilayer Perceptron (MLP) based Artificial Neural Network algorithm is based on the relationship that if the output gives wrong results, then the weights are corrected so that the error can be minimized and the network response is expected to be closer to the target. The multilayer perceptron also has the ability to fix the weight of the hidden layer. This makes ANN a popular and useful model for classification, grouping, pattern recognition and prediction. The complete application of ANN can be evaluated with respect to data analysis factors such as accuracy, processing speed, latency, performance, fault tolerance, volume, scalability and convergence [23] [24].

2. Methods

The method in this research is to combine the criticality assessment approach to determine predictive assessment priorities using Failure Mode and Effect Analysis (FMECA) fuzzy and the Multilayer Perceptron (MLP) approach using the Artificial Neural Network (ANN) method. While the steps for making the Hybrid Predictive Method (HPM) in detail follow the flow chart in Figure 1. There are 4 steps in making the HPM method.
2.1. Development of Criticality Assessment Using Reliability Tools

Step 1. Identify the Function, Functional Failure and Failure Effect
This step is very important to do in order to identify performance, effectiveness, input or output, speed and other factors for each functional. The identification of function in each equipment is determined based on the function of the equipment in the system. Functional failure is a failure of equipment in carrying out its functions in the system due to failure mode or cause of failure. FMECA is expected to be able to facilitate the identification process of potential causes.

Step 2. Analyze the risk level of failure mode to determine criticality
This step is to determine the level of severity, likelihood and detection. Severity relates to how serious the effects or consequences are caused by the failure mode. Likelihood is the frequency of failure of equipment, while detection level is a measure of a design control that can detect potential causes of failure. The measures of severity and likelihood refer to the ABS Classification guidelines [25], while the detection levels refer to the research by Wang [26]. Table 1-3 show the description of severity, likelihood and detection level.

Table 1. Severity level [25]

| Severity Level | Descriptions for Severity Level | Fuzzy Number |
|----------------|---------------------------------|--------------|
| 1              | Minor, Negligible,              | [0 0.5 1]    |
| 2              | Major, Marginal, Moderate       | [1 1.5 2]    |
| 3              | Critical, Hazardous, Significant| [2 2.5 3]    |
| 4              | Catastrophic, Critical          | [3 3.5 4]    |

Table 2. Likelihood level [25]

| Likelihood level | Likelihood Descriptor | Description       | Fuzzy Number |
|------------------|-----------------------|-------------------|--------------|
| 1                | Improbable            | Fewer than 0.001  | [0 0.5 1]    |
|                  |                       | events/year       |              |
| 2                | Remote                | 0.001 to 0.01     | [1 1.5 2]    |
|                  |                       | events/year       |              |
| 3                | Occasional            | 0.01 to 0.1       | [2 2.5 3]    |
|                  |                       | events/year       |              |
| 4                | Probable              | 0.1 to 1          | [3 3.5 4]    |
|                  |                       | events/year       |              |
| 5                | Frequent              | 1 or more         | [4 4.5 5]    |
|                  |                       | events/year       |              |
Table 3. Detection level [26]

| Detection level | Detection Descriptor | Description                                                                 | Fuzzy Number |
|-----------------|----------------------|-----------------------------------------------------------------------------|--------------|
| 1               | Very High            | Very high chance the design control will detect a potential cause of failure or subsequent failure mode | [4 4.5 5]    |
| 2               | High                 | High chance the design control will detect a potential cause of failure or subsequent failure mode | [3 3.5 4]    |
| 3               | Medium               | Moderate chance the design control will detect a potential cause of failure or subsequent failure mode | [2 2.5 3]    |
| 4               | Low                  | Low chance the design control will detect a potential cause of failure or subsequent failure mode | [1 1.5 2]    |
| 5               | Very Low             | Very low chance the design control will detect a potential cause of failure or subsequent failure mode | [0 0.5 1]    |

Step 3. Fuzzy Logic Simulation

The step in the fuzzy logic simulation is to input the fuzzy values on the elements of severity, likelihood and detection. The step of fuzzy logic simulation generally consists of three processes, namely: (1) fuzzification of the input membership function, (2) rule evaluation, (3) defuzzification. Figure 2 shows the process of fuzzy logic simulation.

![Fuzzy Logic Simulation Process](image1)

Figure 2. The process of fuzzy logic simulation [20]

The input membership function consists of Severity (S), Occurrence (O) and Detection (D). They have a representation of the triangle curve. Meanwhile, the fuzzy output has a trapezoidal and triangle curve representation. Tables 1-3 and Table 4 show membership functions and fuzzy numbers. The rules made in the fuzzy logic simulation are IF-THEN rules and then processed using the Mamdani Method.

Table 4. Membership function of FRPN output

| FRPN level    | FRPN conversion | Type of Curve | Fuzzy Number |
|---------------|-----------------|---------------|--------------|
| Very Low      | Low             | Trapezoidal   | [0 0 10 20]  |
| Low           | Medium          | Triangle      | [20 30 40]   |
| Medium        | Medium          | Triangle      | [40 50 60]   |
| High          | High            | Triangle      | [60 70 80]   |
| Very High     | Trapezoidal     | [80 90 100 100]|

![Multilayer Perceptron Network](image2)

Figure 3. The architecture of multilayer perceptron network [27]
2.2. Development of Predictive Assessment Using Artificial Neural Network (ANN)

This step is a process of forecasting the results of condition monitoring data. The result of the forecasting assessment is the diagnostic assessment engine. Forecasting assessment uses the Multilayer Perceptron (MLP) approach with the Artificial Neural Network (ANN) method. Multilayer perceptron (MLP) approach is assisted using ANACONDA Python software. Multilayer perceptron (MLP) have one or more layers that are located between the input layer and the output layer (having one or more hidden layers), as shown in Figure 3. The MLP algorithm has been described in detail and then worked on using ANACONDA Python software.

3. Result and Discussion

The object of this research is MAK 8 M32C. Then data is collected on the fuel system (fuel oil system), lubricating system (lubricating oil system), cooling system (cooling system), and starting air system. Data of condition monitoring is obtained based on the results of FMECA Fuzzy on critical equipment. Table 5 shows the specification of diesel engine.

| Item                     | Specification                  |
|--------------------------|--------------------------------|
| Type of Engine           | MAK 8 M32C                     |
| Cylinder configuration   | 8 in-line                      |
| Bore                     | 320 mm                         |
| Stroke                   | 480 mm                         |
| Stroke/bore ratio        | 1,5                            |
| Swept volume             | 38,7 l/cyl                     |
| Output/cylinder          | 500/kW                         |
| BMEP                     | 25,9 bar                       |
| Revolutions              | 600 rpm                        |
| Mean piston speed        | 9,6 m/s                        |
| Turbocharging            | Single log, option: pulse      |
| Direction of rotation    | Clockwise, option: counter-clockwise |

3.1 Criticality Assessment

The initial step in determining FMECA is to determine the function, functional failure, failure mode and failure effect. FMECA worksheets can be used to facilitate this analysis. Tables 6 shows examples of FMECA worksheets on the Main Engine.

| Equipment | Function | Functional Failure (Loss of function) | Failure Mode (Cause of failure) | Failure Effect (What happens when it fails) | Fuzzy Risk Priority Number (FRPN) | Risk Level |
|-----------|----------|---------------------------------------|---------------------------------|--------------------------------------------|---------------------------------|------------|
| MAK 8 M32C| CE-ME-001| The main engine does not able to function as main propulsion (total failure) | 1 Main engine fails to operate due to breakdown | The breakdown that occurs in the main engine causes the engine to be unable to operate / engine stop | 90.5 | High |
|           |CE-ME-001| Main engine fails to start on          | 2 Main engine fails to start on | The main engine fails to start on demand causes the | 70 | High |
FMECA worksheet is applied to the main engine and supporting systems. The value of Fuzzy Risk Priority Number is obtained from the simulation results of fuzzy logic using Matlab. Figure 4 shows modeling in Matlab simulation.

![Image](image_url)

**Figure 4.** The input, process, output plot in the fuzzy MATLAB

The rules are simulated using Mamdani algorithm. The Mamdani method used the function of the min and max aggregation implications, so the Mamdani method is called the min-max method.

\[
\mu_{gk}(y) = \max \left[ \min \left[ \mu A^1_k(x_i), \mu A^2_k(x_j) \right] \right]_k
\]  

(1)

For \( k = 1,2, \ldots, n \), \( A^1_k \) expresses fuzzy set of pairs of antecedents of \( -k \), and \( B^k \) is a consequence fuzzy set of \( -k \).

![Image](image_url)

**Figure 5.** The distribution of criticality level in FMECA fuzzy for all failure modes

The simulation results using Matlab are a fuzzy risk priority number which is converted into high, medium, or low risk levels. Analysis on the main engine and supporting system showed that the risk level was 10% failure mode with a high risk level, 67% medium risk, and 23% low risk from a total of 339 failure modes. Figure 5 shows the distribution of criticality level in FMECA fuzzy for all failure modes.

3.2 Predictive Assessment

According to FMECA fuzzy results, the failure modes that directly causes the main engine to experience high risk failure are the main engine fails to operate and start due to total failure. While the failure modes cause partial failure are the main engine does not perform well due to external leakage, overheating, spurious stop, erratic output, and structural degradation.

The failure modes that indirectly (related to the main engine supporting system) cause the main engine to experience high risk failure are the DFO transfer pump, HFO transfer pump and FO supply pump, lubricating oil pump, LO transfer pump, Main compressor was damaged and failed to start.
Meanwhile, the failure modes that cause partial failure are DFO transfer pump, HFO transfer pump and FO supply pump, lubricating oil pump, LO transfer pump failure due to structural degradation. Therefore, condition monitoring and predictive assessment are carried out on the following parameters: (a) Exhaust gas temperature, (b) Combustion pressure, (c) Compression pressure.

3.2.1 Condition Monitoring and Predictive Assessment on Exhaust Gas Temperature
Data collection for condition monitoring and predictive assessment is carried out on exhaust gas temperature, due to the engine has potential to overheat. Data condition monitoring for exhaust gas temperature is done by taking periodic data (monthly). The simulation of exhaust gas temperature prediction is done 50 times on each cylinder of the engine to get accurate results. The predicted value is the average value of 50 simulated times.

The result of the prediction of exhaust gas temperature in all conditions of cylinders 1-8 show an increase in the predicted 8 months, but it is still lower than the limits for the technical operation of the MAK 8 M32 main engine. Prediction results of the exhaust gas temperature for the periodic month can be seen in figure 6.

![Figure 6. The prediction of exhaust gas temperature in cylinders 1-8](image)

![Figure 7. The prediction of combustion pressure in cylinders 1-8](image)
3.2.2 Condition Monitoring and Predictive Assessment on Combustion Pressure

The data collection of condition monitoring and predictive assessment is carried out on combustion pressure, because there is a potential for the engine to not perform well due to spurious stop and erratic output. If cylinder components such as pistons, piston rings or liners are worn or leaked, the rated compression pressure will not be achieved and combustion will be inefficient. Referring to the statement of Martyr et al [28], the ship's crew needs to monitor combustion pressure to ensure that the engine remains in its performance condition. The data taken from combustion pressure for predictive assessment is the maximum combustion pressure.

The results of trending monitoring of all cylinders 1-8 can be seen in figure 7. Of all the cylinders have the same pattern, namely in 2016 the value of combustion pressure decreased, while in 2017 and 2018 it had increased again. Meanwhile, from 2019 to 2020 trending began to show a decline again, but it was not too significant. This is in line with the effect of combustion pressure on exhaust gas temperature. The higher combustion pressure value, the higher heat release as described by Kitayama et al [29] and Martyr et al [28], see figure 8.

Figure 8. The prediction of compression pressure in cylinders 1-8

3.2.3 Condition Monitoring and Predictive Assessment on Compression Pressure

Condition monitoring and prediction that have been carried out affect the diagnostic assessment on the main engine [30]. The results of the current diagnostic assessment indicate the condition of the main engine is normal. However, the trending of the exhaust gas temperature prediction showed an increase, while the combustion and compression pressure showed the trending decreased.

Therefore, Hybrid Predictive Method (HPM) has the advantage to cultivate opportunities of predictive and risk-based maintenance application. Hybrid Predictive Method can classify high risk failure modes and predict the time when the parameters reach the allowable technical operation limit. This technical operation limit determines the time for scheduling maintenance/overhaul actions. In this research, predictive assessment using an Artificial Neural Network based on Multilayer Perceptron (MLP) has been validated with an error of less than 5%.

4. Conclusion

The analysis of FMECA fuzzy on the main engine and supporting system showed that the risk level was 10% failure mode with a high risk level, 67% medium risk, and 23% low risk from a total of 339 failure modes. The high risk level is obtained in failure modes which have a fuzzy risk priority number (FRPN) value of 60-100. Whereas at the medium risk level the FRPN value ranges from 40-60, and the low risk level has a FRPN value of 0-40. According to FMECA fuzzy, condition monitoring and predictive assessment are carried out on the following parameters: (a) Exhaust gas temperature, (b)
Combustion pressure, (c) Compression pressure. Condition monitoring and prediction that have been carried out affect the diagnostic assessment on the main engine. The results of the current diagnostic assessment indicate the condition of the main engine is normal. However, the trending of the exhaust gas temperature prediction showed an increase, while the combustion and compression pressure showed the trending decreased. This is an indicator that the survey schedule must be carried out immediately. Hybrid Predictive Method (HPM) has the advantage to cultivate opportunities of predictive and risk-based maintenance application. Hybrid Predictive Method can classify high risk failure modes and predict the time when the parameters reach the allowable technical operation limit. This technical operation limit determines the time for scheduling maintenance/overhaul actions.

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