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Main Engine Performance Evaluation with Forecasting Assessment based on Condition Monitoring Data in Exhaust Gas Temperature

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Abstract:- Operation and maintenance are the main elements in every operational activity of the ship. Inadequacy in terms of ship engine maintenance could increase the rates of failures in the equipment that could lead to environmental problems, altering the performance, and would possibly create a large impact of business loss over the decline of availability on the vessels, increasing the downtime, and also potentially broaden the potential for major accidents that occur and endangering lives on board. The main engine on the ship is not only the most important part but also the most dominant component that often undergo problems. In actual conditions, the damage that occurs to an engine is very complex and would lead to fatality if there is a lack of proper monitoring and maintenance activities to be carried out when the ship is in operational condition. Before repairs are to be made onto the damage suffered by the ship's diesel engine, it is necessary to detect any damage to the engine in prior. In this study, the authors developed a combination method to detect or diagnose an engine based on its condition monitoring data on the exhaust gas temperature. The proposed method is a combination or a fuse of two methods, on Failure Mode and Effect Criticality Analysis (FMECA) and the Forecasting Assessment method using Artificial Neural Network (ANN). FMECA is intended to bottom-up the events that lead to failure and measure the level of criticality on the engine. Forecasting Assessment is used to predict future values from all major engine cylinders of the exhaust gas temperature. With the combination of the methods above, it is expected that the prediction of time and action in the maintenance process are adept to be carried out on the ship's engine. The results of this study were consisting of 23 equipment and 99 failure modes detected in the lubricating oil system. From the overall failure mode, the critical level distribution had a low-risk level (24%), medium risk (64%), and high risk (12%). Based on the condition monitoring data on the exhaust gas temperature, the forecasting assessment was obtained and the maximum error value of 4.31% is validated through comparison of actual observations recorded directly on the ship for forecasting towards 12 months forth.

Keywords:- *Condition Monitoring; Exhaust Gas Temperature; FMECA; Forecasting Assessment; Main Engine.*

I. INTRODUCTION

A diesel engine is a type of internal combustion engine that uses compressed heat to ignite and burn fuel that has been injected into the combustion chamber [1]. To ensure the operation of the engine on board, there are several systems that must be considered, such as fuel oil system, lubricating oil system, cooling system, and starting and compressed air system. The system above majorly affects the performance of the engine operations on board [2]. Each engine has different specifications and requirements according to the engine maker company that issued the engine project guide.

Amidst the maritime industry, several marine diesel engine providers have been well-known among the ship building industry, such as Wartsila, MAN, Yanmar, Daihatsu, MTU, Caterpillar, and so on [3]. Within diesel engines, there are several types of damage and interference that can occur. Some examples of the damage that can arise in marine diesel on ships are as follows: abnormal exhaust smoke, hard starting, excessive crankcase pressure, no fuel, black out [4].

Figure 1. below shows the percentage (%) that caused engine failures due to maintenance errors, inspections, and operational on main engine reaching approximately 65%. On the other hand, the graph also shows similar causes of maintenance errors, inspection and operational on lubricating oil (21%), maintenance errors, inspection, and operational causes on the auxiliary engine (10%), lack of overall maintenance management (1%) and other causes (3%). P&I Club (Protection and Indemnity Insurance) [5] also explains in Figure 2. about engine failures that affect ship operations. An estimation of 80% of the damage major

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causes is related to the main engine, as shown in pink on the graph. Most of the time, the diesel engine problems occur around the combustion chamber (cylinder cover, cylinder liner, piston, turbocharger and others) as well as with crank pins and bearings.

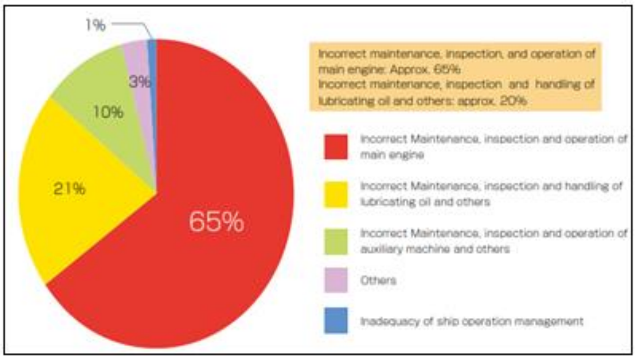

Fig. 1:- The causes of ship accidents (engine damage) 2009-2014 [5]

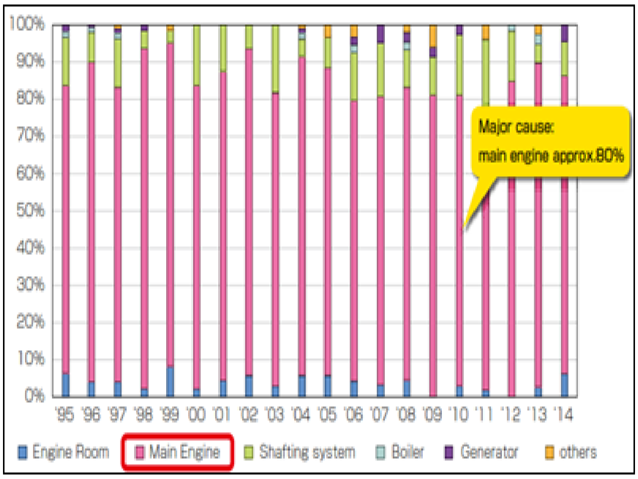

Fig. 2:- Engine damage effect on altering the ship's operation [5]

Maintenance is an activity to handle or maintain and protect the machinery or equipment at its best conditions so that it can be used to carry out the production according to the plan. In other words, maintenance is an activity that is needed to retain and restore the engine or work equipment to the best condition so that it can carry out production optimally.

The growing awareness of infant mortality, affecting the development of the bath-tub curve pattern in the second generation. Meanwhile, in the third generation in the 1980s to 2000s, the type of failure changes in equipment is not only displayed in one curve but into six types of failure types or in terms of treatment known as six failure patterns. The six types of failure are statistically 11% age-related and 89% is a random failure.

Maintenance can be divided into two categories; Planned Maintenance and Unplanned Maintenance. Unplanned Maintenance which also known as Breakdown Maintenance is unplanned maintenance, maintenance that is carried out when there is damage to the engine or work equipment so that the engine cannot operate normally or stop operating completely. Planned maintenance is a planned maintenance activity, where maintenance activities are carried out well before the engine is damaged. This type of treatment is called Preventive Maintenance [6].

Based on ship accident data with engine problems due to maintenance, which can cause the ship to fail to operate. Ship failures will increase companies that have charter vessels. Because it has a low-performing vessel or in other words does not have enough contribution by the user.

Therefore, in this study, the authors developed a combination of methods to detect or diagnose an engine based on condition monitoring data at the temperature of the exhaust gas. The proposed method is a combination or a fuse of two methods, on Failure Mode and Effect Criticality Analysis (FMECA) and the Forecasting Assessment. FMECA is intended to approach bottom-up events that cause engine failure and measure the critical level of failure [7]. The Forecasting Assessment is used for modeling and analyzing the prediction of the future values of time series in the failure mode that has been obtained from FMECA. Alongside the development of this model, it is expected to be able to predict the time and action in the maintenance process carried out on the ship's engine.

II. RESEARCH BACKGORUND

In identifying the important systems or components of ship engines and for analyzing their physical parameters, Lazakis et al [7] used a reliability approach to determine the level of components criticality on the engine cylinders on board as the input parameters in predicting damage. Engine damage prediction is done using the Artificial Neural Networks (ANN) method by monitoring the exhaust gas temperature on the main engine. Research in other Risk-Based Maintenance (RBM) by Diamantoulaki & Angelides [8] uses the Probabilistic Risk Assessment (PRA) approach before determining maintenance scheduling techniques by expert judgment. Research using probabilistic risk assessment and expert judgment has also been conducted by [9] [10].

FMEA was first published as FME(C)A in the United States Armed Forces Military Procedure documentation. In 1960, NASA worked on the FMEA application with a different name for spacecraft [11]. The application of the Failure Modes and Effects Analysis (FMEA) was applied by [12] to find out the cause of failure on the components on board. The application of FMECA [13] for research into gas supply systems for liquefied natural gas fuels to verify their performance in improving the reliability of the design process.

Accordingly, the FMECA results will then be used in determining the maintenance process based on its condition monitoring data. Condition monitoring data can be analyzed using signal processing and data analysis to detect equipment failures.

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A. Failure Mode and Effect Criticality Analysis (FMECA)

The Diagnostic Assessment process uses an approach with the Failure Mode Effect and Criticality Analysis (FMECA) method. The FMECA method provides a bottom-up approach by looking at the ship engine failure mode or its cause database which leads to engine failure.

FMECA is expected to be able to facilitate the identification of potential causes. The next stage of the analysis process will use the 4th edition of the OREDA (Offshore Reliability Data Handbook) data.

Table 1. is the ISO-14224: 2016 catalog for failure modes in the combustion engine as follows:

No	Definition	Description
1.	Fail to start on demand	Unable to start the engine
2.	Fail to stop on demand	Unable to stop or incorrect shutdown process
3.	Spurious stop	Unexpected shutdown of engine
4.	Operation without demand	Undesired start
5.	Breakdown	Serious damage (seizure, breakout, explotion)
6.	High output	Overspeed / output above specification
7.	Low output	Output below desired specification
8.	Erratic output	Oscillating or hunting
9.	External leakage – fuel	Fuel gas or diesel leak
10.	External leakage utility medium	Lube oil, coolant, etc
11.	Internal leakage	E.g. internal cooling water leakage
12.	Vibration	Excessive vibration
13.	Noise	Excessive noise
14.	Overheating	Excessive temperature
15.	Parameter deviation	Monitored parameter exceeding tolerances
16.	Abnormal instrument reading	E.g. false alarm, faulty reading
17.	Structural deficiency	E.g. cracks in cylinder head, support
18.	Minor in-service problems	Loose items, discoloration, dirt, etc
19.	Other	Specify in command field
20.	Unknown	Inadequate / missing information

Table 1:- Failure Mode Combustion Engine (ISO-14224)

Failure Mode and Effects Analysis (FMEA) is a method used to measure and analyze the safety of a product or process. Inputs from FMEA are data plans, diagrams, probabilities, and frequencies based on its historical data, while the output is a list of the most critical risks and several targets of risk mitigation [12].

FMEA is a tool utilized for risk management that has the quality against the limits of implementing a complete security system. This technique provides a risk analysis as a comparison for one component of failure against the causes of failure that could be avoided. Risk is a measure of the combined consequences of its failure mode and the tendency of the failure occurring in the system. The results of the calculation on its greatest risk are the most important failure priorities for the planned improvement.

B. Forecasting Assessment / Artificial Neural Network (ANN)

Forecasting Assessment designed to predict the operational conditions of the engine and supporting system in between the variety of seaworthy conditions. The results of the Forecasting Assessment are the engine's diagnostic hardiness. The steps in determining Forecasting Assessment with Artificial Neural Network (ANN) are as follows:

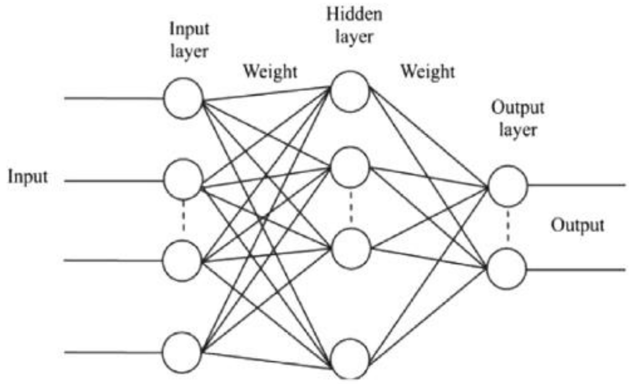

Fig. 3:- Artificial Nueral Network Structure [7]

Artificial Neural Network (ANN) is a technique or approach for information processing that is inspired by the workings of the biological nervous system, especially on human brain cells in processing information. The key element of this technique is the structure of information processing systems that are unique and varied for each application. Neural Networks consist of a large number of information processing elements (neurons) that are interconnected and work together to solve a particular problem, which is generally a matter of classification or prediction [7].

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Albeit artificial neural networks in recent times have become increasingly important in time series applications [14] [15]. Some methodological deficiencies continue to exist, such as network selection, architecture and learning algorithms. Aizenberg [14] conducted a time series analysis using multilayer neural networks to estimate oil production in the Gulf of Mexico. They conclude that the choice of instilling dimensions from time-series data is a challenging and ongoing task that requires additional research efforts. Noor [16] applied ANN modeling to marine diesel engines to predict their performance in terms of output torque, brake power, brake specific fuel consumption and exhaust gas temperature using as input data various engine speeds and loads.

III. CASE STUDY & RESULT

In this chapter, it explains the steps of analysis carried out in processing the data and the results that have been obtained to find out how the exhaust gas affects the performance of the main engine and determine the level of criticality and symptoms of failure in the main engine system on board. Furthermore, after the FMECA has done, the modeling with Forecasting Assessment is used as a monitoring framework for Condition Monitoring to assess the performance of the Main Engine system on board later on.

A. Object Research

The data that will be used for the research completion process includes data on operating vessels, on General Cargo Vessel with complete data in Table 2. As follows:

General Information of Research Object	
Year Built	: 1997
Type of Ship	: General Cargo Vessel
Flag	: Indonesia
LOA (m)	: 105
B (m)	: 16
H (m)	: 9
Gross Tonnage	: 4559
Net Tonnage	: 2873
Main Engine Spesification	
Engine maker / Type	: MAK 8M-32
Number of Cylinder	: 8
Power Output	: 3520 KW ; 4787 HP
Engine Speed	: 600 rpm
Bore	: 320 mm
Stroke	: 480 mm

Table 2:- Ship Particular Research Object

B. Failure Mode and Effect Criticality Analysis (FMECA)

In the diagnostic assessment process using the Failure Modes Effect and Criticality Analysis (FMECA) method approach, FMECA provides a systematic method to organize the study of certain systems or processes in the case of failure analysis. The FMECA method provides a bottom-up approach by looking at the ship engine failure mode or its cause database which leads to engine failure.

a) Determining Severity Level or Example Consequance

This stage is related to how serious the effects caused by damage (failure mode) in general. In the 2016 edition of ABS Guidance notes on Reliability-Centered Maintenance Techniques, the severity is classified based on the loss of containment, safety, and operational. Each failure mode will be evaluated on the three severity levels. The severity taken for the risk establishment is the worst severity of the three. The table of severity can be seen in Table 3. - Table 5.

Severity Level	***Description for Severity Level***	***Definition for Severity Level***
1	*Minor, Negligible*	*Little or no response necessary*
2	*Major, Marginal, Moderate*	*Limited response of short duration*
3	*Critical, Hazardous, Significant*	*Serious/significant commitment of resources and personnel*
4	*Catastrophic, Critical*	*Complete loss of containment. Full scale response of extended duration to mitigate effects on environment*

Table 3:- Severity level based in the loss of containment

Severity Level	***Description for Severity Level***	***Definition for Severity Level***
1	*Minor, Negligible*	*Minor impact on personnel/No impact on public*
2	*Major, Marginal, Moderate*	*Professional medical treatment for personnel/No impact on public*
3	*Critical, Hazardous, Significant*	*Serious injury to personnel/Limited impact on public*
4	*Catastrophic, Critical*	*Serious injury to personnel/Limited impact on public*

Table 4:- Severity level based on safety

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Severity Level	***Description for Severity Level***	***Definition for Severity Level***
1	*Minor, Negligible*	*No damage to affected equipment or compartment, no significant operational delays*
2	*Major, Marginal, Moderate*	*Affected equipment is damaged, operational delays*
3	*Critical, Hazardous, Significant*	*An occurrence adversely affecting the vessel's eaworthiness or fitness for service or route*
4	*Catastrophic, Critical*	*Loss of vessel or result in total constructive loss*

Table 5:- Severity level based on its operational

b) Assessment on the Frequency of Damage (*Current Likelihood*)

At this stage, the frequency analysis of each damage is carried out individually. The following are the damage frequency categories as in Table 6.

Likelihood level	***Likelihood Descriptor***	***Description***
1	*Improbable*	*Fewer than 0.001 events/year*
2	*Remote*	*0.001 to 0.01 events/year*
3	*Occasional*	*0.01 to 0.1 events/year*
4	*Probable*	*0.1 to 1 events/year*
5	*Frequent*	*1 or more events/year*

Table 6:- Frequency of occurring damages (Current Likelihood)

c) Risk Matrix Example Format

The Risk Assessment Matrix is a tool used to assess each risk to determine whether actions needed to be taken against a particular risk.

An example of a Risk Matrix used in assessing risk levels according to ABS Guidance notes on Reliability Centered Maintenance can be seen in Table 7

Saverity Level	***Likelihood of Failure***				
	Improbable	***Remote***	***Occasional***	***Probable***	***Frequent***
4	*Medium*	*Medium*	*High*	*High*	*High*
3	*Low*	*Medium*	*Medium*	*High*	*High*
2	*Low*	*Low*	*Medium*	*Medium*	*High*
1	*Low*	*Low*	*Low*	*Medium*	*Medium*

Table 7:- Frequency of occurring damages (Current Likelihood)

Failure Rate (per year) = Value is obtained from the Offshore Reliability Data Handbook (OREDA)

1. The next step will determine the Probability of Failure (PoF)
2. The next step will determine the Consequance of Failure (CoF)
- Loss of Containment (C)
- Safety (S)
- Operational (O)
3. It will later be concluded with the Final Qonsequence (FC) to asses the variety of its criticality group.

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FMECA - MAIN ENGINE Failure Modes, Effects and Criticality Analysis	Project	: FMECA - Main Engine
	Created by	: Donny Endra Prastya
	Department	: Marine Engineering

EEQUIPMENT		FUNCTION		FUNCTIONAL FAILURE (Loss of function)		FAILURE MODE (Cause of failure)	FAILURE EFFECT (What happens when it fails)	Failure Rate (per year)	PoF	CoF C	CoF S	CoF O	CoF FC	RISK
CE-ME-001 Main Engines - MAK, 8M32, 2 Cycle	1	CE-ME-001 as Main Propulsion	A	The main engine does not able to function as main propulsion (total failure)	1	Main engine fail to operate due to breakdown	The breakdown that occurs in the main engine causes the engine to be unable to operate / engine stop	1.6051824	5	1	1	3	3	High
					2	Main engine fail to start on demand	The main engine fail to start on demand causes the engine to be unable to operate / engine stop	35.473182	5	1	1	2	2	High
			B	The main engine does not able to function as main propulsion according to its specification (partial failure)	1	The main engine is not performing well due to external leakage	engine perform less	5.6641284	5	2	1	2	2	High
					2	The main engine is not performing well due to low output	engine perform less, power less	0.3694968	4	1	1	2	2	Medium
					3	The main engine is not performing well due to high output	wasteful of fuel oil	0.7751724	4	1	1	2	2	Medium
					4	The main engine is not performing well due to overheating	It can severely damage the engine, engine can stop	0.6844188	4	1	1	3	3	High
					5	The main engine is not performing well due to parameter deviation	engine perform less	0.3694968	4	1	1	2	2	Medium
					6	The main engine is not performing well due to spurious stop	engine perform less, engine can stop	6.0835572	5	1	1	3	3	High
					7	The main engine is not performing well due to vibration	lead to failure of the propulsion system, structural failures of the primary structure and damage to shipboard equipment	0.2528136	4	1	1	2	2	Medium
					8	The main engine is not performing well due to erratic output	engine perform less	4.9429176	5	1	1	2	2	High

Table 8:- FMECA – Main Engine

FMECA - LO SYSTEM Failure Modes, Effects and Criticality Analysis	Project	: FMECA - LO SYSTEM
	Created by	: Donny Endra Prastya
	Department	: Marine Engineering

EEQUIPMENT		FUNCTION		FUNCTIONAL FAILURE (Loss of function)		FAILURE MODE (Cause of failure)	FAILURE EFFECT (What happens when it fails)	Failure Rate (per year)	PoF	CoF C	CoF S	CoF O	CoF FC	RISK
LO-PUMP-003 No 2 Lub Oil Pump	1	To transfer Lub.oil from LO sump tank to LO cooler and main engine	A	The pump does not able to transfer Lub.oil from LO sump tank to LO cooler and main engine (total failure)	1	The pump fail to operate due to breakdown	There is no flow to LO cooler and main engine	0.8027664	4	3	1	1	3	High
					2	The pump fail to start on demand	There is no flow to LO cooler and main engine	0.267618	4	3	1	1	3	High
			B	The pump does not able to transfer Lub.oil from LO sump tank to LO cooler and main engine according to its specification (partial failure)	1	The pump fail due to low output	The pump perform less	0.5351484	4	2	1	1	2	Medium
					2	The pump fail due to parameter deviation	The pump perform less	0.267618	4	2	1	1	2	Medium
					3	The pump fail due to sporious stop	The pump perform less	0.8027664	4	2	1	1	2	Medium
					4	The pump fail due to structural deficiency	The pump perform less, It can severely damage the pump	1.0703844	5	2	1	1	2	High
					5	The pump fail due to external leakage	The pump perform less, lub.oil contain contaminant	0.267618	4	2	1	1	2	Medium
					6	The pump fail due to vibration	The pump perform less	0.267618	4	2	1	1	2	Medium

Table 9:- FMECA – Lubricating Oil System (LO System)

It can be seen in Table 8. One of the failure modes that have the highest risk value is overheating, which is very influential on the performance of the main engine. In addition, from the results of the P&I Club (Protection and Indemnity Insurance) investigation, other causes were attained such as maintenance errors, inspection and handling of lubricating oil (21%). The causes of ship accident cases (engine damage) 2009-2014 is in line with the results of the FMECA on the Lubricating Oil System, where there are numerous equipment and failure modes that have a high critical level, one of which can be seen in Table 9. Lube Oil Pump which has the functions to transfer lube oil from the tank to the lube oil cooler and also to the main engine.

There are two possible functional failure events, where the first is on how the pump cannot transfer lube oil from the settling tank to the lube oil cooler, leading to the failure mode of the pump to break down due to failure whereas the pump fails to meet the needs on-demand. This is deemed to be very high risk because it does not flow to the lube oil cooler and also the main engine that it affects the high exhaust gas temperature on the main engine.

C. Forecasting Assessment

Artificial neural networks are mathematical or computational models that are inspired by the functional structure of biological neural networks. In most cases, an artificial neural network is an adaptive system that changes its structure based on external and internal information that flows through the network during its learning phase [17].

In training with the supervision and learning phase, there are a number of pairs (input-output targets) used to train the network. On each training, the input is given to the network. The network will process and create its output. The difference between the network output with the target (the desired output) is an error that occurred. The network will modify the weight according to the error. One example of supervision model is Multilayer Perceptron (MLP) [18].

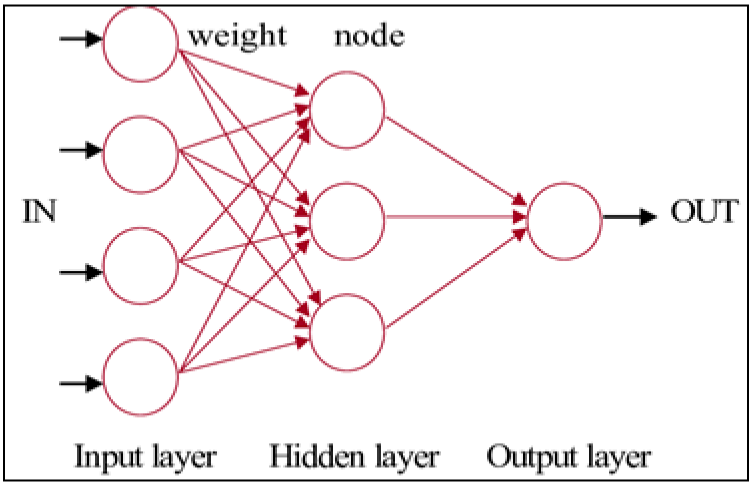

Fig. 4:- Multilayer Preception Structure [17]

This algorithm is based on a simple relationship, i.e. if the output gives an incorrect result then the weight balancer is corrected so that the error can be minimized and the subsequent network response is expected to be closer to the target. Multilayer Perceptron (MLP) is also capable of improving the weighing on hidden layers.

Multilayer Perceptron Analysis (MLP) with time-series forecasting in this study is using ANACONDA software in the form of Python programming language. The results of forecasting are the target data from MLP. Table 10. shows the data design table on the MLP work-frame.

The following are the steps for forecasting the condition monitoring data.

1. Data collection henceforth is used as the basis for forecasting.
2. Creating the data set
3. Building the model
4. Predicting the result

Pattern number-	**Data input (x_1,x_2)**		**Target**
	X_1	**X_2**	
1	Data -1	Data -2	Data -3
2	Data -2	Data -3	Data -4
.	.	.	.
.	.	.	.
dst	Data n-2	Data n-1	Data ke-n

Table 10:- Planned data

Generall, this algorithm can be described as mentioned when the network is given an input pattern as a training pattern. Thus, the pattern goes to the units in the hidden layer to be passed on to the output layer units. Afterward, the output layer units give a response called the network output.

D. Case – 1 : Forecasting Assessment Exhaust Gas Temperature (Retrieval of Monthly)

Case 1 is forecasting assessment which is taken from monthly data per year. Data for each month is derived from the exhaust gas temperature monitoring from February 2016 to October 2019 can be seen in the example of Table 11.

Data Retrieval Schedule	Cylinder number							
	I	II	III	IV	V	VI	VII	VIII
EGT 2016 (Feb) :	395	395	395	395	390	395	390	380
EGT 2016 (Mar) :	380	390	380	390	380	385	390	385
EGT 2016 (Apr) :	390	385	390	395	375	390	390	385
EGT 2016 (May) :	405	390	400	390	380	400	395	395
EGT 2016 (Jun) :	390	380	395	385	395	405	400	395
EGT 2016 (Jul) :	390	395	400	395	395	400	400	400
EGT 2016 (Aug) :	400	395	390	395	400	395	390	390
EGT 2016 (Sep) :	395	390	380	385	390	390	395	395
EGT 2016 (Oct) :	395	395	395	395	400	400	400	395
EGT 2016 (Nov) :	399	395	391	389	394	392	396	390
EGT 2016 (Dec) :	400	405	400	400	400	395	400	400

Table 11:- Example on Exhaust Gas Data Temperature in 2016

Data obtained from each cylinder per month are later be performed through time-series forecasting using ANACONDA software with the Python programming language. The results of the forecasting data show the predictions for the next 12 months that can be seen in Table 12.

The maximum exhaust gas temperature is used as a limitation on engine operation related to the strength or material resistance of the engine, if there are tendencies to be in a high exhaust gas temperature continuously, there are several causes that can be predicted. The process of incomplete combustion and imperfect combustion are interrelated in Figure 5.

Data Retrieval Schedule	Cylinder number							
	I	II	III	IV	V	VI	VII	VIII
Predict (Month + 1)	367.414	374.311	373.860	362.324	362.247	361.763	366.974	369.357
Predict (Month + 2)	366.652	375.933	374.625	361.437	366.808	366.349	368.537	375.871
Predict (Month + 3)	365.325	377.815	374.340	362.077	369.504	366.987	375.421	374.339
Predict (Month + 4)	367.691	382.099	373.784	360.781	370.177	367.784	374.129	380.187
Predict (Month + 5)	371.689	385.773	374.381	363.278	368.894	373.593	374.291	382.552
Predict (Month + 6)	372.602	389.882	375.803	361.420	369.230	377.626	378.929	384.263
Predict (Month + 7)	372.291	393.346	377.039	361.723	370.751	379.218	378.831	386.917
Predict (Month + 8)	373.988	396.319	377.741	361.032	370.290	376.721	378.580	389.376
Predict (Month + 9)	374.225	399.326	379.426	362.214	372.566	377.063	381.505	393.491
Predict (Month + 10)	374.399	402.658	380.107	362.216	373.831	380.266	383.696	395.379
Predict (Month + 11)	376.691	406.547	382.917	363.497	373.360	384.303	384.252	398.998
Predict (Month + 12)	378.370	410.352	383.204	362.886	375.035	386.359	386.119	400.649

Table 12:- Forecasting on the Exhaust Gas Temperature 12 months and forth

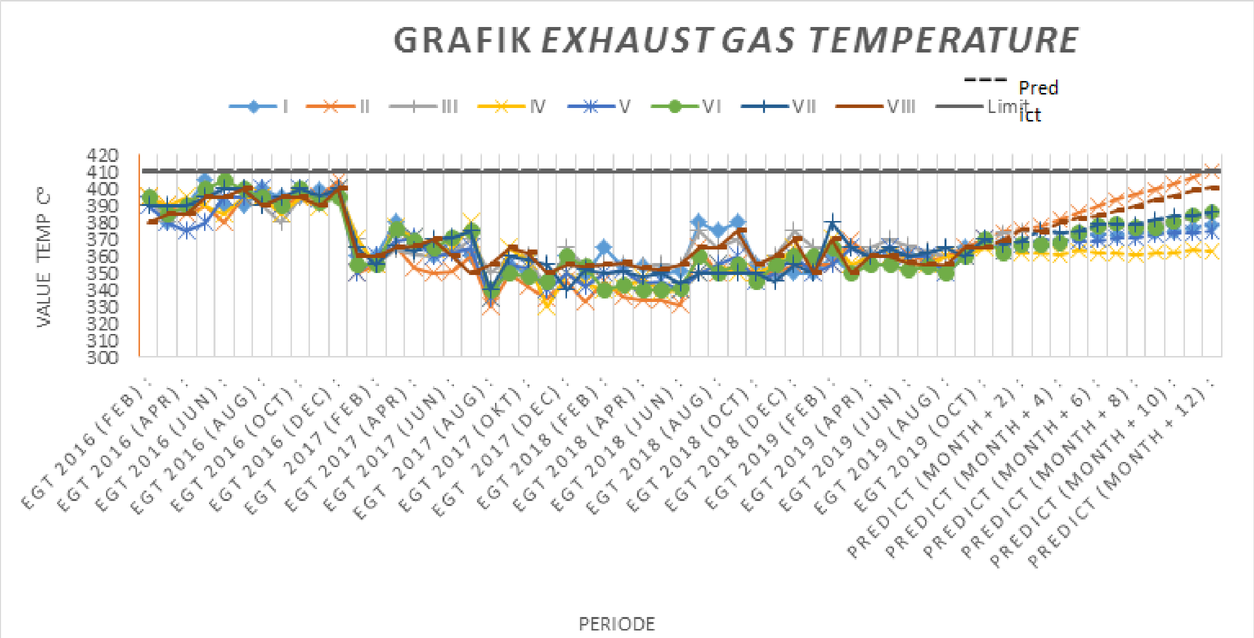

Fig. 5:- Time Series data on Exhaust Gas Temperature in 2016-2019 with its forecasting in 2020

Based on Table 12. and Figure 5., it can be seen that the trending of 2016 exhaust gas temperature in the engine of the first research object has a high enough value, where on average, each cylinder touches a temperature of 390-400°C if compared to the trending in 2017 and the trend in 2018 compared to the prior year of 2017 has a decline in an average temperature of 360°C. This occurred in 2017 due to the history of an overhaul in the piston, hence the exhaust gas temperature is relatively lower if compared to 2016. Meanwhile, the temperature tends to be constant up to July, where it has increased and has the tendencies to continue rising until October 2019. After forecasting, it can be seen that cylinder 2 in the 12th month of 2020 has advanced the specified limit of 410°C. The escalation in the exhaust gas temperature is an indicator that the main engine needs to be inspected for its cylinder or piston. In 2020, the ship is planned to be directed into an annual survey.

The prediction or forecasting of condition monitoring data every month for the next 45 months can be used to predict the performance of the main engine by the crew or owner of the ship for at least the next year. This will help the crew or owner to plan maintenance actions before the assets are damaged.

Recommendations given are as follows:

1. Preparation for maintenance (survey or overhaul) of the machine in reference of the previous measurement history according to the Class.
2. The class does not provide recommendations for replacement of spare parts, but only provides tolerance limits for measurement results, whereas it has exceeded the tolerance limits of spare parts, it must be replaced.
3. Not later than at least 1 month before the survey schedule (annual, intermediate, special survey) or according to company policy. This is because purchasing time is required to prepare the items needed during overhaul so that it does not increase the ship's down time.
4. Some spare parts to prepare for overhaul.

No	Range of spare part	No	Range of spare part
1	Main bearings	8	Piston, trunk oiston type
2	Connecting rod bearing	9	Piston rings
3	Cylinder liner	10	Piston Cooling
4	Cylinder cover	11	Cylinder lubricator
5	Valves	12	Fuel injections pump
6	Hydraulic valve drive	13	Gaskets and packings
7	Piston, Crosshead type	14	Exhaust gas system

Table 13:- Spare parts for overhaul

E. Case – 2 : Forecasting Assessment Exhaust Gas Temperature (Comparison of Actual and Forecasting Data)

On the ships, it is important to check the performance of the main engine from time to time to ensure the condition of the engine is working in good condition or not as shown in Table 14.

Cylinder 1	**On Board**	**365.00**	**370.00**	**370.00**	**375.00**	**380.00**
	ANN Prediction	358.85	362.55	364.99	367.82	373.82
	Error	1.68%	2.01%	1.35%	1.91%	1.63%
Cylinder 2	On Board	360.00	365.00	375.00	370.00	370.00
	ANN Prediction	362.44	358.37	360.85	364.32	361.30
	Error	0.68%	1.82%	3.77%	1.53%	2.35%
Cylinder 3	On Board	360.00	360.00	380.00	370.00	365.00
	ANN Prediction	368.93	373.26	364.82	367.21	364.04
	Error	2.48%	3.68%	3.99%	0.75%	0.26%
Cylinder 4	On Board	355.00	365.00	355.00	355.00	360.00
	ANN Prediction	356.42	349.25	354.32	355.61	356.17
	Error	0.40%	4.31%	0.19%	0.17%	1.06%
Cylinder 5	On Board	360.00	365.00	365.00	360.00	370.00
	ANN Prediction	364.50	362.73	362.73	361.32	360.87
	Error	1.25%	0.62%	0.62%	0.37%	2.47%
Cylinder 6	On Board	360.00	360.00	360.00	350.00	365.00
	ANN Prediction	360.40	363.40	364.77	362.75	369.89
	Error	0.11%	0.94%	1.33%	3.64%	1.34%
Cylinder 7	On Board	370.00	375.00	370.00	365.00	375.00
	ANN Prediction	370.98	370.46	367.40	370.63	373.19
	Error	0.26%	1.21%	0.70%	1.54%	0.48%
Cylinder 8	On Board	375.00	375.00	370.00	375.00	370.00
	ANN Prediction	365.109	370.893	369.646	371.045	369.901
	Error	2.64%	1.10%	0.10%	1.05%	0.03%

Table 14:- Comparison of on board values with MLP – ANN Predictions for the Exhaust Gas Temperature for all cylinder

Based on the data above, the comparison of actual data on General Cargo Vessel with MLP - ANN Prediction for Exhaust Gas Temperature on each Cylinder does not occur significantly. In contrast, the forecasting value approaches the actual value and the error value according to [7] not more than 5% where it can be said to be valid enough.

IV. DISCUSSION & CONCLUSIONS

From the results of data processing and analysis related to the problem formulation and objectives in this study, the following conclusions can be drawn:

1. Based on the results of FMECA (Failure Modes Effect and Criticality Analysis). The FMECA method provides a bottom-up approach by looking at the failure mode or causal database of the main ship's engine. There are 23 equipment and 99 failure modes in the Lubricating Oil System. From the overall failure mode, the critical level distribution has a low-risk level (24%), medium risk (64%), and high risk (12%). One that indicates the engine has failed can be seen from the increase of Exhaust Gas Temperature.
2. Based on the results of Forecasting Assessment using ANN (Artificial Neural Network) modeling assisted by Python programming language, it can be used as a comprehensive tool in predicting exhaust gas temperatures where a maximum error value of 4.31% is obtained for forecasting the next 12 months.
3. Based on the combination of the results from the FMECA and Forecasting Assessment, it indicates that the main engine performance conditions are currently in good condition.

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