A SEMI AUTOMATED MODEL FOR IMPROVING VESSEL SYSTEM RELIBAILITY AND MAINETANANCE MANAGEMENT

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DESCRIPTION

A platform for a predictive machinery condition monitoring approach based on machinery health and component criticality is proposed. The methodology is based the following
Phase 1: Onboard data collection for machinery health log, maintenance, repair and overhaul records.
Phase 2: Data pre-processing and labelling
Phase 3: Diagnostics fault classification.
Phase 4: Suggestion for improvement on data and maintenance management

MOTIVATION

The research was performed to identify:

1. Fault labelling and Classification
2. Suggest ways to improve machinery condition monitoring through data management.

MAIN RESULTS

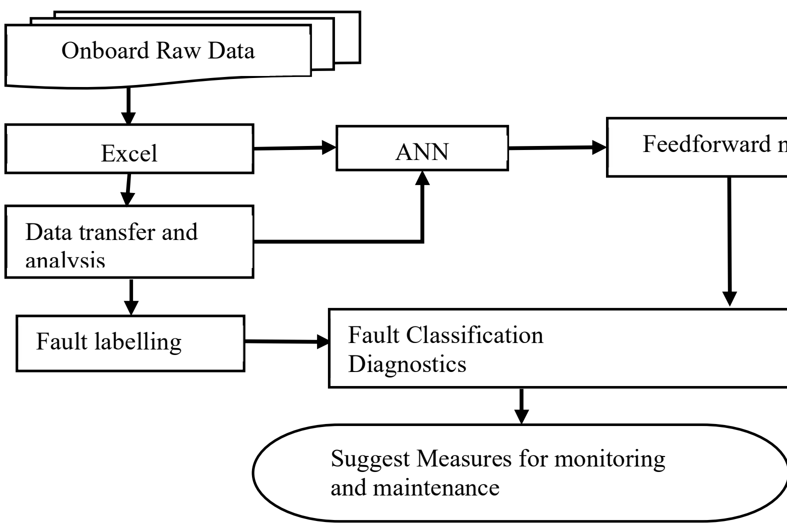

Figure 3: Research methodology

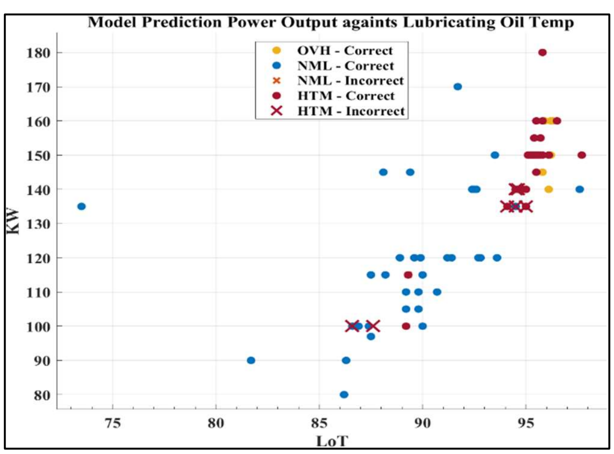

Figure 6: Fault Class

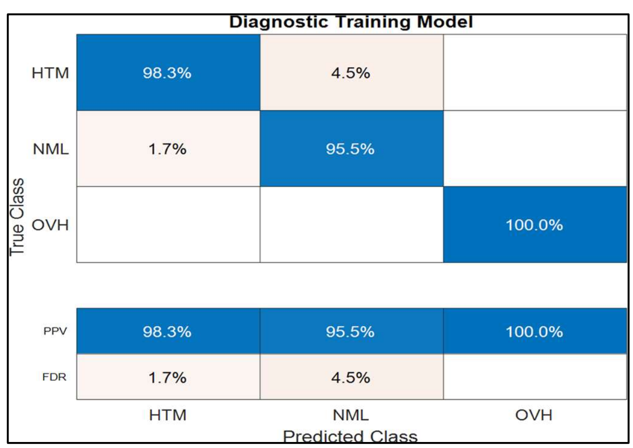

Figure 7: Model Evaluation

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A SEMI AUTOMATED MODEL FOR IMPROVING NAVAL VESSEL SYSTEM RELIABILITY AND MAINTENANCE DATA MANAGEMENT

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ABSTRACT

The demanding nature of Naval operational requirements leads to rapid deterioration and decline in the reliability of ships systems and machineries. In most Navies ships built with design life of 25-30 years begin to significantly decline in performance around 7-8 years after joining service. Consequently, these leads to frequent and often prolonged downtime and huge maintenance cost. The Nigerian Navy like other navies is equally faced with this situation in a challenging manner due to the introduction of new platforms and to non-standardised data management. Therefore, a data management approach that is focused on the use of maintenance, repair, and overhaul (MRO) data is proposed. The proposed approach will build on the existing data collection and management practiced in the Nigerian Navy while identifying alternatives for both onboard and fleet level maintenance data collection and management. In this regard a platform for a predictive machinery condition monitoring approach based on failure mode and component criticality is proposed. In this research a methodology for data collection and fault labelling is presented. Diagnostic analysis using Feedforward Artificial Neural Network classification model was used for fault classification.

Keywords: Mission Critical, Bayesian Belief Network, Failure Mode Effect and Criticality Analysis, Artificial Neural Network, Prediction Data Collection, Fleet.

1. Introduction

Maintenance data management plays a vital role in ensuring any asset fulfils its intended use over the expected life span of the asset or a system of that asset[1, 2]. The need for improvements in data collections arise from the technological advancement in machinery and system configuration. This is further strengthen by the rapid evolution witnessed in maintenance strategy over the last 4 decades with shifting interest towards predictive condition monitoring [2-4]. Therefore, this gave rise to data collection activities aided by improvements in sensor technologies enabling, improve system reliability, risk reduction and reduced environmental impacts. Accordingly, these advances in machinery health monitoring capabilities have revolutionise maintenance approach especially in those organisations that are able to embrace and adopt sensor technology to improve system diagnostics. Improvement of sensors technology has given rise to the installation of expert's systems on machineries and system which help with collection, display and diagnostics of the machinery or system health status in real-time[5]. The harnessed data is utilised in data management systems by organisations with large asset holding or asset management companies in Computerised Maintenance Management Systems (CMMS) or similar platforms for the management of maintenance and spare parts.

The motivation for the adaption of advanced condition monitoring system allows for remote monitoring and online transmission of data which is primarily enabled by the internet and commonly referred to as Internet of Things (IoT). These technologies are mainly deployed to ease constraints related to location of machinery, criticality of component, operation environment and remoteness of location. Other factors include operation safety factors, unmanned operations, and Original Equipment Manufacturers (OEM) or customer demands. Nonetheless there still remains the challenge with data format, collection and transmission, security, and integration of system platform[6].

In this regard this paper presents a semi-automated model for ship machinery data collection and transmission. Accordingly, the paper is presented in 5 sections; sections 1 is the introduction, section 2 is literature review on maintenance data management and section 3 will be the methodology. Section will present Results and Discussion while the conclusion and future work will be in section 5.

2. Critical Review on Maintenance Data Management

The essence of maintenance data management is to make sense of the information available in a set of data collected from single or multiple machinery. Therefore [6] defines data as any reinterpretable representation of information in a formalised manner suitable for communication. While ship data as described in [7] is a measurement value from shipboard machine and equipment to which at time stamp is added. It therefore follows the collection of data for maintenance purpose must meet certain standards in order to qualify as source of information that can be used for further analysis. Maintenance engineers have for long depended on machinery data as main source of information for understanding the present and future health condition of the machinery. Moreover, the evolution of maintenance towards predictive condition-based maintenance and condition monitoring has seen the application of several other technologies such as sensors capable of individual component condition monitoring, online real time monitoring, thermography etc.These developments enabled the implementation of supervisory control and data acquisition (SCADA) hence expanding the possibility of remote control and monitoring of systems [8]. SCADA relies largely on sensor data analytics to provide insight on machinery health within the offshore wind energy and in some unmanned maritime vehicle[9, 10]. A broad methodology utilising various sensor data and technologies has been presented in the INCASS project which provides research data base and methodology for both ship machinery and structure and structure risk analysis enabled by the combination of sensor data, data analysis tools for machinery health and reliability[2, 11].

2.1 Condition Monitoring on Ships

Condition Monitoring as a maintenance strategy relies much for its success on data management by the crew onboard a ship, this is more so as advance diagnostics analysis depend on actual sensor data for analysis and data collection approach [12]. The collection of data for ship maintenance purpose can be categorised into structural and machinery data, structural maintenance planning is mainly based on inspection data and non-destructive teste procedure including accident reports or ship company observation of issues such as corrosion. On the other hand, Machinery health data covers all data to do with deck machineries, auxiliaries, and propulsion engines; such as failure report, repair data and maintenance data. These, can be further categorised into maintenance repair and overhaul data and machinery health monitoring data as shown in figure 1. In this regard a ship structural and machinery monitoring and maintenance was presented based on the outcome of a measurement campaign as part of Inspection Capabilities for Enhanced Ship Safety (INCASS) case study conducted on board container ships and provides a customised methodology for monitoring important machinery systems [13, 14]. The paper explores how data analytics can be used to help in predicting the future condition of a vessel's assets; to enable operators to monitor vessels in real-time, record and analyse their histories and search for anomalies. According to the author the weakness of Knowledge based diagnostic approach is in its reliance on expertise and detailed knowledge of possible failures and how to detect them. On the other hand, the data-driven approach does not require deep knowledge of how a fault occurs and develops, but instead relies on training a computer model using historical data [15]. When the model finds an anomaly in behaviour, the equipment expert can then be notified to investigate the problem. A further issue raised by the paper is the risk of online diagnostic for naval ships due to intrusion on maintenance data and location privacy[16]. This are serious concerns for Naval ships which the author suggested a periodic monitoring data transmission or provision of bespoke maintenance system. Currently some of these technologies are being tested on board both naval and merchant ships, equipment being monitored includes gas turbines, diesel generators and reduction gears. Others are diesel engines, power and propulsion systems and drive train.

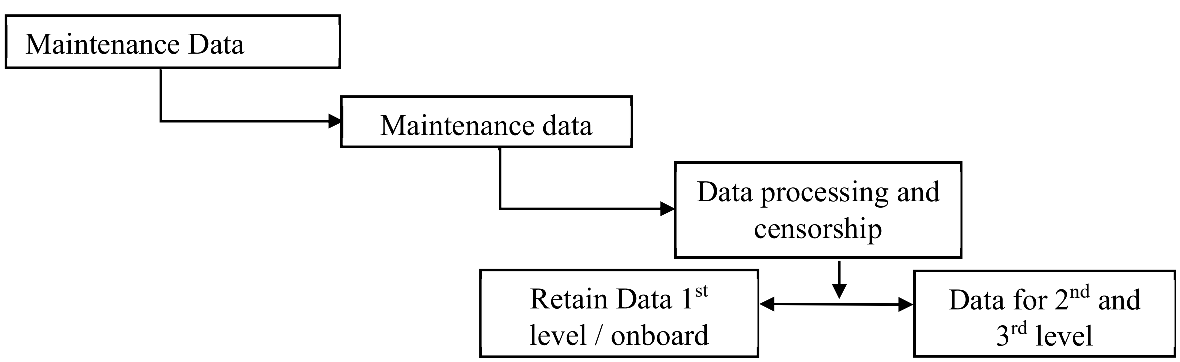

Figure - 1 Onboard Maintenance Data Management structure

2.2 Artificial Neural Networks

In general, there 2 types of machine learning namely supervised and unsupervised learning. The supervised machine learning is used to train a model with labelled data, that is the features to be looked out are already known, therefore the algorithm is trained to look out for those features in the input data. On the other hand, unsupervised learning deals with unlabelled data which means the algorithm will identify the unique features in the data and partition it accordingly. Unsupervised learning is useful for exploring data in order to understand the natural patten of the data especially when there is no specific information about significant incidents in the data that can easily point to some fault indicators. Artificial neural network ((ANN) is a machine learning algorithm that can be used to enable diagnostics or pattern recognition in a data set . ANNs are described as networks composed of nonlinear computational elements that work in parallel and arranged in a manner similar to biological neural interaction[17]. The main parameter that determines an ANN model is the number of layer hidden layers between the input and the output neurons and the hidden layer sizes [4]. ANN are attractive for diagnostics or classification models as they can learn from past examples of the provided data and can easily identify subtle features with no prior knowledge.

Accordingly, ANN are widely employed for multiple tasks such as clustering, forecasting, prediction, pattern recognition, classification, and feature engineering[18]. The use of ANN and Regression technics was employed to estimated vessel power and fuel consumption where the model was able predict to predict actual vessel fuel consumption in real time [19]. The use of ANN for fault classification has been employed by [12]using self-organising map an ANN clustering algorithm analyses the health parameter of a marine diesel engine looking at exhaust gas temperature, piston cooling outlet temperature and piston cooling inlet pressure. Therefore, the performance of ANN in prediction and classification as reviewed in [20, 21] was presented to be good in handling nonlinear high dimensional data having fewer data set. In this regard building the success of ANN this work will apply the use of ANN on a labelled data for diagnostic analysis on a marine diesel generator.

2.2 Sources of Maintenance data

The challenges with information management on board and shore maintenance base has been highlighted in the paper. As the authors identified the issue is not on getting data but harmonising the relevant raw data for maintenance plaining among the relevant stake holders. While the authors have recommended further research on the influence of knowledge source upon information exploitation, another area relevance could be streamlining of multiple information sources from onboard to shore maintenance bases in order to provide adequate but quality data [22]. A classical work for onboard data collection was presented in INCASS MRA tool [23] and provides data source for ships maintenance as well as tools relevant to system reliability analysis[4]. Cheliotis,[24] presented data driven multiple regression algorithms for predicting fuel consumption of a ship main propulsion engine based on two different shipboard data acquisition strategies. The strategies were noon-reports and Automated Data Logging & Monitoring (ADLM) systems in which the paper highlighted the relevance of the ADLM over the noon-reports due to its increased frequency of data logging and reduced error. Overall sensors located at important point around machinery and other critical components provide the primary data needed for maintenance data and machinery health management[21]. On the other hand, shipboard operators provide additional details as regards failures and unscheduled maintenance, though this repots can as well be provide via ADLM systems that can identify certain failures. However as highlighted in automated monitoring system have some limitations in failure data reporting and monitoring. This is more relevant when the role of auxiliary systems is being considered especially those not integral to the main machineries.

In this regard, [13] discussed a system of predicting machinery health monitoring using ANN and FTA for reliability analysis, the methodology has successfully identified and defined measurement for machinery data through step-by-step demonstration of the process and identification of critical component using FTA. Moreover, ISO 19847 and ISO19845 provides standard guidelines and definition for onboard ship data collection, storage, management, and transmission via the internet. Nonetheless there already exist commonly understood formats for managing and collecting data onboard ships that are generated via various sources on board, as shown in table 2. Although, there may be nomenclature difference for instance between merchant and naval ships, but the records may still be referring to the same objective. It is a standard requirement for merchant ships to historical records of ship repair and maintenance being managed by Classification society who also provide additional standards and guidelines for data collection and management [15, 25]. The aforementioned is not the same for naval ships nonetheless similar procedures and guidelines are followed for collecting data as provided in [6, 11]. Therefore, in addition to maintaining hard copy records of machinery failure and repair reports within the ship technical department. A navy ship also maintains the ship bridge log, officer of the watch (OOW) incident report book and ship operational state among other records report. These documents provide vital information on the location, speed, time, engine speed, generator(s) online, as well as other system operational within a given time. The records provide hourly updates of operational state and consumption rates of important machinery. Typically, a machinery health consists of time series data points of some important parameters, such as temperature, pressure, vibration, consumption rates, outputs, speed, load, deflections, and clearances.

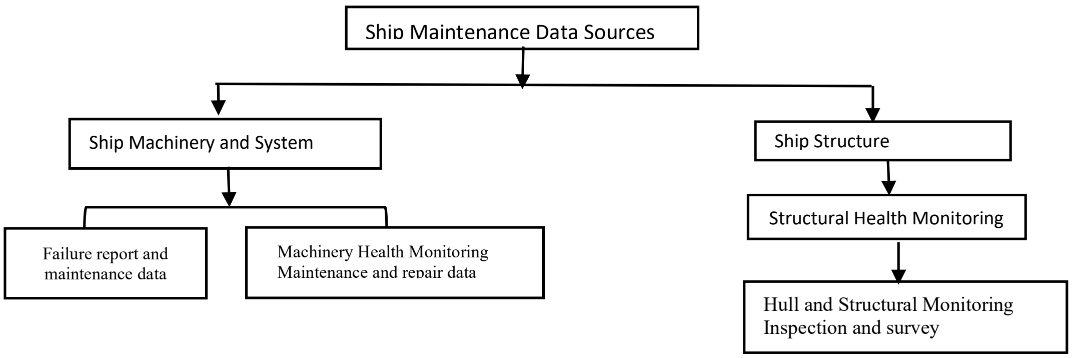

Figure 2: Maintenance data sources

3 Methodology

The research presented a methodology for enhancing data collection onboard ships and provides a system that ship operators can utilised to build an in-house data collection platform. The approach is based on collecting and transforming data from onboard ships with no formal electronic data collection system, however, maintains a robust structured data records. Overall, this work is a part of research endeavour to build a Platform for Ship Machinery Preventive Condition Monitoring based on system data and reliability analysis. The first step is the data collection campaign onboard an Offshore Patrol Vessel (OPV). Data obtained included maintenance and repairs data as well as raw machinery log data. Thereafter the data was transformed to the appropriate format using excel, figure 3 is a representation of the methodology approach in this paper.

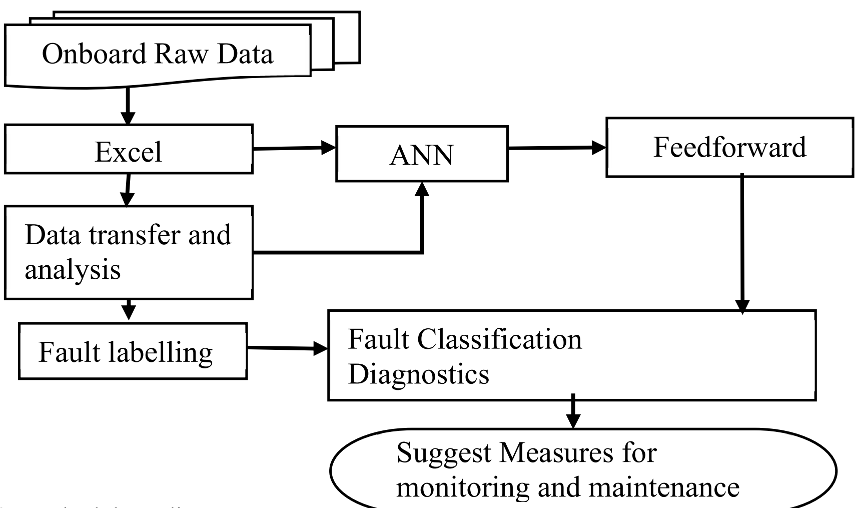

Figure 3: Methodology diagram

3.1 Data Transfer and analysis

The machinery log data collected was an unlabelled time series hourly log data for fresh and raw cooling water temperatures and pressure, exhaust gas temperature, lubricating oil temperature and pressure, power output and running hours, table 1 is sample of the data ranges collected. In addition to the timeseries data, a maintenance, failure and repair (MFR) record of individual machinery was collected. The timeseries data was in manuscript form while the text data for the MFR data was in word format. The MFR provides details on time of failure and cause of failure, while the timeseries data only gives the values of parameter at the respective time. Therefore, there was no indication of failure or the operational condition of respective machinery at any giving time except for start and stop periods.

Table 1:Diesel generators health parameter range

DG health parameter	Normal range	Abnormal range		Alarm
		Operator	OEM	
Freshwater Temperature A/ B-Bank	76-82	85 C	90 C	90-92 C
Exhaust gas Temperatures A/B-Bank	250-520	480 C	500 C	520 C
Lub Oil Temperature	40-95	90	110	113
Lub oil Pressure	0.45-0.6	0.8	0.1	0.12
Engine power output (kilowatt)	100-350KW	240KW	400KW	440KW

Consequently, first task after transcription to excel format data was to carry out pre-processing data by removing nonnumeric (NAN) values, and initial outlier removal by using interquartile range based on the operational data ranges as provided by the Original Equipment Manufacturer (OEM) and the Operator. The process was used to set the lowest values, normal values and highest values. Therefore, mean value of each variable was derived using arithmetic in equation 1, which can also be gotten as the average value using Q3 – Q1= Q2 of the data values. Next was getting the, Q2 which is taken as the interquartile range, while Q3 represent 75% of the sample and Q1 represent 25 percent of the data, the quantiles can be computed by using equation 2-3. Therefore, after obtaining the quartiles a value of 15% was added to the upper limits to account for the disparity between the OEM and operator's limits. Therefore, this helped improved the validity of the data by eliminating the relatively very low operating parameter values to become more acceptable . The 15% was the upper limit accepted by the operator as an indication of fault while any value 25% more than limit is a sign of failure.

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

$$Q_1 = \frac{N}{4} \tag{2}$$

$$Q_2 = \frac{N}{2} \tag{3}$$

$$Q_3 = 3\left(\frac{N}{4}\right) \tag{4}$$

3.2 Data Labelling

Following the above analysis, the data was labelled to identify the faults and operating condition for machine learning purpose. Therefore, considering that there was no actual indication of faulty data from the operators' log, the research relied on expert knowledge and operators' recommendation on data alarm limits to form the bases of fault identification, also provides the lower and upper acceptable operating limits for the diesel generator. The fault class label for the diagnostic analysis was derived based on the labels as well as additional information from the failure data. The failure data was used to compare start- stops times and corresponding incident reports, which sometimes gives some valuable information regarding log readings. In this regard, a nested IF – ELSE analysis was conducted to get the fault class and operating temperature condition, the process is illustrated in figure 4.

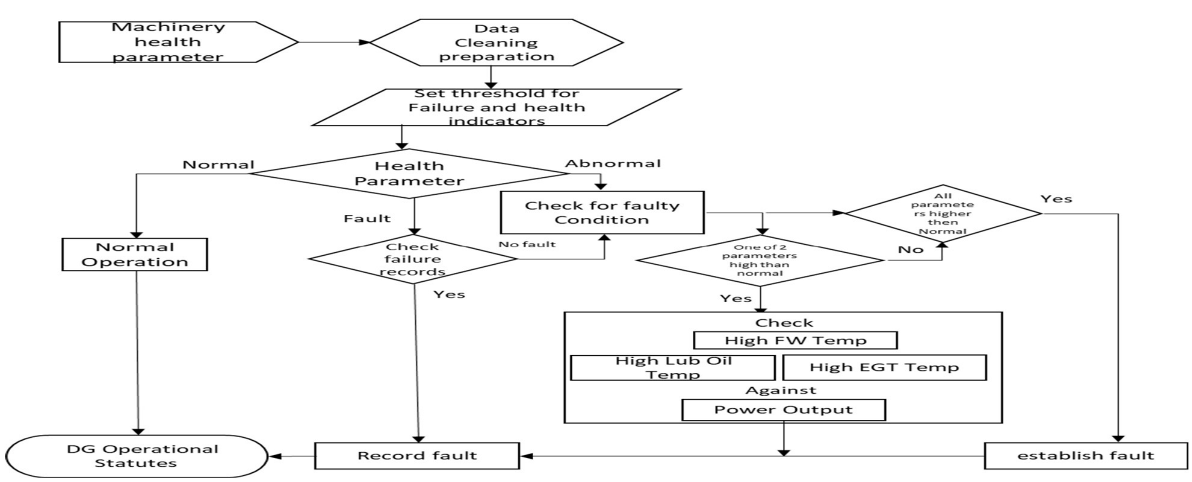

Figure 4: Fault labelling

3.3 ANN Diagnostics

Diagnostics analysis involves recognising patterns in the data that indicates the presence of variations pointing to a change in the normal health parameters of the system or machinery of interest. A supervised ANN feedforward neural network was implemented for the classification analysis. Feedforward ANN is a time series algorithm that can be used for both function fitting and pattern recognition[26]. The Feedforward networks usually have single or multilayer hidden sigmoid neurons followed by a series of output neurons. Multiple layers of neurons with nonlinear transfer functions enable the network to learn nonlinear relationships between input and output vectors[27].

A two-layer feedforward network with sigmoid activation and SoftMax output neurons were adopted for the study based on equation 5. The sigmoid activation function, equation 6, helps to improve the prediction capability of the neurons by adding bias and non-linearity while the SoftMax activation function, equation 7, is a probability function with values between 0 and 1. The most likely probability being 1 and vice-versa. Both sigmoid and SoftMax are used for classification problems, and they help improve the model's capability[18].

$$y_k\,(x,w) = \sigma\left(\sum_{j=i}^{M} w_{kj}^{(2)}\, h\left(\sum_{i=1}^{D} w_{ji}^{(1)} + w_{j0}^{(1)}\right) + w_{k0}^{(2)}\right) \qquad 5$$

$$\sigma(x) = \frac{1}{1+\,e^{-x}} \qquad 6$$

$$\frac{\exp\,(a_k)}{\sum_j \exp\,(a_j)} \qquad 7$$

4 Results and Discussions

The methodology was implemented on a set of diesel generator used for power generation on board a naval patrol vessel. Hourly generator log data covering more than 2000 operating hours over a duration of about 8 calendar months was collected. The data was an unlabelled data therefore it had been cleaned and labelled, initial data cleaning was done at data transfer using excel while a further data cleaning was achieve using data analysis tools to clear more of the outliers and feel in missing values. Therefore, using the quantile analysis in excel the data limits for the diesel generators was derived as shown in table 2. The values in table 2 provides a good data that reflects the operator's data limits as presented earlier in table 1 and will further improve the model quality. A correlation analysis was conducted to gain further inside on the relation among the parameters. There were about 12 parameters collected however it was 7 of the 12 that proved useful for the study. A regression correlation (R-Value) on comparing all 7 the targets features was conducted as presented in figure 5. The R-value is measure of how well the variation of the inputs is with the target, values close to one show good fit or relationship between the features. Therefore figure 5 below it show that 5 out the 7 selected features have responds greatly to any shift in power output given kilowatt. The obtained R-values were then considered in chosen the feature for the next step of the analysis

Table 2: Derived data limits

Future	RPM	LoP	FWT - A	FWT - B	LoT	FWP	EGT- A	GET - B	Power (KW)
Minimum	1791	0.32	56	58	59	0.04	160	154	10
Q1	1798	0.39	64	71	86	0.08	303	309	100
MEDIAN	1800	0.433	65.2	73.9	87.45	0.078	329.5	321.9	120
Q3	1800	0.456	66.2	75.6	89.3	0.083	350.4	342.65	140
Maximum	1901	382	81.4	91.4	97.7	0.884	3340.3	3114	240
Q2(Mean)	1799	1.00	65.26	73	87	0.09	335	331	123
IQR	2	0.065	2	4.8	3.6	0.008	47.05	33.25	40
IQRx1.5	3	0.10	3	7.2	5.4	0.012	71	50	60
Lower limit	1795	0.30	61	64	80.3	0.063	233	260	40
Upper limit	1803	0.553	69.2	82.8	94.7	0.095	421	393	200

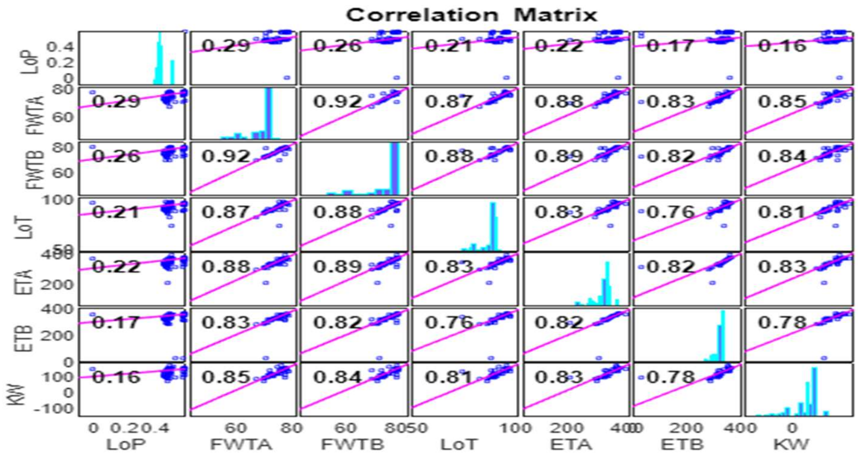

Figure 5: Regression Correlation Matrix

4.1 ANN Diagnostics

A feed forward ANN with 2 layers based on sigmoid and SoftMax activation function using the MATLAB pattern recognition app was used for the classification analysis. The collected machinery health parameters went through initial exploratory data analysis thereafter a clustering analysis which is not presented in this work due to space was conducted for feature engineering. The analysis consisted of 7 data points consisting of Power output(kw). Exhaust gas temperature (ET)A and B, Fresh Water temperature (FWT) A and B, Lubricating Oil temperature (LoT) and Lubricating Oil Pressure (LoP). The time series data of about 1000- data points was used, the data was divided in 3, 70 % percent for training, 15% testing and 15% validation. The training was concluded after about 200 epochs while testing and validation with hold out data was concluded on less than a minute. On completing the training, the model was evaluated using the Positive Predictive Values (PPV) and False Discovery Rate (FDR) approach shows that the model has performed well for the diagnostics and can be deployed or adopted for the particular set of generators. Although considering the datapoints it is believed that the model might behave slightly different with larger data set. Nonetheless in all the classes the has model has achieved more than 95 % accuracy between the true and predicted class Figure 6 shows the performance of the model in identifying the 3 classis namely High temperature(HTM), Normal (NML) and Overheating(OVH), while table 3 shows the data range for the respective classes.

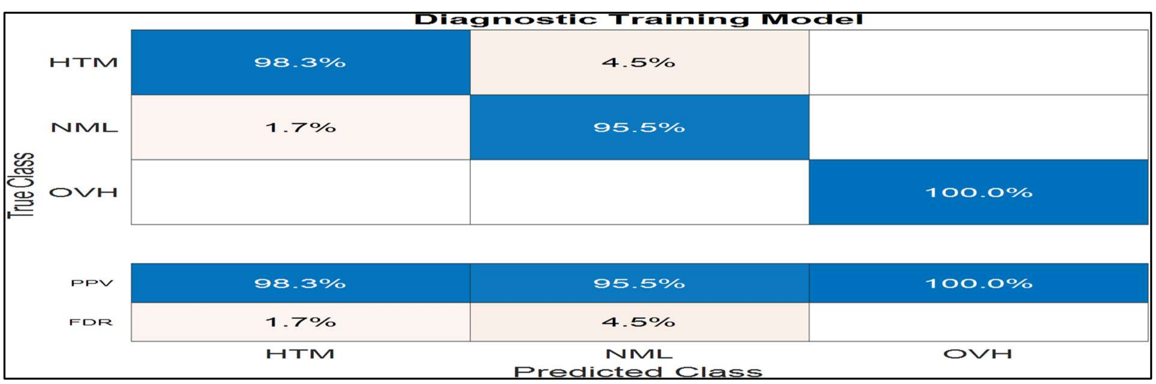

Figure 6:Model evaluation

Table 3: Data Labels used for diagnostic analysis

Fault	Fault Identity	Fault Parameter	Temperature Ranges(^{0}C)	Operating State
Normal Temperature	NTM	Normal Lubricating Oil Temperature	80-110	Normal
High Temperature	HTM	High Lubricating Oil temperature	110-115	Abnormal
Overheating	OVH	Engine Overheating	Max 120	Fault/Failure

The model was later presented with data from another generator for diagnostic analysis based on the same labelled parameters using power output(KW) as independent variable while lubricating oil temperature (LoT) as predictor. The choice of LoT out of the 5 parameters was premised on the correlation R-value. Moreover, the other 4 variables have some level of disparity between the individual banks, this difference is also present in the R-value in the correlation plot with a difference of 0.04 for the exhaust temperatures while 0.01 for the cooling water temperature which will require further investigation. Figure 7 shows the fault class location on the chart.

As can be seen the model was able to classify about 4 instances of overheating, but more important is that all the incidences were preceded by high temperature situations. The 2 arrows on the chart points to incidents of high temperature levels at low power output, this situation are important because they point some other serious issue other than the usual problems of sea chest blockage or scaling. A typical problem here could be poor atomisation or tappet clearance setting. Hence models like this also points to salient issue in the data that might not have been reported or noticed in normal reports. This numbers may be insignificant however, the impact over time could lead to significant reliability issue. Moreover, one of the most frequent problems in the repair report was overheating related challenges to do with sea chest blockages and scaling of heat exchanger tubes which reduce the heat transfer efficiency of the heat exchangers.

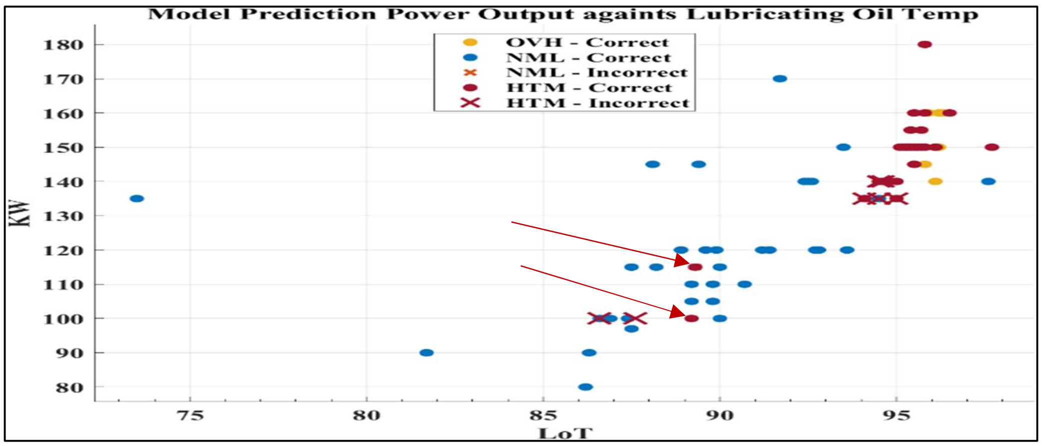

Figure 7: Fault Classes

4.2 SUGGESTIONS FOR MAINTENANCE ACTION

The proposed methodology demonstrates a simple approach that can be implemented onboard ships and be extended to shore maintenance offices or base in case of fleet maintenance requirements. It can also be used as a bridge to cross from manual data collection and management to automated data management. Nonetheless, some level of human interface will be needed especially onboard naval ships. Therefore, implementing the methodology for the case study ship and other ship will be based on a structured maintenance data management that will require a unified structure for data collection on board ships. Before moving to the data aspect, a look at the diagnostic data chart there is an indication of that the DG under concern has recorded a reasonable periods of high temperature operation. High temperature record from lubricating oil reading is a serious sign of degradation in machinery health. Therefore, despite the usual problem with sea chest blockages it is important that protective measures such use of sacrificial anodes and monitoring their depletion is enforced. Similarly, use of heat exchanger additives that can control water hardness and reduce scaling should in place, alternatively provisioned could be made to provide treated water for that purpose as well as periodic testing of water in the exchangers for contaminants.

Improved monitoring of sea water flow rate and re-evaluating alarm levels could reduce high temperature operations at lower load. An intelligent alarm system that can take values from lubricating oil temperature, output and sea water flow rate can greatly reduce failures and enhance reliable operation of the generators. Moreover, the logic approach describe in the methodology can be adopted by Ships to manage their data as well as provide a system of extracting the most relevant information for shore establishment. Overall, the system will be able to establish priority level according to the maintenance task responsibility. The ship staff being the first level of maintenance will manage and hold data on simple failures and faults that require that are easily manage on board and do not involve extended repairs time. The second level of maintenance is the shore establishment, which receive maintenance request that are beyond ship staff or may require longer repair time, or bigger logistics. In this regard the ship staff are to share any consistent anomaly in the health records with the second level of maintenance, who can then make a projection for intervention or push to the third maintenance level which may require OEM attention or complete overhaul.

4.3 Standardised Data Collection and Management

Standardised data collection approach is the most fundamental aspect of any efficient maintenance system especially data driven approaches aimed at improving condition monitoring. A template can be made for machinery log using Microsoft excel spread sheet with standardised columns for each class of ship providing details such a condition of equipment at the time of shutdown and location of ship while data was recoded. For a start template can be made for some vital equipment on board. Thereafter, a data transmission and management plan will be required due to the size of data to be managed. Depending on some specifics such as information security and cost implications, a choice can be made to hire a company that can provide big data solutions to help with handling transmission and managing the server at shore maintenance units and Fleet maintenance office. Alternatively, a dedicated data centre can be provided which can run and manned by the staff of the company and configured to received data via voice or text message.

A big data analytic centre will be required to help harmonise information coming from ships to shore maintenance centres and to central maintenance control or operations office. These centres can automatically present an overview of ship system and equipment at the shore maintenance office and the main operations office. Therefore, the setup will provide a summary of the operations status of each ship, identify common problems across ship class, account for most frequent failures and most important course of failure. There may be need to provide additional training to personnel on the sue and benefit of the system. Furthermore, the system at central operations can be programmed to provide further information regarding possibility of extended down times due to spare parts and technical expertise. The information and analysis conducted at the different levels of maintenance can be used to form the bases of spare parts accusation, system redesign, platform suitability appraisal etc.

5 Conclusion and Future Work

Machinery data analysis based on data collected onboard a ship was conducted to demonstrate a system of semi-automated data management process. Considering, the technology gap, the methodology can provide a systematic procedure that ships, and operators can migrate to data automated data management with minimum distribution. The tools used for the analysis easy can adopted onboard. The methodology was implemented on a set of diesel generator used for power generation on board a naval patrol vessel. Unlabelled time series data covering about 2000 operating hours over a duration of about 8 calendar months was analysis and labelled to bring 3 main classis NML,HTM and OVH. A feed forward ANN with 2 layers and based sigmoid and SoftMax activation function using the MATLAB pattern recognition app was used for the classification analysis. The analysis consisted of 7 data point consisting of Power output(kw). Exhaust gas temperature (ET)A and B, Fresh Water temperature (FWT) A and B, Lubricating Oil temperature (LoT) and Lubricating Oil Pressure (LoP). The time series data of about 2000-time stamp, the data was divided into 3, 70 % percent for training, 15% testing and 15% validation. The training was concluded after 200 epochs while testing and validation with hold out data was concluded on less than a minute. Positive Predictive Values (PPV) and False Discovery Rate (FDR) the classes the has model has achieved more than 95 % accuracy between the true and predicted class. Therefore, the results indicates that the model has performed well for the diagnostics and can be deployed or adopted for the particular set of generators

Data plays avital role in maintenance management, therefore efficient management of machinery logs, defect and repair data are critical to the successful implementation of any maintenance strategy. This becomes more important when minimising operational impact or cost of maintenance, failures, downtime, and the environment are considered through the life cycle of the asset or machinery. Accordingly, the NN needs to embrace data driven maintenance management in order to improve the efficiency of the current PMS regime. It is understood that sufficient data is collected onboard, but this data is not in a form that can allow for meaningful maintenance decision to be made. Therefore, some steps to implement ship maintenance data management and analysis in line with were outlined. The proposed approach is hinged on 4 areas that includes, standardised data collection across ship of the same class, electronic data management system developing a data transmission and management plan for FGSs from ships and provide big data analytic centre at the HQLOC for the FMO.

The research is an aspect of overall research endeavour to build a Platform for Ship Machinery Preventive Condition Monitoring based on machinery health data and reliability analysis. Therefore, the research is moving to conduct regression analysis for system degradation which will be analysed together reliability analysis output providing an overall machinery reliability outlook. Moving forward these outputs will provide individual or collective inputs for a maintenance decision support system based on Bayesian Belief Networks.

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