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FAULT TREE ANALYSIS AND ARTIFICIAL NEURAL NETWORK MODELLING FOR ESTABLISHING A PREDICTIVE SHIP MACHINERY MAINTENANCE METHODOLOGY

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SUMMARY

A dynamic fault tree model for a ship main engine is developed in order to analyse and identify critical systems/components of the main engine. The identified most critical systems are then used as input in an artificial neural network. An autoregressive dynamic time series neural network modelling approach is examined in a container ship case study, in order to monitor and predict future values of selected physical parameters of the most critical ship machinery equipment obtained from the fault tree analysis. The case study results of the combination of the fault tree analysis and artificial neural network model demonstrated promising prospects for establishing a dense methodology for ship machinery predictive maintenance by successfully identifying critical ship machinery systems and accurately forecasting the performance of machinery parameters.

1. INTRODUCTION

Maintenance deals with systems that are subject to deterioration and failure with usage and age. For systems on board ships, it is extremely important to avoid failures during actual operation because it can be dangerous or disastrous in terms of performance, safety and economic losses. The performance of the vessel generally deteriorates with time as a result of fouling or degradation of machinery systems and components. Unwanted failures result in economic impact in form of higher maintenance costs and lower machine reliability and availability. With reduced manning levels and the ever increasing competition, ship maintenance has become one of the major challenges in the marine industry. Technological advances and high cost of ownership have resulted in considerable interest in advanced maintenance techniques. As a consequence, the maritime industry is seeking for increased reliability, maximum uptime and optimal operational efficiency, as well as ensuring safe and sustainable environmental performance in harsh environments.

Optimisation of maintenance is challenging due to highly restrictive and harsh operating conditions of ships in addition to the high level of uncertainty accompanied by these operating conditions. Compared to other industries, data gathering and processing is not always possible as similar equipment in diverse conditions may have different failure patterns. Data is not collected in standard ways which would aid in successful decision making [1]. An additional issue is the constant appearance of new equipment, which makes historical records obsolete and lays other aspects on the replacement decisions.

Efforts have being made to transform corrective/preventive maintenance techniques into predictive ones. Condition monitoring is considered as a major part of predictive maintenance. It assesses the operational health of equipment, in order to provide early warning of potential failure such that preventive maintenance action may be taken. Predictive maintenance consists in deciding whether or not to maintain a system according to its state [2]. Moreover, predictive maintenance focuses on failure prediction, occurring through follow-ups with a specific systematic on parameters and equipment conditions. This type of maintenance did not emerge as a replacement for corrective and preventive maintenance, but as an additional tool, which seeks to minimize maintenance costs and losses in equipment through the monitoring of specific parameters [3].

As part of the above, this paper focuses in combining a Fault Tree model and then an Artificial Neural Network (ANN) for forecasting selected machinery parameters. Fault Tree Analysis (FTA) is a top-down approach which uses failure rates, mean time between failures and minimal cut sets to evaluate the reliability and availability of the examined system [4]. FTA can be applied both in a qualitative and quantitative way. The objective of a Fault Tree is to evaluate the probability of occurrence of the top event. Moreover, Fault Trees are also used to display the causes and consequences of events, identify system critical components and evaluate changes in design amongst other things. Fault Tree diagrams provide important information regarding the likelihood of a failure occurring and the means by which this failure could occur. They can be constructed at any point of a design stage and the FTA results can help improve system safety.

Raza and Liyanage [5] stated that there has been an increasing demand for testing and implementing intelligent techniques as a subsidiary to existing monitoring programs and that Artificial Neural Networks (ANNs) have emerged as one of the most promising techniques in this regard. The equipment condition and the fault developing trend are often highly nonlinear and time-series based. ANNs can be used due to their potential ability in nonlinear time-series trend prediction. Therefore this paper initially proposes the analysis of a Fault Tree model for the main engine of a ship in order to identify the most critical systems/items of the main engine. Physical parameters of the identified systems are then used as input in the ANN model in order to monitor and predict their future values.

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This paper is organized as follows: Section 2 briefly describes the research background, containing information regarding predictive maintenance, FTA and ANNs. Section 3 presents and defines the overall methodology. A case study is presented in Section 4 and results are presented in Section 5, followed by the concluding remarks contained in the last section.

2. BACKGROUND

2.1 MAINTENANCE

Ships are part of the marine transportation system and are crucial assets of the supply chain. In this respect, maintenance tasks affect the reliability and availability standards of the shipping industry and are an important factor in the lifecycle of a ship that can minimize down-time and reduce operating costs [9]. The importance of maintenance is demonstrated by the fact that it is the only shipboard activity to have one whole element assigned to it [6]. Also, due to the impact of shipping on the environment and the importance of the safe operation of ships; ship owners and operators pursue to adopt a maintenance plan and procedures that will reduce costs, promote the lifecycle integrity and enhance the energy efficiency of the ship.

Initially, corrective maintenance was applied to ships followed by successful preventive maintenance actions due to International Safety Management (ISM) code [6] and regulations and was then followed by predictive maintenance advances [7]. Predictive maintenance did not emerge as a replacement for corrective and preventive maintenance, but as an additional tool, which seeks to minimize, through the monitoring of specific parameters, maintenance costs and losses in equipment [3]. Therefore, predictive maintenance differs from preventive maintenance by concentrating maintenance on the actual condition of the machinery rather on some predefined schedule dictated by predefined time intervals or system operating hours. Consequently, predictive maintenance is used to define required maintenance tasks based on quantified material and equipment condition. It uses modern measurement and signal processing methods to accurately predict and diagnose items/equipment condition during operation [8].

2.2 FAULT TREE ANALYSIS

Reliability assessment tools include Reliability Block Diagrams (RBD), FTA, Failure Modes Effects Analysis (FMEA), Failure Modes Effects and Criticality Analysis (FMECA), Markov analysis and Bayesian Belief Networks (BBN). FTA is one of the basic methods of assessing reliability. The FTA method allows detailed examination of the system operation principles during the design, operation and accident investigations.

Fault Tree diagrams are a graphical design technique following a top-down approach. It uses a graphic model of the pathways within a system that can lead to a projected, undesirable event or failure. The pathways interconnect contributory events and conditions, using standard logic symbols and the basic constructs in a fault tree diagram are gates and events. The fault tree analysis module is based on sets of rules and logic symbols from probability theory and Boolean algebra. Gates represent logic operators that link the various branches of the fault tree together and determine whether the top event can occur or not. Basic events can be defined as the lower level events in each fault tree branch.

FTA uses failure rates, mean time between failures and minimal cut sets to evaluate the reliability and availability of the system. Moreover, fault trees are also used to display the causes and consequences of events, identify system critical components and evaluate changes in design amongst other things.

Lazakis et al. [7] presented a predictive maintenance strategy utilizing FMECA and FTA by considering the existing ship maintenance regime as an overall strategy including technological advances and decision support system by combining existing ship operational and maintenance tasks with the FTA and FMECA tool.

An innovative ship maintenance strategy is also presented by Turan et al. [4] based on criticality and reliability assessment while utilising the FTA tool with time-dependent dynamic gates in order to accurately present the interrelation of the components for a diving support vessel.

Lazakis and Olcer [9] introduced a Reliability and Criticality Based Maintenance (RCBM) strategy by utilizing a fuzzy multiple attributive group decision-making technique, which is further enhanced with the employment of Analytical Hierarchy Process (AHP). The outcome of this study indicated that preventive maintenance is still the preferred maintenance approach by ship operators, closely followed by predictive maintenance; hence, avoiding the ship corrective maintenance framework and increasing overall ship reliability and availability.

2.3 ARTIFICIAL NEURAL NETWORKS

A neural network can be defined according to Principe et al. [10] as distributed, adaptive, generally nonlinear learning machines built from many different processing elements that receive connections from other processing elements and/or itself. Several distinguishing features of ANNs [11] make them attractive for the development of prognostic tools. First of all, opposed to the traditional model-based methods, ANNs are data-driven and self-adaptive methods, meaning that there are few a priori assumptions about the models under study. They learn from past examples and capture subtle functional relationships among the data even if the underlying relationships are hard to describe or unknown. ANNs do not rely on prior principles or statistics models and can significantly simplify the model synthesized process. They can readily address modelling problems that are analytically difficult and for which conventional approaches are not practical, including complex physical processes having nonlinear, high-order, and time-varying dynamics. Secondly, ANNs have good generalisation capabilities and are universal functional approximators. They are also nonlinear. Real word failure models are generally non-linear. However, these models are still limited in that they are based on a little knowledge of underlying law.

The application fields of neural networks can be categorised with respect to different criteria, such as industrial application, type of reliability problem, life cycle phase in which the algorithms are predominantly applicable and the type of learning problem. The building block of a neural network is a neuron [12], which has several inputs a_n, each of these inputs are multiplied by weights w_{ij} and then added up. Weights are adaptive coefficients within the network that determine the intensity of the input signal [13]. Often a bias is added b_j, which is the node's internal threshold. The result is the neuron activation z as shown in the following equation:

$$z = \sum_{i=1}^{n} a_i w_{ij} + b_j$$

Time series modelling and forecasting has fundamental importance to various practical domains. The main aim of time series modelling is to carefully collect and rigorously study the past observations of a time series to generate future values for the series. Time series forecasting can be termed as the act of predicting the future by understanding the past.

Although linear models possess many advantages in implementation and interpretation, they have serious limitations in that they cannot capture nonlinear relationships in the data which are common in many complex real world problems. Neural nets have the potential to represent any complex, nonlinear underlying mapping that may govern changes in a time series [14]. Zhang et al. [15] showed that neural networks are valuable tools for modelling and forecasting nonlinear time series while traditional linear methods are not as competent for this task. The lack of systematic approaches to neural network model building is probably the primary cause of inconsistencies in reported findings.

With the increased availability of monitoring data on the condition of systems and equipment, neural networks are increasingly applied in the field of fault detection [16], fault diagnostics [17] and for predicting the residual useful life [18].

3. METHODOLOGY

The methodology suggested in this paper initially generates a generic model approach, utilising the capabilities of fault tree modelling. Subsequently, the ANN model is applied for the transition of the generic model into a specific model. The aim of the FTA is to calculate and identify the most critical subsystems/components of the top main system. Once the most critical items of the FTA have been acquired, physical parameters associated with these items are used as input in the ANN in order to conduct a time series analysis aiming in predicting their future values. Figure 1 provides an overview of the methodology approach.

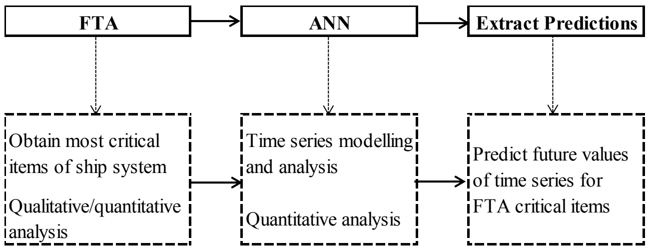

Figure 1: Methodology

3.1 FTA MODEL

A very important part of FTA is the system definition. The basis of the system definition is the fault tree diagram which defines all interconnections and components of the system. Also, reliability parameters should be identified and the system definition must identify important assumptions regarding the system and the conditions that indicate that the components of the system have failed. The top event should also be clearly defined as if a top event is not concisely defined then the fault tree can possibly become too large and complex, resulting in an unfocused system analysis.

One of the advantages of FTA is that it is an event-oriented method. In addition to considering failures in hardware, fault trees can take into account the undesirable events that can possibly occur due to software failures, environmental influences and human errors during the stages of maintenance and system operation. On the other hand, one of the biggest disadvantages of FTA is that all events leading to the top event must be foreseen and the contributors to the occurrence of these undesired events must be anticipated. In addition, FTA requires analyst skill and can be time-consuming, thus costly.

The following steps are usually performed when constructing a fault tree [19]:

- Definition of the FTA scope
- Identification of the top event.
- Identification of the first level events.
- Connection of the first level events with the top event by using gates.
- Identification of the second level events.

- Connection of the second level events with first level by using gates.
- Repetition of the above steps for all subsequent event levels.

3.1(a) Fault Tree Minimal Cut Sets

The FTA can be conducted in a qualitative or quantitative manner, depending on the type of data available. If no data is available, a fault tree can be analysed qualitatively by using minimal cut sets. Qualitative analysis is used to identify what combinations of events cause the top event to occur.

A cut set is a set of basic events, which if they all occur, will result in the top event of the fault tree occurring. A minimal cut set is a combination (intersection) of primary events sufficient for the top event. The combination is a "*minimal*" combination in that all the failures are needed for the top event to occur; if one of the failures in the cut set does not occur, then the top event will not occur (by this combination). To determine the minimal cut sets of a fault tree, the tree is first translated to its equivalent Boolean equations. One of the main purposes of representing a fault tree in terms of Boolean equations is that these equations can then be used to determine the associated minimal cut sets.

The minimal cut set expression for the top event can be written in the general form according to [19]:

$$T = M_1 + M_2 + \ldots + M_k$$

where T is the top event and M_i are the minimal cut sets, each of them consisting of a combination of specific component failures. The general n-component minimal cut can be expressed as:

$$M_i = X_1 \bullet X_2 \bullet \ldots \bullet X_n$$

where $X_1, X_2, \ldots, X_n$ are basic component failures.

If data such as mean time between failures, failure rates, probabilities are available, the fault tree can use quantitative calculation methods and also reliability importance measures [4] such as Birnbaum, Criticality and Fussell-Vesely to identify and calculate most critical items.

3.1(b) Fault Tree Gates

Logic operators known as gates determine how events are generated. A basic event represents the lowest level of a fault tree. Gates are used to represent the failure logic paths between various levels of the tree. Gates can be either static or dynamic. A static gate indicates that the order of the inputs of a gate do not matter, therefore are not sequence-dependent as in dynamic gates. On the other hand, in dynamic gates, the order of the occurrence of input events is vital for determining the output. If dynamic gates are used, then the fault tree becomes a dynamic fault tree. The most common static gates include the AND, OR and Voting gates. An AND-gate indicates that the output occurs if and only if all the input events occur. The OR-gate is used to specify that the output occurs if and only if at least one of the input events occurs. The Voting-gate occurs when at least m out of n input events occurs. Dynamic fault tree gates include the Sequence Enforcing-gate, Priority AND-gate, Spare-gate and Functional Dependency-gate amongst other. The Priority AND-gate indicates that the output will occur if and only if all the input events occur in a particular order from left to right. Thus, items need to fail in temporal order from left to right to trigger the event. Similarly, the Sequence Enforcing-gate forces events to occur in a particular order from left to right. This implies that the left-most event must occur first and that an event connected to such a gate will be initiated immediately after the occurrence of its immediate left event.

3.2 ANN ARCHITECTURE

Data has to be pre-processed prior to using it in the Artificial Neural Network. Also, the neural network architecture has to be established in order to design a network capable of modelling a time series problem and accurately predicting future values of that time series. Figure 2 demonstrates the methodology implementation followed for the neural network structure.

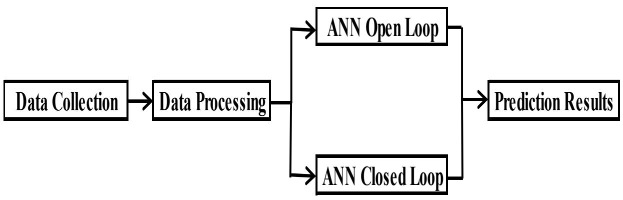

Figure 2: ANN Methodology

Once the data has been processed, the neural network is firstly modelled in open loop and is then converted to closed loop for multistep-ahead predictions.

3.2(a) Data Preparation & Processing

Before the data can be analysed in the neural network, it has to be correctly processed in order to achieve a correct analysis and improve the efficiency of network training.
A time series is a sequential set of data points, measured typically over successive times. It is mathematically defined as a set of vectors y(t), t = 0 ,1 , 2 ,...,d where t represents the time elapsed [20]. The variable y(t) is treated as a random variable. The measurements taken during an event in a time series are arranged in a proper chronological order. The future values of a time series y(t) are predicted only from the past values of that series. This form of prediction is called nonlinear autoregressive and can be written as:

$$y(t) = f(y(t-1), \ldots, y(t-d))$$

Where y_t is the observation at time t; and d is the dimension of the input vector or number of past observations used to predict the future; and f is a non-linear function. The data is prepared by shifting time by the minimum amount to fill input states and layer states for network open loop and closed loop feedback modes. This allows the time series data to be trained with the dynamic neural network. Finally, data is divided into two subsets in the network for training and testing purposes. The training set is used for computing the gradient and updating the network weights and biases and the test data is used to measure how well the network generalizes overall.

3.2(b) Neural Network Modelling

An artificial neural network consists of interconnection of neurons. The neurons are usually assembled in layers [12]. Each layer has a number of simple, neuron processing elements called nodes or neurons that interact with each other by using numerically weighted connections [21]. Generally a neural network consists of n layers of neurons of which two are input and output layers, respectively. The former is the first and the only layer which receives and transmits external signals while the latter is the last and the one that sends out the results of the computations. The n-2 inner ones are called hidden layers which extract, in relays, relevant features or patterns from received signals.

The interconnectivity defines the topology of the ANN [5]. The network topology describes the arrangement of the neural network. Successful ANN modelling is based upon the number of neurons, number of hidden layers, values of the weights and biases, type of the activation function, structure of the network, training styles and algorithms as well as data structure. However, the best structure is the one which can predict behaviour of the system as accurately as possible. A crucial step in the building of a neural network model is the determination of the number of processing elements and hidden layers in the network. Hidden nodes are used to capture the nonlinear structures in a time-series. Since no theoretical basis exists to guide the selection, in practice the number of hidden nodes is often chosen through experimentation or by trial-and-error.

ANNs learn the relation between inputs and outputs of the system through an iterative process called training [22]. Neural networks are trained for input data and the output is computed. The error obtained by comparing outputs with a desired response is used to modify the weights with a specific training algorithm. This procedure is performed using training data set until a convergence criterion is met. Neural networks have different learning algorithms for training. The choice of a particular learning algorithm is influenced by the learning tasks a neural network has to perform. The training performance is evaluated using the following performance measures, namely the Mean Square Error (MSE) average sum of square errors and Correlation Coefficient (R) given by the following equations respectively [23]:

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}\left(d_{ij} - y_{ij}\right)^2}{NP}$$

$$R = \frac{\dfrac{\sum\left(x_i - x_{mean}\right)\left(d_i - d_{mean}\right)}{N}}{\left[\left(\dfrac{\sum\left(d_i - d_{mean}\right)^2}{N}\right)\left(\dfrac{\sum\left(x_i - x_{mean}\right)^2}{N}\right)\right]^{0.5}}$$

where P = number of output processing elements; N = number of exemplars in the data set; y_{ij} = network output for exemplars i at processing element j ; and d_{ij} = desired output for exemplars i at processing element j.

A nonlinear autoregressive dynamic neural network is used for the prediction. A hyperbolic tangent transfer function in the hidden layer and linear transfer function in the output layer are employed, capable of approximating any function with a finite number of discontinuities. The system is firstly modelled as an open loop system to train the network accurately up to the present with all of the data in order to achieve correct predictions; and is then transformed to closed-loop for calculating multistep-ahead predictions. During training, the network weights and biases are updated after all of the inputs and target values have been presented to the network. The network is autoregressive as the only inputs are lagged target values. The neural network is trained using the Bayesian regularization backpropagation algorithm. The term backpropagation refers to the process by which derivatives of network error, with respect to the network weights and biases, can be computed. Bayesian regularization algorithm provides better generalization performance and is most suitable for small data sets compared to other training algorithms. The performance of the network is evaluated using the MSE performance measure and Correlation Coefficient R.

The open loop network is a feed-forward back propagation network. Then, for the multistep-ahead predictions, the open loop network is converted to a Recurrent Neural Network (RNN) closed-loop system, by creating a feedback connection from the output to the network input, thus making the network dynamic. The first two time steps of the input are used as input delay states in order to model the dynamic system.

RNNs can store sequential information in the form of historical data and can be used in forecasting. For example, in an RNN, the input nodes are taken as the value of the current condition X_t and values of the previous time-series condition (X_{t-1}, X_{t-2}, X_{t-3},…, X_{t-d} and X_n). The value of the output X_{t+1} can provide a one-step-ahead prediction of a time-series condition, which is a function of the current value X_t and time-lagged values of the previous condition (X_{t-1}, X_{t-2}, X_{t-3}, … , X_{t-d} and X_n). The predicted value X_{t+1} of a time series, one-step ahead in the future is given by the following equation:

$$X_{t+1} = F\left(X_t, X_{t-1}, X_{t-2}, \ldots, X_{t-l}, \ldots, X_n\right)$$

Where, l is the time lag, X_{t+1} is the predicted value, X_t is the current value or condition and X_{t-d} is the values of previous condition lagged by time d. The closed-loop network is show in Figure 3.

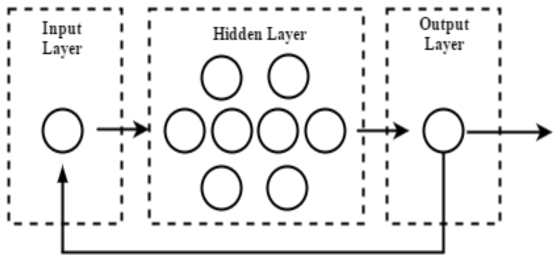

Figure 3: Closed-loop dynamic neural network

4. CASE STUDY

The described methodology is applied for the case study of a Panamax container ship. A Fault Tree model is constructed for the system of an eight cylinder two stroke marine diesel engine. Once the Fault Tree has been constructed and analysed, the most critical subsystems/components of the top main system are identified. Then, physical parameters (e.g. temperature, pressure) associated with the critical items of the Fault Tree are used as input in the ANN in order to conduct a time series analysis aiming in predicting their future values.

4.1 FAULT TREE MODELLING BOUNDARY

As with any modelling technique, the boundaries of a FTA must be defined prior to the construction of the fault tree. In general, defining the boundaries of the analysis involves defining what is in the analysis and what is out of the analysis. Figure 4 displays the boundary condition for the main engine.

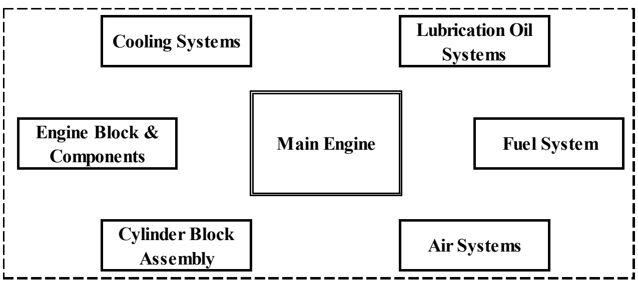

Figure 4: Boundary condition of main engine including sub-systems

As observed in Figure 4, the main engine is divided into six categories which include namely the cooling systems, lubrication oil systems, fuel system, air systems, cylinder block assembly and engine block and components. The cooling system is further divided into the jacket water cooling and central cooling system. The jacket water cooling system consists of the jacket fresh water cooling pump and jacket water cooling and the central cooling system of the sea chest strainer, sea water pipes and central cooler. The lubrication oil system includes the lube oil filter, pump, valves and lube oil cooler. Furthermore the fuel system resembles the lube oil system with the addition of the fuel injectors. The air systems are further separated into the main air system and scavenging air system. In the cylinder block assembly system, the system has been separated into the cylinder system which includes the cylinder head and liner and the piston assembly including the piston crown, rings, stuffing box and connecting rod. Finally, the engine block and components group contains components of the main engine such as the crankshaft, crankcase, camshaft and various bearings. In total, 39 basic events were created in the fault tree representing the components of the various main engine sub-systems as illustrated in Table 1.

Lube Oil Filter	Air Cooler, Piping
Main Lube Oil Pump	Air Cooler
Lube System Valves	Scavenge Air Port
Lube Oil Cooler	Scavenge Air Receiver
J.F.W Cooling Pump	Scavenge Air Manifold
Jacket Water Cooling	Air Receiver
Sea Chest Strainer	Cylinder Head
Sea Water Pipes	Cylinder Liner
Central Cooler	Piston Crown
Fuel Piping System	Piston Ring
Fuel Oil Filter	Piston Rod Stuffing Box
Fuel Pumps	Piston Connecting Rod
Fuel Valves	Camshaft Bearing
Fuel Injector	Thrust Bearing
Main Air Compressor	Main Bearings
Air Distributor	Crankshaft
Air Starting Valves	Crankcase
Air Filter	Camshaft
Auxiliary Blower	Exhaust Valves

Table 1: List of components used for fault tree

For each system and associated component, physical parameters such as temperature, pressure are measured in order to monitor their condition. Key parameters in performance observations include amongst others:

- Engine speed
- Barometric pressure
- Compression pressure
- Fuel pump index
- Exhaust gas temperatures and pressures
- Scavenge air temperature and pressure
- Air and cooling water temperatures prior and after scavenge air cooler.

Table 2 illustrates a sample of physical parameters monitored for the systems and components included and modelled in the Fault Tree analysis. In total, 20 physical parameters are monitored associated with the 6 systems used in the Fault Tree of the main engine as seen in Figure 5.

System	Parameter	Physical Measurement	
		Temperature	Pressure
Cylinder	Scavenging Air	•	
	Exhaust Gas Temperature Outlet	•	
	Jacket Fresh Water Cooling Inlet		•
Piston	Piston Cooling Lube Oil Inlet		•
Lube Oil Cooler	Sea Water Inlet	•	
	Sea Water Outlet	•	
Thrust Bearing	Thrust Bearing Lube Oil Outlet		•

Table 2: Physical parameters for main engine systems

Based on the FTA and utilising Table 2, the selected physical parameters are then used as input for the ANN.

4.2 ARTIFICIAL NEURAL NETWORK

The data composed for analysis of the selected physical parameters was collected through an on board measurement campaign as presented in Raptodimos et al. [24]. The neural network uses a univariate time series data set. The data monitored on board the container ship case study, represents 30 continuous per hour records of physical parameters regarding systems such as the ones shown in Table 2. The ANN constructed consists of one hidden layer with 8 hidden nodes as illustrated in Figure 3. The ANN receives these values as input as a univariate time series data and attempts to predict the upcoming values as output.

5. RESULTS

Results are firstly shown for the FTA of the main engine. Finally, based on the Fault Tree Analysis, results are shown for the Artificial Neural Network.

5.1 FTA RESULTS

A four level fault tree for the ships main engine is constructed including 39 basic events and 14 gates as described in Table 1. Qualitative analysis is performed in order to obtain the minimal cut sets of the fault tree, which provide insight into weak points of complex systems. Figure 5, displays a fragment of the main engine fault tree.

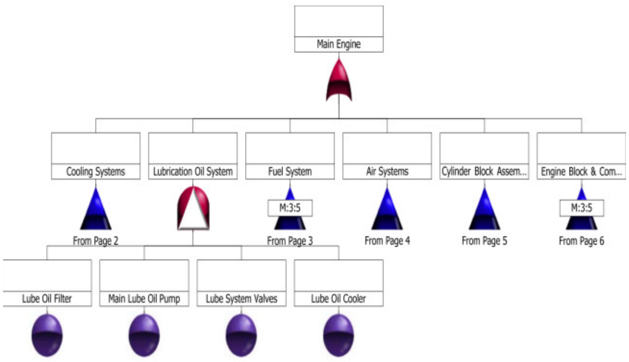

Figure 5: Main engine fault tree diagram

The cooling systems are modelled using an AND gate assuming both the jacket water cooling and central cooling system have to fail. The lubrication oil system has been modelled using a Priority-AND gate, assuming as seen in Figure 5, that the lube oil filter has to occur before the pump, vales and then lube oil cooler occur. By using dynamic gates, the fault tree becomes a dynamic fault tree. The fuel system has been designed using a Voting gate of 3 out of 5 systems and the air system has been modelled as an AND gate assuming that both the main air system and scavenge air system have to occur. The engine block and components gate is composed of a Voting gate assuming that any three of the bearings, crankshaft, crankcase, camshaft or exhaust valves have to occur. Table 3 displays the top five minimal cut sets obtained from the main engine FTA.

1	Cylinder Head	Piston Crown	Piston Ring
2	Cylinder Head	Piston Crown	Piston Rod Stuffing Box
3	Cylinder Liner	Piston Crown	Piston Ring
4	Crankcase	Crankshaft	Camshaft
5	Fuel Oil Filter	Fuel Pumps	Fuel Injector

Table 3: Top five fault tree minimal cut sets

All the minimal cut sets are of third order. As observed, the first three cut sets involve systems/components that were constructed in the cylinder block assembly gate illustrated in Figure 6.

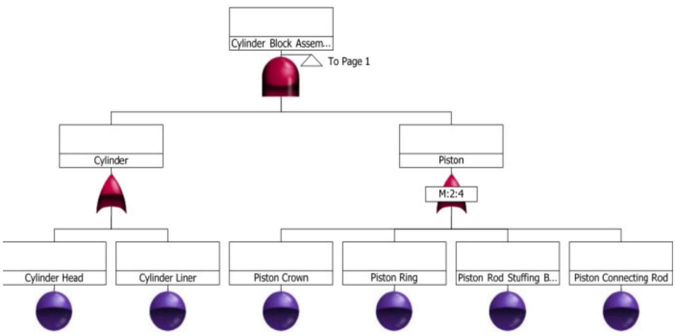

Figure 6: Cylinder block assembly sub-system

Figure 6 shows the cylinder block assembly system modelled with an AND gate, the cylinder OR gate and the piston sub-system modelled with a 2 out of 4 Voting gate.

Since the minimal cut sets have been calculated and involve systems and components inside the cylinder, based on Table 2, physical parameters such as the cylinder exhaust gas temperature can be used as input in the ANN in order to further monitor and examine the performance of the specific system.

5.2 ANN RESULTS

The ANN constructed attempts to predict the upcoming five cylinder exhaust gas temperature values as output, for cylinder 1. The results obtained from the network for predicting the future upcoming five values in time are illustrated in Figure 7.

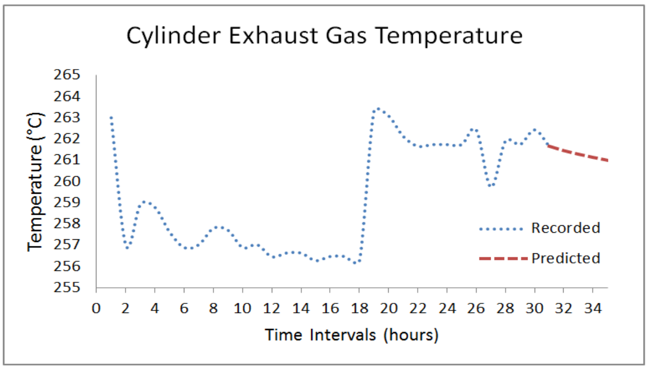

Figure 7: Cylinder 1 exhaust gas temperature prediction graph

Figure 7 illustrates the graph of the recorded values and predicted ones against time. The recorded temperatures are within the range of 254 degrees to 283 degrees Celsius. Variations in temperature, especially the rise of the exhaust gas temperature at some points is observed and is mainly caused by an increase in the engine and fuel load. This is due to the engine governor regulating the engine speed, as the vessel is also sailing at a constant speed of 10 knots. Moreover, these variations could be the result of the specific cylinder condition.

5.2(a) ANN Validation

The results of the ANN are examined and validated using two approaches. The first approach uses the network performance in terms of the regression plots R for the training and testing data as shown in Figure 8 and the error autocorrelation as shown in Figure 9.

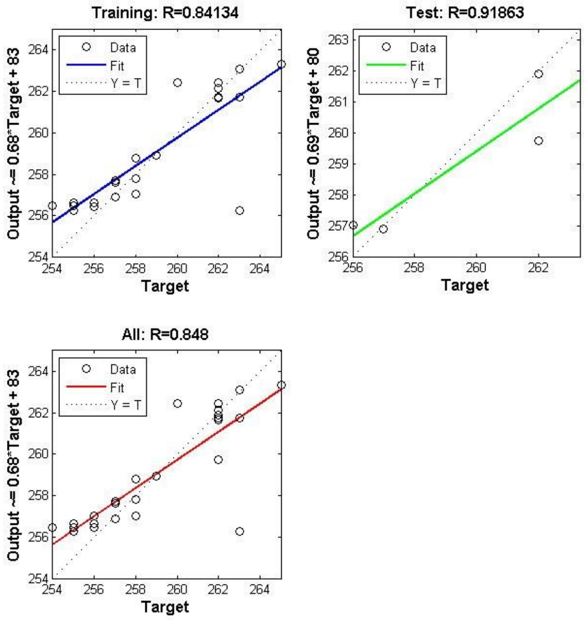

Figure 8: Regression results for training and test data of neural network

The correlation coefficient R, regression plot, is a good measure of how well the network has fitted the data. The regression plot shows the actual network outputs plotted in terms of the associated target values. Regression values measure the correlation between outputs and targets. A correlation coefficient R value of 1 implies a perfect fit of outputs exactly equal to targets. Figure 8 displays the network outputs with respect to targets for training and test sets. Bayesian regularization does not use a validation set but includes this in the training set. The training data indicate a good fit as does the test results showing values of R greater than 84% and 91% respectively. For all data sets, the fit is very good.

Error autocorrelation is used to validate the network performance. The error autocorrelation function defines how the forecast errors are interrelated in time. For a faultless prediction model, there should be one non-zero value that should occur at zero lag implying that the forecast errors are entirely uncorrelated with each other. Therefore, if the network has been trained well then besides the centre line which shows the mean squared error, all other lines should fall within the confidence limits as successfully shown in Figure 9.

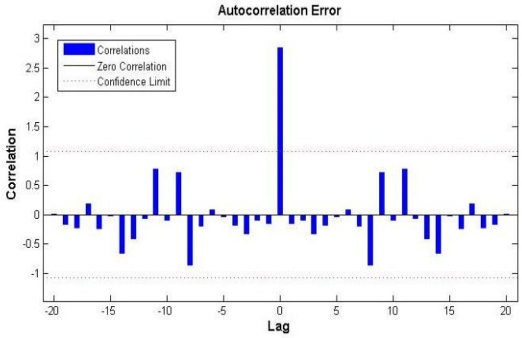

Figure 9: Autocorrelation of error

In the second network validation approach, a sensitivity analysis is conducted [25]. The network predicted values for the temperature are compared with the actual values recorded on board the vessel as seen in Table 4 in order to validate the network prediction accuracy.

Prediction	Recorded Onboard	ANN Prediction	Error
hours	°C	°C	
+1	263.00	261.66	0.51%
+2	260.00	261.45	0.56%
+3	262.00	261.29	0.27%
+4	262.00	261.14	0.33%
+5	263.00	261.00	0.76%

Table 4: ANN prediction results versus actual results

As seen from Table 4, the error difference between the values indicate that the predicted values are extremely close to the actual monitored temperature values recorded on board the vessel, thus verifying the performance and accuracy of the trained network.

6. CONCLUSIONS

Marine automation, electrical and propulsion systems, sensors, robotics, advanced materials, big data analytics, are a few of the categories that can describe the concept behind smart ships. The question of how much data, which data, and how often this should be collected and how has also risen; as although companies adopt condition based maintenance schemes, there seems to be an issue in processing, analysing and utilising the recorded operational data. Intelligent ships will enable owners to make more rapid operating decisions, by analysing real time data, providing real-time information regarding the condition of on board equipment. Thus, this will lead to the evolution of maintenance from fixed intervals, towards tailored predictive maintenance applications, which will optimise maintenance and operation planning and will also boost performance and safety. Therefore, it is clear that such developments have the potential of transforming the design, construction and operation of commercial ships.

This paper proposed the combination of a Fault Tree model with ANN in order to create a generic model in terms of obtaining the most critical systems and components of a main engine through qualitative analysis using minimal cut sets. A minimal cut set is the smallest set of basic events which result in the occurrence of the top event. The set is minimal in the sense that if any of the events do not occur, then the top event will not occur by this combination of basic events. Physical parameters of the most critical systems and components identified from the fault tree are used as input in an artificial neural network for time series analysis and prediction.

The data used for the network represents cylinder exhaust gas temperatures while the vessel was in transient operation. Since no faulty data or failures occurred during the on board measurement, the obtained data does not cover the whole operational range of the system. The case study provided accurate results for predicting upcoming temperature measurements based on previous monitored values. The data monitored represents continuous per hour temperature values. The network predicted values for the temperatures are then compared with the actual values recorded on board the vessel which indicated that the network is capable for time series analysis and has good predictive capabilities.

An important issue in ANN model building is how large the training and/or test sample sizes should be. In the ANN literature, large sample size for training is often suggested for sufficient learning and to ease the overfitting effect in training a neural network. However, Kang [26] found that neural network models do not necessarily require large data sets to perform well, as also demonstrated in this paper, in which the Bayesian regularization algorithm provided sufficient generalization performance capabilities for a small data set. However, the question of how much data is sufficient still exists and ANN models are still limited in that they are based on a little knowledge of underlying law.

In conclusion, the predictive results obtained can be utilised within a maintenance and condition monitoring framework in order to assess the performance of ship machinery equipment based on current and real time information and can be used for prognostic and diagnostic purposes and applications. Finally, it is possible to extend the neural network capabilities by investigating additional analysis in terms of also including temperature ranges with various engine loads and other parameters, which will increase the network generalisation and accuracy.

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