An artificial neural network approach for predicting the performance of ship machinery equipment

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ABSTRACT: Inadequate ship machinery maintenance can increase equipment failure posing a threat to the environment, affecting ship performance, having a great impact in terms of business losses by reducing ship availability and increasing downtime and moreover increasing the potential of major accidents occurring, endangering lives onboard. 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. Condition monitoring is defined as the collection and interpretation of the relevant equipment parameters for the purpose of the identification of the state of equipment changes from normal conditions and trends of the health of the equipment. The equipment condition and the fault developing trend are often highly nonlinear and time-series based. Artificial Neural Networks (ANNs) can be used due to their potential ability in nonlinear time-series trend prediction. Therefore this paper proposes the use of an autoregressive dynamic time series ANN in order to monitor and predict selected physical parameters of ship machinery equipment that contribute to the overall performance and availability, in order to predict their future values that will illustrate their performance state that will eventually lead to the correct maintenance actions and decisions.

KEYWORDS: Neural networks, predictive maintenance, condition monitoring, time series

1 INTRODUCTION

Maintenance deals with systems that are subject to deterioration and failure with usage and age. Most authors in maintenance management literature, one way or another, agree on defining maintenance as the "set of activities required to keep physical assets in the desired operating condition or to restore them to this condition" (Pintelon and Parodi-Herz, 2008). The growing importance of maintenance has generated an increasing interest in developing and implementing optimal maintenance strategies that can improve system reliability, prevent the occurrence of failures and reduce maintenance costs of deteriorating systems. Ever-increasing business pressures have been putting the maintenance function under the spotlight as never before. Technological advances and high cost of ownership have resulted in considerable interest in advanced maintenance techniques.

According to British Standard (2012), Condition Based Maintenance (CBM) is defined as the maintenance policy carried out in response to a significant deterioration in a machine as indicated by a change in a monitored parameter of the machine condition. The heart of CBM is condition monitoring which aims in collecting data regarding equipment conditions. Condition monitoring technologies are applied through various tools by recording and evaluating different measureable parameters. Data can include vibration, acoustic, temperature, current signal, oil and lubricant data.

With reduced manning levels and the ever increasing competition, ship maintenance has become one of the major problems in the marine industry. The marine industry is seeking for increased reliability, maximum uptime and optimal operational efficiency, as well as ensuring safe and sustainable environmental performance. Optimisation of maintenance is challenging due to highly restrictive and harsh operating conditions of ships. The optimisation is even more complicated due to the high level of uncertainty accompanied by these operating conditions. Compared to other industries, data pooling is not always possible as similar equipment in different conditions may have different failure patterns. Another issue, is the constant appearance of new equipment, which makes historical records obsolete

and puts other aspects on the replacement decisions. Data is not collected in standard ways on deterioration in order to use the data in successful decision making (Dekker, 1996).

Raza and Liyanage (2009) stated that there has been an increasing demand for testing and implementing intelligent techniques as a subsidiary to existing condition monitoring programs and that ANNs have emerged as one of the most promising techniques in this regard. Neural nets have the potential to represent any complex, nonlinear underlying mapping that may govern changes in a time series (Tang and Fishwick, 1993). A time series is a sequence of time-ordered data values that are measurements of some physical process. 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. A neural network is a mathematical structure that is capable of identifying complex nonlinear relationships between input and output data sets (Adjallah et al., 2007). They are powerful tools for modelling, especially when the underlying data relationship is unknown.

This paper is organized as follows: Section 2 briefly explains the research background of this paper containing information regarding maintenance, condition monitoring and ANNs. Section 3 presents and defines the overall methodology. The case study and results are presented in Section 4 followed by the concluding remarks contained in the last section.

2 RESEARCH BACKGROUND

2.1 *Maintenance & Condition Monitoring*

Maintenance describes the maintenance, control, execution and quality of those activities which will reasonably ensure that design levels of availability and performance of assets are achieved in order to meet business objectives (Brown and Sondalini, 2014). Several authors have tried to categorize maintenance. Garg and Deshmukh (2006) classified the existing maintenance literature into six areas. These areas are categorized into maintenance optimisation models, maintenance techniques, maintenance scheduling, maintenance performance measurement, maintenance information systems and maintenance policies. According to Sherwin (2000) the reason why maintenance is organised as it is are in many cases historical rather than logical. In general, maintenance types can be classified into three main categories, namely corrective, preventive and predictive maintenance.

Predictive maintenance is the use of modern measurement and signal processing methods to accurately predict and diagnose items during operation (Sharma et al., 2011). It attempts to detect the onset of degradation and focuses therefore on failure prediction, occurring through a systematic monitoring of equipment or component 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, through the monitoring of specific parameters, maintenance costs and losses in equipment (de Faria Jr et al., 2015).

Condition monitoring has a number of important benefits. Unexpected failures can be avoided through the possession of quality information relating to the on-line condition of the system and the consequent ability to identify faults or problems while still in the incipient phases of development; maintenance programmes can be condition based rather than periodically based; the plant may be utilised more optimally through the use of information relating to the plant's real-time condition and/or performance. Condition monitoring technologies are applied through various tools by recording and evaluating different measureable parameters. These technologies include vibration monitoring, noise monitoring, thermography, oil analysis and tribology, combustion performance monitoring and electrical signature analysis. Sullivan et al. (2010) also refers to various condition monitoring technologies and techniques such as lubricant/fuel, wear particle, bearing temperature, infrared thermography and motor current signature analysis.

Raza and Liyanage (2009) stated that there has been an increasing demand for testing and implementing intelligent techniques as a subsidiary to existing condition monitoring programs and that ANNs have emerged as one of the most promising techniques in this regard.

2.2 *Artificial Neural Networks*

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 (Tan et al., 2012), fault diagnostics (Tamilselvan and Wang, 2013) and for predicting the residual useful life (Tian et al., 2010).

A neural network can be defined according to Haykin (1998) as a massively parallel distributed processor made up of simple processing units that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain within two respects; knowledge is acquired by the network from its environment through a learning process and interneuron connection strengths known as synaptic weights are used to store the acquired knowledge. A more pragmatic definition that emphasizes the key features of this technology can be given after Principe et al. (1999) as: “ANNs are distributed, adaptive, generally nonlinear learning machines built from many different

processing elements that receive connections from other processing elements and/or itself". Figure 1 displays a structure of a typical ANN with input, hidden and output layers.

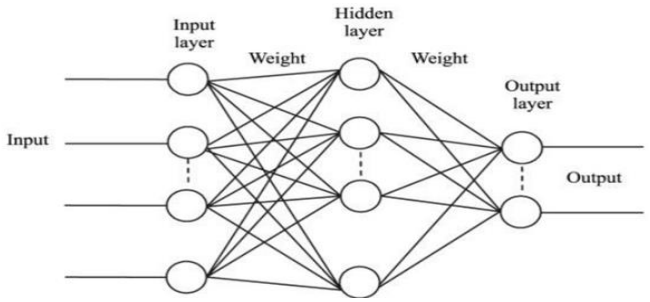

Figure 1. Artificial Neural Network structure

Applications of ANN can be found in condition monitoring (Yang et al., 2002), fault diagnosis, sensor validation, modelling, simulation and control. Because neural networks are a data-based method, they are universally applicable to systems from different industrial application fields for system reliability prediction, diagnostics and prognostics. They have been applied among others for applications in nuclear power plants, mining, for different industrial applications of motor bearings, electric machines and cutting tools. With respect to the type of the learning problem, the four major application types are clustering, classification, pattern recognition and forecasting and prediction (Yam et al., 2001). Forecasting and prediction involves extracting past patterns for predicting future values.

Several distinguishing features of ANNs (Zhang et al., 1998) 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 priori principles or statistics models and can significantly simplify the model synthesized process. They can readily address modeling problems that are analytically difficult and for which conventional approaches are not practical, including complex physical processes having non-linear, high-order, and time-varying dynamics and those for which analytic models do not yet exist. Secondly, ANNs have good generalisation capabilities. After learning the data presented to them, ANNs can only correctly infer the unseen part of a population even if the sample data contain noisy information. Thirdly, ANNs are universal functional "approximators" and have more general and flexible functional forms than the traditional analytical and statistical methods can effectively deal with. Finally, they are non-linear. 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.

3 METHODOLOGY

The performance of the vessel is observed through monitoring physical parameters such as pressure and temperature for various critical machinery equipment and systems located in the engine room. The data composed for analysis was collected through an onboard measurement campaign as presented in Raptodimos et al. (2016). This 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.

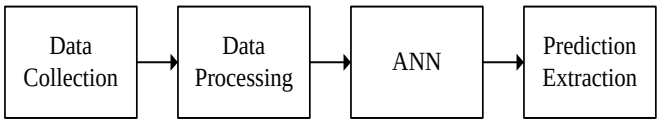

Figure 2. Methodology for extracting time series predictions

3.1 *Neural Network Architecture*

An artificial neural network consists of interconnection of neurons. The neurons are usually assembled in layers (Barad et al., 2012). Each layer has a number of simple, neuron processing elements called nodes or neurons that interact with each other by using numerically weighted connections (Peng et al., 2010). 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 (Raza and Liyanage, 2009). 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. In the selection of number of processing elements to suit the network a trade-off has to be made. A large number of processing elements mean large number of weights, though this can give the network the possibility of fitting very complex discriminating functions, too many weights can produce poor generalizations. On the other hand very small number of processing elements reduces the discriminating power of a 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.

In determining the number of hidden layers to be used, there are two methods in the selection of network sizes. One can begin with a small network and then increase its size (growing method); the other method is to begin with a complex network and then reduce its size by removing not so important components (pruning method) (Oladokin et al., 2006). The determination of the number of hidden layers and nodes are crucial since if there are too many hidden layers, the neural network will not learn the underlying pattern, while with too few the neural network will not pick up the full details of the underlying patterns in the data.

ANNs learn the relation between inputs and outputs of the system through an iterative process called training (Asgari et al., 2011). 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), (Oladokin et al., 2006) given by Equation 1 and Equation 2 respectively:

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}\left(d_{ij}-y_{ij}\right)^2}{NP} \quad (1)$$

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

where P = number of output processing elements; N = number of exemplars in the data set; yij = network output for exemplars i at processing element j ; and dij = desired output for exemplars i at processing element j.

Another closely related issue in ANN model building is how large the training and/or test sample sizes should use. 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 (1992) found that neural network models do not necessarily require large data sets to perform well.

3.2 *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. The neural network used in this paper as described in Section 4, uses a univariate time series data set. 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:

$$y(t) = f\big(y(t-1), \dots, y(t-d)\big) \quad (3)$$

Where yt 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 nonlinear 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 three subsets in the network for training, validation 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.

4 CASE STUDY

The methodology described in the previous section is applied to a case study of a Panamax container ship. The study aims to successfully predict future values in time, for the exhaust gas temperature of one cylinder of a two stroke marine diesel engine. The time series data collected consists of 30 hourly measurements of the cylinder exhaust gas temperature. The neural network created aims in predicting ahead for the next upcoming 5 exhaust gas temperature measurements.

4.1 *Structure of the Neural Network*

A nonlinear autoregressive dynamic neural network is used for the prediction. The data is fed as input into the network by using a transfer function. Transfer functions are used to generate output from the neuron input and are used to allow the network to learn

nonlinear and linear relationships between input and output vectors. 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. The network has one hidden layer with 8 neurons as shown in Figure 3.

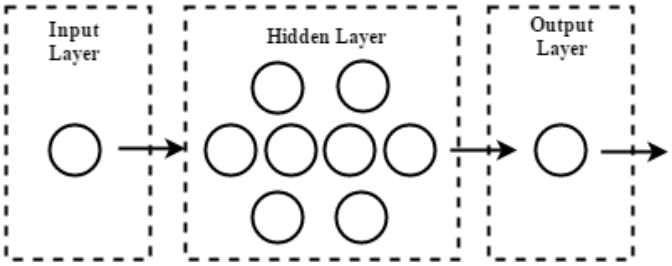

Figure 3. Open loop neural network

Then, for the multistep-ahead predictions, the open loop network is converted to a closed-loop system, by creating a feedback connection from the output to the network input, thus making the network dynamic. The first two timesteps of the input are used as input delay states in order to model the dynamic system.

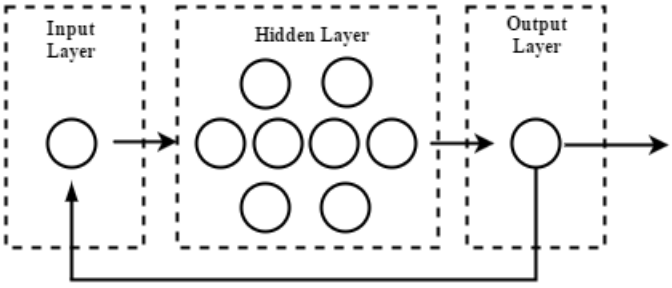

Figure 4. Closed-loop dynamic neural network

4.2 *Performance of the Neural Network*

The correlation coefficient R, regression plot, is a good measure of how well the network has fit 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 5 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.

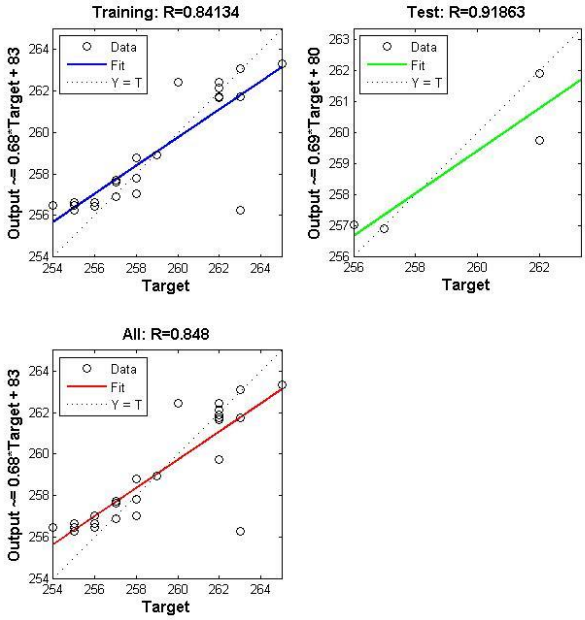

Figure 5. Regression results

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 occcur 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 center line which shows the mean squared error, all other lines should fall within the confidence limits as shown in Figure 6.

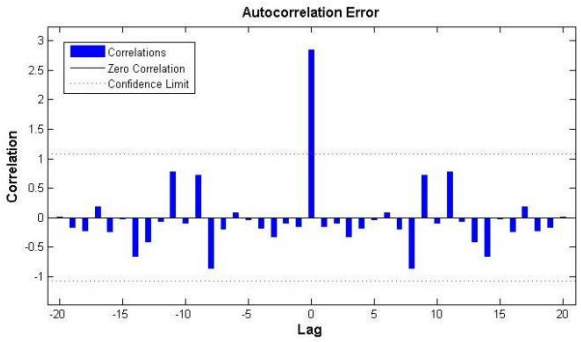

Figure 6. Autocorrelation of error

4.3 *Prediction Results*

Figure 7 demonstrates the results obtained from the network for predicting the future upcoming 5 values in time for the cylinder exhaust gas temperature. The data monitored represents 30 continuous per hour temperature values recorded. The ANN constructed, receives these values as input as a univariate time series data and attempts to predict the upcoming 5 temperature values as output. The network predicted values for the temperature are then compared with the actual values recorded onboard the vessel.

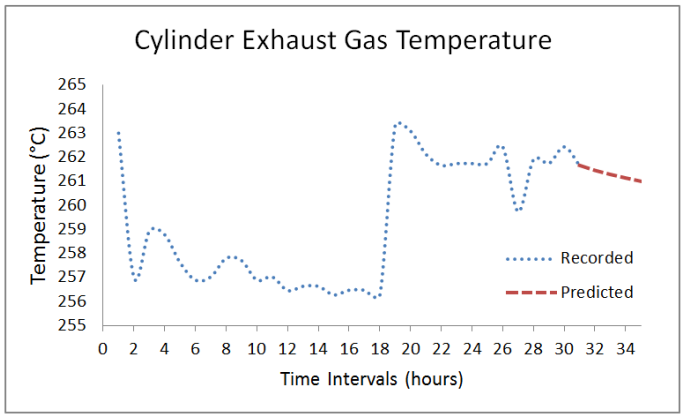

Figure 7. Exhaust gas temperature prediction graph

As illustrated in Figure 7, 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 load. This is due to the engine governor regulating the engine speed, as the vessel is also sailing at constant speed.

The network predicted values for the temperature are then compared with the actual values recorded onboard the vessel as seen in Table 1 in order to validate the network prediction accuracy

Table 1. ANN prediction results versus actual results

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%

As seen from Table 1, the error difference between the values indicate that the predicted values are extremely close to the actual monitored temperature values recorded onboard the vessel, thus verifying the performance and accuracy of the trained network.

5 CONCLUDING REMARKS

ANNs are capable of providing accurate time series predictions. They learn from past examples and capture subtle functional relationships among the data even if the underlying relationships are hard to describe or unknown. They do not rely on priori principles or statistics models and can significantly simplify the model synthesized process. Moreover, the methodology described can be applied to a various number of equipment simultaneously in order to obtain an overall prediction model. Because neural networks are a data-based method, they are universally applicable to systems from different industrial application fields. 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. Another closely related issue in ANN model building is, what is the best way to split up the data, and how large the training and/or test sample sizes should be.

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 onboard 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 ANN constructed received these values as input as a univariate time series data and predicts the upcoming temperature values as output. The network predicted values for the temperatures are then compared with the actual values recorded onboard the vessel which indicated that the

network is capable for time series analysis and has good predictive capabilities.

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.

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