Prognostics Framework for Remaining Life Prediction of Cutty Sark Iron Structures

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ABSTRACT

The Cutty Sark is undergoing major conservation to slow down the deterioration of the original Victorian fabric of the ship. The conservation work being carried out is "state of the art" but there is no evidence at present for predictions of the effectiveness of the conservation work 50 plus years ahead. A Prognostics Framework is being developed to monitor the "health" of the ship's iron structures to help ensure a 50 year life once restoration is completed. This paper presents the prognostics framework being developed using three prognostics approaches: Physics-of-Failure (PoF) models, Data-driven methods and a fusion approach integrating both former approaches. "Canary" and "Parrot" devices have been designed to mimic the actual mechanisms that would lead to failure of the iron structures. A PoF model based on decrease of corrosion rate over time is used to predict the remaining life of an iron structure. Mahalanobis Distance (MD) is used as a precursor monitoring technique to obtain a single comparison metric from multiple sensor data to represent anomalies detected in the system which could lead to failures. Bayesian Network models integrating remaining life predictions from PoF models with information of possible anomalies from MD analysis, are used to obtain more accurate predictions of remaining life. As a demonstration, PoF models and MD analysis are applied to a pair of "canary" and "parrot" devices for which corrosion data was generated using temperature, humidity and time as the factors causing corrosion.*

1. INTRODUCTION

The Cutty Sark is a composite-built vessel with a wrought iron frame and teak and rock elm strakes fastened to it. Conservation work is currently being carried out due to extensive deterioration of the wrought iron frame and timber planking (Campbell, 2005). On completion of the conservation work, a decision support system will be put in place to monitor and predict the "health" of the ship's iron structures in the future. The decision support system will be built upon the prognostics framework to achieve these aims. Corrosion is the main cause of deterioration of the wrought iron framework. Various forms of corrosion are prevalent on Cutty Sark and monitoring of the rates of these different corrosion types is a challenge. Common intrusive measurement techniques have high risk of damage to the Victorian fabric of Cutty Sark structures. Additionally, information on the corrosion of wrought iron structures in the literature is scarce. There is are few models that attempt to predict corrosion rate due to different influencing factors such as relative humidity, temperature, time of wetness, chloride concentration and other contaminants in the environment.

The aim of this paper is to present the prognostics framework being developed for the iron structures of the Cutty Sark. This paper is organized into the two main sections. The first section describes the prognostics framework along with the different methodologies integrated within. The second section provides a demonstration of the prognostics framework developed.

2. PHM APPROACH FOR CUTTY SARK IRON STRUCTURES

The prognostics and diagnostics terminologies are used to describe the broad range of processes which aim to determine material condition at present time and also at a later predetermined time. Diagnostics is the process of determining the current state of a system (Hess et al., 2005) while prognostics is the process of predicting its future state.

2.1 Overview of Prognostic Methodologies

The environmental conditions and lifecycle loads under which a system is subjected to are not usually taken into account by commonly used reliability prediction methods. Prognostics and health management approach accounts for environmental conditions and lifecycle loads subjected to a system to assess the current and future "health" of a system (Pecht et al., 2007). The prognostic techniques employed for the Cutty Sark can be classified into the following (Kumar and Pecht, 2007):

1. *Canary Devices:* These are prognostic devices integrated into a specific system incorporating the same failure mechanisms as the embedded system, but failing at a faster rate than the actual system.

2. *Physics-of-Failure(PoF):* Failures in a system are usually due to the processes occurring within and around the system. The PoF methodology aims to carry out prognostics by first calculating the cumulative damage accumulation due to various failure mechanisms within a particular environment of a system and then analyzing this information to give predictions of remaining life of the system.

3. *Precursor Monitoring and Data Trend Analysis:* Two main steps are involved: (i) FMEA to identify the precursor variables for monitoring, (ii) Development of a reasoning algorithm to correlate the change in the precursor variable with the impending failure.

4. *Data-Driven Methods:* These methods are typically derived from machine learning techniques such as (i) models that establishes a set of interconnection relationships between input and output where the parameters of the relationship are adjusted with more information, (ii) detection algorithms that learn a model of the nominal behaviour of a system and the indicates an anomaly when new data fails to match that model (Vichare and Pecht, 2006).

2.2 Prognostic Framework for Cutty Sark Iron Structures

The Prognostic Framework for *Cutty Sark* Iron Structures is based on the model shown in Figure 1. Descriptions and details of how the three main prognostics approaches, as mentioned in section **2.1,** will be used to predict the "Health" of *Cutty Sark* iron structures are discussed in Sections 3-6.

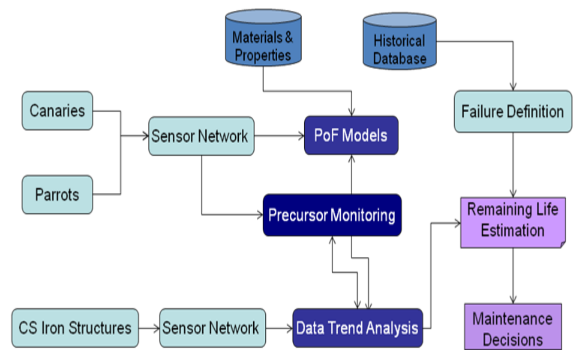

Figure 1: Prognostics Framework for Cutty Sark Iron Structures

3. CANARY AND PARROT DEVICES

3.1 Origin of Canary Devices

The word "canary" is derived from one of the coal mining's earliest systems for warning of the presence of hazardous gas using the canary bird. Because the canary is more sensitive to hazardous gases than humans, the death or sickening of the canary was an indication to the miners to get out of the shaft. The canary thus provided an effective early warning of catastrophic failure that was easy to interpret (Vichare and Pecht, 2006). In PHM, the same idea is used such that canary devices are used in the actual systems providing advance warning of failures. Canary devices are accelerated devices which will fail according to similar failure mechanisms to that of the actual system being monitored and will fail faster than the actual system under the same environmental and operational loading conditions, thus providing an early warning of failure.

3.2 Design of Canary and Parrot Devices for Cutty Sark and HMS Warrior

A similar methodology will be implemented for the prognostics framework of Cutty Sark iron structures, the main purpose of which is to provide an awareness of the onset of degradation mechanisms before any major failure of the iron structures occurs. Along with Canary devices, Parrot devices have been introduced to be used in situations where the quantitative measurements on the actual system are hard to obtain. The parrot devices are built with similar material and represent the same configurations of the actual iron structures.

Trials of the Canary and Parrot Devices are currently being commissioned on HMS Warrior for a one year period. These Canary and Parrot devices will be placed in pairs in locations experiencing different environmental conditions within HMS Warrior.

The degradation of the canary devices will be assessed using accelerated testing and the degradation levels will be calibrated and correlated to the degradation levels of the parrot devices which in turn will be calibrated and correlated to the actual failure levels of the iron structures.

4. PHYSICS OF FAILURE MODEL FOR CUTTY SARK IRON STRUCTURES

Physics-of-Failure methodology is based on the principle that failures result from fundamental mechanical, chemical, electrical, thermal and radiation processes. The Physics-of-Failure model used here predicts remaining life with regard to deterioration due to corrosion. Corrosion is the main cause of failure for Cutty Sark iron structures.

PoF models for Cutty Sark would ideally incorporate most of the environmental and operational loads identified as influencing factors causing corrosion (e.g. environmental loads, relative humidity, temperature, chloride ion concentration, external support structure, operational loads, material properties and geometry). However there are few such models which have been investigated and developed to date. Hence the generic "Linear Bi-logarithmic Law" for atmospheric corrosion (Pourbaix, 1982) is used as a starting point for the PoF model for Cutty Sark structures.

4.1 Linear Bilogarithmic Law for Atmospheric Corrosion

The Linear Bilogarithmic Law for Atmospheric Corrosion first introduced by Pourbaix (Pourbaix, 1982), represents corrosion rate as a function of time based on the understanding that the buildup of corrosion products often tends to reduce the corrosion rate over time according to Eq. (1),

$$P = At^{B} \qquad (1)$$

Where P is corrosion penetration, t, exposure time, A, corrosion during the first year and B, a measure of long term decrease in corrosion.

5. DATA-DRIVEN METHOD: MAHALANOBIS DISTANCE ANALYSIS

5.1 Overview of Data Driven Methods

Data-driven methods encompass algorithms that learn models directly from the data rather than using a hand-built model based on human expertise. (Schwabacher, 2005) Common approaches feature the following: (i) variants of neural networks, (ii) fuzzy logic, (iii) Bayesian networks, (iv) Support Vector Machines and (v)various types of anomaly detection algorithms. While application of these approaches in industry have been successful to a certain degree for diagnostics purposes, implementation of these approaches for prognostics purposes is still very much at an exploratory stage.

5.2 Precursor Monitoring using Mahalanobis Distance Analysis

A precursor indication is usually a change in a measurable variable that can be associated with subsequent failure. (Vichare and Pecht, 2006) Failures can then be predicted by using a causal relationship between a measured variable that can be correlated with subsequent failure. Prediction of remaining life using PoF models very often encompasses significant uncertainties due to inaccuracy of the model itself, inaccuracy in measurement processes and varying environmental and operational loads which might not have been taken into account in the model. Precursor monitoring becomes an essential tool in determining the current "health" of a system and also providing an indication of anomaly developing which can affect remaining life.

For the scope of this work, the following precursor variables have been identified: weight change, dimension change and electrical resistance. Data Trend Analysis is carried out to predict any impending failure using Mahalanobis Distance analysis (MD). It is a distance measure based on correlation between two or more variables from which patterns can be identified and analysed. Using Mahalanobis Distance, a single metric can be obtained from data from multiple sensors for various performance factors to represent anomaly from a system.

6. BAYESIAN NETWORK MODELS FOR PROGNOSTICS FRAMEWORK

Bayesian Network (BN) is currently being investigated as a tool for integrating information processed from model-based and data-driven techniques used for this work into the prognostics framework. A Bayesian network is a probabilistic graphical model that represents a set of variables and their probabilistic independencies. Bayesian networks are usually used to represent the probabilistic relationships between cause and effect. Nodes represent the various variables of the system (defined over all its possible states) and the connecting arrows indicate the causality between these variables. Bayesian Networks are based on the Bayes' Rule in Eq. (2):

$$\boldsymbol{P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}} \qquad (2)$$

An integration of model-based and data-driven prognostics is proposed for the prognostics framework with the aim of addressing the following issues. A certain degree of uncertainty in the prediction of remaining life from PoF models for corrosion prevails due to the lack of understanding of the complex processes involved in corrosion of iron structures. Calibration of the canary and parrot device devices will not always be possible. Good training data is required for data trend analysis of precursors to deliver reliable results of anomaly detection. Bayesian Network models have been developed for the canary/parrot device pairs. Further description follows in section 7.

7. DEMONSTRATION OF PROGNOSTICS FRAMEWORK UNDER DEVELOPMENT

The following subsections describe an example which has been set up to demonstrate the methods described in the previous sections.

7.1 Setup for Demonstration

A dataset of corrosion rates based on a range of relative humidity, temperature and time was generated (Figure 2) and is used to test the prognostics framework as shown in Figure 3.

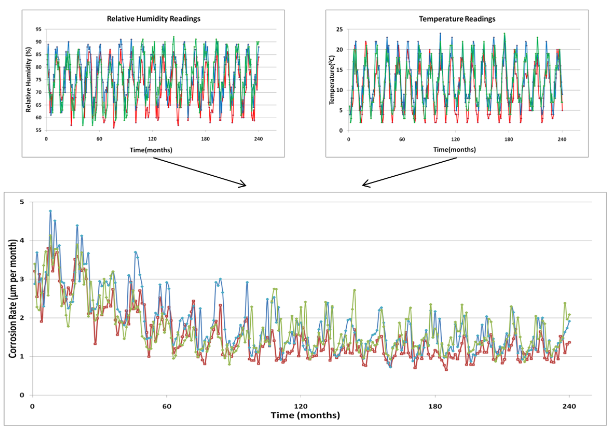

Figure 2: "Real" Corrosion Dataset generated

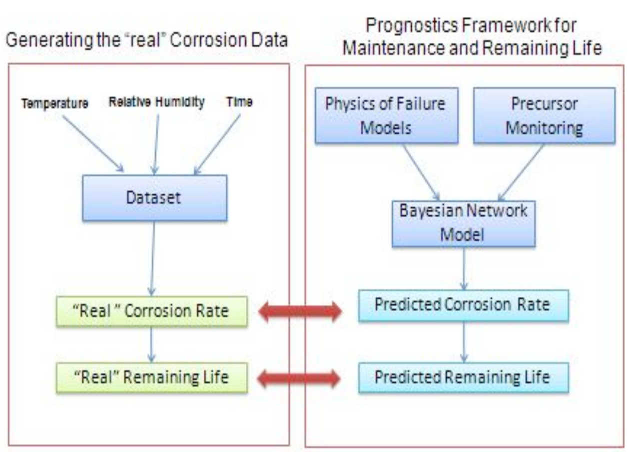

Figure 3: Using generated "Real" Corrosion Data to develop and test the Prognostics Framework

The prognostics methodologies are tested for a parrot device (L= 20000 µm, W= 10000 µm, D= 12000 µm, wrought iron material) and a canary device (L= 20000 µm, W= 10000 µm, D= 6000 µm, wrought iron material) as shown in Figure 7, under two scenarios:

- Scenario 1 (Normal): normal relative humidity and temperature conditions provide 20 years of life for the parrot and 5 years for the canary.
- Scenario 2 (Mixed): normal conditions during the first 8 years, then harsher conditions after 8 years, resulting in 16 years life for the parrot device

7.2 PoF Model: Linear Bilogarithmic Law to determine remaining life of Canary and Parrot devices

The PoF model discussed in Section 4.1 is used to predict remaining life of Canary (Scenario 1) and Parrot (Scenario 1 and 2) devices. Corrosion data generated for the first year is used to determine A and B using linear regression on Eq. (3):

$$\ln(P) = \ln(A)+B\ln(t) \qquad (3)$$

For this demonstration, assuming failure in a canary or parrot device is defined as the corrosion penetration being more than 3% of the initial depth of the device, the predicted remaining life of the device can then be calculated using Eq. (4):

$$t= e^{(\ln(0.03*D)-\ln A)/B} \qquad (4)$$

This process is repeated each year to update the predicted remaining life of the devices. In Figure 4, the first few years show predictions of remaining life considerable lower than expected which is due to the higher rates of corrosion occurring in the first few years, thus predicting a shorter remaining life. Afterwards, the predicted remaining life is very close to the "actual" life for the parrot. In Figure 5, the predicted remaining life changes trend after 8 years reflecting the changes in environmental conditions causing failure in the parrot earlier than predicted earlier.

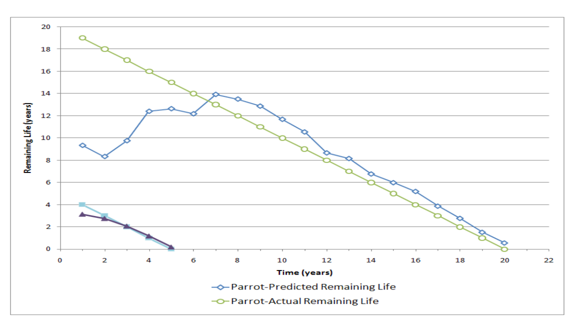

Figure 4: PoF for Canary and Parrot Devices under Scenario 1

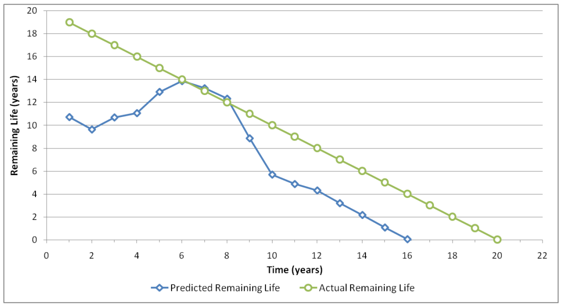

Figure 5: PoF for Parrot Device under Scenario 2

7.3 Mahalanobis Distance Analysis of precursors for Canary and Parrot devices

Mahalanobis Distance analysis is carried out for both canary and parrot devices using the following precursors: (i) dimension change rate, (ii) weight change rate, (iii) electrical resistance change rate and (iv) time. Equation (5) calculates the square of the Mahalanobis Distance:

$$\boldsymbol{D}^2 = (\boldsymbol{x}-\boldsymbol{m})^T \boldsymbol{C}^{-1}(\boldsymbol{x}-\boldsymbol{m}) \qquad (5)$$

Where D^2 is Mahalanobis distance, x, of data from sensors for observed parameters , m, vector of mean values of independent variables from training set and C^{-1} , inverse covariance matrix of independent variables from training set.

The data from the four precursors obtained from the dataset for scenario 1 (considered to represent ideal environmental conditions) over a year is used as training sets for parrot and canary device to obtain a threshold MD value. MD Analysis of precursor values for Scenario 2, for both canary and parrot devices is carried out. MD Values higher than the threshold value indicates anomalies in the system.

Figure 6 shows the graph of MD values over time for the training set for canary device where a threshold value of 7 was selected.

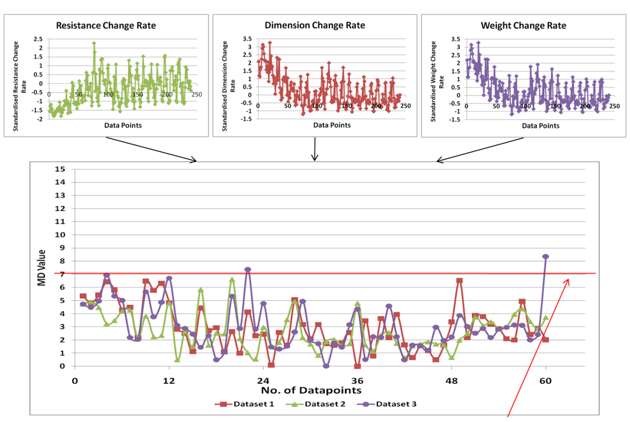

Figure 6: MD Analysis of Training Set for Canary Device

Figure 7 shows how the MD value stays within the MD threshold limit as expected during the first year (Scenario 2). But after the first year, the MD values are consistently above the MD threshold value due to harsh conditions (Scenario 2) resulting into higher values from precursors for the canary device.

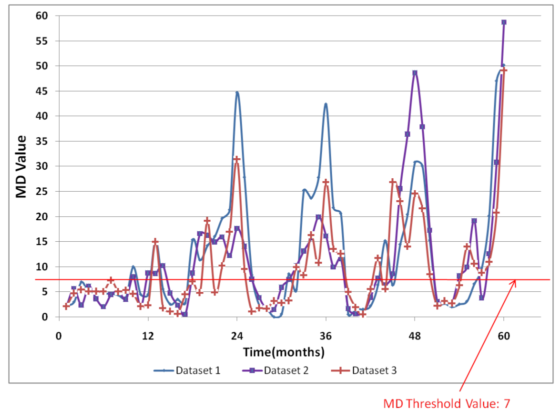

Figure 7: MD Analysis of Canary under Scenario 2

7.4 Using Bayesian Network models to update predicted remaining life of iron structures

A Bayesian Network model has been built with the aim of integrating information processed from model-based and data-driven prognostics to obtain updated predicted remaining life of the iron structures. Remaining life predictions from PoF models provide input for the top layer nodes representing the causes of failure. Mahalanobis Distance Analysis results provide information for the bottom layer presenting the effects of failure. The nodes in the middle layer represent the remaining life prediction of the canary and parrot device as well as that of the ship iron structure. Two additional nodes are representing time are include into the model to account for the point in time at which the model will be run.

Figure 8 shows a Bayesian network model for Cutty Sark. The distribution of predicted remaining life from the PoF models represents the factors influencing the remaining life prediction for the canary and parrot devices. The sensor data indicating the current "health" of the canary and parrot devices are processed using MD analysis of which the distribution of MD values are fed into the Bayesian network.

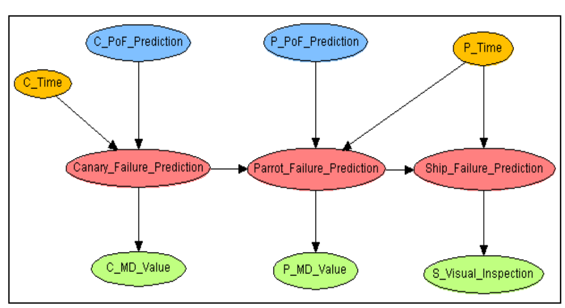

Figure 8: Bayesian Network Model for Cutty Sark Iron Structures

The following two graphs show preliminary results of the Bayesian Network model built. At a predefined time interval, the updated probability distributions (for nodes representing PoF and MD for Canary/Parrot devices) are fed into the BN model. The BN model then computes the new probability distributions for (i) canary failure prediction, (ii) parrot failure prediction and (iii) ship iron structure failure prediction. Figure 9 shows the graph of the probability distribution of remaining life of a "healthy" iron structure (experiencing normal environmental conditions throughout its life) over time. Figure 10 shows the graph of the probability distribution of remaining life of an "unhealthy" iron structure (experiencing harsh environmental conditions throughout its life) over time.

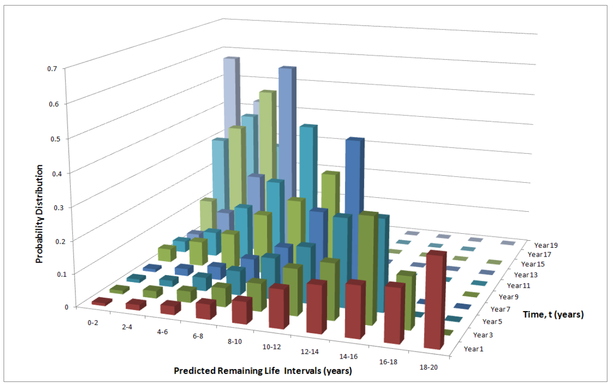

Figure 9: Probability Distribution of Remaining Life of "Healthy" Iron Structure over time

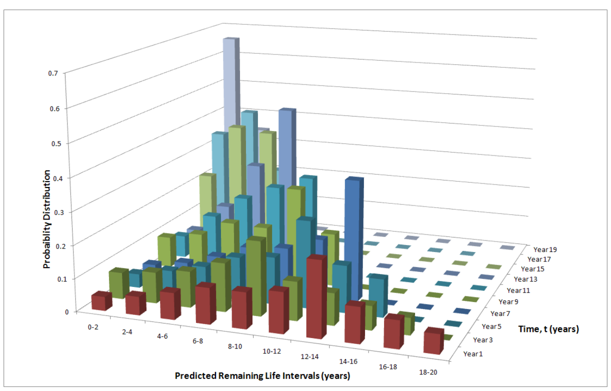

Figure 10: Probability Distribution of Remaining Life of "Unhealthy" Iron Structure over time

8. CONCLUSION AND FUTURE WORK

A prognostics framework using the model-based and data-driven prognostics as well as a fusion of both has been presented. The concept of canary and parrot devices have been introduced with the aim of gathering useful information on the behaviour of *Cutty Sark* iron structures in different environmental conditions. The main methods used within the prognostics framework has been demonstrated: a Physics-of-Failure model based on rate of decrease of corrosion rate over time was used to predict remaining life of the canary and parrot devices and Mahalanobis Distance Analysis was carried out on failure precursors for both canary and parrot devices to detect high corrosion rates of the iron structures. Various complex corrosion processes contribute to the deterioration of iron structures. Thus the prediction of remaining life of iron structures would benefit best from a prognostic framework that can capture the different forms of failure that can occur as well as make predictions of the future "health" of the iron structures with consideration of the many influencing factors contributing to those failures. Bayesian Network has been used to integrate remaining life prediction from PoF models and anomaly detection from data trend analysis of precursors to give more accurate predictions while handling the uncertainty in those predictions in a mathematically rigorous manner. Future work involves extending the PoF models and the reasoning algorithms used for the data trend analysis of the failure precursors. A dynamic version of the current Bayesian Network model will also be investigated.

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