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Application of Monte Carlo Techniques with Delay-Time Analysis to Assess Maintenance and Inspection Policies for Marine Systems

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Abstract: This paper presents a methodology applying Monte Carlo methods with delay-time analysis to test the effects of scheduled maintenance and inspection actions on factors affecting the operational efficiency of a marine system which is subject to degradation. The aim is to demonstrate how a Monte Carlo model incorporated into delay time analysis can be used to predict the transition behaviour of a system under analysis. The model presented in this paper focuses on the effects on system failure probability and downtime of various maintenance and inspection policies. The impact on spare part requirements is also investigated.

Keywords: Monte Carlo Analysis, Delay-Time Analysis, Marine, Maintenance, Inspection, Spare Parts

1. Introduction

Maintenance and inspection policy is an important part of any study assessing Reliability, Availability, Maintainability and Safety (RAMS). A number of papers are available on the subject of maintenance optimisation and decision making for engineering systems[1-10]. Maintaining key systems contributes substantially to the effective operation of a marine vessel. Maintenance can be described as a combination of all technical and administrative actions, including supervision actions, intended to maintain or restore a state in which the system can perform its required function[11].

Due to the large number of factors which may affect maintainability it is difficult to optimise maintenance and inspection policies for a given system. As well as aspects such as system unavailability and crew costs additional factors must be considered to ensure that the implementation of maintenance and inspection policies are not overly detrimental to productivity. Factors such as the effective stocking of spare parts can have a major influence on system operation due to factors such as downtime which may be incurred as a result of having insufficient spare parts for repair[12]. Spare part stocking is especially important in the marine industry as vessels will often operate in remote locations where the ordering of additional parts is not desirable. As well as ensuring that sufficient numbers of spare parts are available should a fault occur, it is important not to over stock due to limited space and cost factors.

The degradation of components is also an important factor when assessing the maintainability of a system. A common method for modelling degradation is to plot the life cycle of a component using a

Weibull distribution[3,13,14]. However, extensive data is required to produce an accurate Weibull distribution and this data is not always readily available. Other methods have been proposed using simulation to model the degradation of a system[15,16]. These methods are of particular interest to the marine industry as it is difficult to obtain sufficient data, concerning reliability, over the life-time of marine systems due to uncertain operating conditions.

A Monte Carlo (MC) model has been developed previously to assess the efficiency of a marine cooling system[17]. The MC model provides reliability data such as system failure probability, downtime and maintainable item contributions taking into account the complex nature of the systems transition behaviour. A method is also included in the previously developed model which determines the failure mode of a given transition. This updates the repair time of components based on the failure mode rather than relying on deterministic repair times. The model was found to produce accurate results for system reliability as well as useful information regarding spare part requirements.

The model presented in this paper develops this MC model by focusing on modelling the effects of scheduled maintenance and inspection actions within the system transition logic. Additionally a method of modelling component degradation has been added and the manner by which spare part stock is assessed has been modified. It has already been shown in previous papers that MC methods can be a valuable tool for the optimisation of maintenance and stock policies for deteriorating systems[15,16,18]. To implement the proposed model MC sampling has been applied in conjunction with an adaptation of Delay-Time Analysis (DTA). The model is intended to realistically assess the effects of maintenance and inspection actions in a single model by allowing said actions to have a direct effect on the analysis of the system under consideration.

2. Background

2.1 Delay - Time Analysis

Currently the most commonly used methods for reliability and maintenance studies are based on the concepts of mean time to failure (MTTF), or mean time between failures (MTBF). These methods can often be unreliable due to the fact that they rely on data that can be inaccurate and can produce unrealistic estimates for reliability data. These methods can often lack sufficient testing verification or validation[19].

The methods of implementation for the inspection algorithms used in the model presented in this paper, draw largely from DTA and are applied using simulation. DTA is an alternative method for analysing inspection policies which provides engineers with a tool to help minimise system downtime as well the downtime of individual components within the system. DTA achieves this by introducing the idea of periodic inspection intervals. If the way in which defects arrive can be modelled along with their associated delay-times, the DTA concept can be applied to understand the relationship between inspection frequency and system failures[20-22]. Fig 1 illustrates how DTA models the behaviour of component failures.

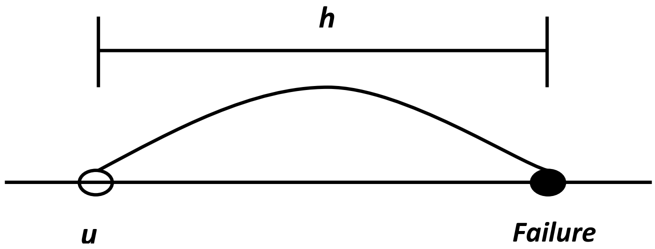

Fig 1: Diagram illustrating Delay-time concepts [Adapted from Christer[19]].

In Fig 1 *u* represents the initial 'tell-tale' time at which signs of a fault may be detected and *h* represents the 'delay-time' from the point *u*, to a failure occurring. The point *u* is used to model the arrival rate of defects and the value of *h* determines the amount of time in which a fault may be detected before propagating to failure. When using DTA to assess inspection policies it is assumed that if an inspection occurs within the period, *h*, the fault is detected and a failure is prevented incurring a significantly reduced downtime for repair. By modelling the failure pattern of a system in this way DTA can compare different inspection policies to determine the best option for detecting the greatest amount of faults. Performing a comparison of the different options allows inspection policies to be implemented such that system reliability and availability are optimised. In the model presented in this paper DTA is applied by using MC sampling to model the arrival rate of failures to determine the arrival rate of defects and the initial point, *u*. In standard DTA the opposite is true such that the point, *u*, is used to determine when a failure will occur. For this reason the method for analysing inspection policies presented in this paper has been dubbed 'reverse – DTA'.

DTA has been previously applied using MC methods by Cunningham et al[11]. The process was separated from the rest of the model focusing only on the applicability of MC methods to DTA. Cunningham et al[11] use MC to facilitate DTA looking at both perfect and imperfect inspections. The model presented by Cunningham et al[11] can be considered in two parts. MC is used to generate arrival rate of defects and delay-times values. The analysis of optimum inspection intervals is considered separately.

The model presented in this paper contains the DTA algorithm within a larger MC simulation. This is so that the process is contained within the modelling of the system and therefore affects the transition logic of the system depending on the outcome of the DTA. Rather than gathering failure data and applying DTA manually the inspection actions taken are intrinsically linked to the system behaviour. This means that the DTA process directly affects the downtime and reliability of the system. The system is modelled such that inspection actions are being carried out throughout the course of the mission time rather than looking at effects of inspection actions after the analysis has been performed. This means that the inspection policy itself can have an effect on the arrival rate of defects.

An assumption of constant arrival rate of defects, k_f, is reasonable for systems that have been running for a long enough period to be considered mature. This assumption is based on the idea that repair actions are perfect. When applying DTA with the assumption of perfect repair this is considered to be the case and the value, k_f, follows a Homogeneous Poisson Process (HPP). The parameters for standard DTA are defined by Christer & Wang[20] in detail.

The model presented in this paper considers repair actions taken upon inspection to be imperfect. In this model DTA is applied in a different way to standard models. This is because the arrival of failures is determined first and the model works backwards to determine when signs of defect were apparent based on the value, *h*. The arrival of failures is obtained using MC analysis based on the failure rate, λ, which varies due to the degradation present in the model. Brown & Prochan[23] suggest that imperfect repair should be considered for models looking at 'minimal repair at failure'. When defining scheduled maintenance actions within the current model, repairs are considered perfect and λ is set to 'as good as new'. This is not true for repair upon inspection, as it is considered that 'minimal repair' actions are taken. For this reason repair actions upon inspection are considered to be imperfect meaning that the arrival rate of defects follows a Non-Homogeneous Poisson Process (NHPP). As with standard DTA it is assumed that inspections are perfect such that faults present upon inspection will always be identified.

In standard DTA it is assumed that downtime is incurred upon inspection regardless of whether a fault is detected. This is because operational research is performed upon inspection meaning the dissection of certain parts is required. In the model presented in this paper it is assumed that all inspections are purely observational meaning that downtime is only incurred if a fault is detected and repair actions are required.

2.2 Degradation of Components

A common assumption in reliability studies is that of constant failure rate when analysing components during their 'steady state' period. Though work has been done on modelling degradation of components much of it requires significant historical data making it difficult to implement accurately[3,13,14,28]. Alternative approaches have been found however, using MC methods to model random degradation by sampling from a distribution that is a function of the failure probability of the component under analysis[16-17]. These models randomly update the degradation of components at different intervals making it possible to assess when the component reaches a predetermined degradation threshold at which the component is considered failed.

The study performed by Barata et al[15] models degradation as a function of the failure rate. A degradation threshold is set based on a failure rate that is considered unacceptable for the component under analysis. The study performed by Cadini et al[16] uses similar methods to suggest a model for condition-based component replacement based on degradation of active components.

Ideas have been drawn from Cadini et al[15] and Barata et al[16] so that a method for determining random degradation can be incorporated into the model presented in this paper. A calculation has be implemented which is used to assess the degradation of the component which is undergoing transition. Based on the level of degradation the manner in which the system transitions, is altered. A model for random degradation has been included as degradation gives additional depth to the model. By taking into account degradation other aspects of the system behaviour such as repair actions are given increased practical meaning within the model.

3. Methodology

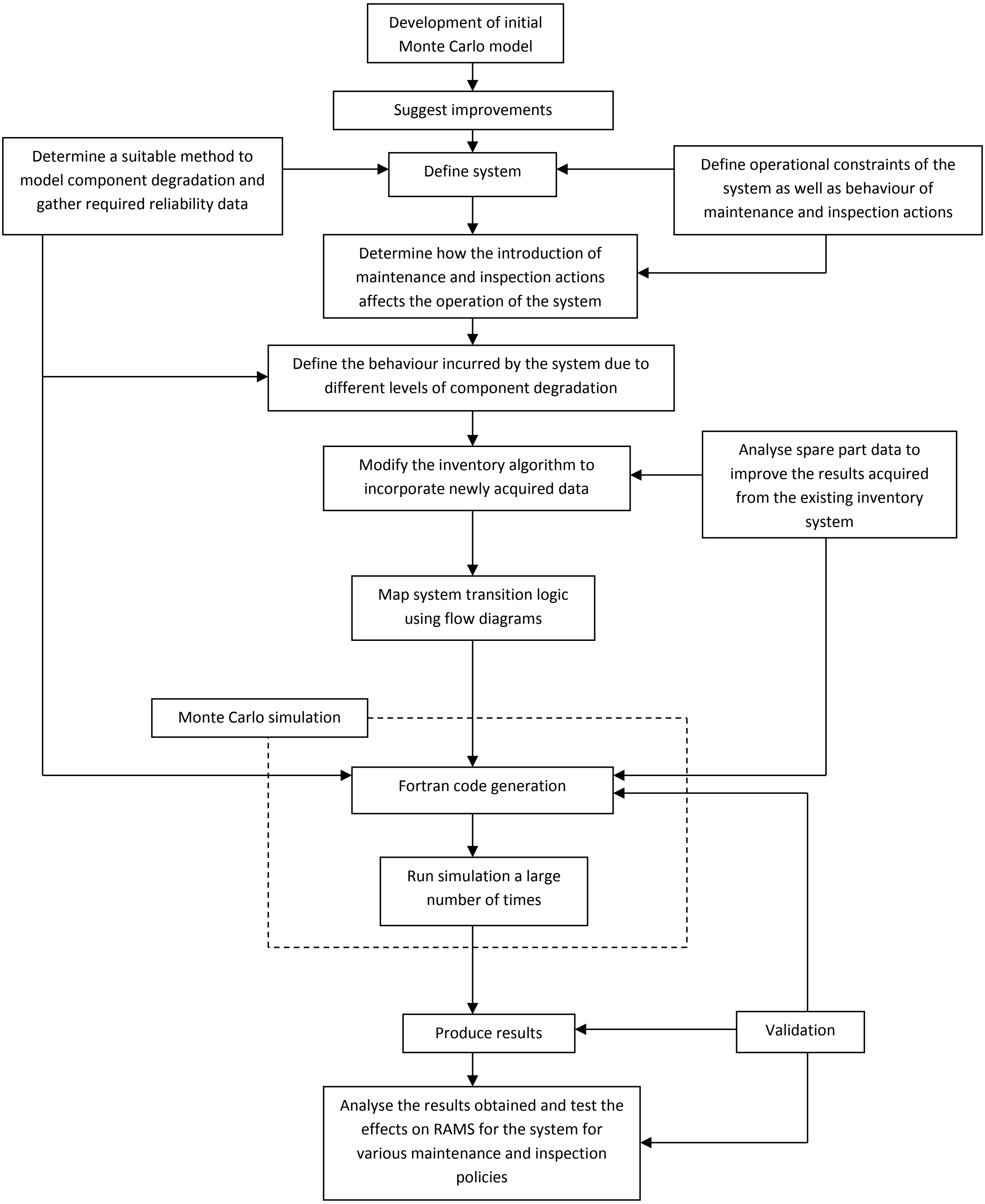

Fig 2: Process of development for proposed Monte Carlo maintenance model.

Fig 2 illustrates the development of the proposed model. After the development of the initial MC model a number of improvements have been suggested to increase the scope of the model for decision making purposes. In order to model the effects of maintenance and inspection policies as well as component degradation a number of additional techniques must be defined. Additional data is also required for the improvement of the previously developed inventory system to assess spare part requirements.

3.1 Defining the System

The general constraints for the system behaviour of the model presented in this paper are defined by the logic of the initial MC model. A simple system is used to demonstrate the logic of the applied methods. This system is shown in Fig 3.

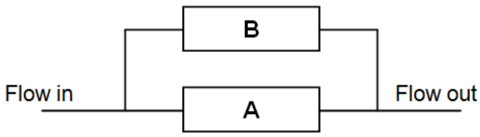

Fig 3: Diagram showing the set-up of a simple system.

The system in Fig 3 consists of two pumps each with three possible states i.e. working (*W*), failed (*F*) and 'cold standby' (*SB*). The system is defined such that only pump B can be in the state SB when pump A is working. Table 1 shows the possible states for the system. The vector **B** represents the state of the system and b_1 and b_2 represent the state of pump A and B respectively.

Table 1: System states and their associated system state vector (**B**).

B	b_1	b_2	**Flow Out?**
1	W	SB	YES
2	W	W	Yes
3	F	W	YES
4	W	F	YES
5	F	F	NO

Table 1 shows the possible states for the system defined by the MC model before the modelling of scheduled maintenance, inspection actions and component degradation has been implemented. A number of additional factors must be considered, to facilitate the implementation of the new methods as these have a significant impact of the operational constraints of the system.

Due to the nature of MC analysis a large number of trials are required to provide accurate data on item contributions for the system. To obtain accurate results the number of trials required is often in excess of 10^6. Over a number of trials a large number of failures will be attributed to each maintainable item and an average can be obtained by dividing the number of contributions by the number of trials. This is always the case when obtaining averages using MC analysis. This then shows how many of the total component failures are attributed to each specific part on average over the specified mission time. The system state vector (**B**) lists the possible states of each constituent component. Under certain conditions, a component's state can change from one to another.

3.2 Modelling Scheduled Maintenance

Over the past decade, there have been many reported developments on scheduled maintenance with reference to the use of DTA[24]. For example, a stochastic model for joint spare parts inventory and planned maintenance optimisation was proposed and demonstrated through the DTA developed for inspection modelling[25,26]. Another example is that the periodic inspection interval for systems with cold standby system was optimised using the DTA[27]. However, it is worth noting that the fundamental theory for modelling scheduled maintenance remains the same. This study uses the basic preventive maintenance theory incorporating the fundamental delay time concept.

The timing of scheduled maintenance in this model is based on system operating time rather than the operational time of each component. The desired time period between scheduled maintenance for each component must be specified to determine how often maintenance will occur during the analysis. When a maintenance action occurs the system transitions as if the component under maintenance has failed, but a failure of the component is not actually logged. After maintenance has been completed the parameters for the component are reset and it is considered to be 'as good as new'. The failure rate, λ, of the component is reset meaning degradation is set to zero, and the time of the next scheduled maintenance is set to the time when maintenance has been completed plus the predetermined period between maintenance actions. The downtime incurred by maintenance is also logged. If the component has failed it is considered that maintenance has been performed to repair the component and the values are similarly updated with the addition that a failure of the component is logged.

Before scheduled maintenance actions are analysed a random transition time, *T*, is generated by MC sampling from the initial model. The component undergoing transition is also determined by MC sampling. Once these parameters are established the model checks which component is next for scheduled maintenance. For the system shown in Fig 3 this is determined by the values *TMNA* and *TMNB* which represent the time when maintenance is scheduled for pump A and pump B respectively. The model then checks whether the current transition has occurred before or after scheduled maintenance should have been performed. For example if it is determined that pump A is due for maintenance first and the system is in the nominal state, **B** =1, the model checks if the transition time, $T > TMNA$. If the transition time, *T*, exceeds the time when maintenance should occur a transition occurs without a component failure at the scheduled maintenance time and the values are updated depending on which component is under maintenance. The initial time for the analysis, T_0, is then set to the scheduled maintenance time and the system is put back online in the appropriate operating condition. Fig 4 illustrates the process of such a transition.

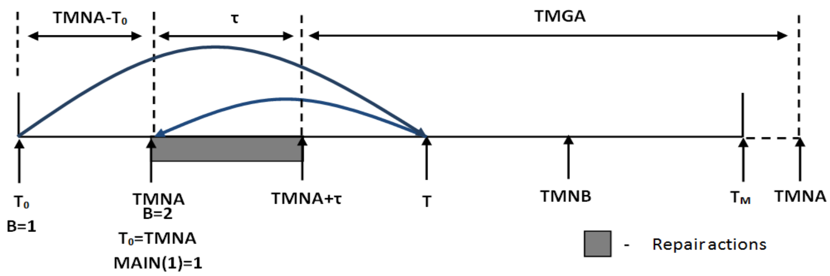

Fig 4: Example transition when scheduled maintenance is performed.

Fig 4 shows that if $T > TMNA$ the random failure obtained from MC sampling effectively does not occur as scheduled maintenance is performed beforehand. This changes the events which have occurred in the system as a transition has taken place before the randomly sampled time. In this case the initial time parameter, T_0, is set to *TMNA* and the analysis continues in state **B** = 2. Subsequent transitions will then check if pump A has become available. Once maintenance is completed the analysis continues from $T_0 = TMNA + \tau$, where τ is the repair or maintenance time. The value of *TMNA* is then updated as shown in Fig 4 where *TMGA* is the period between scheduled maintenance for pump A. In Fig 4 $TMNA > T_m$, where T_m is the mission time for the analysis, meaning no subsequent maintenance actions on pump A will be performed during the analysis period. It is assumed that if no subsequent transitions have been detected, scheduled maintenance has been performed without effect on the system.

In Fig 4 the value, *MAIN (1)* has been presented. This is a value which determines the nature of the transition of pump A. For example, if *MAIN (C)* = 1 the transition has been caused by scheduled maintenance and if *MAIN (C)* = 0 the transition has been caused by a random failure, where, *C*, is a value representing the component under analysis (i.e. *C* = 1 and 2 for pumps A and B respectively). This has been implemented to reduce the number of system states. Note that if *MAIN (C)* = 1, a component failure is not logged by the model. The addition of scheduled maintenance gives rise to a number of additional system states. This is due to the fact that each component can be in the states *W, F*, and *SB* as well as the additional case of the component being under scheduled maintenance. Table 2 shows the system states for the system in Fig 3 when maintenance is possible where, '*M*' signifies that the component is under maintenance.

Table 2: Possible system states for maintenance model test case.

B	b_1	b_2
1	W	SB
2	W	W
3	W	M
4	W	F
5	M	W
6	M	M
7	M	F
8	F	W
9	F	M
10	F	F

The value, *MAIN(C)*, allows the system states shown in Table 2 to be reduced to those presented in Table 1. Rather than defining the logic for an entirely different system state an algorithm is implemented based on *MAIN(C)* to determine the nature of the previous transition. Looking at Table 2 it can be considered that **B=**3 and **B**=4 are the same system state with certain variables modified based on the value of *MAIN(C)* from the previous transition. It is important to update this value as it can determine whether or not a system failure occurs later in the analysis. If a component failure causes the system to become unavailable and the value of *MAIN(C) =* 0 for the previous transition then a system failure, *SF*, will be logged as both components are failed. If the value of *MAIN(C) =* 1 for the previous transition however, system downtime is logged but *SF* is not updated as it is considered that the previous component is not failed as it has been taken offline voluntarily.

Consider again the case where pump A is scheduled for maintenance next. If the transition time, $T < TMNA$, then no subsequent maintenance actions have yet been performed and the system transitions as if a random component transition has occurred. If it is determined that a failure has occurred, the system will transition at T. At this point corrective maintenance is performed on the failed component in the same manner as if the component had been taken offline for scheduled maintenance. The key difference with this mode of transition, aside from the time at which the failure has occurred, is the value of *MAIN(C)*. The value of *MAIN(C)* is 0 rather than 1 showing that the component is failed rather than under scheduled maintenance. The value of *TMNA* is still updated upon the component coming back online as actions equivalent to scheduled maintenance have been performed upon the failure occurring.

The model has been defined such that scheduled maintenance will not occur if taking the component offline for maintenance will cause the system to become unavailable. If this is the case the maintenance schedule for the system is delayed by the period between the time when scheduled maintenance should have occurred and the time when a sufficient number of components are online such that taking a component offline for maintenance will not lead to system unavailability. This means that the system cannot enter a state equivalent to that of **B** = 6 in Table 2. The state **B** = 9 is still viable as the failure of pump A may occur after pump B has been subject to maintenance.

It is important that the model determines component downtimes due to scheduled maintenance between the time of last transition, T_0 and T_m where no subsequent transitions have occurred. At the end of each trial the model checks how many maintenance actions are scheduled to occur between T_0 (equal to 0 if no transition occurs previously) and T_m. Once this is established the model updates the component downtimes due to maintenance before exiting for the next trial.

3.3 Modelling Inspection Actions

When modelling inspection actions it is considered that any corrective repairs performed upon the detection of a fault incur less downtime than scheduled maintenance or random failures as only 'minimal repair' actions are performed. If a fault is identified upon inspection the repair actions performed are considered to be imperfect and the component is subject to random degradation. Unlike scheduled maintenance, inspections are performed based on the operational time of components rather than system operating time meaning that only components which are active will be inspected.

A form of DTA has been applied within the MC analysis to allow the effects of varying inspection policies to be modelled in a single analysis. Rather than generating fault occurrences, MC sampling is used to provide component failure times for the initial developed model. Using so called, 'reverse-DTA' inspections are analysed by looking at the time of failure. Then by using a predetermined h value the model works backwards to find the initial point, u. With this the model is capable of determining whether an inspection has been performed within the delay time period. Fig 5 illustrates this process.

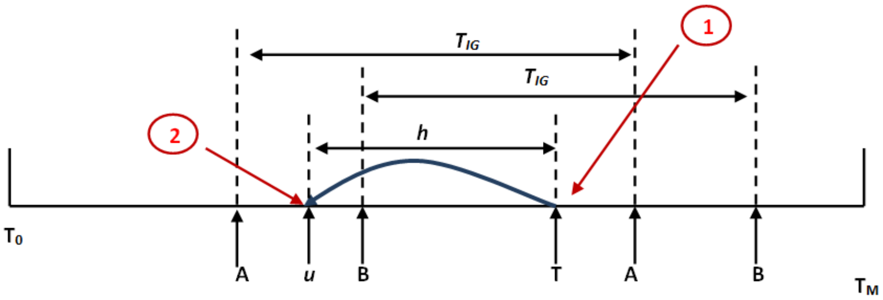

Fig 5: Illustration of inspection analysis.

At point 1 in Fig 5 the failure time, *T*, is obtained by MC sampling. At point 2 the time at which the initial 'tell-tale' sign, *u*, occurs is identified by moving backward by the value of *h*. With this established the model checks whether an inspection has been performed between *u* and *T* to determine whether the fault has been identified. The points marked 'A' represent inspection actions for a policy which would fail to identify the fault. Conversely the points marked 'B' represent an inspection policy in which the fault would be identified. Note that the value, T_{IG}, is the predetermined gap between inspection actions. The desired time between inspections must be defined to determine how often the components are to be inspected. The calculation in Equation 1 determines how many inspections will occur during the mission time.

$$NI = INT(b)(T_m \div T_{IG}) \tag{1}$$

where:
NI = No. of inspection actions throughout the proposed mission time;
T_m = Mission time for the analysis.
NB. The function, INT (b), in Equation 1 rounds the value to largest integer value not exceeding b, where b is equal to $T_M \div T_{IG}$.

The delay-time, *h*, is defined by the user based on the components within the system. When a transition occurs the current operating time of the component which has caused the transition must be determined. This is calculated as shown in Equation 2.

$$OP_C N = OP_C O + (T - T_0) \tag{2}$$

where:
OP_CN = Operating time of the component at transition time, *T* (current operating time);
OP_CO = Previous operating time of component (operating time when previous transition occurred; equals zero at start of each trial);
T = Transition Time (Actual time transition occurs within the mission time of the analysis);
T_0 = Initial Time (Actual time at point of previous transition; equals zero at start of each trial).

When considering a system with multiple components the operating time must be updated for each of the active components at the point of transition. The operational time of the component is used to determine if the latest inspection has identified a fault before a failure occurs. If the inspection fails to identify the fault the system transitions due to a random component failure at time, *T*. If the inspection identifies the fault, the transition occurs based on the level of degradation of the component. If the degradation level exceeds the maximum value it is considered that the component is equivalent to being failed and the component will transition in the same manner as if a random failure has occurred at the time the fault is detected (*FT*). If the degradation level is acceptable the component will transition at time, *FT,* but the downtime incurred is reduced by *IR*, which is the factor by which the repair time is reduced if a fault is addressed during inspection before it has propagated to failure.

With maintenance and random failures spare parts are required for repair. This is not true when corrective maintenance is performed upon inspection as it is considered that 'minimal repair' is performed as the component has not yet failed. However, as 'minimal repair' is performed the component is not 'as good as new' and the degradation level is not reset to zero[23].

3.4 Modelling Component Degradation

Intermittent data regarding the state of the components throughout their lifetime is not readily available for marine systems. Due to the lack of data for the components in this study, it is not possible to generate a suitably accurate distribution for degradation over time. A method for modelling degradation has been incorporated in the current model however, as neglecting degradation would decrease the scope of other methods which have been applied. For the purpose of this model degradation is considered to be random and is represented by modelling the degradation as a modification of the failure rate, λ, for the component under analysis. If a fault is detected upon inspection it is considered that the component is no longer 'as good as new' and the component is randomly degraded. This raises the failure rate for the component increasing the likelihood that the component will fail later in the mission time. The calculation for random degradation as a function of the component failure rate can be seen in Equation 3.

$$\lambda_M = (RD \times \lambda) + \lambda_M^* \tag{3}$$

where:
λ_M = Component failure rate modified by degradation;
λ_M^* = Component failure rate before the modification due to further degradation;
RD = Random variable, *U ~ [0,1)*;
λ = Nominal component failure rate.

Equation 3 is performed upon inspection and the value of λ_M determines the manner in which the component transitions. The degradation threshold is defined by the value λ_{MAX}. The value of λ_{MAX} represents a component failure rate which is considered to present an unacceptable risk. If, $\lambda_M \geq \lambda_{MAX}$, the component is in excess of the degradation threshold and is considered to be in a state, equivalent to failure.

If it is found that, $\lambda_M \geq \lambda_{MAX}$, maintenance is performed and the degradation is reset so that $\lambda_M = \lambda$, representing that the component is 'as good as new'. This also occurs if repairs are performed on the component due to scheduled maintenance or corrective maintenance following a random failure. Though maintenance is performed if a fault is found upon inspection, the value of λ_M remains the same due to the 'minimal repair' actions performed. This presents a downside to inspection repairs as the system will be operating at a reduced level of reliability for a longer period of time.

Modelling degradation in this way gives scheduled maintenance actions additional meaning within the model. By resetting the degradation upon scheduled maintenance it means that the risk of taking a component offline for a period of time can have a positive effect on the long term reliability of the system.

3.5 Modification of Inventory System

An inventory system has been previously developed using MC sampling and data from an OREDA study[29] to provide results for the contribution of specific replacement parts within a system[17]. The initial model has limited scope due to incomplete data and the fact that only one replacement part is attributed to each failure. The number of replacement parts for a maintainable item is usually much smaller than 1 (i.e. << 1) within the mission time[17]. Additional data has been gathered and modifications have been made to increase the scope of this inventory system.

Improved data has been acquired from OREDA[30] in which the information on part contributions is more comprehensive than that used previously. Due to the fact that the data has been acquired has been taken from offshore installations certain item contributions have been omitted as some factors do not apply to components operating specifically in the marine industry. Schematics for the components under analysis have been obtained showing the parts which can be replaced within each component. The parts shown in the schematics which are required for repair due to each of the item contribution stated in OREDA[30] have been determined by consulting an expert with over 15 years of experience as a chief engineer. The spare part requirements for each failure have been modelled in the system logic so that the model provides data on how many of each of the parts contained within the schematic are required over a specified mission time. It is also taken into consideration that certain items contributions require multiple parts for repairs to be performed due to ‘knock-on’ effects.

The effect of scheduled maintenance on spare part requirements has also been modelled. Certain items for each active component are always replaced during scheduled maintenance. To incorporate this into the model an algorithm has been implemented to update the number of the relevant spare parts required when scheduled maintenance is performed on a specific component.

3.6 Mapping System Transition Logic & Code Generation

Once the methods have been established it is necessary to map the system transition logic using flow charts. The previously developed MC model is used as a basis for this process but the additional methods presented significantly alter the possibilities for system transitions.

With the logic of the system determined completely, Fortran code is generated to model the processes of the newly applied methods within the system under analysis. With this complete the simulation is run for a large number of trials (N) to aggregate the results for the key parameters under analysis.

4. Case Study

The proposed model has been applied for use to optimise maintenance and inspection policies as well as spare part stocking options. The system for which the model has been applied is the main engine sea water cooling system taken from the “MV Hamnavoe”, a RO/RO passenger ferry. The component layout for the system under analysis is shown in Fig 6.

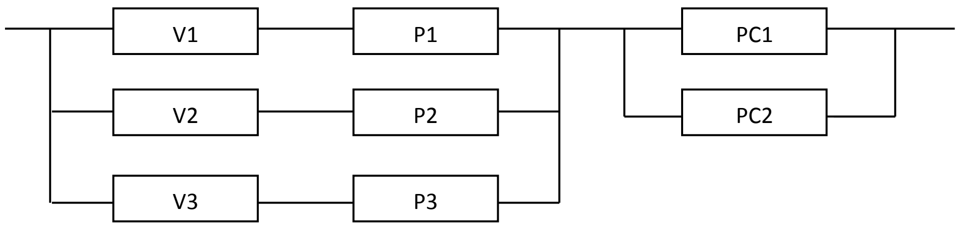

Fig 6: Simplified cooling system under consideration [Adapted from Cunningham et al [28]].

The components *V1, V2, V3, P1, P2, P3, PC1* and *PC2* represent valve 1, valve 2, valve 3, pump 1, pump 2, pump 3, plate cooler 1 and plate cooler 2 respectively. There are eight components in the system under analysis, each with three possible states, working, failed or standby (*W, F* or *SB*), giving rise to 3^8 = 6,561 system states. The state *SB* can be grouped with *W*, as although components in *SB* are offline they are still available and the transition from *SB* to *W* is instantaneous. This gives rise to 2^8 = 256 system states. Though there are 8 components only five are operating at any given time, namely two valves, two pumps and one plate cooler. The system is defined such that a minimum of two vales, two pumps and one plate cooler must be available for the system to operate properly. By considering the operational constraints and using Boolean Representation Method (BRM) the number of possible system states is reduced to 34; with 21 working states and 13 failed states. The basic logic for the working states is defined by the initial MC model with all other states resulting in system unavailability.

The failure rate for each component has been taken from OREDA[30] and the system failure rate (λ_S) is the sum of the failure rates for the active components. Each component has a number of different failure modes incurring different failure mode specific repair times and maintainable item contributions. Modifications have been made to the initial MC model to incorporate the new methods employed, but the general constraints of the system remain the same with regard to basic failures. Some key factors must be addressed when applying the proposed methods to the cooling system under analysis.

The degradation threshold must be set relating to the failure rate, λ, for each component. For this case study the system has been defined such that a component is considered failed if its modified failure rate, λ_M, is over double the nominal value (i.e. λ_{MAX} = (λ×2)). Additionally the policies for scheduled maintenance and inspection actions under analysis must be defined to determine the scope of the analysis. This is performed by defining the time between these actions so that it can be determined how often these actions occur for the system within the mission time, T_m. The value, T_m for this case study is based on an analysis period of 1 year (i.e. 8760 hours). As previously stated inspections only incur downtime if a fault is detected and the downtime incurred is significantly reduced. The value, *IR*, determining the factor by which downtime is reduced when repairs are performed pre-emptively upon fault detection is ¼ of the failure mode specific repair time. The downtime incurred by scheduled maintenance actions has been defined as slightly higher than the average repair time for each component as it is considered that a thorough analysis is performed when scheduled maintenance takes place.

For the cooling system presented, multiple component operating times must be updated upon transition whether they have caused the transition or not. This is because although they may be in a steady state they are still operational and simulated inspections are being performed without incident. For this reason the component operating times of all active components are updated by the same amount as the increase in the operational time of the component undergoing transition during the current system state.

As scheduled maintenance is performed at specified points within the mission time it means that components which are not active may still be scheduled for maintenance. When a transition occurs in the cooling system, the maintenance scheduling of all components must be checked. As scheduled maintenance causes a change in the system state vector, **B**, it is only the earliest scheduled maintenance action which affects the current transition. After the effects of scheduled maintenance have been analysed the maintenance schedule for the system is updated accordingly and the analysis continues.

An integer value, *C*, has been assigned to each component in the system which alters certain key values based on the component undergoing transition. For components *V1, V2, V3, P1, P2, P3, PC1* and *PC2* the integer value of *C* is 1, 2, 3, 4, 5, 6, 7 and 8 respectively. The value applies to the time of next scheduled maintenance action (*TMN* (*C*)), the time at which components are brought back online (*TT* (C)), the operational time of components (*OP* (C)), the component failure rates (λ (*C*)/λ_m (*C*)), component downtimes (*DT* (*C*)) and the modifier *MAIN* (*C*). This has been done to make the modelling of the system transition logic more efficient as many system states behave in the same manner with only the specific component variables being affected.

In the previously developed MC model the value for the system failure rate, λ_S, was constant throughout this analysis[17]. This is no longer true due to the degradation model. Due to degradation the failure rate for each component can be altered. This additional factor means that a calculation must be performed before the transition time, *T*, is sampled. This updates the value of λ_S to equal the sum of the failure rates of the components which are active taking into account their current level of degradation. The degradation level of individual components affects the nature of transitions by inspection as well as determining whether or not spare parts are required for repair. Unlike scheduled maintenance actions repairs are always performed if a fault is detected upon inspection regardless of the system state.

With the parameters for the analysis defined the methods can be applied to model the system transition logic of the cooling system incorporating the effects of the new methods. Though there are 21 different working states for the cooling system the transition logic can be separated into four distinct types based on the condition of the system. This is such that many of the system states follow the same patterns as others regarding logic but the variables within the logic change depending on the system state. The four working conditions affecting the transition logic for the system are defined as follows:

- Condition 1: The system is in the nominal state; all components are subject to maintenance; system downtime cannot occur directly.
- Condition 2: A single plate cooler is failed/under maintenance; maintenance actions cannot be performed on plate coolers; system downtime can be caused by an additional plate cooler failure.

- Condition 3: A single valve/pump is failed/under maintenance; maintenance actions cannot be performed on valves or pumps; system downtime can be caused by an additional failure of either a valve or a pump.
- Condition 4: A single valve/pump plus a single plate cooler are failed/under maintenance; maintenance actions cannot be performed on any component without system unavailability; the failure of any subsequent component will result in system downtime.

Any other parameters than those defined by Conditions 1-4 will result in the system being in a state other than working. This could be offline due to maintenance or failed. With this, detailed flow diagrams of each working state can be produced to illustrate the system transition logic. The logic for the system is the same for all states operating under the same condition; it is only the variables which are updated that are altered based on the specific components which have undergone transition.

Once the system transition logic has been determined for all system states, the inventory algorithm and the final calculations are applied to complete the model. The final calculations aggregate the results found during the MC analysis to provide average values.

5. Results

Results obtained by the application of the proposed model to the cooling system are now presented. Firstly the model has been applied to the same case as the previously developed MC model to test the effects of the newly applied methods. The model has then been applied to the case study in Section 4 for varying maintenance and inspection policies to assess optimal policies for the system over a specified mission time. Finally the convergence of the MC model is tested to ensure the results remain accurate for varying values of N. The reliability data such as failure rates, failure mode specific repair times and maintainable item contributions for components in the system has been taken from OREDA[30]. The data is based on ball valves, centrifugal machinery pumps and plate heat exchangers. For comprehensive data on these components consult OREDA[30]. As previously stated the downtime associated with scheduled maintenance differs from the data in OREDA[30]. The downtime incurred by scheduled maintenance actions is higher than the average downtime for each component. The downtimes for scheduled maintenance have been set to 10 hours, 30 hours and 14 hours for valves, pumps and plate coolers respectively. The reduction factor in downtime incurred for repairs upon inspection is constant for all components at ¼ of the repair time incurred by the selected failure mode.

5.1 Test Results

The first stage in gathering results is to check whether the new methods affect the model in a manner that is expected. Testing is necessary to ensure the model is working correctly before further results are obtained for analysis. This also serves as partial validation of the proposed methods. A number of result sets have been gathered from the model where certain aspects of the new methods are omitted. This is done by setting the times for maintenance and inspection intervals to much higher than the mission time, T_m. The methods are still present within the model but they have no effect on the system operation as their associated actions never occur. These tests are performed using the same operational constraints and mission time as the case for which the previous MC model was applied. The different results sets are explained below.

- Result Set 1: Scheduled maintenance and inspection actions are omitted.
- Result Set 2: Scheduled maintenance is omitted but inspection actions are included.
- Result Set 3: Inspection actions are omitted but scheduled maintenance is included.
- Result Set 4: Inspection actions and scheduled maintenance are included (Complete model).

It should also be noted that where inspection actions are omitted no component degradation is present. The mission time, T_m, for which each test is performed, is equal to 532. The number of trials, N, is set to 10^7 as this provides a suitable level of accuracy in the results. Table 3 shows the output values for key reliability data obtained for each of the result sets.

Table 3: Results obtained from various tests excluding certain aspects of the proposed model.

	Result Set 1	Result Set 2	Result Set 3	Result Set 4
FV1	1.08E-02	8.04E-03	3.39E-03	2.48E-03
FV2	2.69E-04	1.17E-04	5.04E-04	3.01E-04
FV3	1.08E-02	8.10E-03	3.72E-03	2.76E-03
FP1	4.19E-01	3.20E-01	1.31E-01	9.74E-02
FP2	1.04E-02	4.68E-03	1.94E-02	1.19E-02
FP3	4.19E-01	3.20E-01	1.45E-01	1.07E-01
FPC1	9.90E-03	7.41E-03	3.49E-03	2.54E-03
FPC2	1.00E-07	1.00E-07	3.00E-07	2.30E-07
DTV1	1.31E-01	1.06E-01	1.99E+01	1.99E+01
DTV2	3.33E-03	1.74E-03	2.00E+01	2.00E+01
DTV3	1.32E-01	1.07E-01	2.00E+01	2.00E+01
DTP1	5.06E+00	4.17E+00	8.95E+01	8.92E+01
DTP2	1.25E-01	6.82E-02	8.97E+01	8.97E+01
DTP3	5.06E+00	4.18E+00	8.91E+01	8.88E+01
DTPC1	1.39E-01	1.12E-01	1.40E+01	1.40E+01
DTPC2	1.44E-05	1.12E-05	1.40E+01	1.40E+01
DTS	1.28E-01	7.95E-02	4.57E-01	3.87E-01
FSYS	2.13E-02	1.10E-02	6.61E-03	3.23E-03
PSF	2.11E-02	1.09E-02	6.58E-03	3.23E-03

Probability of system failure (*PSF)* and average downtime of the system (DTS) are highlighted in Table 3 as they are the key values of interest for the analysis. This is because the analysis focuses on the effect to the system as a whole rather than the individual components within the system. The average number of failures for the system (*FSYS*) is also provided. Values relating to individual components are also presented. The variables *FV1*, *FV2*, *FV3*, *FP1*, *FP2*, FP3*, FPC1* and *FPC2* show the number of failures for valve 1, valve 2, valve 3, pump 1, pump 2, pump 3, plate cooler 1 and plate cooler 2 respectively. Additionally the variables *DTV1*, *DTV2*, *DTV3*, *DTP1*, *DTP2*, DTP3*, DTPC1* and *DTPC2* show the downtimes for valve 1, valve 2, valve 3, pump 1, pump 2, pump 3, plate cooler 1 and plate cooler 2 respectively. The mission time over which the analysis runs regarding the results shown in Table 3 is relatively short when considering maintenance scheduling.

Results Set 1 is the initial test with all maintenance and inspection actions omitted. When applying the same reliability data from OREDA[30] to the previously developed MC Model it is found the these results are in agreement showing that the model works correctly with the maintenance and inspection schedules set outside of the mission time. This shows that with maintenance and inspection omitted the core workings of the model remain the same despite the significant alterations to the transition logic.

With the introduction of inspections in Result Set 2 a reduction in system downtime and failure probability can be seen. The inspection intervals for this test have been set to 24 hours. The reduction is expected as inspections introduce a possibility of component failures being prevented as well as incurring a significantly reduced downtime upon taking the component offline.

With the introduction of scheduled maintenance in Result Set 3 it can be seen that while the failure probability is significantly reduced, the downtime of both the system and individual components is noticeably increased. Though this is to be expected the increase in downtime is more apparent in this test due to the relatively short mission time. With components being taken offline voluntarily the component downtimes are increased due to the fact that they will always be taken offline within the mission time. This also affects the system downtime as it means that with components being offline more frequently, if a random failure does occur, the likelihood that it will occur when another component is under maintenance is increased giving a greater chance the system to become unavailable. The increased downtime incurred by maintenance also emphasizes this effect. Though the downtime is increased the failure probability is reduced as the maintenance actions can stop the majority of component failures from occurring by performing preventative repair actions. The time periods between maintenance actions for this test have been set to 250 hours, 125 hours and 300 hours for valves, pumps and plate coolers respectively. Note that pumps are maintained more frequently due to their significantly higher failure rate; this practice has been used throughout this analysis.

Finally in Result Set 4, where the model is fully operational it can be seen that the output values are somewhat of a hybrid between Result Set 2 and Result Set 3. This is such that the system failure probability is reduced further and the system downtime lies between Result Sets 2 and 3. This is because both maintenance and inspection actions, increase the reliability of the system but have opposite effects on the downtime of the system.

As well as the reliability data shown in Table 3 the effect on spare part requirements for Results Sets 1-4 has also been observed. The most significant change to spare part requirements can be found for Result Set 3 when scheduled maintenance is added. This is because certain items are always replaced during scheduled maintenance meaning that the demand for these items is affected significantly depending on the frequency of maintenance actions. Some sample data has been taken looking at the average requirement of seals for pumps in the test cases to highlight this effect. In Result Set 1 the average requirement for pump seals is 3.21×10^{-1} whereas in Result Set 3 the requirement is increased to 8.94[17]. Also the addition of inspection actions lowers the spare part requirements slightly. This is because repairs upon inspection assume that no parts are replaced meaning there is less chance of spare parts being needed.

5.2 Case Study Results

The frequency of scheduled maintenance actions has been altered whilst keeping the frequency of inspection actions constant. The maintenance schedule is altered by changing the input variables representing the period between maintenance actions. The maintenance of pumps occurs much more frequently than the other components due to a significantly higher failure rate. The maintenance schedules have been assigned to the model with this criterion in mind. When looking at the results of the analysis shown in Figs 7 and 8 it is the maintenance interval for pumps which the results are concerned. This is because the analysis is more sensitive to the maintenance of pumps than that of valves and plate coolers due to the increased number of transitions attributed to pumps. Table 4 shows the corresponding values for the maintenance intervals of valves and plate coolers when compared with pumps.

Table 4: Showing maintenance increments used for analysis of case study.

	MAINTENANCE INTERVAL (Hours)		
	Pumps	**Valves**	**Plate Coolers**
1	720	2,000	2,500
2	1,720	3,000	3,500
3	2,720	4,000	4,500
4	4,720	6,000	6,500
5	6,720	8,000	8,500
6	9,720	10,000	10,500

Table 4 shows the maintenance intervals for each stage of the analysis. The purpose of altering the maintenance frequency in this way is to determine how it affects key output values obtained from the model. The maintenance intervals have been assigned taking into account their mean time to failure (MTTF). The initial settings for maintenance shown in the first row of Table 4 are assigned such that scheduled maintenance occurs before the MTTF. The mission time has been set to 1 year (8760 hours) for the analysis. Taking this into account the MTTF of both valves and plate coolers is much higher than the mission time used for the analysis. For this reason the maintenance intervals for valves and plate coolers are set to arbitrary values that are significantly higher than that of pumps. After the initial settings the maintenance intervals are increased by equal amounts for all components. The policy stated in row 6 of Table 4 represents a case where no maintenance actions take place as they are outside of the mission time. Inspections have been defined such that they take place every 24 hours and the delay-time, *h*, is equal to 6 hours. Figs 7 and 8 show the results of the analysis for key parameters with varying maintenance policies.

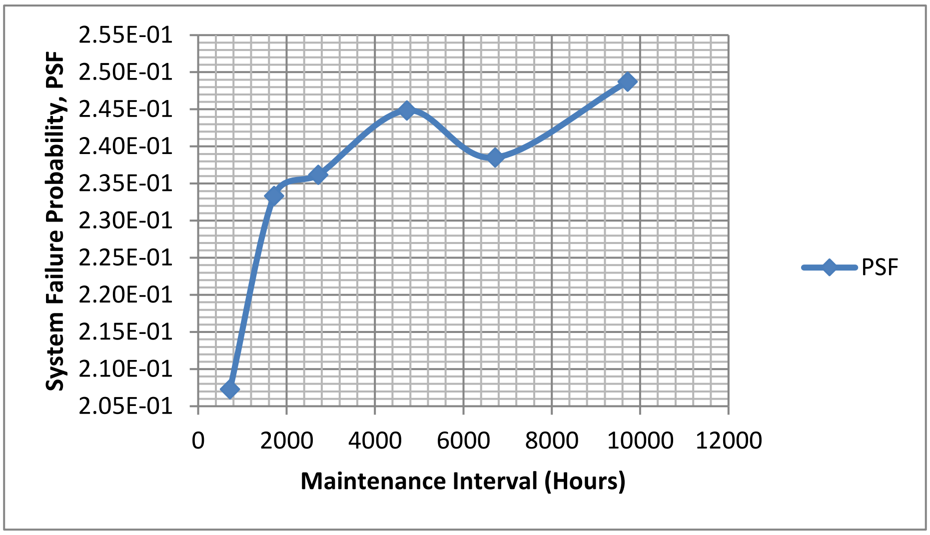

Fig 7: Graph showing how *PSF* varies as maintenance frequency is altered (T_m = 8760 hours)

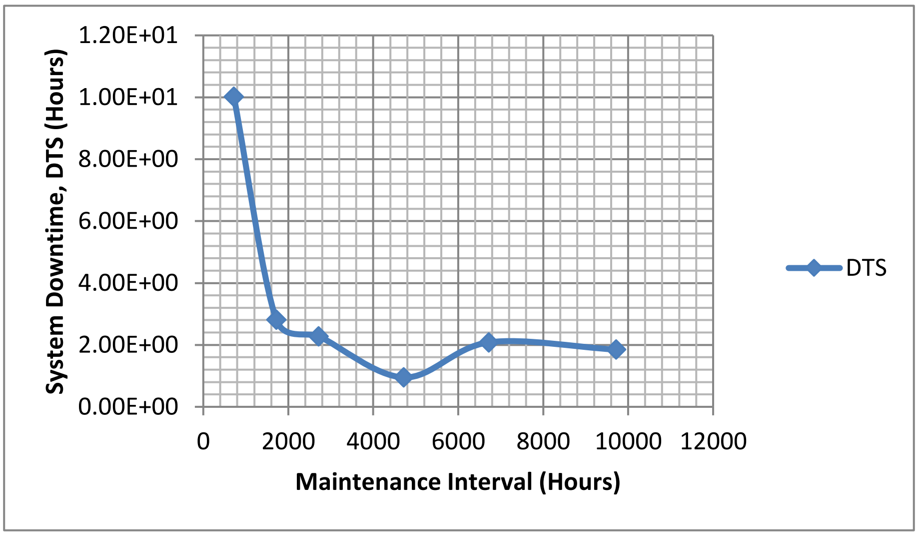

Fig 8: Graph showing how *DTS* varies as maintenance frequency is altered (T_m = 8760 hours).

It can be seen in Figs 7 and 8 that in general as the frequency of maintenance actions decreases the probability of system failure (*PSF)* increases and the system downtime (*DTS)* decreases. This is as expected due to the downtime associated with maintenance as well as the potential to prevent failures. At one point in Fig 7 however, there is a spike in the value of *PSF* and then a reduction with the next setting for maintenance frequency. This indicates that by setting the maintenance frequency to some value within this range it has caused the system to behave differently deviating from the usual pattern. It should be noted that at these points scheduled maintenance actions only take place once within the mission time it is only the time at which scheduled maintenance occurs which has changed. This indicates that the frequency of scheduled maintenance is not the only factor which affects the systems operation. The anomaly is also present at the same point for *DTS* in Fig 8. This shows that for the defined maintenance and inspection policies, the model identifies a point which minimises downtime at the cost of a slightly increased *PSF* value. The fact that the rest of the results obtained behave in a uniform manner indicates that the model is functioning correctly as intended. This means that it is unlikely that the aberration in the results is due to an error in the model. This result is something that was not possible to predict but provides an indication of an optimum policy for reducing downtime in the system. This provides useful information for decision making which may not be apparent with other analysis techniques.

In addition to the results shown in Figs 7 and 8 results have been obtained regarding how maintenance scheduling affects the number of spare parts required for the system. Tables 5 and 6 show some sample data for spare part requirements.

Table 5: Showing spare part requirements for maintenance policy (1).

VAVLES:		PUMPS:		PLATE COOLERS:	
PART NAME	**NUMBER REQUIRED**	**PART NAME**	**NUMBER REQUIRED**	**PART NAME**	**NUMBER REQUIRED**
Body	2.55E-02	**Pump Casing**	8.61E-02	**O-Ring**	6.04E+00
Bumper	5.79E-02	**Pump Cover**	8.61E-02		
Packing Nut	7.73E-02	**Impeller**	7.00E-01		
O-Ring(3_3)	1.18E+01	**Shaft Key**	4.78E-01		
O-Ring(2_3)	1.18E+01	**Wear Ring**	2.66E+01		
Stem	3.10E-02	**Bearing Bush**	2.62E+01		
Ball	1.18E+01	**Bearing Plug**	2.70E-01		
Handle	7.11E-02	**Pump Shaft**	3.98E-01		
Pin	7.11E-02	**Distance Ring**	8.61E-02		
Body Cap	9.21E-03	**Mechanical Seal**	3.13E+01		
O-Ring (1)	1.18E+01	**Grease Seal**	1.72E-01		
Spring	1.18E+01	**Bearing Cover**	5.40E-01		
Seat	1.18E+01	**Bearing Housing**	5.40E-01		
Positioner	1.50E-02	**Circlip**	2.70E-01		
		Bearing Sleeve	2.62E+01		
		Ball Bearing	5.32E+01		
		Propeller Shaft	3.35E-01		
		Motor Coupling	1.14E-01		
		O-Ring	9.37E+01		
		Seal	3.07E+01		
		Lubricating Nipple	2.40E-01		
		Grease Plug	1.20E-01		
		Drain Plug	5.20E+01		
		Lubricating Pipe	1.20E-01		
		Pump Foot	6.46E-01		
		Motor Pedestal	1.14E-01		
		Actuating Device	8.61E-02		
		Diaphragm	8.61E-02		
		Filter(s)	2.29E-01		
		Filter, Cyclone	9.32E-01		
		Flow, Indicator	9.35E-01		
		Pressure, Indicator	1.73E+00		
		Temperature, Indicator	6.95E-01		
		Vibration, Indicator	6.19E-01		
		Power Supply(3 Ph)	8.61E-02		
		Priming Unit	7.55E-01		

Table 6: Showing spare part requirements for maintenance policy (4).

(N=10^7, TM=8760, OREDA (2009), TMGV= 6000, TMGP = 4720, TMGPC = 6500, TIG =24, h = 6)					
VAVLES:		**PUMPS:**		**PLATE COOLERS:**	
PART NAME	**NUMBER REQUIRED**	**PART NAME**	**NUMBER REQUIRED**	**PART NAME**	**NUMBER REQUIRED**
Body	2.79E-02	**Pump Casing**	9.57E-02	**O-Ring**	2.05E+00
Bumper	6.30E-02	**Pump Cover**	9.57E-02		
Packing Nut	8.41E-02	**Impeller**	7.77E-01		
O-Ring(3_3)	2.91E+00	**Shaft Key**	5.31E-01		
O-Ring(2_3)	2.91E+00	**Wear Ring**	1.84E+00		
Stem	3.42E-02	**Bearing Bush**	1.36E+00		
Ball	2.88E+00	**Bearing Plug**	3.01E-01		
Handle	7.73E-02	**Pump Shaft**	4.41E-01		
Pin	7.73E-02	**Distance Ring**	9.57E-02		
Body Cap	1.02E-02	**Mechanical Seal**	7.06E+00		
O-Ring (1)	2.90E+00	**Grease Seal**	1.91E-01		
Spring	2.86E+00	**Bearing Cover**	6.02E-01		
Seat	2.90E+00	**Bearing Housing**	6.02E-01		
Positioner	1.65E-02	**Circlip**	3.01E-01		
		Bearing Sleeve	1.36E+00		
		Ball Bearing	3.72E+00		
		Propeller Shaft	3.72E-01		
		Motor Coupling	1.27E-01		
		O-Ring	2.09E+01		
		Seal	6.38E+00		
		Lubricating Nipple	2.67E-01		
		Grease Plug	1.33E-01		
		Drain Plug	2.31E+00		
		Lubricating Pipe	1.33E-01		
		Pump Foot	7.18E-01		
		Motor Pedestal	1.27E-01		
		Actuating Device	9.57E-02		
		Diaphragm	9.57E-02		
		Filter(s)	2.53E-01		
		Filter, Cyclone	1.03E+00		
		Flow, Indicator	1.04E+00		
		Pressure, Indicator	1.92E+00		
		Temperature, Indicator	7.71E-01		
		Vibration, Indicator	6.86E-01		
		Power Supply(3 Ph)	9.57E-02		
		Priming Unit	8.39E-01		

As expected decreasing the frequency of scheduled maintenance generally decreases the average amount of parts needed. This is not the case for all parts however; the parts required upon scheduled maintenance drop noticeably whereas demand for other parts is increased. This is because more random failures are occurring allowing parts to contribute to failure which would not, if adequate maintenance had been performed.

The results from the analysis for varying inspection intervals are now presented. As with scheduled maintenance the inspection analysis is performed by keeping the frequency of scheduled maintenance constant. The intervals for scheduled maintenance for this analysis are 720, 2000 and 2500 hours for pumps valves and plate coolers respectively. It is well understood that different components would have different delay times due to their failure modes and other reasons such as operational conditions. However, for ease of demonstration of the proposed approach, the delay-time, *h*, for all inspection policies has been set 6 hours as this is significantly lower than the lowest inspection interval as well as being high enough so that the effects of inspection are apparent. The inspection intervals that have been used for this analysis are 1 day (24 hours), 2 days (48 hours), 1 week (168 hours), 1 month (672 hours), 6 months (4032 hours) and 10,000 hours (over a year). The initial inspection interval is set to 24 hours as it has been suggested by expert opinion that this is standard practice for inspections on marine vessels. The intervals are increased progressively with the final value being such that inspection does not occur during the time of analysis. For the analysis of the case study the inspection intervals are the same for all components. Figs 9 and 10 show the results of this analysis.

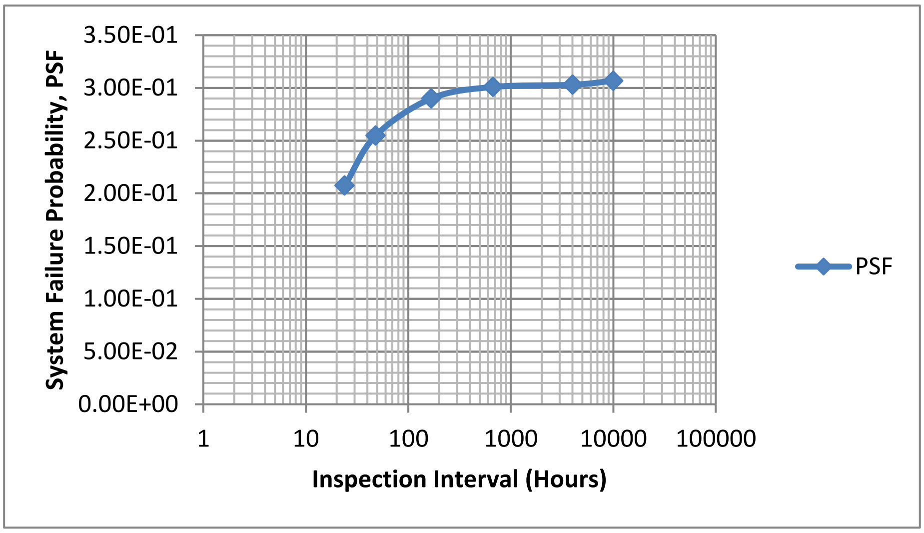

Fig 9: Graph showing how *PSF* varies as the inspection interval is altered (T_m = 8760 hours).

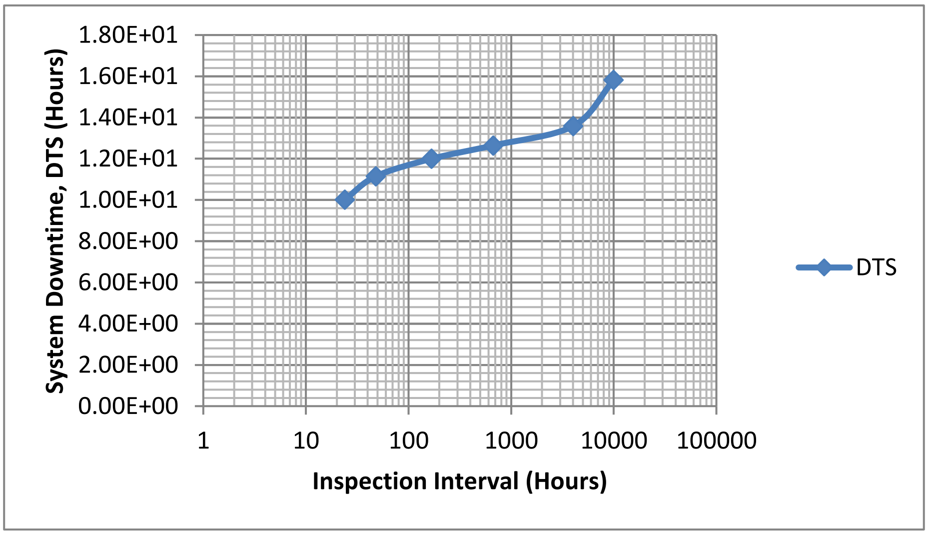

Fig 10: Graph showing how *DTS* varies as the inspection interval is altered (T_m = 8760 hours).

As can be seen in Figs 9 and 10 both the system failure probability and downtime increase as the interval between inspection actions increases. This is as expected as inspection actions have a chance to reduce downtime as well as preventing certain component failures. It can be seen from this analysis that there is no disadvantage to regular inspections and inspecting the system more frequently increases its operational efficiency by reducing downtime and increasing reliability. This is due to the fact that for this model inspection actions only incur downtime if a fault has been identified. Inspections are considered to be observational meaning a component does not have to be taken offline for an inspection to be performed. The model has been defined in this way to reflect inspections which take place whilst a vessel is in operation. This would not be the case if standard DTA had been applied to the model as it is considered that operational research is performed requiring components to be taken offline.

The spare part requirements for the system are also reduced when more frequent inspections are performed. This is because ‘minimal repair’ actions are taken upon a fault being detected and it is considered that no spare parts are required for these actions. For example when inspections are performed every 24 hours, the average requirement for mechanical seals is 31 units for the specified maintenance schedule. For the same maintenance schedule the average requirement for mechanical seals is increased to 32 units when inspections are performed every 48 hours. Though inspection intervals affect the number of spare part required, the impact is far less significant than when altering scheduled maintenance actions.

The degradation algorithm also becomes a factor when inspection actions are in place as it means that components can be operating with reduced reliability. With scheduled maintenance in place however it is possible for the system to repair degradation at certain scheduled points meaning the likelihood that degradation will propagate to failure is reduced. For the results obtained it is found that the benefit of inspections outweighs the fact that unavailability may be experienced due to the analysis of degradation upon inspection.

5.3 Convergence of Results

Finally the accuracy of the results obtained from the model must be tested. The model has been tested for the case study for a varied number of trials, *N*. This has been done to test the scope of the proposed MC model. It is necessary to determine that the results are suitably accurate and do not diverge. The test has been performed using the initial maintenance frequencies shown in row 1 of Table 4. The standard inspection interval of 24 hours is also in place. Figs 11 and 12 show the convergence of *PSF* and *DTS* as the value of *N* is increased.

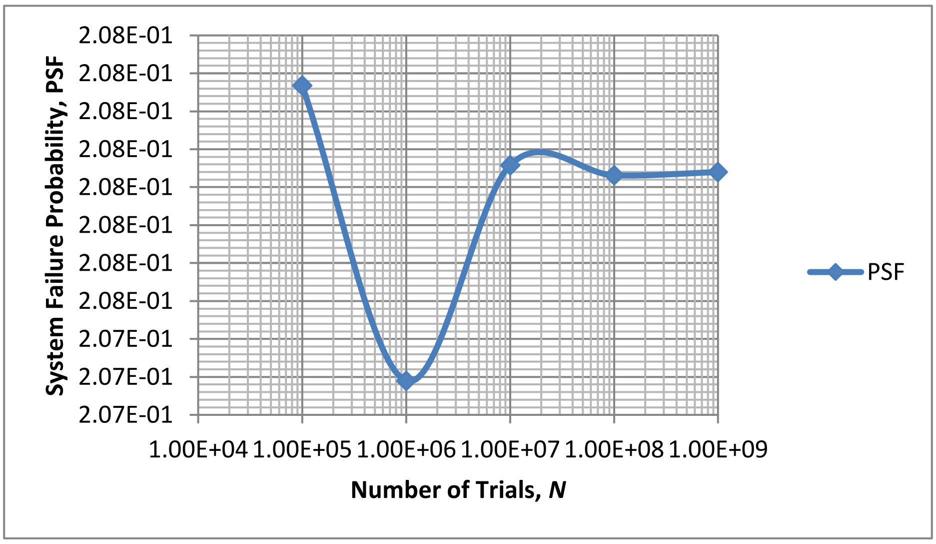

Fig 11: Graph showing convergence of *PSF* as number of trials, *N* is increased.

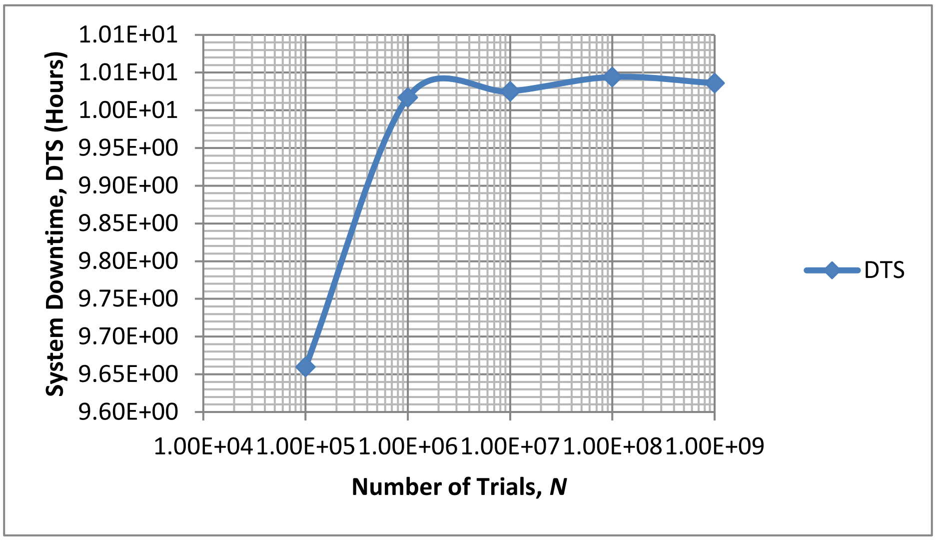

Fig 12: Graph showing convergence of *DTS* as number of trials, *N* is increased.

As can be seen in Figs 11 and 12 the results for both *PSF* and *DTS* converge at around 10^7 trials with only a slight variation as the number of trials is increased. The difference between the results from 10^6 and 10^7 trials is around 0.3% and 0.1% for *PSF* and *DTS* respectively. The variation in the results is suitably low such that it can be considered insignificant showing that the results obtained are valid for a number of *N* values. For the case study results an *N* value of 10^7 has been used as it provides suitably accurate results in a manner that is efficient.

6. Discussion

Looking at the results for varying maintenance schedules the outputs from the model are largely as expected. It can be seen that the highest level of maintenance is where the system is most reliable. However, in general it can be said that that lower maintenance frequencies are better for the system due to significantly reduced downtime and spare part requirements. These reductions far outweigh the increased reliability experienced due to frequent maintenance. As with *PSF* an anomaly is found for the results regarding *DTS* for the maintenance policy stated in row 4 of Table 4. Unlike the results for *PSF* the results at this point represent a minimum for system downtime. This means that row 4 of Table 4 represents the best maintenance policy for optimising system availability.

The anomaly shown in Figs 7 and 8 has not been anticipated and is of significant interest to the analysis of the model. Dubi[32] states that the assertion that systems have a "monotone" behaviour i.e. that improving any unit in the system improves the system is unfounded in reality, suggesting that it is not always possible to predict the effects of varying factors for complex systems using analytical methods. The anomalous result indicates that the model has identified something that changes the effect of scheduled maintenance when applied at the points specified. The model is capable of identifying a critical point in the analysis which would be difficult to determine using standard methods. This is a very useful function of the model as it can be seen that the point where this aberration occurs is actually a minimum for system downtime with the reliability being slightly higher than other options with low downtimes. This provides the optimum level of maintenance scheduling when the inspection policy is set to a daily bases. When inspection actions are taken every 24 hours the optimum frequencies for maintenance actions are 6,000, 4,720 and 6,500 hours for valves, pumps and plate coolers respectively for the cooling system under analysis.

When analysing the system for various inspection policies the results obtained are as expected. Having regular inspections decreases probability of system failure as well as the system downtime. This indicates, for the purpose of this study, that there is no disadvantage to increasing the regularity of inspection actions. Downtime due to inspection is not significant in this model as inspections are considered to be observational and downtime is only considered when a fault is found. As in the manufacturing industry, for which DTA was initially developed, it is required in the marine industry that inspections are implemented requiring component dissection which in-turn incurs downtime. Unlike the manufacturing industry these inspections are generally performed during periods of inactivity such as when a vessel is dry-docked. As the model presented is concerned only with the operating time of the system the assumption of no downtime for inspections is valid when applying DTA in the marine industry. In the case where a fault is found upon inspection the downtime is lower than for a random failure meaning that inspections only serve to increase availability. If man-hours for inspections are also considered it would be the case that more regular inspections yield a higher level of man-hours. This is undesirable due to cost factors and the adverse effect it would have on the efficiency of crew management.

7. Conclusion

The purpose of the model presented in this paper is to provide data on the effects of scheduled maintenance and inspections for a system in the marine industry to facilitate decision making. Factors such as these can have a significant effect on efficiency as they contribute to reliability as well as cost factors associated with system operation.

The results for the case study presented in this paper serve to show how MC analysis can be used in conjunction with methods such as DTA to provide comprehensive data on the effects maintenance and inspection policies for a system that is subject to degradation. The model is applied using the proposed methods such that the complexities of the operation of the cooling system are reflected in the results obtained. Applying the proposed methods in a single model allows maintenance and inspection policies to have a real effect on the system rather than performing a separate analysis once the behaviour of the system is defined. This allows optimisation decisions to be made with a high degree of confidence as the model reflects real parameters which affect the operational efficiency of marine systems.

By modifying a previously developed method the model is capable of determining how altering maintenance and inspection policies affects the number of spare parts required for the mission time. This analysis of spare part stock control is useful when considering repair or replace options for key components within a system. By combining the proposed methods data is provided for aspects including reliability, availability and spare part requirements for varying parameters. In addition the model is able to identify factors which are hard to determine using analytical methods due to the complexity with which the system under analysis is modelled.

The data obtained from the model in this chapter can be used to perform analyses for optimising key factors which are critical to the efficiency of marine operations. It is suggested that the data obtained from this model is suitable to facilitate a cost-benefit analysis to be used for further analysis of the optimisation of marine operations.

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