A Model Assessing Cost of Operating Marine Systems Using Data Obtained From Monte Carlo Analysis

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Abstract: This paper presents a methodology for analysing the cost of operating marine systems under varying conditions. Data obtained from a previously developed Monte Carlo analysis is applied to assess the operational costs for various maintenance and inspection policies. The concept of Total Insured Value is also applied to determine the cost attributed to risk. The aim is to show that Monte Carlo analysis can be adapted to provide information on various factors affecting operational costs to be used for decision making to optimise the efficiency of marine systems. A method of modelling the effects of lead times due to un-stocked items has also been included to increase the scope of the analysis.

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

1. Introduction

A major factor which affects the efficiency of marine operations is the cost incurred by the various actions which are performed during the operation of marine systems. The efficiency of maintenance and inspection policies can have a significant effect on the cost of operation for engineering systems. A number of previous studies are available concerning the effects which scheduled maintenance and inspection actions have, on the cost of system operation [Bijwaard & Knapp 2009, Jones et al 2009a, Knapp et al 2011].

Another factor which must be considered when analysing the cost of marine operations is the cost related to the risk of a potential accident. This can be directly related to maintenance and inspection policies. Knapp et al (2011) discuss how effective inspections can increase the survival rate of a vessel and relate this to the risk of an accident occurring. When analysing risk as a function of cost it is important that methods are employed to sufficiently predict the cost of events which may occur due to a potential accident. Knapp et al (2011) employ the concept of Total Insured Value (TIV) to relate the risk of an incident to the potential for a total loss event occurring. This concept of TIV is based on the components identified by Wood (1995). A number of papers are present on the subject of assessing the cost of accidents in various sectors of the marine industry [Goulielmos & Giziakis 1998, Talley 1999, Talley 2002, Guarin et al 2009]. This research into the costs related to marine operations highlights the importance of cost as a major factor in the decision making process.

The cost of operating is certainly one of the key parameters which are desirable to optimise throughout the engineering industry. It can often be difficult when assessing Reliability, Availability, Maintainability and Safety (RAMS), to make decisions which optimise system operation. An effective RAMS study should obtain information on the actions that will help provide desirable outcomes for all key parameters under analysis. To obtain adequate information for decision making it is important that Cost-Benefit Analysis (CBA) is applied. CBA provides a means by which decisions can be made in a logical manner. The application of CBA to marine RAMS problems allows engineers to view clearly the strengths and weaknesses associated with various operational management options [Spiro & Parfitt 1995, Wang et al 2010].

CBA can often be difficult to implement in the marine industry due to the variation of operations from vessel to vessel. In addition to this the cost of operations in the marine industry is very high meaning that system testing can often be overly expensive. For this reason actions to improve operational efficiency of systems such as risk control options (RCOs) are often implemented on a reactive basis. This means that sufficient data for CBA can be hard to acquire for marine operations. Due to the difficulty of applying CBA in the marine industry research into the subject area is ongoing. Well established decision making tools such as Formal Safety Assessment (FSA) and Delay-Time Analysis (DTA) have been applied in the marine industry in order to effectively analyse key cost factors incurred during vessel operations [Lois et al 2004, Jones et al 2009a]. Recently the concept of TIV has been applied in the marine industry to analyse the effectiveness of RCO's by quantifying risk as a function of various cost factors incurred during accidents [Bijwaard & Knapp 2009, Knapp et al 2011]. Studies such as Knapp et al (2011) establish that TIV can be used to facilitate CBA for marine operations.

The cost model presented in this paper draws from methods used in DTA as well as adapting the methods used by Knapp et al (2011) to model risk as a function of cost. By utilising data from a previously developed Monte Carlo (MC) model and applying the concept of TIV to represent risk, the model presented provides results concerning the costs incurred when applying varying operational constraints to a marine system. By altering the options for maintenance and inspection policies the model shows how the various component costs are affected for the system under analysis. As well as showing the different components of cost the model presents a single value of cost for the system under analysis.

The aim of this study is to show that the results obtained from MC analysis can be adapted to be useful for various aspects which are key to the decision making process in marine operations. By applying data from the MC model a number of factors affecting the cost of operation can be assessed in a single analysis.

2. Background

2.1 Application of Monte Carlo Model

Data acquired from a previously developed MC model has been used in this study to assess the operational costs of a marine cooling system [McNamara 2013]. The MC model was constructed based on well established concepts from a variety of sources [Sobol 1974, Rubinstein 1981, Marseguerra & Zio 2002]. It is assumed that the reader understands the basic concepts of MC methods. The initial purpose of the MC model was to test the effects of different maintenance and inspection policies on the efficiency of the system over a specified mission time, focusing in reliability, availability and spare part requirements. A number of additional factors were also assessed concerning the components within the system. Each of the factors analysed by the MC model have an associated cost factor. This means that it is possible to use the data acquired from the MC model to assess how maintenance and inspection policies affect the cost of operating the system under analysis.

The MC analysis takes into account a wide range of factors allowing the various factors affecting operational efficiency to be modelled in a realistic manner. The model is able to distinguish different failure modes, updating the repair time based on the failure mode rather than using deterministic repair times. MC sampling has also been used to model the effect of scheduled maintenance actions within the system mission time. The spare parts required for repair and maintenance is also assessed by the model providing average requirements for each part during the analysis period. Additionally a form DTA was applied within the MC model to assess the effects of periodic inspections. By applying DTA inspections have a chance to reduce the downtime by detecting a fault before it has propagated to failure [Christer & Wang 1995]. Unlike scheduled maintenance actions inspections only incur downtime if a fault is detected as inspections are considered to be purely observational. Each of the factors modelled has an impact on the reliability, downtime and spare part requirements for the components in the system as well as the system as a whole. This allows data to be acquired on a number of factors affecting the operational costs for the system.

When implementing traditional DTA a cost model is usually included to determine the cost-effectiveness of the inspection policy under analysis. These cost models focus on costs due to downtime as well as other factors such as repair costs and crew wages for the staff necessary to implement the policies [Jones et al 2009a]. With this in mind it is suggested that the results obtained in from the MC model are useful to analyse cost-effectiveness. Using methods similar to those applied to DTA the data from the MC model has been adapted to determine the costs attributed to downtime within the system due to all of the actions which have been modelled. Note that standard DTA analyses cost per unit time whereas the model presented analyses the total cost over the mission time under analysis. Aside from costs due to downtime such as 'off-hire' costs, methods have been applied to determine additional costs such as crew wages, repair and maintenance costs and cost of replacement parts which are affected by the actions modelled. A model to represent risk as a function of cost is also applied by applying the reliability data from the MC model to the concept of TIV.

Aside from when assessing the effects of lead times the MC model requires no modification to obtain the necessary data. The results obtained directly relate to the cost factors which are under analysis in this study. When modelling the effects of lead times slight modifications are necessary to represent the effect on system operation if a specific item is not available for repair. The model presented adapts existing methods to perform a CBA using data from MC analysis to determine the effectiveness of maintenance and inspection policies as well as spare part stock options. Applying the results from MC analysis in this manner allows a number of different policies to be efficiently analysed, reducing the need for manual testing.

2.2 Cost Factors Associated with Marine Accidents

Determining the costs related to the risk of incidents in the marine industry can be very difficult when performing a CBA. The costs incurred for a given incident depend on the average cost to the concerned parties which are known as base values. The available literature on incident costs shows that it can be very complex to determine base values for incident costs in the marine industry [Knapp et al 2011].

Various studies have been performed on key aspects which contribute cost to accidents which occur in the marine industry [Goulielmos & Giziakis 1998, Talley 1999, Talley 2002, SAFEDOR 2007, Vanem et al 2008, Guarin et al 2009]. Wood (1995) identifies four key aspects of marine incident costs to be loss of assets, loss of cargo, loss of lives and pollution to be analysed to establish base values for vessel accident costs. Knapp et al (2011) suggest that the most comprehensive base value for the cost of incident risk is the Total Insured Value (TIV).

TIV is based on total loss incidents which are considered to be accidents with significant loss of assets. Based on the key aspects identified by Wood (1995) and applied to insurance cover this consists of cost of hull and machinery, third party liability coverage, oil pollution coverage for oil tankers and cargo values for cargo carrying vessels. Cargo values do not apply to passenger ships and are instead replaced by liability limits for passengers [Knapp et al 2011]. Additionally Knapp et al (2011) suggest that for most total loss accidents all aspects of TIV are not incurred and 'logit' models are presented which provide data on the likelihood of each aspect of TIV being incurred for a given accident relevant to different vessel types. This data is very useful as it allows the cost of risk based on the TIV to be calculated given that the probability of a total loss incident occurring is known.

Looking at the concept of TIV it is clear that it can give a reliable estimate of the costs incurred by accidents as it is based on insurance values which take into account all the stakeholders in the operation of a given vessel. Insurance companies also have an abundance of data which allows them to accurately estimate the average of each cost component for a given vessel type. The concept of TIV has been used in conjunction with data from a variety of sources as well as the data obtained from the MC model to translate the risk of operation into a value of cost in the model presented in this paper. This allows the model to take into account all key factors which impact the cost of operation for the system under analysis.

3. Methodology

Fig 1 shows the process for the development of the proposed model. Before the cost model is applied the parameters for the analysis of the system must be defined. With the scope of the analysis decided the MC model is performed using simulation to represent the desired analysis. Upon obtaining the results from the MC model they must be analysed to determine which factors of the cost model are affected by their outcomes. With this done the proposed methods are used to determine the cost-effectiveness of the system for varying parameters. After the main analysis has been performed modifications are made to the MC model so that the effects of lead times due to un-stocked item can be assessed.

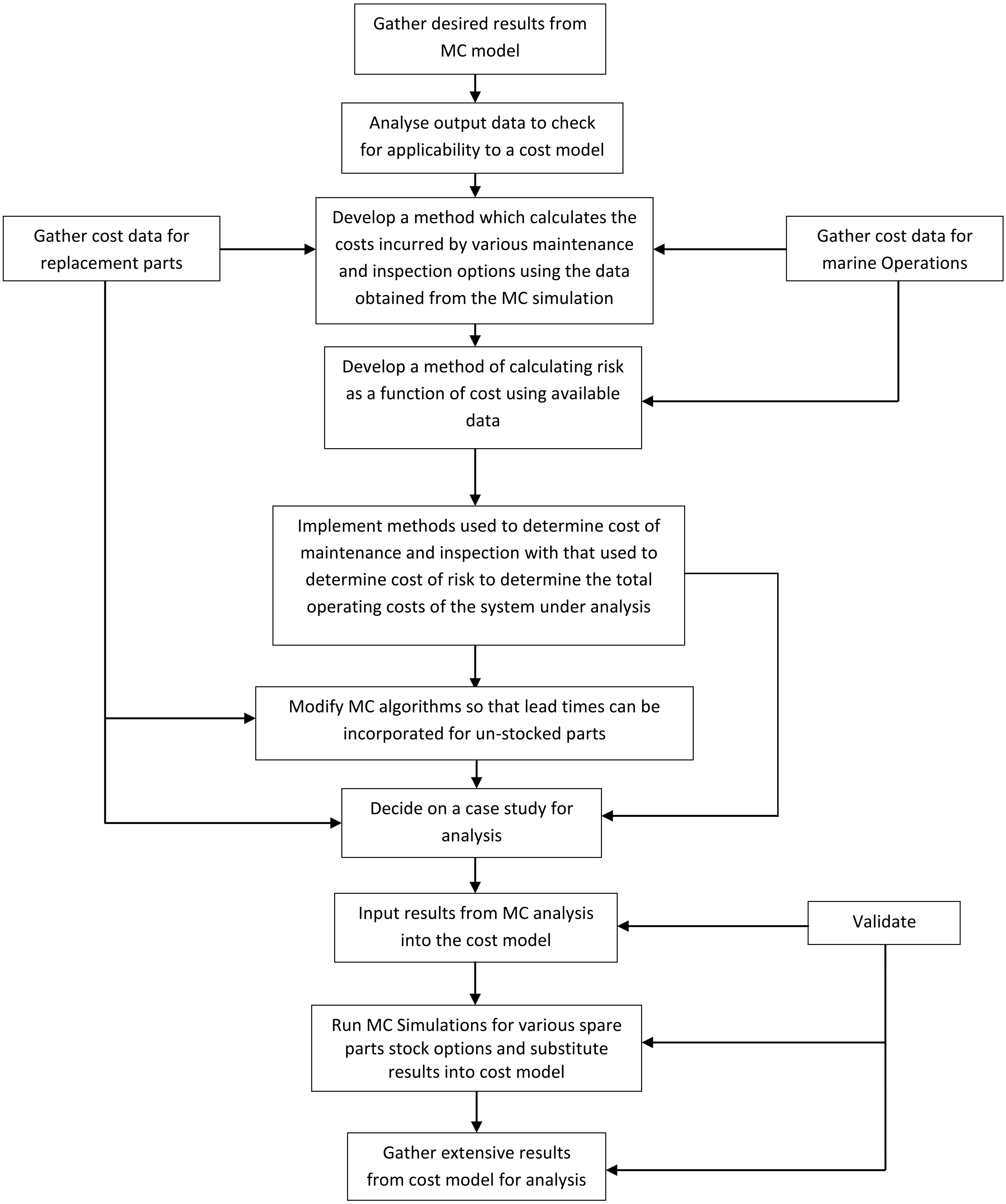

Fig 1: Process of development for proposed cost model.

3.1 Calculation of Maintenance and Inspection Costs

The proposed cost model is not only concerned with the costs incurred by the implementation of maintenance and inspection policies but also the costs which are incurred as a result of the effects on the system. For example, this could mean that by having more frequent maintenance the downtime of the system is increased which results in cost incurred by loss of productivity. Given the nature of the MC model the cost model is constructed such that the costs are calculated based on the specified mission time rather than on a per unit time basis. The basic calculation for the costs incurred by the maintenance and inspection actions can be seen in Equation 1.

$$Cost_{\boldsymbol{mib}} = Cost_{\boldsymbol{i}} + Cost_{\boldsymbol{m}} + Cost_{b} \tag{1}$$

$Cost_{mib}$ represents the total cost affected by maintenance and inspections over the specified mission time. $Cost_i$ is the cost of inspection actions, $Cost_m$ is the cost of maintenance and $Cost_b$represents the breakdown costs. Each of the cost factors shown in Equation 1 are comprised of a number of different aspects to work out the value over the time specified. A breakdown of these cost factors is now given. Equation 2 shows how the value for $Cost_i$ is determined.

$$Cost_i = Cost_{ip} \times (I_n \times T_i) \tag{2}$$

$Cost_{ip}$ is the hourly cost of inspection personnel, I_n is the number of inspections over the specified mission time and T_i is the average time in hours, for an individual inspection. $Cost_{ip}$ is the hourly pay of a second engineer who would be employed to perform the inspection actions. I_n is worked out based on the number of hours between inspections and dividing it by the specified mission time, the lower integer of this value denotes the number of inspections. This value is then multiplied by the number of active items liable for inspection. T_i << average repair time, as is the case when implementing DTA [Christer & Wang 1995]. The calculation for determining $Cost_m$ is now shown in Equation 3.

$$Cost_m = \left(Cost_{mp} \times ADT\right) + SP \tag{3}$$

$Cost_{mp}$ is the hourly cost of employing personnel required for maintenance actions. *ADT* is the accumulative downtime of the components in the system and *SP* is the average cost of the spare parts required for the system. For this calculation $Cost_{mp}$ is the same as $Cost_{ip}$ as it is assumed that a second engineer performs both actions. This may vary in special cases. The *ADT* value is calculated as the sum of the downtimes for each individual component. This has been used as, unless lead times are present, any time a component is unavailable it is being repaired and will therefore, incur maintenance costs. The value *SP* is calculated by multiplying the average number of parts needed for a given analysis by the cost of a single unit. It has been necessary to research these costs as they are dependent on the type of components being used in the system. This depends on the type of vessel under analysis. The final component of $Cost_{mib}$ is $Cost_b$ which is calculated as seen in Equation 4.

$$Cost_b = (Cost_d \times DTS) + SE \tag{4}$$

$Cost_d$ is the cost incurred due to loss of productivity. *DTS* is the system downtime and *SE* is the cost of any special equipment that is required upon breakdown. The value of $Cost_d$ is obtained from existing data and is dependent on the vessel type and function. This value is commonly known as 'off-hire' cost and is an estimate of the capital that the vessel generates daily. In order to work with the data from MC model it is necessary to translate these values into hours. The value of *DTS* is taken directly from the MC analysis as this is the amount of time the system is unavailable for the specified set up. The final value is *SE* which is a one off cost of hiring any special equipment that is needed upon breakdown. This may be anything from the need for rescue craft to hiring specialised personnel to deal with the situation.

With these calculations explained it can be seen that by applying the data from MC analysis into a cost model it is possible to assess the effects which altering maintenance and inspection policies have on the cost of operations. By combining these calculations it is intended that this model can be used to assess the effectiveness of decisions regarding inspections and scheduled maintenance by analysing a single value.

3.2 Calculation of Costs Attributed to Risk

It has been decided for the current model that the cost of risk is based on the risk of a total loss incident occurring. Knapp et al (2011) suggest that TIV is the most comprehensive method for determining the base value costs in a total loss incident. In this study TIV is used in conjunction with the reliability data from MC analysis to assess the cost of risk based on the chance that a total loss incident will occur. TIV consists of a number of different factors [Wood 1995].

Firstly the cost of hull and machinery (HM) is agreed upon by the underwriter and the owner in which the primary concern is that the insured value is sufficient to cover the mortgage of the vessel [Knapp et al 2011]. Data sources such as the shipping intelligence network of Clarkson's can provide up to date data on current prices for numerous vessel types [SINC 2012]. Third party liability (TPL) coverage is another contributor to TIV. TPL is the insurance coverage for crew members and other staff working on board a vessel covering incidents involving death, injury or negligence etc. This is covered by the P&I clubs used by the crew members and can vary depending on the type of ship and the area in which it is operating etc. Next oil pollution limits (POL) must be considered. It should be noted that this only becomes a factor when an oil tanker is the vessel under analysis. These limits are in excess to the TPL used by the P&I clubs [Knapp et al 2011]. The pollution limits depend on the size of the ship. These limits are estimated at around 6.9 million dollars for ships with gross tonnage up to 5000, with an extra $1000 per tonnage above 5000. The upper limit of the pollution limits are around 90 million dollars for ships with gross tonnage above 140,000 [Knapp et al 2011, IOPC 2008]. The final component of TIV for which this study is concerned is the value of the cargo carried by a vessel (CAR). This value can differ greatly depending on the nature of the cargo being carried and should be assessed on a case by case basis. With the values for these factors acquired it is possible to assess the TIV for a given vessel. Equation 5 shows the upper value of TIV.

$$TIV = v_1 + v_2 + v_3 + v_4 \tag{5}$$

The variables, v_1, v_2, v_3 and v_4 are the cost values of each component of TIV (i.e. HM, TPL, POL & CAR). It is suggested in Knapp et al (2011) that the value of TIV shown in Equation 5 is the upper limit of TIV rather than its average. This is because in a total loss incident all aspects of TIV are not always incurred. Knapp et al (2011) present 'logit' models to work out the likelihood of each component of TIV being incurred for a number of vessel types. This alters the value of TIV so that the average is obtained by the calculation shown in Equation 6.

$$TIV(p) = (p_1 \times v_1) + (p_2 \times v_2) + (p_3 \times v_3) + (p_4 \times v_4) \quad (6)$$

The values p_1, p_2, p_3 and p_4 are the probabilities that each of the four components of TIV will be incurred by a total loss incident. With this adjusted value of TIV it is possible to predict the average cost of a total loss incident for a given vessel. With the method for calculating TIV explained it is now possible to explain how the cost of risk can be obtained for the current model. By applying the reliability data from MC analysis it is possible to adjust the value of TIV obtained from Equation 6. By applying system reliability data the value of TIV is modified based on the chance of a total loss incident occurring. This is calculated as show in Equation 7.

$$Cost_{Risk} = PSF \times TIV(p) \quad (7)$$

PSF is the probability of system failure obtained from MC analysis. Note that the calculation shown in Equation 7 suggests that if the system under analysis fails a total loss incident will definitely occur. This is a very unlikely scenario as it is rarely the case that a single system failure will result in the loss of a vessel. For this reason it is necessary to modify Equation 7 to give a more realistic estimation of the average cost attributed to the risk of losing a vessel. Equation 8 shows this modified calculation.

$$Cost_{Risk} = PSF \times CPL \times TIV(p) \quad (8)$$

CPL is a conditional probability that the failure of the system under analysis will propagate to a total loss incident. This conditional probability can be obtained using a number of existing methods given that adequate data is available. For example Bayesian networks are often applied to establish conditional probabilities for failure propagation [Jones et al 2009b, Wang et al 2010]. For the model applied in this study however, it was possible to obtain the *CPL* value from existing data found in the Marine Accident Investigation Branch (MAIB) incident reports [MAIB 2002]. It should be noted that with enough data the MC model developed previously could also be used to obtain the data regarding conditional probabilities. This could be implemented by performing the same analysis on other key systems which contribute to the propagation of a total loss incident and combining the results. With the calculation shown in Equation 8 it is possible to estimate the cost of the risk to the vessel under analysis. Note that the value of *PSF* is already time dependant so it does not need to be modified.

3.3 Acquisition of Data

Much of the required data is present from the results of MC analysis; however additional data is required regarding certain costs attributed to marine operations. The additional data is concerned with costs specific to the scenario for which the model is tested. It is first necessary to obtain cost data regarding the wages of crew needed to implement maintenance and inspection policies. This has been obtained by consulting expert opinion of a chief engineer of over 15 years experience. The cost is based on the monthly salary of a second engineer and converted to hourly pay to be used to work out the cost, in man-hours, of maintenance and inspection actions.

The cost of spare parts required has been obtained by consulting a second expert working in the shipping industry with over 10 years experience as an operations director. Before submitting the maintainable item specifications to this expert the exact specification of the parts required for the system must be determined. This involves research into the class of vessel being analysed.

A factor which contributes significantly to the cost of inspection and maintenance is the ‘off-hire’ costs incurred by system downtime. This has been obtained by reviewing reports of yearly incomes for vessels with similar specifications and taking an average of the monthly capital generated [DHT 2008].

Most costs attributed to TIV can be obtained from reliable sources or are based on standard guidelines which can be extrapolated to work out costs for a given vessel [IOPC 2010, Knapp et al 2011, SINC 2012]. It is however, necessary to perform further research relating to costs of cargo. This involves a process of obtaining up to date information on the cargo that is to be transported for the desired analysis [COCP 2012]. Additionally the conditional probability for total loss (*CPL*) is obtained by reviewing MAIB incident reports [MAIB 2002].

3.4 Implementation of Proposed Methods

With the cost of maintenance and inspection calculated as well as cost of risk, the total cost incurred by the operation of the system can be calculated as seen in Equation 9.

$$Cost_{TOT} = Cost_{mib} + Cost_{Risk} \tag{9}$$

$Cost_{TOT}$ is the total cost of operating the system for the parameters decided. This is the main value used for decision making. In general it can be said that the lower this value is the better the option under consideration. This is because risk has been converted to cost and therefore, does not need to be considered separately.

In order to facilitate the implementation of the proposed model the methods are applied to an EXCEL spreadsheet. This is done so that the results from MC analysis can be easily interchanged so that the output values regarding cost can be analysed. With the spreadsheet created and all the additional data inputted to the model it is a simple matter of inputting the results from MC analysis for a number of different parameters and comparing the results for optimisation purposes. Aside from $Cost_{TOT}$ individual cost components are also provided so that the areas in which cost has increased or decreased can be analysed more comprehensively allowing the user to observe areas which may need attention in order to improve the efficiency of the systems operation.

3.5 Application of Lead Times

Given that the previously developed MC model is able to assess spare part requirements it is possible to model the effects of lead times due to un-stocked items. The cost model presented makes it possible to determine the average cost of stocking the necessary parts needed to maintain a system. Upon analysis of the results from the MC model it was found that some of the replaceable parts have a very small chance of being needed during the course of the specified mission time. Upon implementing the proposed cost model it is found that some of these parts have relatively high costs. Additionally it has been noted that a number of these parts would not be kept in stock based on standard marine engineering practices. The nature of the MC model is such that it gives average requirements for the parts needed over the mission time. Due to this fact when implementing the cost model these parts are found to drive the cost of operations up significantly. This is because their cost is high even though they are rarely required. It is for this reason that a method has been implemented allowing the inventory system to be modified to model the effect of not stocking certain items.

If a required item is not stocked on a vessel a lead time will be incurred by the time taken for the item to be delivered so that the system can be repaired. This has an effect on the functionality of the system as it effectively increases the repair time of the component for which the item is required. This effect can be modelled by making some minor alterations to the MC model. After determining which maintainable items will not be stocked the chance that an omitted item will be required for each failure mode must be determined. This is done by analysing the item data and determining which parts contribute to each failure mode. The chances of the omitted part being needed for the failure mode must then be determined. For example the failure mode 'Service Problems' (*SP*) for valves has three possible contributors (Bonnet, Closure Member, and Valve body w/internals). If it is decided that the bonnet is not stocked this would affect the transition behaviour for the failure mode. The weights of the three contributors stated previously are 5.53, 7.43 and 1.86 respectively, totalling 14.82 for the entire failure mode. A bonnet is needed to repair a failure due to 'Bonnet' or 'Valve body w/internals' these contributors make up 49% of the overall failure mode. This means that if a valve fails by the mode *SP* and a bonnet is not stocked there is a 49% chance that lead times will be incurred.

By making slight modifications to the MC algorithms, a value *PLT* is assigned to each failure mode. *PLT* is the probability that lead times are incurred due to un-stocked items. A value for the lead time, *LT*, (hours) incurred is also specified by the analyst based on the situation. By generating a random number, *RLT, U ~ [0, 1]*), an MC sample is taken from a discrete distribution containing only two values (*PLT* and 1-*PLT*) once the failure mode has been determined by the logic of the MC analysis.

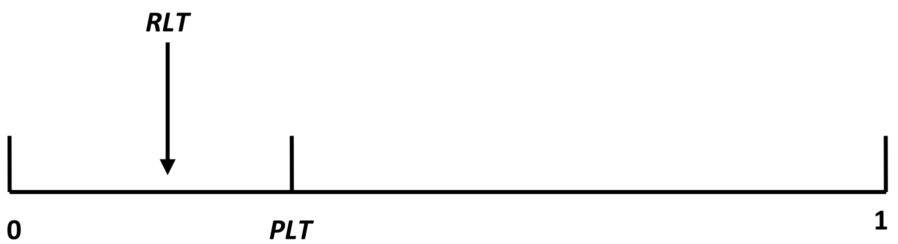

Fig 2: Diagram illustrating the method of determining whether lead times are incurred.

The example shown in Fig 2 shows that $RLT \leq PLT$. In this case it would mean that the omitted items have caused lead times to occur. This means that the repair time, $\tau = \tau + LT$. This is modelled by an IF function which occurs after the selection of the failure mode. If $RLT > PLT$ lead times would not be incurred and τ would remain unaltered.

An additional modification made concerns the inventory systems application to the cost model presented. This modification is more of a decision made than a method that was employed. Certain items which contribute to failure do not have to be replaced if they cause a failure. For example a failure due to an instrument is more likely to be due to an abnormality rather than the instrument being broken. For this reason, the cost of certain items has been omitted in the current model. This means that the cost of a replacement is not added to the overall cost but the cost of the downtime incurred as well as other aspects is still taken into account.

With the lead time algorithm in place it is possible to re-run the analysis omitting parts based on various criteria to test the effects on the system outputs. This coupled with the proposed cost model allows the user to assess whether it is cost-effective to stock certain items.

4. Case Study

With the development of the proposed methodologies and modifications explained as well as the necessary data gathered it is possible to apply the proposed model to a case study. The system under analysis for this case study is a simplified cooling system for a marine engine room. The cooling system consists of three ball valves, three centrifugal pumps and two plate coolers. The functionality of the system has been modelled using MC analysis and the reliability data and spare part information for the components is based on data from OREDA (2009). Though the OREDA study concerns parts operating in the offshore industry the cooling system can be considered suitably generic such that the data can be applied to components operating in the marine industry.

Due to the application of the proposed cost model the characteristics of the vessel for which the cooling system operates must be clearly defined. This is because the cost of parts and other operational factors used can vary widely depending on size and classification of the vessel. The vessel for which the cooling system operates is a double hulled Aframax oil tanker carrying crude oil. The specification for the vessel for which this case study is concerned is loosely based on the MT 'Mare Nostrum' [MES 2009]. That is that the deadweight (DWT) has been reduced slightly for this case study to represent an Aframax tanker with a median cargo carrying capacity.

The MT 'Mare Nostrum' has an overall length of 245 m and beam of 42 m with a compliment of 29 personnel. It has DWT of 110,295 metric tonnes with a gross tonnage (GT) of 59,611. To represent an average Aframax tanker this DWT has been reduced to 100,000 metric tonnes and based on the conversion for the MT 'Mare Nostrum' the GT is subsequently reduced to 54,000. One key attribute for which knowledge is required is the engine that the cooling system is servicing so that the specification of the parts required can be determined. The MT 'Mare Nostrum' uses a MITSUI-MAN B&W Diesel Engine 7S60MC x 1 set with a maximum continuous output of 14,280 kW x 105 rpm and a service speed of 14.9 knots [MES 2009]. The case study is used for analysis the of maintenance and inspection decisions over a mission time, T_m, of 1 year (8760 hours).

Project guides are available for MAN B&W which provide information on the specifications for various systems which affect the operation of the engine including the cooling system [MAN B&W 2012]. With the required capacities of the cooling system known a search of manufacturers is necessary to decide on specific parts fitting the specification. Once the part types are decided the specifications are submitted to an expert to obtain cost estimates for the items present in each component. Expert opinion is required for this as it can prove difficult to obtain the data from the manufacturers of the specific components. The cost estimates for these items are then applied to the inventory system to represent the cost of the spare parts used for repair. The costs attributed to each spare part can be found in Table 1.

Table 1: Cost of spare parts needed for repair per unit.

BALL VALVES		**CENTRIFUGAL PUMPS**		**PLATE COOLERS**	
Part Name	**Cost ($)**	**Part Name**	**Cost ($)**	**Part Name**	**Cost ($)**
Body	30	Pump Casing	8000	O-Ring	30
Bumper	2	Pump Cover	3500		
Packing Nut	2	Impeller	3500		
O-Ring(3_3)	1	Shaft Key	10		
O-Ring(2_3)	1	Wear Ring	400		

Stem	10	Bearing Bush	500		
Ball	20	Bearing Plug	50		
Handle	10	Pump Shaft	2500		
Pin	1	Distance Ring	100		
Body Cap	30	Mechanical Seal	300		
O-Ring (1)	2	Grease Seal	150		
Spring	5	Bearing Cover	400		
Seat	10	Bearing Housing	1200		
		Circlip	10		
		Bearing Sleeve	250		
		Ball Bearing	200		
		Propeller Shaft	2500		
		Motor Coupling	200		
		O-Ring	10		
		Seal	110		
		Lubricating Nipple	25		
		Grease Plug	25		
		Drain Plug	25		
		Lubricating Pipe	40		
		Pump Foot	400		
		Motor Pedestal	800		
		Diaphragm	150		
		Filter(s)	50		
		Filter, Cyclone	600		

As well as spare parts costs a number of other cost attributes are required to apply the proposed cost model to the case study presented. The salary used for inspection and maintenance staff in this study is $8000 per month based on the wage of a second engineer. This is converted to hourly pay based on a shift of 8 hours per day. It should be noted that aside from maintenance it is considered for this case study that standard inspections, given a fault is not detected, have a duration of 15 minutes. This can be decided by the analyst but this value was selected for this case such that inspection time, $T_i << \tau$, as should be the case when performing DTA [Christer & Wang 1995].

With the spare parts costs and crew wages acquired it is possible to determine the values of $Cost_i$ and $Cost_m$. To calculate $Cost_b$, 'off-hire' costs for standard Aframax tankers must be obtained. Quarterly reports show the average capital generated and an average value was taken as $30,500 per day [DHT 2008]. This is again converted to hours and combined with the system downtime to determine the 'off-hire' costs incurred over the mission time. Note that it is assumed that operation ceases if a system failure occurs. Looking at Equation 4 it can be seen that the cost of special equipment required is included in the cost of breakdown. In this case no special equipment is required for a standard breakdown of the cooling system. By applying the data obtained from the MC analysis and using the proposed methods, the cost of implementing the maintenance and inspection policies, $Cost_{mib}$, can be calculated.

In addition to $Cost_{mib}$ it is necessary to work out the specific costs attributed to TIV for the vessel. Data for the cost of hull and machinery was acquired from Clarkson's Shipping Intelligence Network based on the average price of a second hand Aframax tanker at the time the data was accessed. This was found to be around $28 million which is the value attributed to hull and machinery for this case study [SINC 2012].

The average value for TPL is this case study has been set to $10 million. This is based on the fact that 98% of total loss incidents for oil tankers in the period of 1978-2002 were within the limit of $8 million [Knapp et al 2011, IOPC 2010]. The value is set at $10 million to account for excess loss insurance [SOCAR, 2008].

To determine the value oil pollution limits a calculation must be performed. This calculation is based on the GT that is stated as 54,000. As discussed the limit is $6.9 million for GT up to 5000 and an extra $1000 for each tonnage above 5000 up to 140,000. Therefore the pollution limit is calculated as shown in Equation 10.

$$\begin{array}{c} \qquad\qquad\qquad [\$] \qquad\qquad [\text{Tonnes}] \qquad [\$] \\ Pollution\ Limit = 6{,}900{,}000 + ((54{,}000 - 5000) \times 1000) \end{array} \tag{10}$$

From Equation 10 the pollution limits come to $55.9 million, which is the value used in this case study.

The final value of TIV which must be calculated is the insured value of the cargo, which for this case study is the crude oil that is carried is by the tanker. This is dependent on the DWT of the ship and the price of crude oil. The DWT of the vessel under analysis in this study is 100,000 metric tonnes. The data accessed stated that the average price of crude oil is $86 per barrel [COCP 2012]. This price then has to be converted into cost per metric tonnes which has been estimated on the basis of 7 barrels per metric tonne. The value of the crude oil carried by the tanker can then be calculated as shown in Equation 11.

$$\begin{array}{c} \qquad\qquad\qquad\qquad [\text{Tonnes}] \quad [\text{bbl}] \quad [\text{bbl/Tonne}] \\ Value\ of\ Insured\ Cargo \ = 100{,}000 \times \ 86 \ \times \ 7 \end{array} \tag{11}$$

This gives an estimated insured value of the cargo at $60.2 million. This value has been applied as the value of insured cargo for the analysis performed in this study.

With the base values for TIV obtained it is necessary to modify these values based on the probability that they will be incurred in a total loss incident. These probabilities have been taken from the study by Knapp et al (2011) which were acquired by the application of 'logit' models. Table 2 shows the probabilities of the occurrence of different aspects of TIV in a total loss incident for a number of vessel types.

Table 2: Average probabilities for TIV components [Adapted from Knapp et al (2011)].

Vessel Type	P(*HM*)	P(*LL*)	P(*POL*)	P(*TPL*)	P(*CAR*)
General Cargo	0.58	n/a	n/a	0.42	0.11
Dry Bulk	0.59	n/a	n/a	0.39	0.10
Container	0.50	n/a	n/a	0.41	0.16
Tanker	0.61	n/a	0.07	0.33	0.12
Passenger Vessel	0.74	0.02	n/a	0.29	n/a

In Table 2, P(*HM*), P(*LL*), P(*POL*), P(*TPL*) and P(*CAR*) represent the probability of the TIV aspects hull and machinery, liability limits, pollution limits, third party liability coverage and value of insured cargo occurring respectively. If a column says n/a it means that the aspect of TIV is not applicable to that vessel type. The row that is highlighted represents tankers which is the data for which this case study is concerned. By multiplying each aspect of TIV calculated for the vessel by the probability of occurrence and taking the sum of all aspects an average cost of a total loss incident for the vessel under analysis is obtained. For the vessel presented in this case study the value of *TIV (p)* is equal to $31,517,000. Note that without the probability modifiers the upper bound value, TIV, is equal to $154,100,000.

With the adjusted TIV obtained the final piece of data required to calculate $Cost_{Risk}$ is the conditional probability that a failure of the cooling system will lead to a total loss incident, *CPL*. The conditional probability data acquired is from a report performed by MAIB [MAIB 2002]. Data is provided for both minor and catastrophic accidents, that is, accidents in which the vessel was lost. During the course of the study a total of 2750 failures are attributed to machinery failure. Of these 53 propagated to a total loss incident of which 12 are due the main engine sea water cooling system. From this the probability that a total loss incident will occur due to a cooling system failure can be extrapolated. Based on the data provided, the value of *CPL* can be calculated by Equation 12.

$$CPL = \frac{53}{2570} \times \frac{12}{53} \tag{12}$$

By calculating as shown in Equation 12 a value of *CPL* is given as 4.67×10^{-3}. This value is used in the case study to represent the chances of a cooling system failure leading to a total loss incident. With this value of *CPL* calculated it is possible to acquire the final value of the cost attributed to risk. By applying the reliability data from the MC model (*PSF*) to the adjusted value of TIV as shown in Equation 8 a value for $Cost_{Risk}$ which is dependent on the maintenance and inspection policy defined by the analyst is obtained.

5. Results

The cost model presented has been tested for various inspection and maintenance policies. The convergence of the previously tested MC modelled has already been proven so as the results of the cost model are directly affected by the previous results there is no need to test convergence [McNamara 2013]. The maintenance and inspection policies have been altered separately for the purpose of analysis. This allows the effects of the decisions made to be observed more thoroughly. The first set of results presented show the effect that changing the maintenance schedule has on the various aspects of operational cost. Table 3 shows the gap between scheduled maintenance for each component in the system for the policies under analysis.

Table 3: Showing maintenance increments used for analysis of case study.

	MAINTENANCE FREQUENCY (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 key cost factors for scheduled maintenance policies 1-6 for the cooling system. The inspection frequency is kept constant for these results at one every 24 hours, with a delay time, *h*, of 6 hours. The results are based on a mission time of 8760 hours (1 year) and the MC analysis used to obtain key values has been performed for 10^7 trials.

Table 4: Showing cost results for cooling system due to varying scheduled maintenance policies.

	$Cost_i$($)	$Cost_m$($)	$Cost_{sp}$($)	$Cost_b$($)	$Cost_{mib}$ ($)	$Cost_{Risk}$($)	Total ($)
1	15,208.33	121,093.07	82,849.48	12,729.81	149,031.22	30,505.02	179,536.24
2	15,208.33	51,008.82	33,905.79	3,575.11	69,792.26	34,338.57	104,130.83
3	15,208.33	37,101.12	24,501.62	2,895.24	55,204.69	34,757.98	89,962.67
4	15,208.33	27,002.47	17,833.91	1,207.29	43,418.09	36,034.91	79,453.00
5	15,208.33	25,678.69	16,951.36	2,761.74	43,648.76	35,099.98	78,748.74
6	15,208.33	21,352.23	14,994.78	2,349.48	38,910.04	36,604.85	75,514.89

Table 4 shows how the total operational costs as well as how the various components of cost change as the maintenance frequency is altered. The first four columns of the results show the results for the various costs which comprise the cost incurred by maintenance and inspection actions, $Cost_{mib}$. $Cost_{sp}$represents the cost of the spare parts required and is also a component of $Cost_m$; this has been displayed separately for analysis purposes. Fig 3 shows how the components of $Cost_{mib}$behave, as the frequency of scheduled maintenance is altered. Note that the maintenance frequencies shown on the x-axis of Fig 3 refer to the gap between scheduled maintenance actions for the pumps in the cooling system; this is also true for Figs 4-6**.**

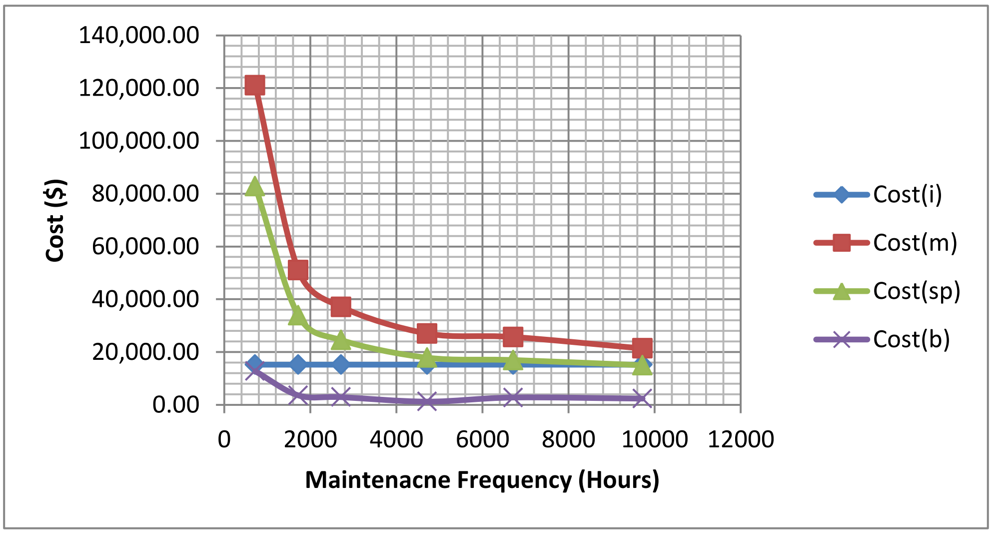

Fig 3: Graph showing the change of $Cost_{mib}$ components as frequency of maintenance actions is changed.

The first thing that should be noted is that the cost of inspection does not change. This is because the inspection policy is kept constant throughout. Looking at $Cost_m$ for which $Cost_{sp}$is a component it can be seen that both decrease as the frequency of scheduled maintenance is decreased. This is expected as less maintenance means less component downtime requiring maintenance crew as well as less parts required for maintenance actions. Also $Cost_b$decreases as taking components offline less often means that system downtime is less likely which therefore decreases the likelihood of 'off hire' costs due to downtime. It should be noted that when applying the parameters defined policy 4 there is a sudden drop in $Cost_b$ which again increases slightly when the parameters policy 5 are applied. This is because $Cost_b$ is sensitive to *DTS* and a reduction in *DTS* was found for the same maintenance policy when analysing the results from the MC model without the cost model. This partially validates that the cost model is working taking into account the values obtained from the MC model. $Cost_b$ is small in comparison with the other values due to high system availability. Fig 4 shows the results for how $Cost_{mib}$ is affected as a whole when altering the frequency of scheduled maintenance actions.

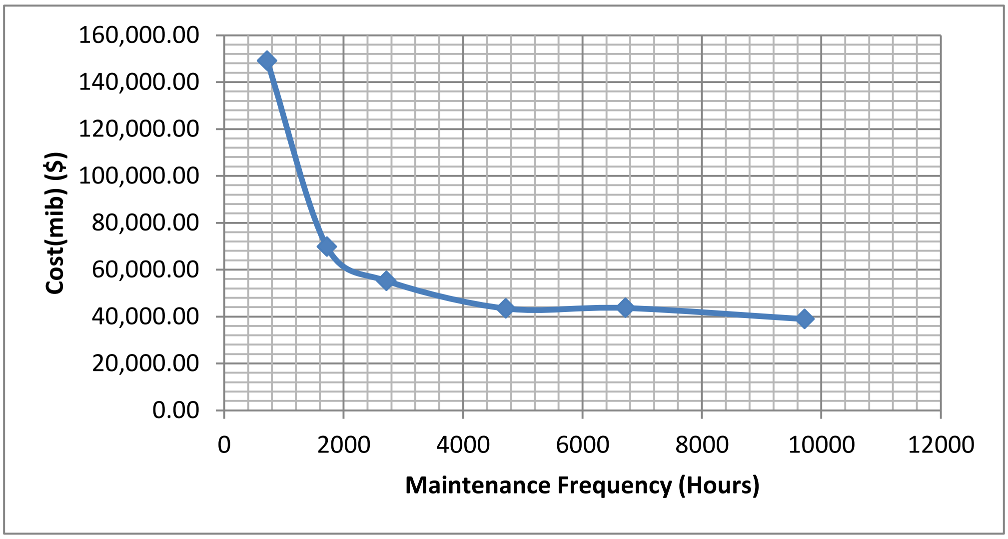

Fig 4: Graph showing how $Cost_{mib}$ varies as the frequency of maintenance actions is altered.

It can be seen that $Cost_{mib}$ follows a similar pattern as $Cost_m$; that is decreasing as the frequency of scheduled maintenance is decreased. This is because for this test $Cost_m$ is by far the biggest contributor to cost, as is evident in Table 4. Fig 5 shows how $Cost_{Risk}$varies, as the maintenance frequency is altered. This is the component of the cost results which relates to TIV.

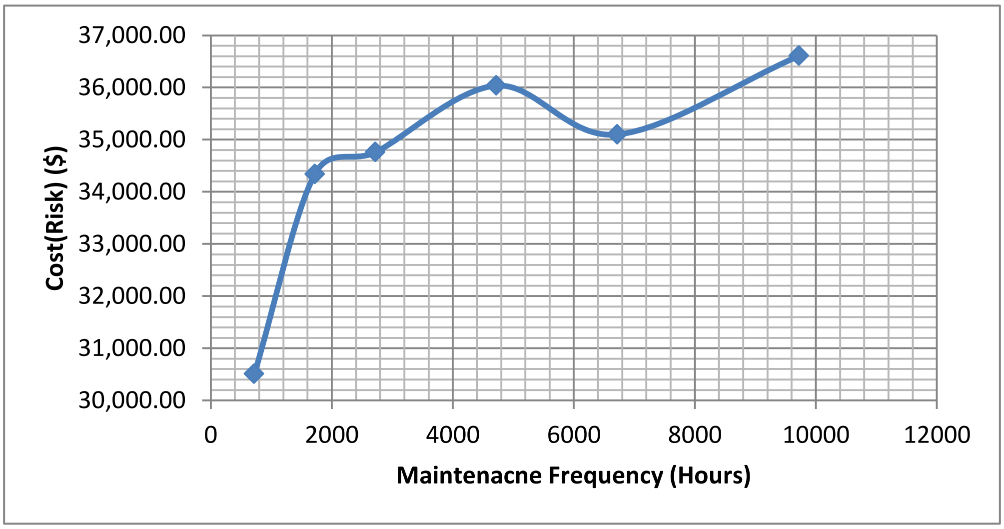

Fig 5: Graph showing variation of $Cost_{Risk}$ as maintenance frequency is altered.

It can be seen in Fig 5 that $Cost_{Risk}$ generally increases as the maintenance frequency decreases. This is because $Cost_{Risk}$ is sensitive to *PSF* from the MC model. This is in agreement with the results from the MC model such that as maintenance frequency decreases *PSF* increases which subsequently increases the potential cost attributed to risk. Additionally the aberration mentioned previously is also present here for the same maintenance policy. As well as a drop in *DTS* an increase in *PSF* was experienced for maintenance policy 4 in the MC model. This explains aberration in the value of $Cost_{Risk}$. The cost of risk is significant as even though the system is highly reliable the chances of a system failure propagating to a total loss incident, is substantial.

Fig 6 shows the results for the total cost of operation with varying maintenance schedules. This takes into account both $Cost_{mib}$ and $Cost_{Risk}$.

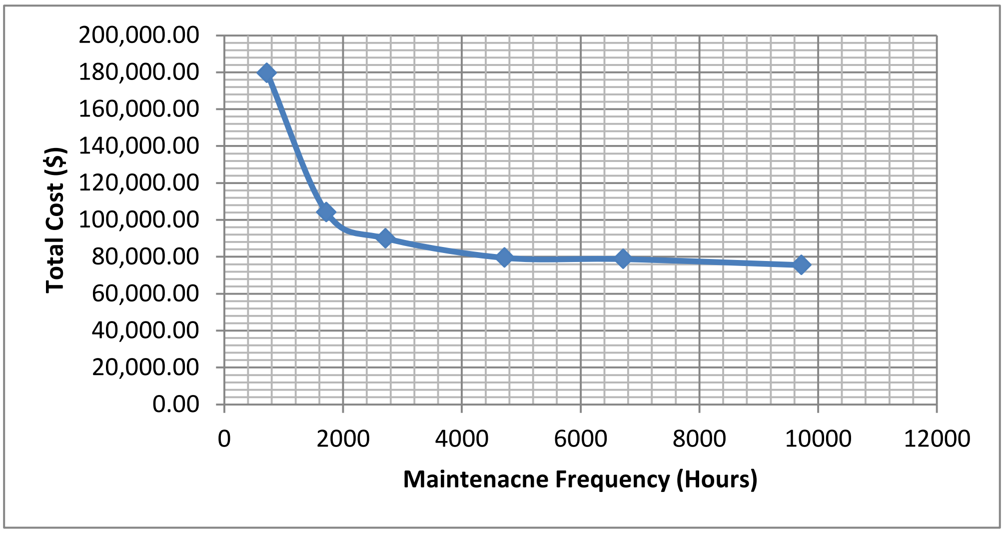

Fig 6: Graph showing how total cost of system operation is affected by varying maintenance frequencies.

As can be seen in Fig 6 the overall cost generally decreases as the maintenance frequency is reduced. The aberration mentioned previously is again present but is further mitigated when looking at the overall cost. It can be seen that the total cost follows the same pattern as $Cost_{mib}$. It should be noted that the frequency of maintenance actions is high in this analysis for a system of this type. This means that the system is more sensitive to costs incurred by maintenance actions than those attributed to risk when maintenance frequency is high. It can be seen that as the maintenance frequency reaches lower values the reduction in cost becomes smaller. As maintenance frequency decreases the increase in system failure probability increases causing the cost of risk to become more significant. This means that as the significance of $Cost_{mib}$ decreases the significance of $Cost_{Risk}$increases. This is expected as reducing the number of maintenance actions reduces costs for spare parts and downtime etc, but leads to cost factors associated risk due to the system becoming less reliable.

Next the cost model has been tested by performing an analysis of the cost variations when the inspection policy for the system is changed. The maintenance actions are kept constant based on the initial test that was performed for policy 1 in Table 4. The delay time, *h*, has also been kept constant at 6 hours. Table 5 show the results for the case study with varying inspection frequencies. The inspection intervals for the results in Table 5 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) for inspection policies 1-6 respectively. Note that the inspection interval is the same for all active components in the cooling system.

Table 5: Showing cost results for cooling system due to varying inspection policies.

	$Cost_{i}$($)	$Cost_m$($)	$Cost_{sp}$($)	$Cost_b$($)	$Cost_{mib}$ ($)	$Cost_{Risk}$($)	Total ($)
1	15,208.33	121,093.07	82,849.48	12,729.81	149,031.22	30,505.02	179,536.24
2	7,583.33	123,474.03	84,697.71	14,167.25	145,224.61	37,481.93	182,706.54
3	2,166.67	125,166.16	86,003.97	15,250.13	142,582.95	42,670.24	185,253.19
4	541.67	125,696.48	86,417.01	16,072.23	142,310.38	44,280.77	186,591.15
5	83.33	125,873.56	86,528.19	17,270.63	143,227.52	44,585.40	187,812.92
6	0.00	125,890.96	86,568.35	20,103.31	145,994.27	45,137.25	191,131.52

Fig 7 shows how the cost components of $Cost_{mib}$ change with varying inspection policies.

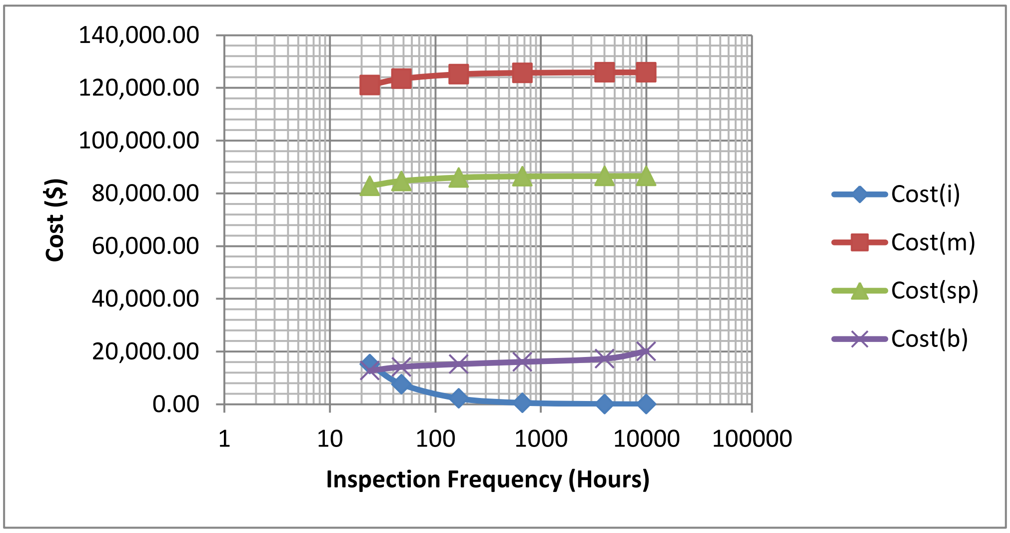

Fig 7: Graph showing variation of $Cost_{mib}$ components as inspection frequency is altered.

As is expected it can be seen that as inspection frequency decreases $Cost_i$ also decreases, eventually reaching zero for inspection policy 6 where no inspection actions are present. This is because $Cost_i$ is solely concerned with costs incurred due to inspection crew wages for this model. It can be seen that $Cost_m$ is also affected by the inspection frequency. The results from the MC model show that inspections have a chance to reduce the downtime of a component failure. With this in mind it can be seen that $Cost_m$ increases as the inspection frequency is reduced. This is because reducing inspection frequency causes more downtime which subsequently increases hours of pay that are required for maintenance crew. It is also the case that $Cost_{sp}$ and $Cost_b$ increase as inspection frequency is reduced. $Cost_{sp}$increases as if a fault is detected upon inspection it is considered that it is repaired without the need for replacement parts unlike if a component is taken offline due to a random failure or scheduled maintenance. $Cost_b$ also increases due to the increased downtime incurred by reducing the inspection frequency. Inspection has a chance of reducing the downtime when a component is taken offline. Increasing the average downtime of individual components also increases the likelihood of system downtime, *DTS*. This means that larger 'off-hire' costs are incurred due to loss of productivity.

Fig 8 shows how the cost due to maintenance and inspection is affected as a whole when altering the inspection policy.

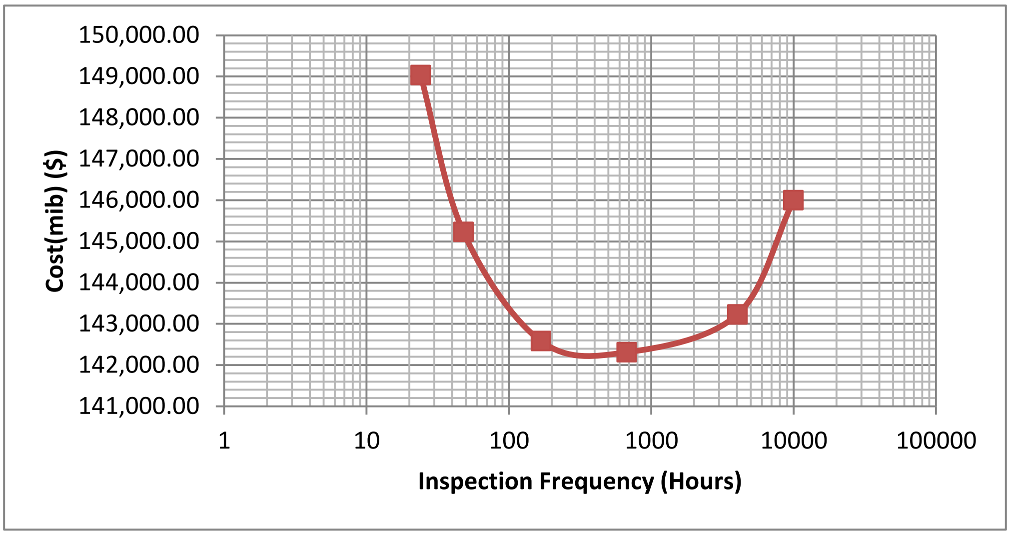

Fig 8: Graph showing how $Cost_{mib}$ varies as the frequency of inspection is altered.

As can be seen in Fig 8 with inspection actions being undertaken every day the value of $Cost_{mib}$ is at its highest. As the frequency of inspection is reduced the cost decreases. However, at the point which inspections are only undertaken every month (every 672 hours) the cost begins to increase again. This is because at first the reduction in man-hours due to reduced inspections outweighs the increase in cost due to increased maintenance and 'off-hire' charges. At this point however the opposite becomes true. The reduction in cost for inspection crew is outweighed by the increased cost due to maintenance and 'off-hire' charges. For this reason the overall cost increases. This is important as it shows an optimum level of inspection when the cost of risk is not taken into account. Looking at Fig 8 it can be seen that the optimum value of $Cost_{mib}$ lies somewhere between weekly and monthly inspections. Fig 9 shows how the results for $Cost_{Risk}$ are affected when altering the frequency of inspection actions.

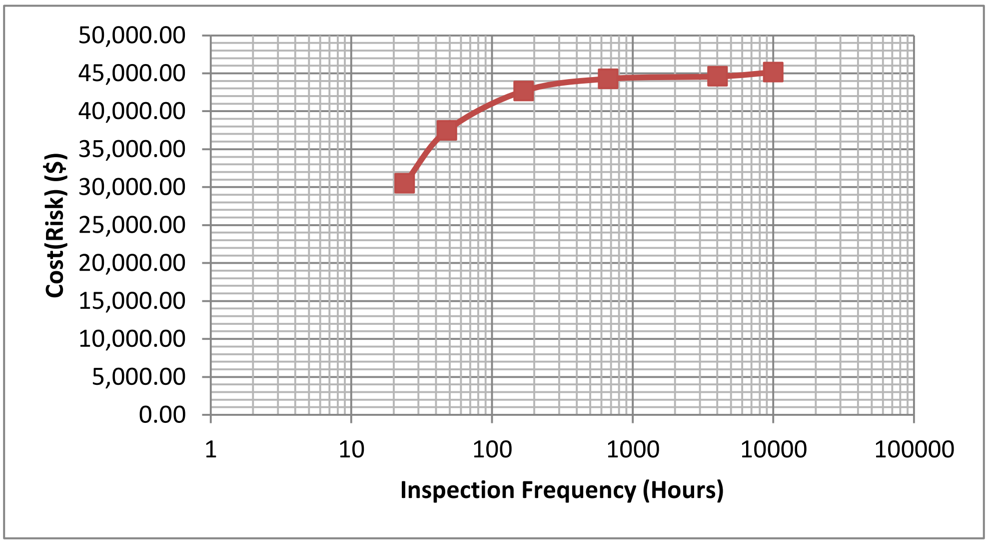

Fig 9: Graph showing how $Cost_{Risk}$ is affected as inspection frequency is altered.

As with the results shown in Fig 5 the value of $Cost_{Risk}$ increases as the frequency of inspection is decreased. Inspections serve to reduce component downtime and reduce the occurrence of simultaneous failures which may lead to a system failure. The increase in the value of *PSF* means the potential cost value for the risk of total loss is also increased by reducing the reliability of the cooling system. It should be noted that $Cost_{Risk}$ is more sensitive to inspections than scheduled over specified mission time. Also even at the highest frequency inspections are much less costly than scheduled maintenance. This shows that for the mission time used in this analysis inspections are more cost-effective at reducing the cost of risk for the vessel. Fig 10 shows results on how the total cost is affected as inspection frequency is altered.

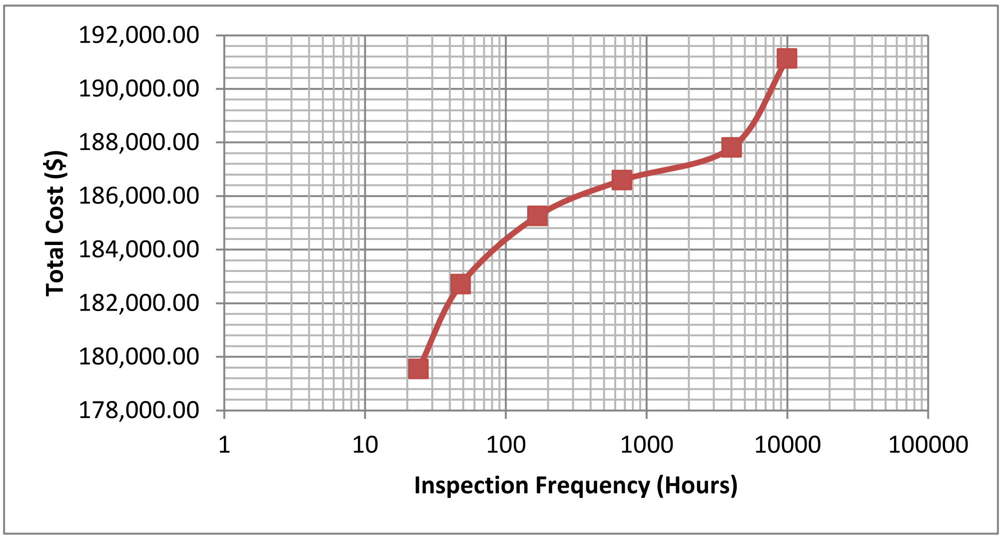

Fig 10: Graph showing how the total operating cost is affected when the frequency of inspection actions is altered.

Unlike the results shown in Fig 6, it can be seen that the results for total operational costs do not resemble the results for $Cost_{mib}$ when the inspection frequency is altered. This is due to the sensitivity of the value for $Cost_{Risk}$ to inspection actions. It can be seen that as the inspection frequency is reduced the total cost increases. Though $Cost_{mib}$ is initially reduced the amount by which $Cost_{Risk}$ is increased is larger causing the overall cost to increase. It can be seen however that between weekly (168 hours) and bi-annual (4032 hours) inspections the increase is not as dramatic. This is because though the value of $Cost_{Risk}$ continues to rise, the value of $Cost_{mib}$ is around its minimum point which reduces the impact of the increased risk. Fig 10 is very useful for showing how the various costs affect the total cost of operation when they are analysed as a single factor. This shows how the model presented is useful for decision making. Looking at the results displayed in Figs 3-10 it can be seen how the proposed cost model can be used to assess the effects of varying maintenance and inspection policies. By entering a number of different data sets, information can be obtained which is useful for decision making for the optimisation of maintenance and inspection policies.

As well as the results in Figs 3-10 results have been gathered to test the effect of lead times due to un-stocked parts for the cooling system. The tests have been performed based on different criteria to observe the effects on the overall cost incurred by the decisions made. Table 6 shows the results for three different part stocking policies.

Table 6: Showing cost results for varying spare part stock policies

	$Cost_{\,i}$($)	$Cost_m$($)	$Cost_{sp}$($)	$Cost_b$($)	$Cost_{mib}$ ($)	$Cost_{\,Risk}$($)	Total ($)
1	15,208.33	119,549.01	81,305.42	13,487.58	148,244.92	33,290.13	181,535.06
2	15,208.33	19,638.64	13,281.18	2,143.50	36,990.48	40,198.21	77,188.69
3	15,208.33	6,357.45	0.00	57,738.85	79,304.63	108,184.02	187,488.65

The results for stock policy 1 are defined using maintenance policy 1 and inspection policy 1. Any item which has an average requirement for repair during the mission time < 0.2 will not be kept in stock. This means that if the item is needed for repair additional component downtime will be incurred due to lead times. For this study the lead time has been set at a standardised value of two days (48 hours). Comparing the results with those in Tables 4 and 5 it can be seen that the total cost of operation has been increased slightly. $Cost_{sp}$ has been reduced but the values of $Cost_b$ and $Cost_{Risk}$ have been increased. $Cost_b$ is increased due to the added downtime incurred by lead times and $Cost_{Risk}$is increased as the system is more likely to be operating without redundancies due to the added downtime. This subsequently increases the overall cost showing that it is better to stock the items.

Stock policy 2 shows the results when the same logic is applied to the system when no scheduled maintenance is performed. These parameters relate to maintenance policy 6 in Table 4. It can again be seen that by not stocking certain parts the overall cost of operation has been increased slightly.

Stock policy 3 uses the same data set as stock policy 2 but the parameters affecting lead times have been altered. For this test it is assumed that no spare parts are stocked so any component failure that occurs will result in lead times. It can be seen immediately that the total cost of operation is much higher; at over double the original value. Even though the cost of spare parts is zero and the value of $Cost_m$ has been significantly reduced, the values of both $Cost_b$ and $Cost_{Risk}$ have been significantly increased. The cost of risk is around ×3 its original value with $Cost_b$ being around ×24 its original value. The added time spent in the failed state means that there is much more risk of a major accident occurring which significantly increases the cost of risk. Also the added time spent offline means that the cost due to loss of productivity is drastically increased. These factors vastly outweigh the cost savings due to spare parts. This makes sense as it would be very irregular for an owner not to stock some key spare parts during a marine operation and this result shows why this option would not be recommended, aside from IMO regulations.

6. Discussion

A model has been presented showing how data acquired via MC analysis can be used to provide information on the costs incurred by various operational parameters. By looking at the results presented it can be seen that the model presented gives useful information for optimising maintenance and inspection policies. By quantifying the risk as a value of cost it allows all aspects of the reliability and availability for the analysis to be quantified as a single value. The lowest total cost refers to the most cost-effective maintenance and inspection policy for the system. The breakdown of costs provided also allows further analysis of what may be causing certain increases in cost so that attention can be paid to the areas which require improvement.

It can be seen from Fig 6 that for the mission time of one year the best option is to have no intermediate scheduled maintenance for the cooling system. Some of the maintenance policies, used for this analysis are unusually frequent. This highlights the excess costs incurred if maintenance is scheduled too frequently. The results for total cost when altering the inspection frequency are opposed to those for scheduled maintenance. It is shown in Fig 10 that the most frequent inspection policy (inspections every 24 hours) yields the lowest total cost. Therefore, for the case study presented it is advised that frequent inspections should be in place to optimise the operational efficiency of the cooling system.

If the model is applied to a different scenario it is likely that the results for maintenance and inspection optimisation would be significantly different. A report by MAIB (2002) states that, 14% of engine fires will result in a total loss incident. It could be the case that an analysis is performed in which it is assumed that a system failure will lead to an engine fire. With this in mind a value of 0.14 is substituted as the value of *CPL* for the same parameters as in maintenance policy 1 in Table 4. This increases the cost of risk from $30,505 to $914,642. In this case the cost of risk far outweighs the cost of maintenance meaning regular maintenance is desirable to increase the reliability of the system and reduce costs.

Looking at the results in Table 6 it can be seen that the omission of parts for the analyses performed serve only to increase the total cost of operation. This is not always the case as the system under analysis and the stock options decided by the user will affect the impact on the overall cost. It should be noted that the effects of implementing lead times may change significantly if key variables such as *CPL* are altered for the system. An additional test has been performed applying the same parameters as stock policy 1 in Table 6. However, when applying the cost model the value of *CPL* has been reduced from 4.67×10^{-3} to 1.48×10^{-4}. This significantly reduces the potential cost of risk and when applying the stock policy the total cost is reduced from $149,999 to $149,300. For the same system operating with these parameters it is more cost effective not to stock certain items. This shows how the effect of un-stocked items varies for system operating under different conditions.

7. Conclusion

The purpose of this study has been to present methods to calculate the different operational costs by utilising data obtained by MC analysis so that the results obtained take into account the complex behaviour of the system under analysis. The model presented is successful in showing the flexibility of MC methods as a tool to be applied for decision making in the marine industry. By means of simulation and the application of a cost model, cost data is obtained which takes into account a number of criteria which are difficult to model using analytical methods. By translating the results obtained from MC to one single cost value maintenance and inspection decisions as well as spare parts stock options can be easily compared. The results of various analyses can then be used to determine optimised policies to increase the efficiency for marine systems.

Accurate cost data has been acquired taking into account a wide range of factors concerning operational costs in the marine industry. The results are presented in a manner that is clear so that definitive optimisation decisions can be made. By combining the proposed methods the model allows the consideration of a variety of options when attempting to optimise the efficiency of marine operations without the need for extensive manual analysis.

The nature of MC analysis allows complex system behaviour to be modelled which can be altered based on the specific requirements of the analysis. The complexity of the behaviour which can be modelled using MC methods is reflected in the results obtained from analysis. It is suggested that the results obtained by MC analysis can be used to facilitate the improvement of other commonly used methods for solving marine RAMS problems.

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