International Journal of
Advances in Scientific Research and Engineering (ijasre)

E-ISSN : 2454-8006

DOI: http://dx.doi.org/10.7324/IJASRE.2018.32575

Volume 4, Issue 1
January-2018

Risk Control and Cost Benefit Analysis of Docking Operation

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ABSTRACT

In this paper, a failure/accident analysis model is proposed to develop the cost-effective safety measures for preventing accidents in dry docking and undocking operations. The model comprises two parts. In the first part is a quantitative failure analysis model built by Bayesian Network (BN) which can be utilised to present the corresponding prevention measures. In the second part, the proposed prevention measures are ranked in a cost-effective manner through a Bayesian Network (BN) approach. A case study is analysed as an illustration. The case study shows that the proposed model can be used to seek out failure/accident causes and rank the derived safety measures from a cost-effectiveness perspective. The proposed model can provide accident investigators with a tool to generate cost-efficient safety intervention strategies.

Key Words: *Bayesian network, Risk control measures, Cost benefit analysis, Dry docking, Undocking operations.*

1. INTRODUCTION

When an accident occurs, it is important to understand the root cause in order to take effective preventive measures. A failure model provides the cause effect analysis. Failure analysis always implies a failure model is a set of assumptions of what the underlying mechanism is . A failure model is an abstract conceptual representation of the occurrence and development of an accident; it describes the way of viewing and thinking about how and why an accident occur[1]. Accident model is also a very important process for providing input into the development of proactive and cost-effective safety measures[2].

Naturally, a qualitative failure model has some weaknesses such as managing information systems for effective safety measures in: availability, performance, security, and modifiability, as well as in predicting values in different future scenarios in today's complex ship docking and undocking operation, which remains a great challenge [3]. First, a great number of factors influence a system's cost-effective safety measures. Second, the factors are intertwined in a complex manner. The researcher who sets out to model these interdependencies thus inevitably faces a discomforting number of modelling choices, all of which to some extent influence the ability of the final assessment framework to provide accurate decision support for managing decisions [3]. Furthermore, all modelling choices represent a cost in terms of collecting the information needed for actually using the model. This cost, whether expressed in money, effort, or time, must be kept under control, lest the entire effort of modelling the cost-benefit effectiveness be misguided [3].

As opposed to other publications addressing similar issues, such as in [4] and [5], this paper adopts Bayesian formalism for expressing these uncertainties. The application of Bayesian networks (BNs) in a graphical environment for decision support using cost-effectiveness enables us to create the most efficient model, given the available information on uncertainties and the cost of data collection. With a hierarchy of nodes and states defined, a BN, which represents the relationship among failure variables, can be constructed. The relationship depicted in any hierarchy structure is mapped onto the BN via its graphical representation with edges connecting nodes at a particular level to those located one level below. Even if the data available before modelling is scarce,

the proposed model forces the modeller to make implicit assumptions explicitly, hence decisions become transparent. Furthermore, cost efficiency is taken into consideration in the early phases [5],[6].
The purpose of cost benefit analysis (CBA) is to compare the costs and benefits associated with the implementation of safety measures. There are many papers carrying out safety assessment using a formal safety assessment (FSA) method, in line with well-established cost-effective criteria [7], [6]. This study applies BN techniques to analyse and verify the relationships among cost and benefit factors in dry docking and undocking operations, using expected cost factors, expected benefit factors, risk reduction factors, reference value factors, and uncertainty factors [6],.

This paper presents findings of analysis of stability and pontoon deck failure in floating dry dock docks, and the dry dock gate failure of graving docks. The exploration and the comparison of two failure model and one accident model are presented. The examinations presented are: (1) the cost effectiveness of a failure model of a large dry dock gate in Birkenhead graving dock, UK, where the results of possible risk control options revisited to help prevent future accidents [7],[6].

The result of this failure/accident analysis model is safety risk measures categorisation. Lessons learned from accidents are important for identifying weaknesses in the present system and avoiding them in future [8]. For existing failure models, the quantitative analysis for failure modes and cost-effectiveness analysis for safety measures are not sufficient. As a response, an extended failure model analysis is constructed to seek failure causes and propose cost-effective safety measures in this chapter. The benefits of applying BN cost-effective measures are obtained where the findings provide great potential to improve the strategic planning of docking and undocking operations, hence adopting more suitable development activities related to risk.

2. LITERATURE REVIEW

The risk control options and cost benefit analysis, of a high level Formal Safety Assessment (FSA) pertaining to floating and graving dry docks according to the FSA guidelines issued by IMO [7]. In this stage different risk control options (RCOs) are identified to control the major risks identified in the previous chapters. The RCOs are then assessed through cost benefit analysis using the standard IMO procedures and criteria for cost effectiveness. The assessment consists of three parts: (a) identification of relevant risk control options; (b) estimation of risk reducing effect of identified RCOs; (b) evaluation of cost benefit of RCOs. The list of prioritised hazards has been used as input for building risk models and for the identification of appropriate risk control options.

Risk control option is Step 3 of FSA, it proposes effective and practical RCOs compromising of the following stages: (1) focusing on risk areas needing control; (2) identifying potential RCOs; (3) evaluating the effectiveness of the RCOs in reducing risk by re-evaluating Step 2 (risk analysis); (4) grouping RCOs into practical regulatory options. The objective of this Chapter is to address points 1-4. The output from this step comprises: (a) a range of RCOs which are to be assessed for their effectiveness in reducing risk, and; (b) a list of interested entities affected by the identified RCOs.

Cost benefit assessment as described in MSC (2003) is to identify and compare the achieved risk reduction and benefits with the costs associated with the implementation of each RCO identified and defined in Step 3. A cost efficiency assessment following the IMO procedure may consist of the following stages: (1) consider the risks assessed in Step 2 (risk analysis) both in terms of frequency, consequence and failure consequence probability, in order to define the base case in terms of risk levels of the situation under consideration; (2) arrange the RCOs in a way to facilitate understanding of the costs and benefits resulting from the adoption of an RCO; (3) estimate the pertinent costs and benefits for all RCOs by reassessing the risk assuming the option under consideration is in place and comparing the risk level to the established base case; (4) estimate and compare the cost effectiveness of each option, in terms of the cost per unit risk reduction by dividing the net cost by the risk reduction achieved as a result of implementing the option; and (5) rank the RCOs from a cost-efficiency perspective in order to facilitate the decision-making recommendations in Step 5. There are several indices used by IMO that express cost effectiveness in relation to safety of life and the environment, two of which are: Gross Cost of Averting a Fatality (GCAF) (eqn. 1), and Net Cost of Averting a Fatality (NCAF) (eqn. 2).

$$\mathrm{GCAF} = \Delta C/\Delta R_s \tag{1}$$

$$\mathrm{NCAF} = \Delta C\text{-}\Delta B/\Delta R_s \tag{2}$$

Where, ΔC is the cost per floating/graving dock of the risk control option during the lifetime of the system, ΔB is the economic benefit per floating/graving dry dock per ship resulting from the implementation of the risk control option during the lifetime of the system (includes environmental and property benefits), ΔR is risk reduction per floating/graving dock, in terms of the number of fatalities averted (ΔR_s).Concerning the analysis of cost effectiveness, its criticism can be elaborated upon the following points.

Firstly, because NCAF/GCAF imposes the maximum cost of averting a fatality, one feels that the avoidance of a fatality, if such is possible, should be done at all costs rather than having this cost fixed [7].

In addition to this ethical dilemma, the continuous adjustment process of NCAF and GCAF values makes their application troublesome. Hence, an ideal situation would be to avoid imposing any maximum values at all or amend the approach by an alternative. Secondly, there is a clear overlap between NCAF and GCAF criteria. Specially referring to the original interpretation of the criteria in [7] : (a) GCAF or NCAF- in principle, either of the two criteria can be used. However, it is recommended to firstly consider GCAF instead of NCAF. The reason is that NCAF also takes into account economic benefits from RCOs under consideration. This may be misused in some cases for pushing certain RCOs rather than other RCOs. If the cost-effectiveness of an RCO is in the range of the criterion, then NCAF may be also considered [7].
Cost-effectiveness analysis is often used as the basis for evaluation of alternative safety measures. In such an analysis, indices of the form 'expected cost per expected number of lives saved' are calculated. This method does not explicitly set a value to the benefit, e.g. value of a statistical life, as is required in a cost-benefit analysis. The cost-effectiveness analysis is a well-established discipline [9]. There is, however, a gap between the theoretical cost-effectiveness analysis and the practical implementation of the tool as providing decision-making support. Ideally, the decision-maker should have a number of methods at hand. Some of these should be detailed and sophisticated and be used when a few safety measures are compared and the consequences of unfavourable decisions are severe. On the other hand, a simplified method to sort out some cost-effective measures for many alternatives in less complicated studies or pre-studies before more sophisticated comparisons is required [9].

Traditional cost-effectiveness indices such as expected cost per expected number of lives saved provide useful insight, but, as pointed out by many analysts and researchers, cost-effectiveness indices based on expected values are not sufficient for evaluating cost effectively. Uncertainty must be considered beyond the cost-effectiveness indices. The main problem is that the expected values are conditional on specific background knowledge, and expected values could produce poor predictions [9]. Surprises may occur, and by only addressing expected values such surprises may be overlooked [10]. A similar idea underpinning these approaches is seen in risk governance framework [11] and the risk framework used by the UK Cabinet Office [12].Many safety measure properties – availability, performance, security, and modifiability, to name a few – share the elusive feature that while they are easy to define *a posteriori*, i.e. after system implementation, such definitions give precious little guidance on how to ensure them *a priori*, i.e. before safety measure implementation. For example, measuring the cost of change of a system *a posteriori* is mere book-keeping [3], but assessing it beforehand is a formidable task. Such assessment must be carried out by measuring variables available prior to the modification [3].

A typical running cost with six key problems will be addressed in this paper [3]: (1) the choice of *a priori* measurement quantity is the problem of finding a measure (complexity) that correlates accurately with the sought *a posteriori* quantity (cost of change); (2) definitional uncertainty must be handled since most concepts of safety measure can be interpreted in many different ways; (3) measurement devices, which range from software tools to expert estimates, are necessary and crucial instruments, but introduce further uncertainties; (4) selection of appropriate scales affects precision and imposes constraints on which statistical operations are permissible to be performed on the data; (5) discretisation of measurement variables simplifies measurements and maps them onto the desired scales, but only at the cost of lost accuracy; (6) the overall accuracy of the model must be weighed against the cost of performing the measurement. Out of several models, the most cost-efficient one always ought to be selected. Therefore, this chapter scrutinises a number of general problems related to measurements of cost-effective-related decision-making activities. It has been argued that these problems are not in general given sufficient thought when making decisions about how to model software systems in failure/accident modelling in docking and undocking a vessel. The risk safety measures used in this paper provide ample proof of the concept regarding the method proposed. However, due to somewhat laborious nature, care should be taken when deciding how and when to model.

3. METHODOLOGY

3.1 Risk Control Measures Identification

The starting point for the suggested approach is the risk control process identification, as described in standards relevant for risk management –[13] and [14]. The key information for evaluating safety measures is: (1) information about safety requirements in regulations; (2) alternative safety measures and their effects and cost; (3) risk reduction effect; (4) information about uncertainty; (5) decision-makers' reference value; and (6) other factors like political issues, media focus, stakeholders' preferences, etc. Attention is paid to aspects 2-5 in the list: the effectiveness, cost, uncertainty, reference value and risk reduction aspects. Aspect number 1 is not subject to the decision-making process in this study, and, although number 5 certainly affects the decision-making process, it is not covered by the cost-effectiveness model presented.

The output from the step of cost-benefit assessment is: (1) costs and benefits for each RCO identified from an overview perspective; (2) costs and benefits for those interested entities which are the most influenced by the problem in question and; (3) cost effectiveness expressed in terms of suitable indices. The purpose of this study only point to 1 and 3 just described. The risk safety measures for gate failure, stability failure and pontoon deck failure are used as an input for cost benefit assessment. The benefits are the avoidance of accidents and these can be measured by evaluating the avoidance of harm to people, damage to property and environment, and other costs. Potential risk control options are: Operations (O) - (proper equipment), Awareness (A) - (improved training, drills to respond to common incidents, special procedures for higher risk evolutions, response plans, emergency plans), Preventive Maintenance (Ma) - (detailed procedures), Monitor (Mo) - (enhanced surveys), Inspection (I) - (improved enhanced surveys), Redesign (Rd) - (alarms, communication equipment, remote sensors, re-check lists for routine evolution) [15]. These are the six categories according to which the risk control options (RCOs) are evaluated. Table 1 presents the RCO for the failure mode of a dry dock gate in Birkenhead, UK.

The expected output of this assessment is to identify cost and benefit for gate failure, stability failure and pontoon deck failure from an overview perspective. The purpose of identifying risk control options is to propose an effective way of minimizing high risks identified from the information produced in the risk assessment. The identification of RCOs can have the following attributes: (1) those relating to the fundamental type of risk reduction (i.e. preventative or mitigating); (2) those relating to the type of action required and therefore to the cost of the action (i.e. the engineering procedural); (3) those relating to the confidence that can be placed in the measure (i.e. active or passive and single or redundant). The practical RCOs' action can be determined by repeating risk analyses and comparing the results to the original case [15].

After the risk items to be controlled are identified, the extents to which the probabilities of undocking operational performance risk are subjected with the relative change in various degrees of RCO implementation [15]. To achieve a balance, the benefit of a RCO must be considered and compared to the cost of its implementation. The cost benefit BN model compares estimated levels of risk against the pre-established criteria and considers the balance between potential benefits. This enables decisions to be made about the extent and nature of treatments required and about priorities [14].

Table 1: Risk safety measures for dry dock gate failure prevention

RCOA	RSM	RCM
		1) Maintenance on rolling rails (Mo)
	1) Maintenance of towing system	2) Maintenance on rollers (Mo)
1. Maintenance		3) Maintenance on system failure (Mo)
	2) Improve awareness on preventing any buoyancy in upper chamber	4) Maintenance on air chamber (O)
		5) Check stability issues (O)
	3) Constantly controlling an even draught	6) Maintenance on flap wires (Mo)
2. Awareness		7) Maintenance on ballast tanks (Ma)
		8) Maintenance on wires (Ma)
	4) Improve structural inspection on structural elements	9) Maintenance of floors (Ma)
3. Inspection		10) Maintenance of walls (Ma)
		11) Maintenance on handrail (Ma)
	5) Monitor loads from water pressure-rolling of recess	12) Maintenance on ladder (Ma)
4. Monitor		13) Prepare against increased sea state (O)
		14) Prepare against high tides (A)
	6) Maintenance on gate water tightness	15) Prepare against hurricane (A)
		16) Increase inspection on the rubber L-shape (I)
5. Prevention		17) Improve strength on sea state effect (A)
	7) Preventing failure of control system	18) Improve strength against hurricane (P)

		19) Check water level (O)
6. Operations		20) Check control system (Mo)
		21) Improve undetactability (P)
	8) Tank Operations issues	22) Inspection on trimming tanks (I)
		23) Improve maintenance on scuttle tanks (Ma)
		24) Improve scrum tank inspection (I)

3.2 Cost-Effectiveness Analysis Factors

In the evaluation of safety measures a cost-effectiveness analysis may be adopted. A cost-effectiveness analysis compares the costs and the effects of a decision alternative, where the cost is measured in monetary terms and the effects are measured in natural units, such as lives saved [16], [17]. Other important factors considered in the cost-effectiveness frameworks are: the reference values (Reed *et al*., 2010), the risk reduction effects [18] and uncertainty [9].

Upon proposing various safety measures, the next step is to carry out cost-benefit analysis (CBA) on each safety measure. CBA aims to rank different safety measures by identifying the benefits from accident prevention and the cost associated with safety measures. The evaluation of costs, benefits and other factors may be conducted using various techniques [7]. However, due to unavailability of reliable data, these factors are very difficult to assess in an exact manner [7].

Safety experts as well as decision-makers often like to use linguistic variables to estimate costs, benefits and other associated factors affecting CBA incurred in safety improvements. Under such considerations, it may be more appropriate to estimate using ranking nodes in a BN, where the BN allows for experts to express their subjective judgements [18]. When applying the proposed cost-effective BN framework, the following activities should be carried out [9]: (1) identify initiating events based on a facilitated brainstorming process supported by a checklist and comprehensive literature review in undocking and docking a vessel in graving/floating dry dock; (2) describe the potential consequences and associated probabilities for each initiating event; (3) categorise the potential consequences and associated probabilities by use of a qualitative or a semi-quantitative approach; (4) identify potential safety measures for initiating events.

A similar method has been used several times in risk analyses in this research. The initial part of this research is the risk assessment process carried out in a workshop where experts on the failure/accident model in floating/graving dock system participated, and the information gathered in the workshop was subsequently refined by the risk analyst for cost-effectiveness analysis. The factors affecting the cost effectiveness model are presented in Figure 1.

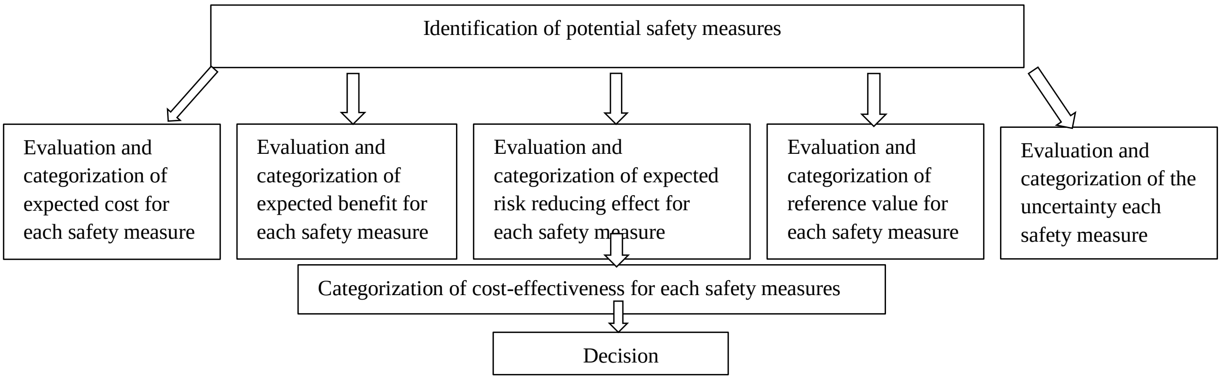

Figure 1: Factors affecting cost-effectiveness

3.3 Expected Cost

As for the expected cost, it is common to use expected values for the cost dimension. Predictions of cost for implementing and operating safety measures can be calculated as several levels of detail. Examples of cost prediction categorisation (in £): very low < 10.000: low ≥ 10.000 and < 100.000: medium ≥ 100.000 and < 500.000: high ≥ 500.000 <1.000.000: and very high: > 1.000.000 [9]. All cost categories are covered in the assessment including, capital, appraisal, failure, operational, maintenance, training, administrative, formal safety assessment cost, cost of result accuracy, etc. [15]. For example, prevention cost is the cost of preventing failures, whilst failure cost is cost incurred as a result of scrap, rework, and failure. Appraisal cost is cost of measurement.

3.4 Evaluation of Expected Benefits

To find the expected benefit, the implementation can be done by paying attention to the expected risk reducing effect. For each risk reducing measure, the expected risk reducing effect should be given a qualitative assessment and description, and then be categorised according to the assigned expected risk reducing effect. Emphasis should be on the description of physical matters. Some answers may need the support of quantitative studies. The categorisation process should be based on some criteria to ensure consistency. What categories need to be applied depends on the level of detail of the analysis. In this study, the five categories used for expected benefit are: very low = no benefit from reduced risk, low = small benefit from reduced risk, medium = medium benefit from reduced risk, high = high benefit from reduced risk, and very high = very high benefit from reduced risk [15]. In the categorisation process, both the initial risk picture determined in the risk assessment and the expected risk reducing effect given the initiating event have to be considered [9].

3.5 Evaluation of Expected Risk Reducing Effect

A coarse evaluation of the risk reducing effect for each safety measure needs to be considered. It is also called the risk reduction after implementation of safety measure. It should be noted that in this factor the risk reducing effect (RRE*i*) is not measured as the product of probability and consequence, but is calculated in terms of reduction in the expected number of fatalities once a specific safety measure is implemented. This implies that, at least for the moment, only consequences incurring fatalities are considered. The risk reducing effect is calculated by:

$$\Delta \, \mathrm{RRE}i = \Delta P_f \,.\, C_f \qquad (3)$$

Where, Δ RRE*i* is risk reduction effect [fatalities year^{-1}], ΔP_f is reduction of accident probability after adopting safety measure [year $^{-1}$], and C_f is the accident consequence [fatalities]. The linguistic scale can be used to estimate the accident consequence [18].

3.5 Reference Value for Each Safety Measure

The results of a cost-effectiveness analysis may be expressed in two main ways: either as a cost-effectiveness ratio or as an effectiveness-cost ratio. The review and discussion of the cost-effectiveness analysis that follows focuses on the cost-effectiveness ratio, which is by far the more commonly used ratio. The reference value (R*i*) clarifies how much money the decision-maker (DM) is willing to pay to obtain one unit of effectiveness. Implementation of the safety measure is preferred to status quo if the decision-maker is willing to pay more to obtain one unit of effectiveness than the cost-effectiveness index expresses, which means that safety measure 1 is preferred to status quo if R is considered [9].

3.6 Uncertainty Effects for Each Safety Measure

Valuable insight is provided through cost-effectiveness indices, but there is a need for a broader consideration of uncertainties, as discussed in [10]. The main argument is that the expected values are conditional background knowledge, and may produce poor predictions. The background knowledge includes historical system performances, system performance characteristics and knowledge about the systems in question. Assumptions are an important part of this knowledge. A result is that a true objective expectation value does not exist due to these uncertainties (U*i*) [9]. *Uncertainty may be regarded as the values predictability of the real outcomes*. High uncertainty may indicate that the *expected risk reduction effect* can give a poor prediction of the real risk reducing effect. The uncertainty categorisation should be based on some criteria to ensure consistency [9].

Three categories are used for the uncertainty dimension: *Low uncertainty*, all the following conditions are met - The phenomena involved are well understood, the models used are known to give predictions with accuracy- The assumptions made are seen as very reasonable- Much relevant and reliable data and/or experience are available - There is broad agreement among experts. For the uncertainty dimension: *High uncertainty*, one or more of the following conditions are met- The phenomena involved are not well understood - The assumptions made represent strong simplifications -Data and/or experiences are unreliable - There is lack of agreement/consensus among experts.

For the uncertainty dimension: *Medium uncertainty*, (i.e. conditions between high and low uncertainty e.g. - The phenomena involved are well understood, but the models used are too simple- Some reliable data and/or experience are available. The degree of uncertainty must be seen in relation to the effect/influence the uncertainty has on the predicted values. For example, a high degree of uncertainty combined with high effect/influence on the predicted values will lead to a conclusion that the uncertainty factor is high.

3.7 Ranking of Safety Measures for Decision Making

After the cost-effective analysis factors of each safety measure are assessed, the outputs should be combined to provide the overall assessment for the safety measures. The expected cost, expected benefit, risk reducing effect, preference values, and uncertainty of the *i*th safety measure can be evaluated using the crisp probability value (CPV) to rank the output safety measures in preference degree using the seven (7) safety states.

3.8 Advantage of Bayesian Network-Based Cost-Effectiveness

Bayesian network techniques are a kind of powerful knowledge representation and reasoning tool under conditions of cost-related uncertainty with various domain expert background. In a practical application, the nodes of a BN represent uncertainty factors, and the arcs are the causal or influential links between these factors. The association with each node is a set of conditional probability distribution (CPD) that models the uncertainty relationships between each node and its parent nodes. Many applications have also proven that Bayesian network is an extremely powerful technique for reasoning the relationship among a number of variables under uncertainty [19].

Compared with other inference analysis approaches for cost effectiveness analysis, BN techniques have four main advanced features in applications. Firstly, all the parameters in the BN have an understandable semantic interpretation [20]. This feature helps users construct a BN directly by using their domain knowledge. Secondly, BN techniques have the ability to learn a relationship among its related variables. This not only allows users to observe the relationships among its variables easily, but also can handle some missing data issues [21]. Thirdly, BN techniques can conduct inference inversely; i.e. BN can conduct bi-direction inference. The fourth advanced feature is that BN techniques can combine *a priori* information with current knowledge to conduct inference as it has both causal and probabilistic semantics in cost-effectiveness analysis. These features will guarantee that using Bayesian networks is a good way to verify those initially identified uncertainty relationships between cost, benefit, risk reduction effect, reference value, and uncertainty factors in the formal safety assessment in docking and undocking a vessel in graving dry docks operation.

4. ILLUSTRATIVE EXAMPLE: COST BENEFITASSESSMENT FOR DRY DOCK GATE FAILURE

In general, there are three main steps when applying Bayesian network techniques for cost effectiveness analysis and setting effective relationships for a practical problem: (1) creating a graphical BN structure for the problem, (2) calculating related conditional probabilities to establish a BN, and (3) using the established BN to conduct inference for finding possible relations among these factor nodes of the BN. The following sub-sections will describe the three steps in detail.

4.2 Creating a Graphical Structure for Cost-Effectiveness Factor Relationships

A graphical BN structure of cost-effectiveness factors' relationships can be created by linking nodes in the structure using lines. These lines in the graphical BN structure express the significant effect relationships between cost-effectiveness factors' nodes. These nodes and relationships shown in Figure 2are considered as a result obtained from domain safety experts (E) and domain decision-makers' (DM) knowledge. In order to test these established relationships, structural learning is needed to improve the BN by using collected real data from docking and undocking operations. BN has 31 nodes and 30 links, and will be used for Bayesian rule-based inference for cost-effectiveness analysis. One BN is constructed by structural and parameter learning, using AgenaRisk desktop decision support software.

The Bayesian cost-effectiveness framework consists of the *node expect cost (Ci)* with five experts' (E1, E2, E3, E4 and E5) input, the node *expected benefit (Bi)* five experts' (E1_1, E2_1, E3_1, E4_1, and E5_1) input, the node *risk reduction effect (RREi)* with inputs A%, B%, C%, D%, and F% which signify a 15%, 25%, 50%, 60%, and 85% risk safety measure reduction respectively, the node *reference value (RVi)* with five decision-makers' (DM1, DM2, DM3, DM4, and DM5) inputs, and the *node uncertainty (Ui)* with five experts' (E1_2, E2_2, E3_2, E4_2 and E5_2) inputs. This model is used to obtain the output *net expected benefit* for each risk safety measure, for ranking purposes.

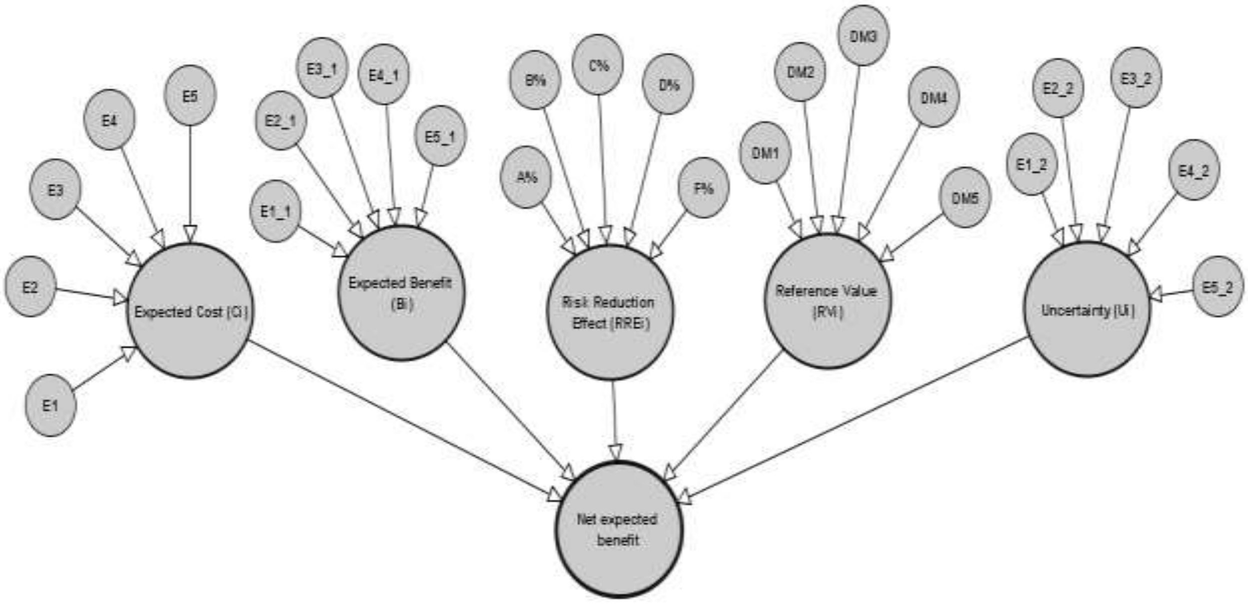

Figure 2: Cost-effective BN framework

4.3 Calculating the Conditional Probability Distributions

Now let X= ($X_{0,\ldots\ldots,}X_m$) be a node set, and X_i (i=0,1….m) be a discrete node (variable) in a Bayesian network B (m = 31) as shown in Figure 2. The CPD for the node X_i is defined as $\beta^B{}_{xi|PA} = P(X_i{=}x_i \mid Pa_i = pa_i)$ [22], where Pa_i is the parent set of the node X_i, pa_i, is a configuration (a set of values) for the parent set Pa_i of X_i and x_i is a value that X_i takes. Based on data collected in surveys, the CPDs of all nodes shown in Figure 2 can be calculated. Before using the BN to conduct inference, learning and establishing the parameters $\beta^B{}_{xi|pai}$ from the data collected should be completed. In general, the easiest way to estimate the parameters $\beta^B{}_{xi|pai}$ is to use frequency. However, as the size of the data used in this study is not very large, using a frequency method may be not very effective [19]. BN is a probabilistic graphical model that represents a set of random variables and their conditional independencies via a directed acyclic graph (DAG) [23]. Conditional probability table (CPT) elicitation is a complicated issue due to a large number of judgements required to quantify the relationships of the BN [24]. [18]also proposed the use of Analytic Hierarchy Process (AHP) and the decomposition method to estimate the CPT for BN nodes. Suppose that a node X (with k states $x_1, x_2,\ldots\ldots x_k$) has n parents ($T^{(1)}, T^{(2)},\ldots. T^{(n)}$).

The determination of the conditional distribution $P(X = x_i \mid T^{(1)}, T^{(2)},\ldots. T^{(n)})$ for all possible state combinations of the parents is a complicated process, especially when n is large or when each parent has a large number of states. Using the decomposition method means the conditional probability with each of the n parents can be calculated separately and then combined, while keeping a close look at the normalisation constant ‘α’ to ensure $\sum P(X = x_i \mid T^{(1)}, T^{(2)},\ldots. T^{(n)}) = 1$. This study, however, proposes the use of ranking nodes with experts’ judgements expressed with WeightedMin truncated distribution.

[25] suggested that ranked nodes represent discrete variables whose states are expressed on an ordinal scale that can be mapped onto a bounded numerical scale that is monotonically ordered with an underlying unit interval, [0,1]. As far as the user is concerned the underlying numeric scale is invisible – the displayed scale is still the labelled one rather than the numeric one, but the latter is used for the purposes of computation (a priori probabilities) and generating CPT. The crucial thing about the ranked nodes is that they can make the BN construction and editing task much simpler than otherwise possible. By defining nodes as ranked nodes, it is possible to define the CPTs that satisfy the criteria described. The 5 and 3 mapping scale and underlying numeric ranking is presented in Table 2 and Table 3. Users of BN never have to construct the mappings. All they need to know is that, irrespective of the linguistic descriptions of the states, the underlying model is working with a numerical scale.

Because it is a numerical scale, the numerical statistical distribution can be defined, and one especially useful distribution is truncated normal (TNormal) and weighted min function (WMIN) which can be used to generate CPTs, rather than the Normal distribution commonly assumed in linear regression for ranked causal nodes, the doubly truncated Normal distribution (denoted *TNormal* hereafter) as defined, for example in [26], where all nodes are truncated in the [0,1] region. Unlike the regular Normal distribution (which must be in the range –infinity to +infinity) the TNormal has finite end points, denoted by TNormal (μ,ϖ^2, 0,1) where μ is the mean and ϖ^2 is the variance.

The priori ranking for E1-E5 is a 5 mapping ranked scaled and a variance $\varpi^2 = 0.2$ and the weights of the experts are E1= 0.1, E2 = 0.2, E3 = 0.4, E3= 0.4 and E5 = 0.5. The nodes E1_1 = 0.1, E1_2 = 0.2, E1_3 = 0.4, E1_4 = 0.5 have a variance $\varpi^2 = 0.01$. The nodes A%, B%, C%, D% and F% have the same weights. The five parent nodes DM, have the following weights DM1= 0.2, DM2= 0.2, DM3= 0.3, DM4= 0.4, DM5=0.5 and variance $\varpi^2 = 0.002$. The parent nodes E1_1 are ranked on 3 points mapped with weights E1_1= 0.1, E2_1 = 0.2, E3_1 = 0.3, E4_1 = 0.3, E5_4 = 0.5. = 0.5.

Table 2: Five (5) scale mapping

Very low	[0,0.2), the range 0 to 0.2
Low	[0.2,0.4), the range 0.2 to 0.4
Medium	[0.4,0.6), the range 0.4 to 0.6
High	[0.6,0.8), the range 0.6 to 0.8
Very high	[0.8,1), the range to 1

Table 3: Three (3) scale mapping

Low	[0,0.333)
Medium	[0.333,0.666)
High	[0.6666,1)

After the prior distributions are determined, the Bayesian network also requires calculation of the posterior distributions of child nodes $\beta^B_{xi|pai}$. To conduct this calculation, this study assumes that the state of each node can be one of the five values: very low, low, medium, high, and very high, or it can be one of the three values: low, medium and high. Next, a weighted min function, WMIN, is used in the following general form:

$$WMIN = \min_{i=1.....n} \left(\frac{w_i X_i + \sum_{i \neq j}^{n} X_j}{w_i + (n-1)} \right) \tag{4}$$

Where $w_i \geq 0$and n is the number of parents nodes, with a suitable variance ϖ_Y^2 that quantifies our uncertainty about the result thus giving: p(Y/X) = TNormal [WMIN(X), ϖ^2,0,1].Thus, WMIN function can be viewed as a generalised version of the normal MIN function. In fact, if all the weights w_i are large then WMIN is close to MIN. At the other extreme, if all the weights w_i =1, then WMIN is simply the average of the X_is. In this case the experts (E) and the decision-maker (DM) need only supply the parameter to both generate the CDP. According to [25] these sets of functions have been sufficient to generate almost the entire ranked node NPTs elicited in practice.

The CDPs of the cost effective Bayesian framework are: P (expected cost_ E1 0.1, E2 0.2, E3 0.4, E4 0.4 and E5 0.5) and has a variance ϖ_Y^2 0.01 that quantifies our uncertainty in a ‘five ranked nodes’: P (expected benefit_ E1_1 = 0.1, E1_2 = 0.2, E1_3 = 0.4, E1_4 = 0.5) with a variance ϖ_Y^2 0.01 that quantifies our uncertainty ranked in a five scale: P (risk reduction effect_ A%, B%, C%, D% and F% have the same weights) with a variance ϖ_Y^2 0.03 that quantifies our uncertainty ranked in a three scale; P (reference value_ DM1= 0.2, DM2= 0.2, DM3= 0.3, DM4= 0.4, DM5=0.5) with variance ϖ_Y^2 0.09 that quantifies our uncertainty ranked in a three scale; P (uncertatinty_E1_1= 0.1, E2_1 = 0.2, E3_1 = 0.3, E4_1 = 0.3, E5_4 = 0.5) with variance ϖ_Y^2 0.09 that quantifies our uncertainty ranked in a three scale. The CPD P (net expected benefit_expected cost = 0.1, expected benefit = 0.2, risk reduction effect = 0.3, reference value = 0.2, and uncertainty = 0.1) with variance ϖ_Y^2 0.08 quantifies our uncertainty ranked in a seven scale.

4.4 Inference

Having created a cost-effective factor relation BN with both its structure and all conditional probabilities defined for its nodes, it can be used to conduct inference among the relationships identified. The inference process can be handled by fixing the states of observed variables, and then propagating the beliefs around the network until all the beliefs (in the form of conditional probabilities) are consistent. Finally, the desired probability distributions can be shown in the network [19]. There are a number of algorithms used to conduct inference in BNs, which have different trade-offs between speed, complexity, generality, and accuracy.

The junction-tree algorithm produced by [27] is one of the most popular algorithms which uses an auxiliary data structure called a junction tree, and computes deep analysis of the connections between graph theory and probability theory, have a limitation such as joint distribution for each maximum clique in a decomposable graph where the initialisation and the process of message passing may miss some important information [27] . Good tool support is therefore needed; both for the purpose of building realistic CPTs that adequately capture expert judgement and ranked nodes.
The normalised data can be dealt with by various computerised packages.

The AgenaRisk software satisfies the requirements of enabling domain and decision-makers without any statistical knowledge to quickly generate distribution, and provides instant visual feedback to check that the CPTs are working as expected. In the process of inference, this allows experts and decision-makers to continually backtrack between previously estimated values and current values of both variance and expert weights in cases that were felt to be similar. Once the CPT is completed the experts could examine the sensitivity of results by running the model with a click of the mouse. The expectation of the resulting marginal distribution for net expected benefits would be monotonic and smooth given the influence factors of expected cost, expected benefit, risk reduction effects, reference value and uncertainty.

4.5 Net Expected Benefit Crisp Probability Value

The resultant node, *net expectedbenefit* output is ranked in a 7 scale: lowest, very low, low, medium, high, very high, highest as presented in Table 4. This table shows its corresponding membership which can be used to obtain the crisp probability value (CPV) used in categorising the risk safety measures using eqn.5.

Table 4: Membership function for crisp probability value

	1	2	3	4	5	6	7
VP	0	0	0	0	0	0.75	1
P	0	0	0	0	0.75	1	0.25
RP	0	0	0	0.75	1	0.25	0
AV	0	0	0.5	1	0.5	0	0
RG	0	0.25	1	0.75	0	0	0
G	0.25	1	0.75	0	0	0	0
E	1	0.75	0	0	0	0	0

$P_1 = P_7^1/P_1^1$, $P_2 = P_6^1/P_1^1$, $P_3 = P_5^1/P_1^1$, $P_4 = P_4^1/P_1^1$, $P_5 = P_3^1/P_1^1$, $P_6 = P_2^1/P_1^1$, $P_7 = P_1$
$P_1^1 = [0.75\ (0.75+1)]6 + [1(0.75+1)]7 = 6.571$, $P_2^1 = [0.75\ (0.75+1+0.25)]5 + [1(0.75+1+0.25)]6 + [0.25(0.75+1+0.25)]7 = 5.75$, $P_3^1 = [0.75\ (0.75+1+0.25)]4 + [1(0.75+1+0.25)]5 + [0.25(0.75+1+0.25)]6 = 4.75$, $P_4^1 = [0.5(0.5+0.5+1)]3 + [1(0.5+0.5+1]4 + [0.5(0.5+0.5+1]5 = 4$, $P_5^1 = [0.25\ (0.25+1+0.75)]2 + [1(0.25+1+0.75)]3 + [0.75(0.25+1+0.75)]4 = 3.25$, $P_6^1 = [0.25\ (0.25+1+0.75)]1 + [1(0.25+1+0.75)]2 + [0.75(0.25+1+0.75)]3 = 2.25$, $P_7^1 = [1\ (1+0.75)]1 + [0.75(1+0.75)]2 = 1.428$

$$Q = 0.217T^1 + 0.248T^2 + 0.301T^3 + 0.357T^4 + 0.439T^5 + 0.634T^6 + 1T^7 \quad (5)$$

5. RESULTS AND DISCUSSION

Table 5: Truth table for risk control options

	RCOA 1	RCOA 2	RCOA 3	RCOA 4	RCOA 5	RCOA 6
E1	M	M	VH	M	H	H
E2	VL	M	VH	H	H	VH
E3	VH	H	H	H	M	H
E4	M	M	L	L	VH	H
E5	M	L	M	M	H	M
E1_1	VL	M	M	M	M	VH
E2_1	M	L	L	M	H	H
E3_1	H	L	L	H	H	H
E4_1	M	VH	VH	VH	H	M
E5_1	H	H	H	M	H	H
A%	L	M	M	L	L	L
B%	L	H	H	L	L	M
C%	L	L	L	L	M	M
D%	L	H	H	H	H	H
F%	M	H	M	H	L	H
DM1	M	M	M	M	H	M

RCOs subjective assessment obtained from expert's opinions and decision maker reference value under uncertainty. Five experts and five decision makers are consulted to obtain truth table.

DM2	L	H	H	M	H	H
DM3	L	L	L	L	H	H
DM4	H	H	H	L	H	H
DM5	L	H	H	H	H	M
E1_2	L	M	M	M	M	L
E2_2	M	M	M	L	M	L
E3_2	M	L	L	L	H	L
E4_2	L	M	M	L	L	L
E5_2	M	M	M	M	M	L

4.7 Running model

Using AgenaRisk desktop, the truth table obtained from participating experts and corresponding decision maker for each RCOs are depicted in Table 5. A total of6 results are obtained for this analysis. A graphical representation of result No. 2 is presented in Figure 3.

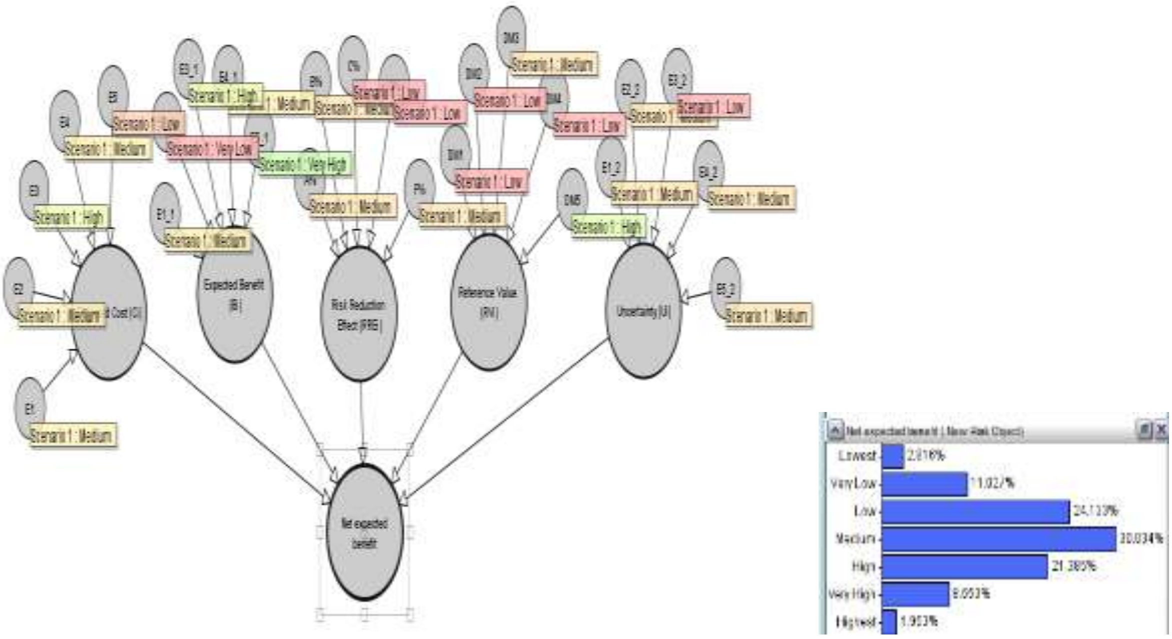

Figure 3: Net expected benefit of implementing RCOA2, Result No. 2

The cost-effectiveness of the safety measure can be effectively categorised in the following order for decision making, *RCOA*: RCOA1, RCOA2, RCOA3, RCOA6, RCOB5, & RCOA4.Over all the inference results obtained through running the TNormal distribution with ranked nodes, twelve (12) main significant results (Net expected benefit result 1-18) are particularly used to categorise the cost-effectiveness of each safety measure. These results are under the evidences that the ‘target node’ is with either ‘high’ or ‘low’ value. For the other situations such as under the evidence that the node is ‘low’, similar results have been obtained.When RCOA4 net expected benefit is highest, we can obtain the probabilities of the other nodes under evidence (Figure 4). Figure 4 shows the effect of expected cost as highest with probabilities ‘0.051’ low and ‘0.26’ high. This suggests that high investment on expected cost affects the net benefit the most as required. The second most important factor is improving on expected benefit. Uncertainty and the reference values affect the net expected benefit the least.

Table 6: Result for study A

	Lowest %	V low %	Low %	Medium %	High %	V High %	Highest %	CPV%	Result No
RCOA1	3.017	11.449	24.474	29.922	20.967	8.332	1.839	1.822	R1
RCOA2	2.816	11.027	24.133	30.034	21.385	8.653	1.953	1.676	R2
RCOA3	0	5.21	16.03	28.143	28.325	16.197	5.144	0.495	R3
RCOA4	0	3.377	12.472	26.039	30.622	19.957	7.022	0.373	R4
RCOA5	0	3.377	12.472	26.039	30.622	19.957	7.022	0.377	R5
RCOA6	0	4.106	13.908	26.942	29.752	18.409	6.196	0.415	R6

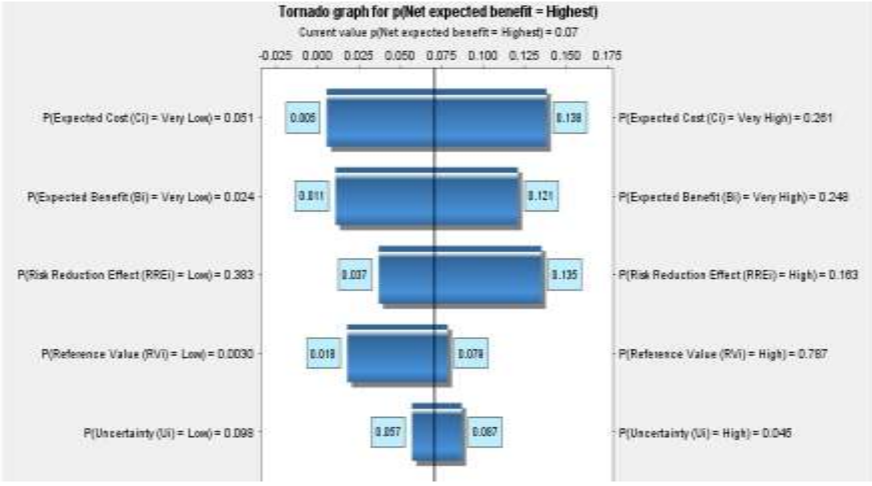

Figure 4: Uncertainty analysis using RCO4A

5. CONCLUSION

One of the most important challenges in building effective BN models to solve real-world cost-effective analysis problems is that of constructing the CTPs. Because of the need to involve busy domain experts and decision-makers (who do not necessarily understand probability theory in detail), it is required to construct the CTPs using the minimal amount of expert elicitation, recognising that it is rarely cost-effective or feasible to elicit complete sets of probabilities values. In the past, other modelling approaches for real applications have been too costly and demanding feasibility. This approach marks an improvement over current practice and has proven to be acceptable to practitioners in other fields.

On a second level, partners and decision-makers need models to produce predictions and supportive decision insights that can demonstrate better results than from methods that require detailed statistical understanding. Also, since this approach has been used in a number of application areas such as for operational risk assessment [25], these results show that the elicitation burden is much reduced by using ranked nodes by simply eliciting a small number of parameters from experts and decision-makers.
On a third level, by applying Bayesian network techniques this study explored and verified a set of relations between cost factors, benefit factors, reference factors, risk reduction effect factors, and uncertainty factors in the application of decision making in docking and undocking ship operation. A cost-benefit factor relation model proposed in this study was considered as domain knowledge and the data collected through a literature survey was evidence to conduct the *inference-basedverification*. Through calculating the node probabilities table (NPT) of these factors, it was found that certain cost factors are more important than others to achieve certain aspects of benefits in relation to reference, risk reduction effect and uncertainty factors:Compared with other risk safety measures in A, increased investments in implementing RCOA1 would significantly contribute to three benefit aspects of reducing stability failure in floating dry dock during docking and undocking a vessel, hence improving a company's image and competitive advantage.

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