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Bayesian decision making of maintenance strategy selection in offshore sectors

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Abstract

Decision making in general is a challenging task in offshore and marine industrial sectors. That is why, calling a reliable method to make a decision is vital such areas. Multi-criteria decision making (MCDM) tools have been widely utilized this fields. However, MCDM methods are deeply suffering from couple of shortages, such as but not limited to the final output is totally depending on qualitative terms, data and model uncertainties are not handled, confidence level of decision is ignored, and it is not considered the factor time into the final decision. In order to deal with the aforementioned shortages, the fuzzy Bayesian structural method as a reliable and powerful tool can be used. The maintenance strategy selection in offshore sectors is utilized as an application of study show the effectiveness of Bayesian structural method. The results also compared with different type of MCDM methods, which showing that Bayesian structural method has high merits over conventional decision-making tools.

Keywords: Bayesian network; Decision making; MCDM methods; Crane.

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1. Introduction

Making a correct, acceptable, or at least proper decision is important for industrial sectors, especially high-tech ones. Therefore, academic and industries are together allocating time and budget to reach an appropriate tool to make a decision in a period of time. What all scientists are doing in different fields is finally to make a right decision. Today, we are in Pandemic situation and chief challenging task is making decision, shall government lockdown the cities, shall government prepaid untrusted vaccines, shall people come together for visiting, and many other questions, which there is not simple answer, even more correct answer. Thus, what one can do is be ensure that he/she considers all factors that playing role in the decision making process. In addition, he/she should update their decision over period of time and have knowledge what is confidence level of their decisions.

In literature, multi-criteria decision making (MCDM) is well known to rank, select, and order a set of alternatives among different types of criteria (Liu, 2016; Yazdi, 2020). According to the M. Yazdi (2019a) provided a history of decision making methods over time. It is highlighted by time MCDM techniques have been received much many attentions. The MCDM methods were extensively applied in such as Analytical hierarchy process (AHP) (Awasthi and Chauhan, 2011; Yazdi, 2017; Zhu *et al*., 2020), TOPSIS (The Technique for Order of Preference by Similarity to Ideal Solution) (Deng *et al*., 2000; Yazdi, 2018a; Yazdi *et al*., 2018), Best-worst method (BWM) (Liao *et al*., 2019; Yazdi *et al*., 2020) and DEMATEL (decision-making trial and evaluation laboratory) (Han and Deng, 2018; Kaya and Yet, 2019; Meng *et al*., 2019; Si *et al*., 2018; Sumrit and Anuntavoranich, 2013), GRA (Grey Relation Analysis) (H.-C. Liu, 2019), Distance measures, VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) (X. D. H. Liu, 2019; Mohsen and Fereshteh, 2017), PROMETHEE (Preference ranking organization method for enrichment evaluation) (Liu *et al*., 2017), ELECTRE (elimination and choice expressing reality) (Yadav *et al*., 2018), BWM (Best-worst method), etc (Chang *et al*., 2013; Gul *et al*., 2018; Liu *et al*., 2017; Nie *et al*., 2018; Ren *et al*., 2017; Rezaei, 2015; Saaty, 1996; Yadav *et al*., 2018) and so on. To correctly use the MCDM methods in this problem, it is necessary to consider different criteria such as environmental protection, reliability, safety, cost, and etc. in the structured hierarchy of the decision-making process. Considering the different performance of the MCDM techniques, selecting an appropriate MCDM tool applicable to the decision-making problem is also significantly important.

However, MCDM methods extremely suffer from different shortages, such as the final output is completely depending on qualitative terms, data and model uncertainties are not handled, confidence level of decision is ignored, and it is not considered the factor time into the final decision. Therefore, it is required to looking for new methods or proposing new framework.

Bayesian Network (BN) as an appropriate mathematics-based method which can be used for decision making purposes and has a significant feature in modeling both quantitative and qualitative variables compared to other MCDM methods. BN has been widely applied as a tool for uncertainty handling and risk assessment purposes in different studies (El-Gheriani *et al*., 2017; Kabir and Papadopoulos, 2019; Khakzad *et al*., 2013; Misuri *et al*., 2018; Mohammad Yazdi, 2019b; Yazdi *et al*., 2019). BN uses a graphical structure to describe causes and effects by utilizing quantification of joining different types of variables. To see how BN can deal with the shortages of conventional decision-making tools, first the nodes in BN can be defined using continues nodes within distributions. Therefore, the output would be represented as a distribution in which shows confidence level. In addition, BN can be updated the input data in case availability; therefore, it deals with data uncertainty. Besides, BN can be further developed as dynamic BN, which come with time. According to the aforementioned points, using BN provides much more realistic results (Yazdi *et al*., 2021).

The contributions of the current study are threefold. First of all, a maintenance strategy selection in offshore sectors is studied. Secondly, dynamic BN is used to make decision over period of time. Finally, a comprehensive comparison is conducted to show the advantages and disadvantages of different methods.

2. Materials and methods

2.1. Bayesian structural method in decision making

In this section, the theoretical context of BN is presented. BN is a directed acyclic graph (DAG), including vertices and edges named as nodes and arcs, respectively, in the available network. In a BN, nodes represent the variables and arcs denote the relations between the two nodes. BN is well-known as a viable tool which has enough capability to consider both uncertainty influence as well as variability. In this accordance, it helps estimate decisions associated with complex decision-making problems (Fenton and Neil, 2018). BN is based on Bayes' theorem. In this case, BN uses the prior information (hypothesis) of a primary event which can further perform a rational statistical inference. In a simple word, backward belief propagation can be obtained when evidence is set to the child node and it will result in the probability distribution of parent node(s). The reverse conditions are also true. In this case, the prior information can be obtained from subjectivity such as experts' judgments or objectivity such as observed data within a frequentist approach (Yazdi and Kabir, 2017; Yazdi and Kabir, 2020; Kabir *et al*., 2018; Daneshvar *et al*., 2020).

Thomas Bayes, a British mathematician, proposed Bayes' rule [1701-1761] (Lynch, 2015). Bayes' rule presents that both probability of X and Y as two variables, can occur when the production of X and Y are given X in terms of probability. The above-mentioned expression can be stated as the following Equation:

$$P(X,Y) = P(X) \times P(Y|X) \quad (1)$$

where, $P(X, Y)$ represents the probability of both variables and which can occur.

With consideration of symmetry law, the Equation (1) can be modified into the Equation (2) as:

$$P(X|Y) = \frac{P(Y|X) \times P(X)}{P(Y)} \quad (2)$$

where, $P(X \mid Y)$ represents the probability of evidence Y when the hypothesis of is true, $P(X)$ is denoted as the prior probability of variable, X,$P(Y)$ is equal to the prior probability the evidence Y occurs (true), and $P(Y \mid X)$ is equal to the posterior probability of X given the evidence of variable Y.

To show the operational features of BN, assuming that in a typical BN, n variables of X_1, X_2, X_3, ..., X_n, are included. In this accordance, the joint probability distribution of variables can be decomposed as Equation (3):

$$P(X_1, X_2, X_3, ..., X_n) = P(X_1 | X_2, X_3, ..., X_n) \times P(X_2 | X_3, ..., X_n) \times P(X_{n-1} | X_n) \quad (3)$$

Subsequently, by simplification, Equation (3) can be streamlined into Equation (4):

$$P(X_1, X_2, X_3, ..., X_n) = P(X_1 | X_2, X_3, ..., X_n) \times P(X_2 | X_3, ..., X_n) = \prod^{n}_{i=1} \times P(X_i | X_{i+1}, X_{i+2}, ..., X_n) = \prod^{n}_{i=1} \times P(X_i | \text{Parrents } (X_i)) \quad (4)$$

Assume that a typical BN is structured having a set of limited variables being , $M = \{X_1, X_2, X_3, ..., X_n\}$ and consists of a set of arcs which illustrates the interdependency and relationships between the existing variables (see Figure 1).

To get more details related to BN, one can refer to the previous literature (Fenton and Neil, 2018).

2.2. Bayesian Network in Decision Making

To use BN in decision making, it required couple steps, which are provided in the following. In step one; all potential factors and sub-factors in our model should be identified. In step two, we need to compute the weight of all factors and corresponding sub-factors. In step three, the causality between the factors and sub-factors should be determined. Finally, the graphical representation of BN should be constructed.

The graphical structure is defined based on the variables and obtaining the causality between the variables. When two nodes are directly connected to each other, thereafter, the parameters can be defined. The parameters can be derived as discrete, truncated Normal (TNormal) distribution, *etc*. The discrete parameters in BN models are typically obtained by node probability tables (NPTs). A typical NPT has probability values for the combination of the states of variables and its incorporated parents. Thus, an NPT contains a number of parameters, which are the Cartesian product of the states of the node and its corresponding parents. Therefore, the NPT would be infeasible in order to be elicited by the experts' judgment, if and only if the variable has a considerable number of parents. TNormal distribution, unlike the Normal distribution, has finite endpoints. Similar to the Normal distribution, the TNormal is categorized by two *mean* and *variance* parameters. Using these parameters, a variety of shapes can be modeled (Xia *et al*., 2018; Yazdi, 2018b).

The top event node will present the alternatives, and those that have the highest weight will receive the highest priority for selection.

3. Application of study and results

There is a decision-making problem to select an on-board machinery (crane) maintenance strategy for offshore operating. The hierarchi-

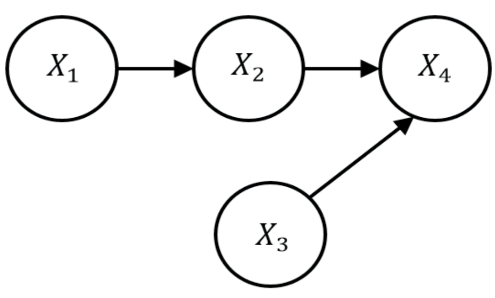

Figure 1. A simple illustration of structured BN with four different variables

cal model of this decision-making assessment procedure is as depicted in Figure 2. As it is highlighted in state of arts “The process of selecting appropriate maintenance strategy is important in order to improve the efficiency of operational marine and offshore machinery. In addition, this would be under uncertain circumstances as a challenging task because of many criteria that should to be considered and modelled” (Asuquo *et al*., 2019). Besides, designing the complex machinery on board of a vessel includes many subjective and unknown parameters in different quantitative and qualitative forms.

Three decision makers have been employed to make a construct the BN by identifying all potential factors, sub-factors, relationships, and interrelationships between the factors. In Table 1 presents the explanation of sub-factors and its contributors. The modelling procedures of the factors are provided in Table 2.

The BN model is structured using GeNie 2.4 software (www.bayesfusion.com) to evaluate all possible alternatives for selecting maintenance strategy. The structured BN model for the first alternative of the maintenance strategy selection based on different factors is illustrated in Figure 2. Four different types of variables are considered to model the factors of maintenance strategy selection. The variables are classified considering the measurement of each variable including (i) qualitative variables (measuring the ordinal scale), (ii) Boolean variables (measuring the dichotomous response, “YES/ NO”, “WORK/NOT WORK”), (iii) continuous variables (measuring the random variables having known probability distribution), and (iv) constant variables having fixed values. A two states Boolean variable of “YES” and “NO” is utilized to model all factors. The state “YES” denotes positive output whereas the state “NO” indicates negative output. As illustrated in Figure 3, the probability of factors being “YES/ NO” is conditional on incorporated sub-factors. As it can be seen from the Figure 3, the priority of maintenance strategy is CBM (0.3951), RCM (0.2544), PM (0.1949), and RTFM (0.1556).

A comparison conducted between the BN model

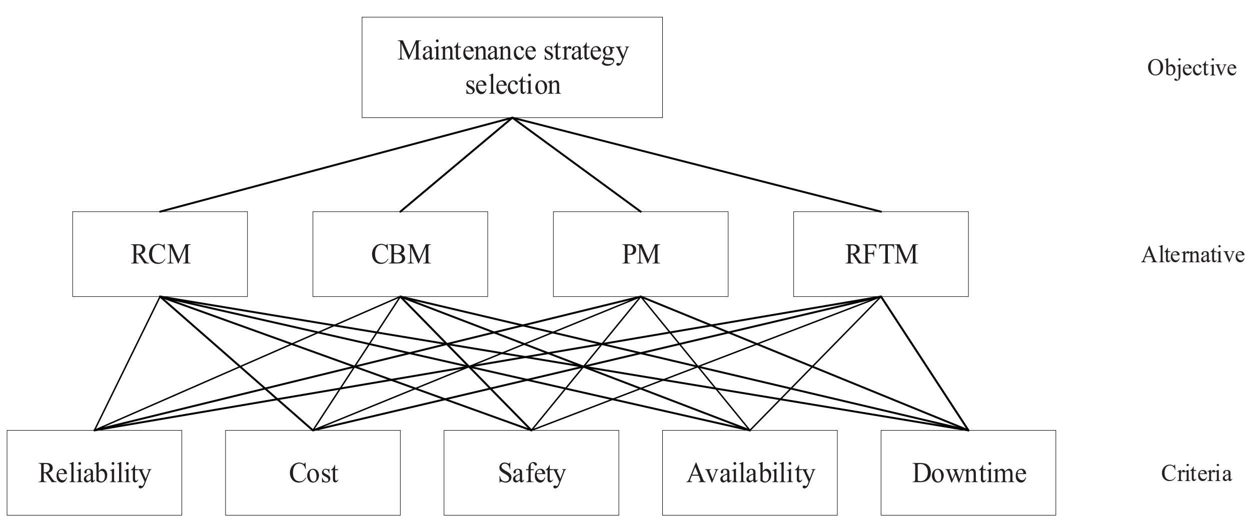

Figure 2. Hierarchical structure of maintenance strategy selection
Note: RTFM, PM, CBM, and RCM stand for Run-to-Failure Maintenance, Preventive Maintenance, Condition Based Maintenance, and Reliability Centered Maintenance, respectively (Adopted after Asuquo *et al*., 2019)

Table 1. Modelling procedure of variables contributed to the sub-factors

Name of variable	The procedure of modeling	Description
Reliability	~ Gamma distribution: Gamma (3,500)	Gamma distribution is used to obtain the reliability in a year for the alternative of maintenance strategy selection.
Cost	~ Triangular (6000$, 10000$, 12000$)	Triangular distribution is used to obtain the maintenance cost with consideration to minimum, most likely, and maximum cost in a year for the alternative of maintenance strategy selection.
Safety	~ TNorm (0.2, 0.01), Lower Bound $=$ $0,$ and upper Bound $= 1$	Truncated Normal distribution with mean and variance is used to obtain safety factor parameter a year for the alternative of maintenance strategy selection.
Availability	~ Weibull (12,8)	2-Parameter Weibull distribution with scale parameter, shape parameter, and location parameter is used to obtain the availability in a year for the alternative of maintenance strategy selection
Downtime	~ Triangular (5, 16, 800)	Triangular distribution is used to obtain the maintenance Downtime with consideration to minimum, most likely, and maximum Downtime in a year for the alternative of maintenance strategy selection.

Table 2. Modelling procedure of factors

Name of variable	The procedure of modeling

Run-to-Failure Maintenance (RTFM)	IF (Reliability = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Cost = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Safety = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Availability = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Downtime = = “YES”, “YES”, “YES”, “YES”, “NO”

Preventive Maintenance (PM)	IF (Reliability = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Cost = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Safety = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Availability = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Downtime = = “YES”, “YES”, “YES”, “YES”, “NO”

Condition Based Maintenance (CBM)	IF (Reliability = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Cost = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Safety = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Availability = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Downtime = = “YES”, “YES”, “YES”, “YES”, “NO”

Reliability Centered Maintenance (RCM)	IF (Reliability = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Cost = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Safety = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Availability = = “YES”, “YES”, “YES”, “YES”, “NO”
	IF (Downtime = = “YES”, “YES”, “YES”, “YES”, “NO”

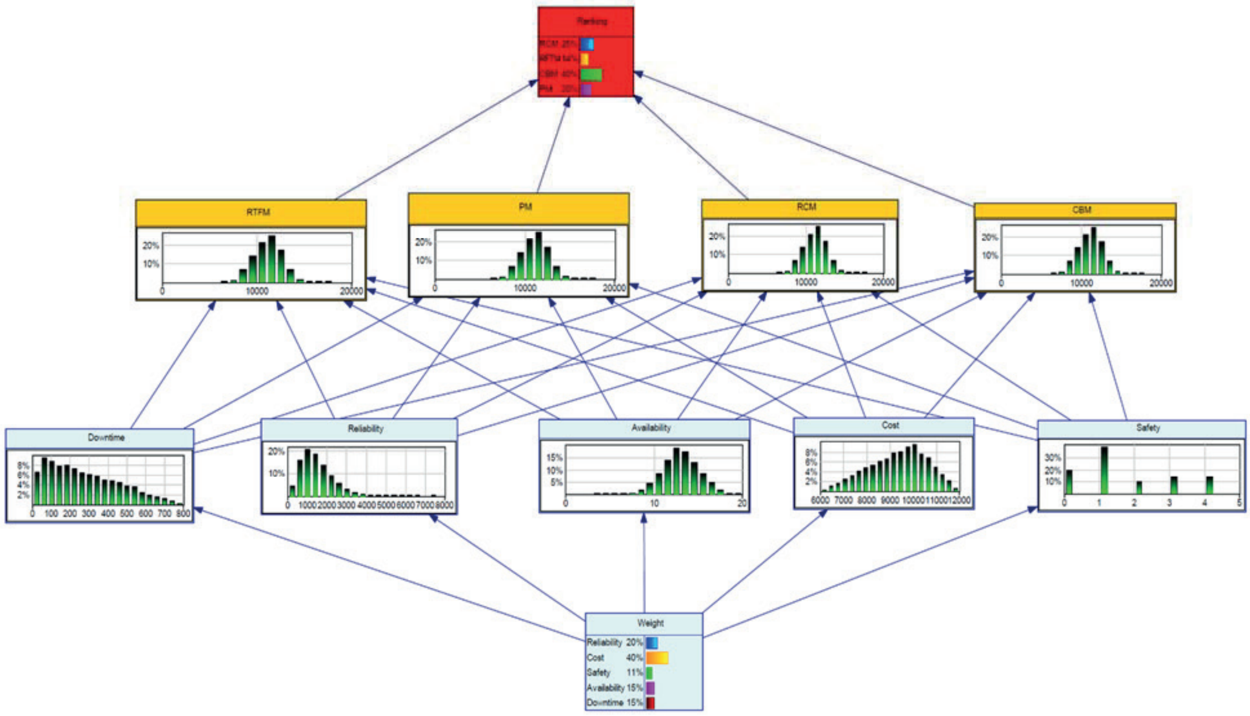

Figure 3. The maintenance strategy selection based on structured BN model (the weights of all sub-factors are provided in a node in constructed BN and they are based on obtained opinions from three decision makers)

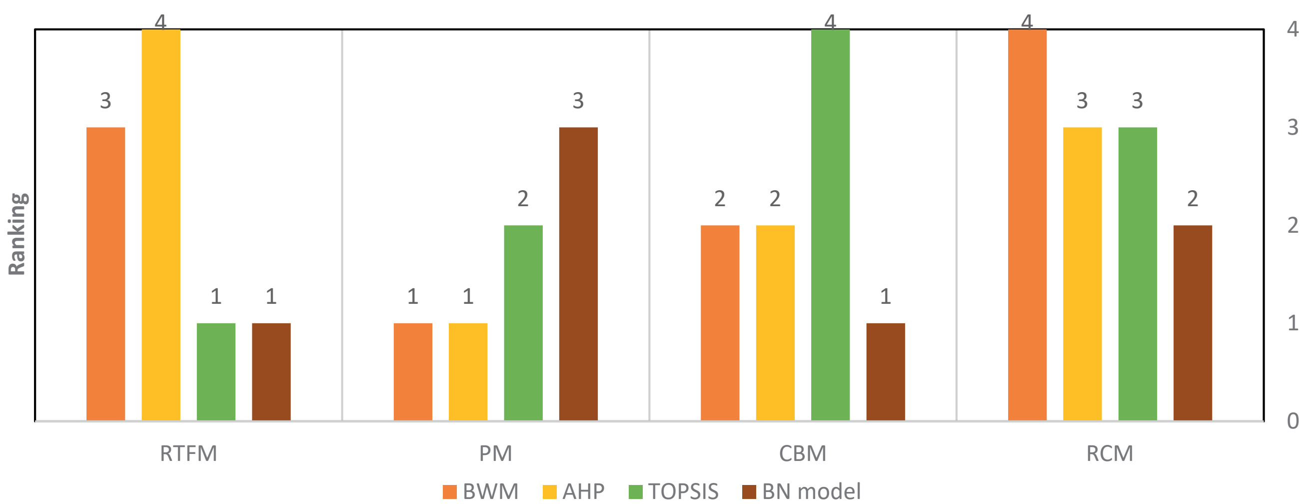

Figure 4. A comparison conducted between BN model and three MCDM techniques

and three MCDM techniques (AHP, TOPSIS, and BWM). The results are illustrated in Figure 4 and it is concluded that the BN model has different results compared with rest of methods. That is because a different distribution is used as input date instead of crisp value. In addition, the confidence level for each factor and sub-factor can be considered as they are represented as distribution. In this study, the confidence level is considered 90%.

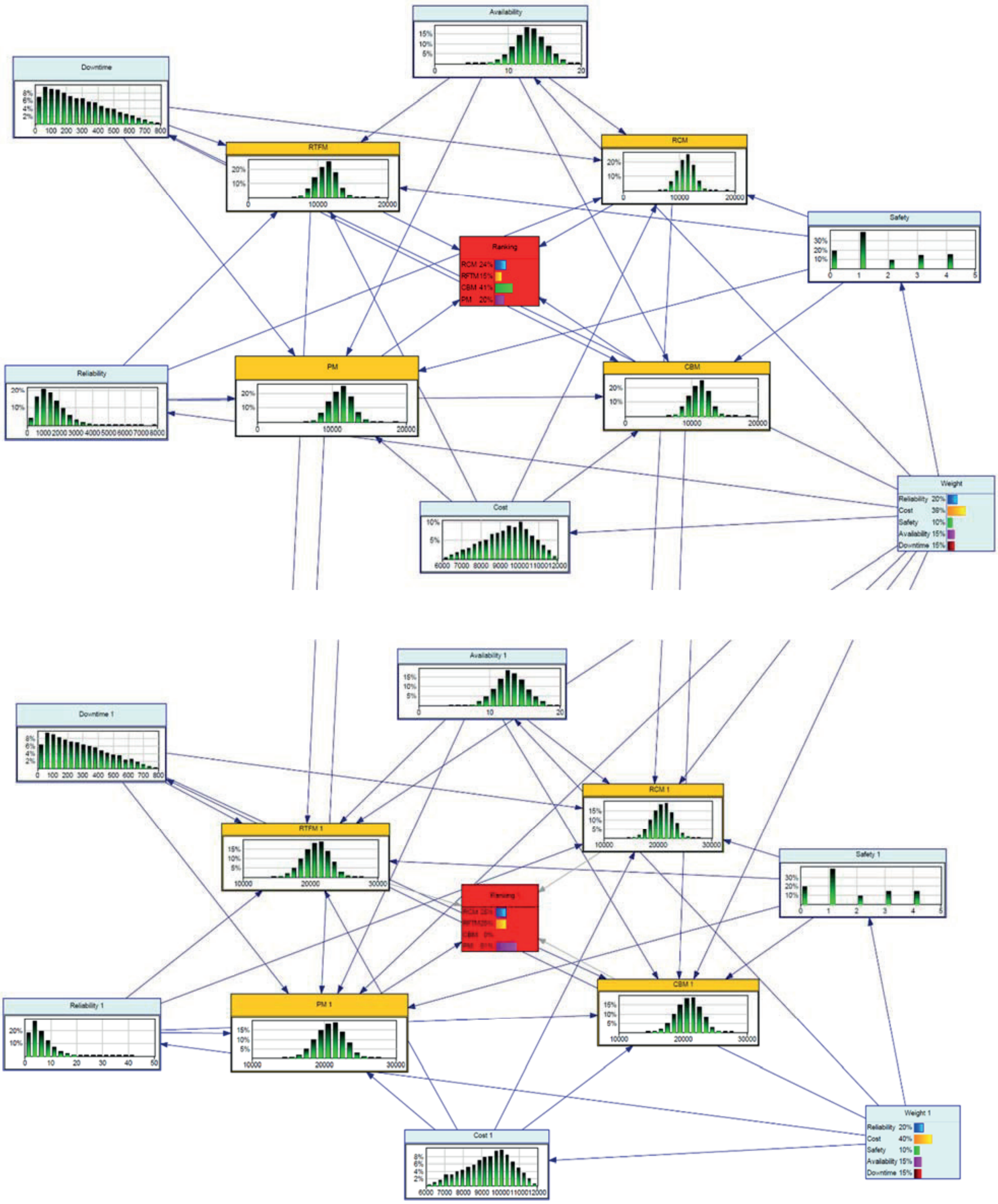

Figure 5. Dynamic BN in time slice t=0 (top) and t=1(down)

Up to this point, BN are playing somehow the same role as MCDM methods. As it is mentioned in the literature, the typical MCDM methods cannot deal with dynamic features. As an example, the current results will be used over a period of time or reconstructing the model for each single year. In the maintenance strategy selection, all of the parameters are varying with time, such as reliability and availability. The factor reliability is also decreasing by time. That is while BN can be used different time slices. Figure 5 shows how dynamic figure maintenance strategy selection can vary over time.

From dynamic feature of BN, it is concluded that at time t=1, the maintenance strategy selection is totally different from what decision makers selected at time t=0. Therefore, decision making can be updated by time showing the effectiveness of BN compare with the typical MCDM tools.

In some realistic cases, we need to set an evidence to show that there is enough information for a sub-factor. Therefore, it would be received the value. In this analysis, it is assumed that sub-factor is equal to 10000$. As it can be seen from Figure 6, the RFTM should be selected as maintenance strategy.

Another shortage of typical MCDM methods is that they cannot consider the causality between the factors and sub-factors. Even the DEMATEL method can only show which factors has highest influence and which factor is receiving the most influence from other factors (Zhou *et al.*, 2017). In next analysis, we consider that there are couples of interrelationships between

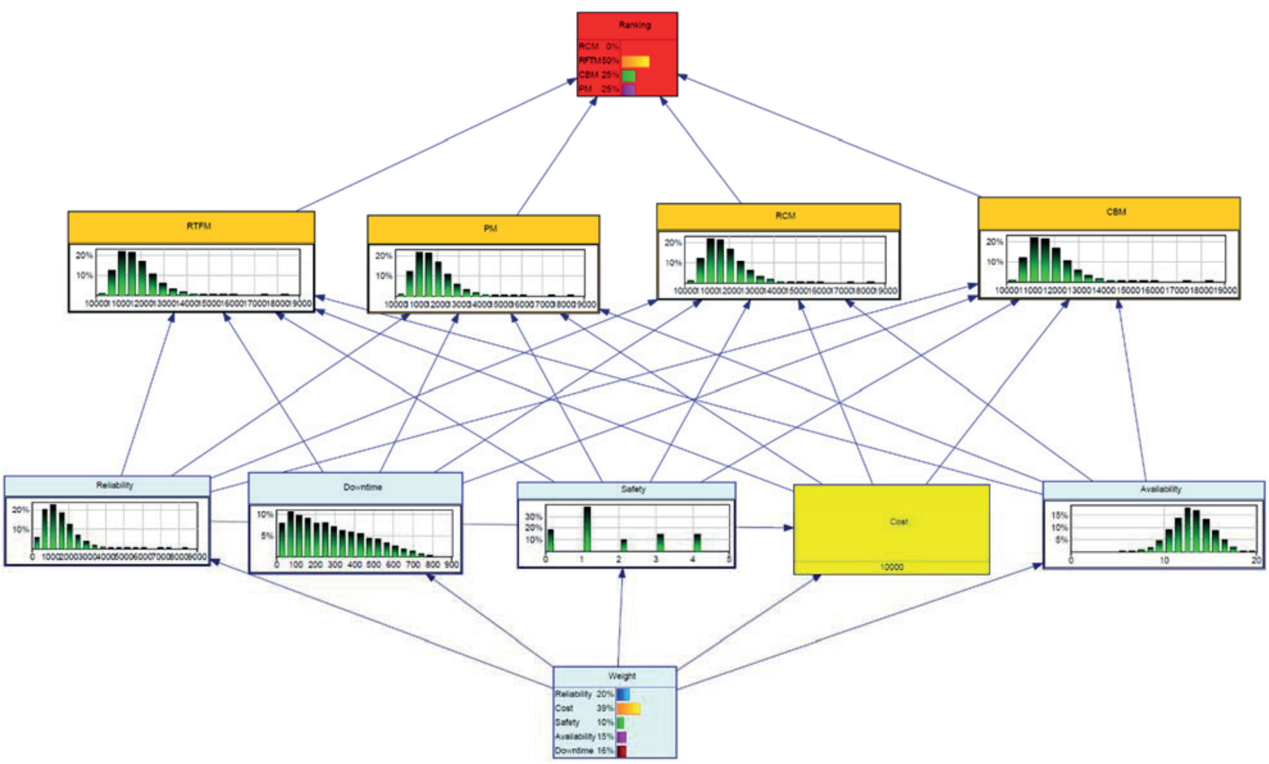

Figure 6. The maintenance strategy selection forward propagation

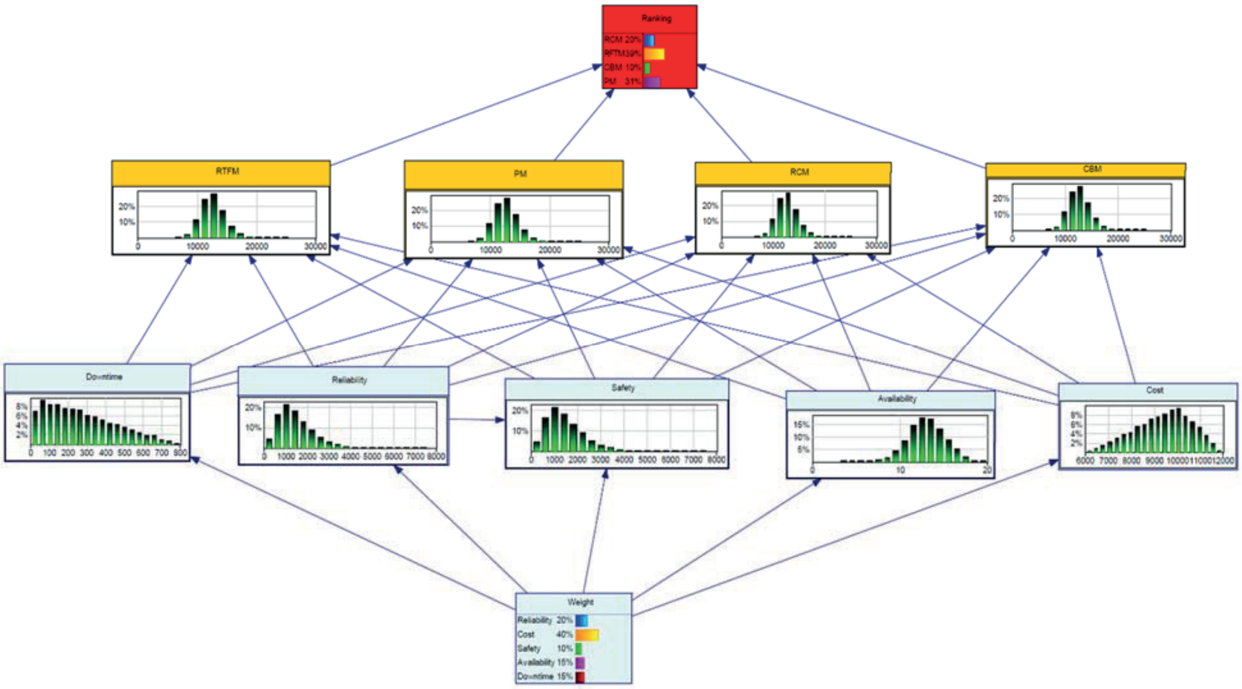

Figure 7. The maintenance strategy selection with consideration of interrelationships

sub-factors. As an example, Reliability has direct influence on Safety. Figure 7 illustrates how BN can consider the interrelationships between the sub-factors. As it is resulted, the interrelationships between the sub-factors can change the result of maintenance strategy selection. In this case the RFTM received highest priority to be selected with probability value of almost 41 %.

Conclusion

In this study, a Bayesian structural method is utilized in order to help decision makers in the decision-making problems. Generally, when the decision-making problem is selecting an alternative among a set of options, different type of MCDM methods are employed. Bayesian structural method has considerable advantages compare with the MCDM tools. That is why, in this study a Bayesian structural method is used to choose a maintenance strategy among four options in offshore industrial sectors. Bayesian network is provided for the application of study to show that its flexibility and efficiency. In addition, a comparison was conducted with MCDM tools in order to illustrate that the difference between BN and typical MCDM techniques.

However, there are couple of challenge have been faced during this study, which are required to be considered as a direction for future studies. First of all, three different decision makers were employed in this study. In literature, it is discussed that the decision maker has highest importance weight would influence the final output (Pasman and Rogers, 2020; Yazdi *et al*., 2017). Thus, it is vital to increase the number of decision maker to make a balance between all options obtained form decision makers. Secondly, the opinions obtained from experts have uncertainties which are required be handed. Fuzzy set theory and its extensions can be utilized in order to handle subjective type of uncertainty. Finally, a framework by providing a hybrid model such as combination of influence diagram and BN can be structured.

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