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Original article

A Fuzzy Rule-Based Bayesian Reasoning Method for Analysing the Necessity of Super Slow Steaming under Uncertainty: Containership

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Abstract

The global economic and financial conditions in 2010 and 2011 were positive and the business trade grew at about twice of the rate of that in 2009. The container shipping players started to enjoy a new chapter of international business trade having struggled to operate their vessels since 2008. So we now have to consider if the shipping business will return to its old strategy? What will happen to the container shipping sector in 10 years from now still remains uncertain. Recently, the uncertain situation globally has been giving shipping companies in difficulty the opportunity to make decision as to whether it is necessary to use super slow steaming for containerships. Therefore, the aim of this study is to analyse the necessity of super slow steaming on containerships despite such uncertainty. A Fuzzy Rule-based Bayesian Reasoning method has been used which incorporates the membership function and 14 selected nodes. Finally, the outcome of this study is 48 rules which have been proposed to assist shipping companies in their decision making processes when dealing with the dynamic business environment. Each rule gives a clear-cut understanding of the result which is able to be applied to real situations the containership industry faces.

Keywords: Super Slow Steaming; Containership; Uncertainty Treatment; Rule-based Method; Bayesian Reasoning Method; Decision Making Technique

I. Introduction

The world's largest cargo ships are travelling at lower speeds than sailing clippers such as the Cutty Sark did more than 130 years ago (Vidal, 2010). The super slow steaming speed is becoming a popular choice for many ship owners and operators especially for the long-haul services in the drive towards greater efficiency, for the benefit of fuel saving and in the name of environmental responsibility. Global issues such as financial crisis, economic recession, emissions, bunker fuel price and market demand have had a huge impact on shipping companies with regard to their decision making processes, especially when determining a suitable speed for containerships on a specific service route. According to the General Manager Innovation and Business Development, Two-stroke, Wartsila Services, Wiesmann (2010), super slow steaming is preferred because it offers greater flexibility to increase their capacity again when the market situation changes.

According to Vidal (2010), Maersk Line with more than 600 ships, has adapted its giant marine diesel engines to travel at a super slow steaming speed without suffering damage. Consequently, the fuel consumption and greenhouse gas emissions can be reduced by up to 30% (Maersk Line, 2010). By reducing the service speed from 25 to 16 knots, the total fuel consumption decreases by almost 190.00 tonnes per day (Abdul Rahman, 2012). The main concern around reducing a vessel’s speed is that the total number of days at out at sea will be longer than usual. As a result, the round journey time can be increased by up to 22 days (Abdul Rahman, 2012). This issue has also been addressed by Cambon (2010), Head of Michelin Ocean Management Committee and also by other shippers. By reducing the service speed from 25 knots to 16 knots, the total round journey time from Asia to Europe increases from 56 days to 77.99 days and the difference between these two speeds is obvious.

Shipping companies always have to deal with making many decisions but the decision regarding the level of vessel speed for operating containerships has to be made based on the current global situation. The objective of this paper is to present the methodology for determining the necessity of having a super slow steaming speed in the container shipping industry despite uncertain factors using a Rule-Based Bayesian Reasoning (RBR) method. Such a method is a popular technique that has been used for dealing with uncertainty in several fields, such as engineering and maritime technology.

II. A Generic Methodology

2.1. Fuzzy Membership Function

A set of qualitative data was used in this study. Most of the necessary data was gathered through interview sessions and a set of questionnaires. A number of experts were selected fitting to their knowledge and experiences in the shipping industry. A combination of opinions from both industrial and academic experts is necessary for the data collection process. A set of questionnaires were sent to the selected experts and were required to express their judgments' on issues described in the questionnaire. All the feedback received from them will be analysed using a trapezoidal membership function (TMF). According to Pedrycz and Gomide (1998), a membership function associated with a fuzzy set Ã depends not only on the concept to be represented but also on the context in which it is used. The graphs of the functions may have different shapes and may have some specific properties (e.g. continuity) (Godaliyadde, 2008). The trapezoidal membership function can be determined according to the following algorithm:

$$\mu_{\tilde{A}}(X) = \begin{cases} 0, if\ x \leq a \\ \frac{x-a}{m-a}, if\ x\ \in]a, m[\\ 1, if\ x\ \in [m, n] \\ \frac{b-x}{b-n}, if\ x\ \in\ ]n, b[\\ 0, if\ x \geq b \end{cases} \tag{1}$$

where $\mu_{\tilde{A}}(X) = 1$ between *m* and *n*, while the lower and upper bounds are represented by *a* and *b* as shown in figure 1.

The “Core” of a fuzzy set Ã is the set of all elements of X that exhibit a unit level of membership functions in Ã and is denoted by Core (Ã) (Kruse *et al.*, 1994; Godaliyadde, 2008). The core (*m*,*n*) of Ã can be shown using a trapezoidal membership function as described in figure 1 where Core (Ã) = $\{x \in X | \mu_{\tilde{A}}(x) = 1\}$. The trapezoidal membership function can also be represented as follows:

$$\tilde{A}(x; a, m, n, b) = max\left\{min\left[\frac{(x-a)}{(m-a)}, 1, \frac{(b-x)}{(b-n)}\right], 0\right\} \tag{2}$$

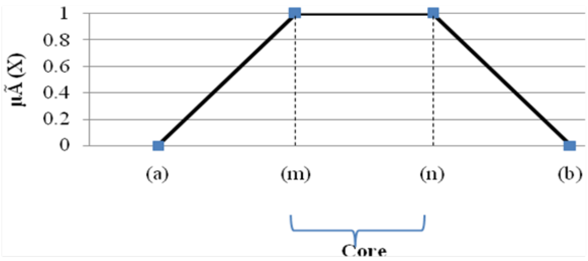

Figure 1: Trapezoidal membership function

Referring to figure 1, if the average value of the expert judgement for a particular node is within the “Core” of the linguistic term, automatically the belief degree value of that linguistic term is equal to 1.0, while if the average value of the expert judgement for a particular node is outside of the “Core” of the linguistic term, then the expected utility value will be used for determining the belief degree of the linguistic term. The purpose of using the utility value is to obtain a crisp value of each state for the conditional probability table (*CPT*) in the BN model.

Assuming that the utility of an evaluation grade H_n is denoted by $u(H_n)$ and $u(H_{n+1}) > u(H_n)$ if H_{n+1} is preferred to H_n (Yang, 2001; Riahi, 2010). $u(H_n)$ stands for the utility values of each linguistic term and can be estimated using the decision maker’s preferences. The utility value of each evaluation grade can be calculated using Equation 3.

$$u(H_n) = \frac{V_{max} - V^n}{V_{max} - V_{min}} \quad (3)$$

where V_{max} is the ranking value of the preferred linguistic term (H_N), V_{min} is the ranking value of the least preferred linguistic term (H_1) and V^n is the ranking value of the linguistic term that has been considered (H_n).

2.2. Establishment of Rule-Based with belief structure

Traditionally, a rule-based inference system has been formed as follows (Duda *et al.*, 1976; Yang *et al.*, 2009):

$$IF\ E_1\ and\ E_2\ and\ \ldots\ E_N, THEN\ H \quad (4)$$

where $E_i\,(i = 1, 2, \ldots, N)$ is the ith piece of evidence and H is an hypothesis suggested by evidence. The individual pieces of evidence (E_i) and the hypothesis (H) of a rule are propositional statements.

The modern style of a belief rule-base (*BRB*) consists of a collection of belief rules and is defined as follows (Liu *et al.*, 2005; Yang *et al.*, 2006; Yang *et al.*, 2009; Zhou *et al.*, 2011):

$$\begin{aligned} &R_k: \quad IF\ A_1^k\ and\ A_2^k\ and\ \ldots and\ A_M^k, \\ &THEN\ \{(\beta_{1k}, D_1), (\beta_{2k}, D_2), \ldots, (\beta_{Nk}, D_N)\}, \left(\textstyle\sum_{i=1}^{N} \beta_{ik} \leq 1\right) \end{aligned} \quad (5)$$

where $A_j^k\ (j \in \{1, 2, \ldots, M\};\ k \in \{1, \ldots, L\})$ is the referential value of the jth antecedent attribute in the kth rule. M is the number of antecedent attributes used in the kth rule and L is the total numberof rules in the rule-base. $\beta_{ik}\ (i \in \{1, \ldots, N\}; k \in \{1, \ldots, L\}$, with L being the total number of the rules in the rule-base) is belief degree to which $D_i (i \in \{1, \ldots, N\})$ is believed to be the consequent if, in the k th packet rule, the input satisfies the packet antecedents$A^k = \{A_1^k, A_2^k, \ldots, A_M^k\}$. If $\sum_{i=1}^{N} \beta_{ik} = 1$, the kth packet rule is said to be complete; otherwise, it is incomplete. Note that $(\sum_{i=1}^{N} \beta_{ik} = 0)$ denotes total ignorance about the output given the input in the kth packet rule.

2.3. A proposed Bayesian reasoning method for rule aggregation

The belief rule in Equation 5 can be further expressed in the form of conditional probability as shown in Equation 6 (Yang *et al.*, 2008; Pearl, 1988; Zhou *et al.*, 2011).

$$\begin{aligned} &\text{Given } A_1^k and\ A_2^k\ and\ \ldots and\ A_M^k, \\ &THEN\ P(D_1) is\ \beta_{1k}, \ldots, P(D_N) is\ \beta_{Nk} \end{aligned} \quad (6)$$

where $A_j^k\ (j \in \{1, 2, \ldots, M\};\ k \in \{1, \ldots, L\})$ has been explained in Equation 5. $P(.)$ denotes the probability.

The Bayesian reasoning method can be applied for combining rules and generating final conclusions, such as the prior probability of D_i $(i \in \{1, 2, \ldots, N\})$ which can be computed using Equation 7 (Yang *et al.*, 2008). Further detailed explanation of the methods can be referred to Abdul Rahman (2012) and Abdul Rahman *et al.*, (2015).

$$P(D_i) = P\left(D_i \mid A_1^k, A_2^k, \ldots, A_M^k\right) P\left(A_1^k\right) P\left(A_2^k\right) \ldots P\left(A_M^k\right) \tag{7}$$

III. Modelling the Necessity of Super Slow Steaming under Uncertainty

Step 1: Model development

A discussion technique with experts has been used in this step in identifying the parameters and for model development. A BN method is used in developing a scientific model for this study (figure 2). The bottom-up approach is used in the model development (Abdul Rahman *et al*, 2015). There are five root nodes involved in this study, namely 1) global warming (GW), 2) global economic conditions (GEC), 3) bunker fuel price (BFP), 4) operating costs (OC) and 5) container market demand (CMD). The node "GW" has one child node which is "Emissions (E)". Also, the node "OC" has one child node which is "Cost Factors (CF)". The node "GEC" has three child nodes, namely "Freight Rates (FR)", "Vessel Supply (VS)", and "Ship Values (SV)". The node "Bunker Fuel Price (BFP)" has two child nodes which are "Miscellaneous Factors (MF)" and "Voyage Costs (VC)". Also, the node "MF" is the child node to the nodes "CMD" and "SV".In this study, all the nodes except the output node "Desirability of Super Slow Steaming (DSSS)" have been grouped into three groups of nodes, namely "Vessel Factors (VF)", "Miscellaneous Factors (MF)" and "Cost Factors (CF)". Such nodes assist shipping companies to make a decision with regard to analysing the necessity of having super slow steaming.

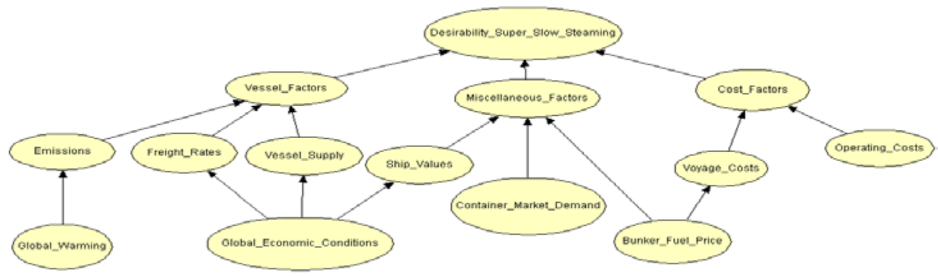

Figure 2: A proposed model for analysing the necessity of having super slow steaming

Step 2: Data collection process

Qualitative data collection is used in this study and all the necessary data was obtained from experts' judgement and explained as follows, for instance:

i) Vessel Factors (VF)

In the BN model, there are three parameters influencing the node "VF" these are 1) Emissions, 2) Freight Rate and 3) Vessel Supply (figure 2). A set of questionnaires were sent to the selected experts for their judgements. In the set of questionnaires, the rate of measurement uses a range of preference numbers between 1 and 10 (table 1). If for the node there exists "*VF=high*", then there is a "*worst condition*" to shipping companies due to the status of its parent nodes.

Table 1: The linguistic terms of the node "Vessel Factors"

Preference Number	Vessel Factors	Meaning
10, 9	high (H)	*Worst* condition
8, 7	reasonably high (RH)	*Poor* condition
6, 5	average (A)	*Average* condition
4, 3, 2, 1	low (L)	*Good* condition

Table 2: The evaluation of the node "Vessel Factors" by the experts

Condition	Antecedent Attributes			Vessel Factors (VF)			Average
	Emissions	Freight Rates	Vessel Supply	Expert A	Expert B	Expert C	
1	high	high	over	8	9	8	8.3333
2	high	high	normal	5	6	5	5.3333
3	high	low	over	10	10	10	10.0000
4	high	low	normal	8	9	8	8.3333
5	low	high	over	5	6	7	6.0000
6	low	high	normal	1	1	1	1.0000
7	low	low	over	7	6	7	6.6667
8	low	low	normal	3	2	3	2.6667

All the feedback received from the experts was analysed using the averaging value technique and the trapezoidal membership function. Given Condition 1 in table 2 as an example, IF "*E=high*" and "*FR=high*" and "*VS=over*", the experts A and C ticked number eight of the linguistic term "*reasonably high*", while the expert B ticked number nine of the linguistic term "*high*". The average output value of Condition 1 is computed using Equation 2 as follows:

$$A = (8 + 9 + 8) \times \frac{1}{3} = 8.3333$$

The average output value of Condition 1 is known to be 8.333. In a similar way, this calculation technique is applied to all of the conditions. The average output value of each condition is transformed into membership functions in order to obtain belief degree values for the four states of the node "Vessel Factors". Basically, if the average output value of a condition is within the "Core" of a particular state or linguistic term, then the belief degree value of that state is known to be 1.000, while the belief degree values of the other states are equal to 0.0000. For instance, the average output value of Condition 2 is 5.3333, within the "Core" values between 5.0000 and 6.0000 (figure 3). Consequently, the belief degree value of the state "*average*" is known to be 1.0000.

However, if the average output value of a condition is between the cores of two linguistic terms/states, for example, the average output value of Condition 1 is 8.3333 which is between 8.0000 (the lower bound of the state "*high*") and 9.0000 (the upper bound of the state "*reasonably* *high*”), then the belief degree value of the state *“reasonably high”* is calculated using Equation 3 as follows:

$$u(H_{reasonably\ high}) = \frac{9.0000 - 8.3333}{9.0000 - 8.0000} = 0.6667$$

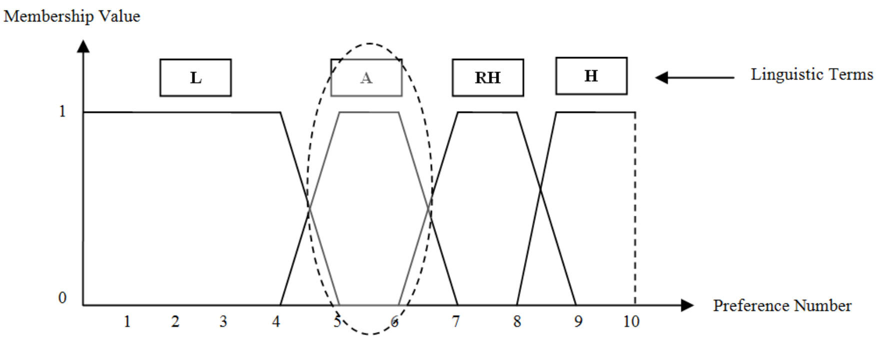

Figure 3: Membership function of the node "Vessel Factors”

The belief degree value of the state *“reasonably high”* is known to be 0.6667, while the belief degree value of the state *“high”* is 1.0000 – 0.6667 = 0.3333. However, the belief degree values of the states *“average”* and *“low”* are 0.0000. The same calculation technique is applied to all the conditions listed in table 2 in order to obtain the belief degree values of the states under the node “Vessel Factors”. Accordingly, such values are transformed into the *CPT* of the node “Vessel Factors” as shown in table 3.

Table 3: The conditional probability table of the node “Vessel Factors”

Emissions	high				low			
Freight Rates	high		low		high		low	
Vessel Supply	over	normal	over	normal	over	normal	over	normal
high	0.3333	0.0000	1.0000	0.3333	0.0000	0.0000	0.0000	0.0000
reasonably high	0.6667	0.0000	0.0000	0.6667	0.0000	0.0000	0.6667	0.0000
average	0.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.3333	0.0000
low	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	1.0000

Step 3: Establishment of RBR with a belief structure

To construct the RBR in order to analyse the necessity of having super slow steaming for containerships, there are three fundamental attributes 1) VF, 2) MF and 3) CF are considered as the antecedent attributes in *IF-THEN* rules, while DSSS is expressed as the conclusion attribute. For example, two belief *IF-THEN* rules can be developed using Equations 4 and 5 as follows:

R_1: IF *VF1=high* and *MF1=good* and *CF1=more cost*,
THEN {*(0.0000, strongly recommended (DSSS1)), (1.0000, recommended (DSSS2)), (0.0000, moderately recommended (DSSS3)), (0.0000, not recommended (DSSS4)), (0.0000, strongly not recommended (DSSS5))*}.

R_3: IF *VF1=high* and *MF1=good* and *CF3=less cost*, THEN {(*0.0000, strongly recommended (DSSS1)), (0.0000, recommended (DSSS2)), (0.6667, moderately recommended (DSSS3)), (0.3333, not recommended (DSSS4)), (0.0000, strongly not recommended (DSSS5))*}.

It can be seen that slight input change from *CF1* to *CF3* has influenced the definition of output. Consequently, the RBR with a belief structure for the node "Desirability of Super Slow Steaming" is partially shown in table 4.

Table 4: The RBR with a belief structure for the node "Desirability of Super Slow Steaming"

Rules	Antecedent Attributes			Desirability of Super Slow Steaming (DSSS)				
No	(VF)	(MF)	(CF)	strongly recommend	recommend	moderately recommend	not recommend	strongly not recommend
1	high	good	more cost	0.0000	1.0000	0.0000	0.0000	0.0000
2	high	good	normal cost	0.0000	0.0000	1.0000	0.0000	0.0000
3	high	good	less cost	0.0000	0.0000	0.6667	0.3333	0.0000
…	…	…	…	…	…	…	…	…
47	low	poor	normal cost	0.0000	0.3333	0.6667	0.0000	0.0000
48	low	poor	less cost	0.0000	0.0000	1.0000	0.0000	0.0000

Step 4: Bayesian reasoning method

To demonstrate the calculation of the selected nodes using a BN theorem, the *CPT*s of the nodes "Bunker Fuel Price" and "Voyage Costs" is given as follows:

a) *CPT* for Bunker Fuel Price (BFP) (without condition)

BFP	
high	0.4615
low	0.5385

For example, $P(BFP=high) = 0.4615$.

b) *CPT* for Voyage Costs (VC)

VC	*Bunker Fuel Price (BFP)* *high*	*low*
more cost	1.0000	0.0000
normal cost	0.0000	0.1000
less cost	0.0000	0.9000

For example, conditional probability $P(VC=normal\ cost \ / \ BFP=low) = 0.1000$.

By using the information in the *CPT* of the node "Voyage Costs", the prior probability value of "*VC=more cost*" can be computed using Equation 6 as follows:

$P(VC=more\ cost) =$

$P(VC=high \mid BFP=high) \times P(BFP=high) + P(VC=more\ cost \mid BFP=low) \times P(BFP=low)$

= (1.0000 × 0.4615) + (0.0000 × 0.5385)

= <u>0.4615</u>

A similar calculation technique is applied, the prior probability values of "*VC=more cost*" and "*VC=normal cost*" are known to be 0.4615 and 0.0539, while the prior probability value of "*VC=less cost*" is 1.0000 – (0.4615 + 0.0539) = 0.4846. These values can also be calculated using the *Hugin* software (Korb and Nicholson, 2003) (figure 4).

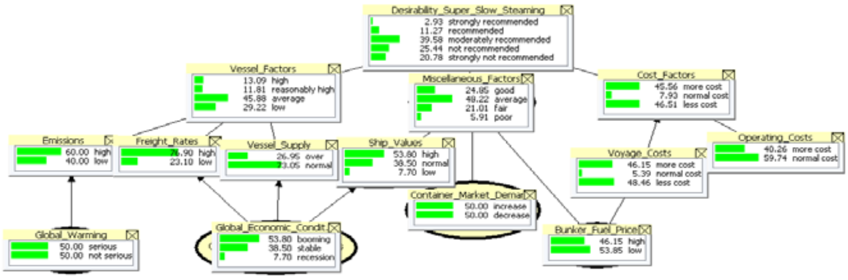

Figure 4: The prior probability value of each node in the proposed BN model

The posterior probability value of the goal node can be computed using Equation 7. For example, given *"GW1=serious"*, *"GEC3=recession"*, *"CMD2=decrease"*, *"BFP1=high"* and *"OC1=more cost"*, the posterior probability values of $P(DSSS \;/ VF_i, MF_j, CF_k)$ are computed as follows:

$$P(DSSS) = \sum_{i=1}^{4}\sum_{j=1}^{4}\sum_{k=1}^{3} P(DSSS \;/ VF_i, MF_j, CF_k)\; P(VF_i)\, P(MF_j)\, P(CF_k)$$

$$= P(DSSS|VF_1, MF_4, CF_1)\; P(VF_1)\; P(MF_4)\; P(CF_1)$$

(The other products of $P(VF), P(MF)$ and $P(CF)$ are 0)

= $(1.0000, 0.0000, 0.0000, 0.0000, 0.0000) \times 1.0000 \; \times \; 0.1000 \; \times \; 1.0000$

= $\underline{(1.0000, 0.0000, 0.0000, 0.0000, 0.0000)}$

This is interpreted to highlight the necessity of having super slow steaming for containerships associated with *"GW1=serious"*, *"GEC3=recession"*, *"CMD2=decrease"*, *"BFP1=high"* and *"OC1=more cost"* is {(*1.0000, strongly recommended*), (*0.0000, recommended*), (*0.0000, moderately recommended*), (*0.0000, not recommended*), (*0.0000, strongly not recommended*)}. The above calculation can also be modelled using the *Hugin* software as shown in figure 5.

In a similar way, the necessity of having super slow steaming for containerships associated with "GW_i *{i = 1 (serious), 2 (not serious)}*", "GEC_j *{j = 1 (booming), 2 (stable), 3 (recession)}*", "BFP_k *{k = 1 (high), 2 (low)}*", "CMD_l *{l = 1 (increase), 2 (decrease)}*" and "OC_m *{m = 1 (more cost), 2 (normal cost)}*" are obtained as partially shown in table 5.

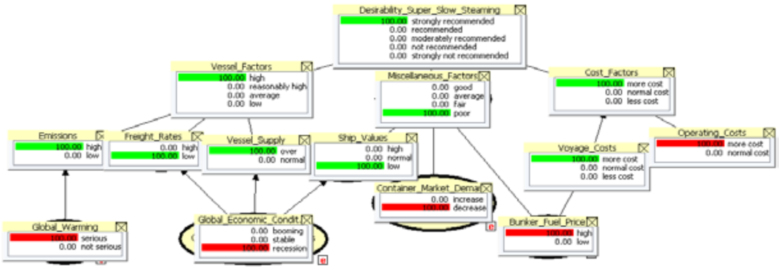

Figure 5: The posterior probability value of the node "DSSS" after giving evidence to the nodes "GW", "GEC", "CMD", "BFP" and "OC

Step 5: Result and discussion

A combination of three different antecedents, namely "Vessel Factors", "Miscellaneous Factors" and "Cost Factors" has produced 48 rules. Referring to each rule in table 5, a state under the node "SSS" with a posterior probability value of more than 50% will be selected for the case study. Given Rule 3 as an example, the necessity of having super slow steaming for containerships is "*0.8100, strongly not recommended*" which is the highest value compared to the other four states. As a result, the decision to choose a particular steam mode is made straight-forward and easy to understand by shipping companies. Most rules in Table 5 can be explained in a similar way as in Rule 3.

In Rule 2, the necessity of having super slow steamingis required a further analysis. For example, 0.9000 (*DSSS3*) + 0.1000 (*DSSS4*) + 0.0000 (*DSSS5*) = 1.0000 belongs to the group of not recommending super slow steaming, while 0.9000 (*DSSS3*) + 0.0000 (*DSSS2*) + 0.0000 (*DSSS1*) = 0.9000 belongs to the group of recommending super slow steaming. The total probability value of the group "*not recommending*" super slow steaming is 1.0000 which is higher than the total probability value of the group "*recommending*" super slow steaming. As a result, the proposed BN model supports shipping companies to not adopt super slow steaming speed in such circumstances. Rules 1, 2, 5, 6, 10, 19, 20, 25, 29, 30, 33, 34, 37, 38, 47 and 48 can be explained in a similar way as Rule 2.

Table 5: A partial RBR with a belief structure for analysing the necessity of the node "DSSS"

Rules	Antecedent Attributes					Desirability of Super Slow Steaming (DSSS)				
No	GW	GEC	CMD	BFC	OC	DSSS1	DSSS2	DSSS3	DSSS4	DSSS5
1	serious	booming	increase	high	more cost			1.0000		
2	serious	booming	increase	high	normal cost			0.9000	0.1000	
3	serious	booming	increase	low	more cost			0.0333	0.1567	0.8100
4	serious	booming	increase	low	normal cost				0.1000	0.9000
…	…	…	…	…	…	…	…	…	…	…
46	not serious	recession	decrease	high	normal cost	0.1800	0.6956	0.1244		
47	not serious	recession	decrease	low	more cost	0.0133	0.2400	0.5307	0.2160	
48	not serious	recession	decrease	low	normal cost		0.2000	0.5600	0.2400	

IV. Conclusions

Due to uncertain situations globally, shipping companies are under pressure to make a decision regarding the necessity of super slow steaming for their containerships. The research carried out was fully conducted using a Fuzzy Rule-based Bayesian Reasoning method. Overall, 48 rules have been produced to assist shipping companies with their decision making under uncertain situations concerning the vessel speed. The developed model is dynamic and the selection of evaluation criteria and sub-criteria can be improved from time to time based on uncertain situations faced by shipping companies.

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