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A Proposed Rule-Based Bayesian Reasoning Appoarch for Analysing Steaming Modes on Containerships

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ABSTRACT

Super slow steaming can make savings on fuel consumption and bunker fuel cost while also releasing fewer greenhouse gas emissions. The sustainability of this speed is beneficial when the bunker fuel price is high enough to offset the additional costs of operating the vessel and the additional inventory costs. A Rule-based Bayesian Reasoning model is therefore proposed for analysing the necessity of super slow steaming speed under uncertainty. The outcomes can be used by shipping companies to determine a suitable steaming speed in a dynamic operational environment.

1. Introduction

From 2000 to 2008, most shipping companies enjoyed very high profit margins in business operations on all routes (Cañero, Cerbán, Piniella, (2011). However, from the middle of 2008, many shipping lines suffered a downturn in their vessels' operation due to the global financial turmoil, the global economic recession and sharp increases in bunker fuel prices. Consequently, the volume of trade demand dramatically decreased on all major routes and ultimately caused a surplus of containerships services. Also, the new regulation of air emissions introduced by the International Maritime Organization (IMO, 2010) has put shipping companies under pressure. Such issues have had an immense impact in determining the suitable speed of containerships on any specific route.

A super slow steaming speed is a speed between 14 and 16 knots (Bonney and Leach, 2010). This speed has been pioneered by Maersk Line after it initiated a trial involving 110 vessels beginning in 2007 (Kontovas and Psaraftis, 2011). Furthermore, China Ocean Shipping Group and its partners in the CKYH alliance (K Line, Yang Ming Marine and Hanjin Shipping) were also reported to introduce super slow steaming on certain routes from November 2009 (Lloyd's List, 2009). Such a speed saves on fuel consumption and bunker fuel cost whilst also releasing fewer greenhouse gas emissions. Therefore, this paper intends to analyse the necessity of having super slow steaming speed on containerships under uncertainty using a combined methods called a Rule-based Bayesian Reasoning (*RBR*) method.

2. Background of methods

2.1. A Trapezoidal Membership Function

According to Pedrycz and Gomide (1998), a membership function associated with a fuzzy set $\tilde{A}$ depends not only on the concept to be represented but also on the context in which it is used. The "Core" of a fuzzy set $\tilde{A}$ is the set of all elements of X that exhibit a unit level of membership functions in $\tilde{A}$ and is denoted by Core ($\tilde{A}$) (Kruse *et al.*, 1994). The core (m,n) of $\tilde{A}$ can be shown using a trapezoidal membership function as described in Fig. 1 where Core $(\tilde{A})=\{x\in K|\mu_{\tilde{A}}(x)=1\}$ between m and n, while the lower and upper bounds are represented by a and b.

A set of questionnaires will be sent to a number of experts for their evaluations. All feedbacks received from all

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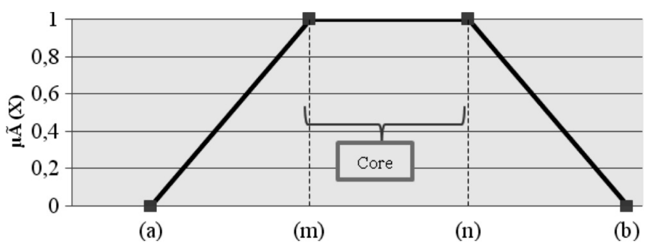

Fig. 1: Trapezoidal membership function.

experts will be aggregated and an average value of expert judgement will be computed using Eq. 1.

$$A = \sum_{n=1}^{N} E_n \times \frac{1}{N} \tag{1}$$

where E_n is the judgement rate given by the expert n, while N is the total number of experts. A is the average output value of the expert judgements.

If the average value of expert judgements 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. If the average value of expert judgements for a particular node is between the lower (a) and upper (b) bounds of two linguistic terms, the belief degree value of each linguistic term ($u(H_i)$) can be calculated using Eq. 2.

$$u(H_i) = \frac{V_{max} - V^l}{V_{max} - V_{min}} \tag{2}$$

where V_{max} is the preferred number of the linguistic term (H_j), V_{min} is the preferred number of the linguistic term (H_1) and V^l is the average value given by experts of the linguistic term (H_i). The utility of a linguistic term H_i is denoted by $u(H_i)$ and $u(H_{i+1}) > u(H_i)$ if H_{i+1} is preferred to H_i (Yang, 2001).

2.2. A Rule-Based Method

A rule-based method consists of *if-then rules*, a bunch of *facts* and an *interpreter* controlling the application of the rules given the facts (Abraham, 2005). These *if-then* rule statements are used to formulate the conditional statements that comprise the complete knowledge base. A single *if-then* rule assumes the form 'if x is A then y is B' and the *if* part of the rule 'x is A' is called the *antecedent* or *premise*, while the *then* part of the rule 'y is B' is called the *consequent* or *conclusion* (Abraham, 2005; Yang *et al.*, 2009). 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):

$$\begin{aligned} &R_k\text{:}IF\ A_1^k\ and\ A_2^k\ and\ \ldots and\ A_{T_k}^k, \\ &THEN\ \{(\beta_{1k}, D_1), (\beta_{2k}, D_2), \ldots, (\beta_{Nk}, D_N)\}, \left(\sum_{i=1}^{N} \beta_{ik} \le 1\right) \end{aligned} \tag{3}$$

with the rule weight θ_k and attributes weights $\delta_{k1}, \delta_{k2}, \ldots, \delta_{kT_k}$ where $\beta_1 ik$ ($i \in \{1, \ldots, N\}$: $k \in \{1, \ldots, L\}$, with L being the total number of the rules in the rule base) is belief degree to which D_i is believed to be the consequent if, in the kth packet rule, the input satisfies the packet antecedents $A^k = \{A_1^k, A_2^k, \ldots, A_{T_k}^k\}$. 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. θ_k is the relative weight of the kth rule, and $\delta_{k1}, \delta_{k2}, \ldots, \delta_{kTk}$ are relative weights of the T_k antecedent attributes used in the kth rule.

2.3. A Bayesian Reasoning Method

The Bayesian Networks (*BN*) method was developed by Bayes in 1761 and Bayes' Theorem was published in 1763 (Bernardo and Smith, 1994). It has become an increasingly popular paradigm for reasoning under uncertainty. Heckerman *et al.,* (1995) provide a detailed list of applications of the BN method. A *Hugin* (Korb and Nicholson, 2003) software tool will be used in this paper. The characteristics of the *BN* method are described as a Directed Acyclic Graph (*DAG*) consisting of nodes, arcs and an associated set of probability tables (Eleye-Datuba *et al.,* 2006). A *Conditional Probability Table (CPT)* associated with each node denotes the strength of such causal dependence. According to Wang and Trbojevic (2007), *nodes* (usually drawn as circles) represent random (i.e. chance) variables such as events that take values from the given domains. *Arcs* are used to represent the direct probabilistic dependence relations among the variables. There are three types of arcs, namely 1) serial, 2) diverging and 3) converging connections. Each relationship is described by an arc connecting an influencing (parent) node to an influenced (child) node and has its terminating arrowhead pointing to the child node.

Bayes's theorem is a mathematical algorithm used for calculating posterior probabilities. 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 as follows (Yang *et al.,* 2008):

$$p(D_i) = p(D_i | A_1^k, A_2^k, \ldots, A_{T_k}^k)\, p(A_1^k)\, p(A_2^k) \ldots p(A_{T_k}^k) \tag{4}$$

where A_i^k ($i \in \{1,2, \ldots, T_k\}$: $k \in \{1, \ldots, L\}$) is the referential value of the ith antecedent attribute in the kth rule. T_k is the number of antecedent attributes used in the kth rule and L is the total number of rules in the rule base. p (.) denotes the probability.

3. Modelling the necessity of super slow steaming under uncertainty

Step 1: Model development

A discussion technique with experts is used in this step. A *BN* model is proposed for developing a scientific model for this study. As a result, there are four parent nodes involved, namely 1) global warming, 2) global economics and financial conditions, 3) bunker fuel prices and 4) operating costs. The node "Global Warming (GW)" has one child node, namely "Emissions (E)" (Fig. 2). Also, the node "Operating Costs (OC)" has one child node which is "Cost Factors". The node "Global Economics and Financial Conditions (EFC)" has four child nodes, namely "Freight Rate (FR)", "Vessel Supply (VS)", "Ship Values (SV)" and "Container Demand (CMD)". The node "Bunker Fuel Prices (BFP)" has two child nodes which are "Global Factors (GF)" and "Voyage Costs (VC)". All the nodes except the output node "Super Slow Steaming" have been grouped into three groups of nodes namely "Vessel Factors (VF)", "Global Factors (GF)" and "Cost Factors (CF)". Such nodes assist shipping companies to make a decision in analysing the necessity of having super slow steaming.

Step 2: Data collection process

A qualitative dataset has been gathered through a set of questionnaires. In the set of questionnaires, the rate of measurement uses the range value between 1 and 10 (Table 1). If the node exists "*VF=high*", it means that 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	State	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

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*". By using Eq. 1, the average output value of Condition 1 is known to be 8.333. The same calculation technique is applied to all the conditions listed in Table 2.

Table 2: The partial evaluation of the node "Vessel Factors" given 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
…	…	…	…	…	…	…	…
8	low	low	normal	3	2	3	2.6667

The membership functions of the node "Vessel Factors" is constructed using the preference number and linguistic terms listed in Table 1. If the average output value of a condition is within the "Core" of a particular state, then the belief degree value of that state is known to be 1.0000, 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 (Fig. 3). Consequently, the belief degree value of the state "*average*" is known to be 1.0000.

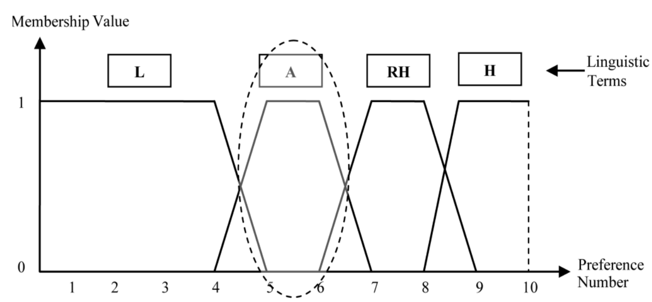

Fig. 3: Membership function of the node "Vessel Factors".

However, if the average output value of a condition is between two states (lower and upper bounds), then the belief degree values of these states are determined using Eq. 2. 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*"). By using Eq. 2, the belief degree value of

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

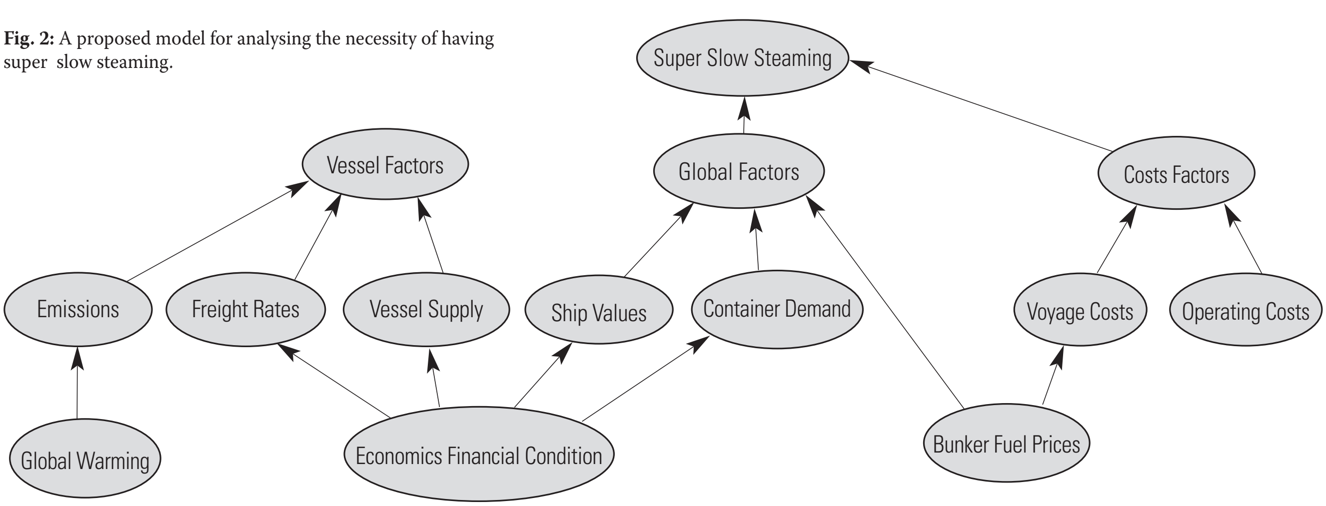

Table 3: The conditional probability table of the node "Vessel Factors".

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

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

Rules	**Antecedent Attributes**			**Super Slow Steaming (SSS)**				
No	**Vessel Factors (VF)**	**Global Factors (GF)**	**Cost Factors (CF)**	**strongly recommended**	**recommended**	**moderately recommended**	**not recommended**	**strongly not recommended**
1	high	good	high	0.0000	1.0000	0.0000	0.0000	0.0000
2	high	good	normal	0.0000	0.0000	1.0000	0.0000	0.0000
3	high	good	low	0.0000	0.0000	0.6667	0.3333	0.0000
…	…	…	…	…	…	…	…	…
48	low	poor	low	0.0000	0.0000	1.0000	0.0000	0.0000

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. The belief degree values of the states *"average"* and *"low"* are 0.0000. Accordingly, such output values are transformed into the CPT of the node "Vessel Factors" (Table 3). In a similar way, the CPTs of all other nodes are obtained.

Step 3: Establishment of Rule-based Bayesian Reasoning (RBR)

Three fundamental attributes 1) Vessel Factors (VF), 2) Global Factors (GF) and 3) Cost Factors (CF) are considered as the antecedent attributes in *IF-THEN* rules, while Super Slow Steaming (SSS) is expressed as the conclusions attribute. The linguistic terms of the three antecedents and conclusion attributes are defined as follows: "VF_i *{i = 1(high), 2(reasonably high), 3(average), 4(low)}*", "GF_j *{j = 1(good), 2(average), 3(fair), 4(poor)}*", "GF_k *{k = 1(high), 2(normal), 3(low)}*" and "SSS_l *{l = 1(strongly recommended), 2(recommended), 3(moderately recommended), 4(not recommended), 5(strongly not recommended)}*". By using these linguistic terms and the calculation techniques described in Step 2, the *RBR* with a belief structure for the node "Super Slow Steaming" is partially summarised in Table 4.

By using Eq. 3, the *RBR* with a belief structure can be performed as follows:

R_1: IF *VF1=high* and *GF1=good* and *CF1=high*, THEN {*(0.0000, strongly recommended (SSS1)), (1.0000, recommended (SSS2)), (0.0000, moderately recommended (SSS3)), (0.0000, not recommended (SSS4)), (0.0000, strongly not recommended (SSS5))*}.

Step 4: Bayesian reasoning

The necessity of having super slow steaming can be computed using Eq. 4. For example, given "*GW1=serious*", "*EFC3=recession*" and "*BFP1=high*", the posterior probability values of *P(SSS|*VF_i*,* GF_j CF_k*)* are computed as follows:

$$P(SSS) = \sum_{i=1}^{4}\sum_{j=1}^{4}\sum_{k=1}^{3} P(SSS|VF_i, GF_j, CF_k)P(VF_i)P(GF_j)P(CF_k)$$

$$= (0.9206, 0.0794, 0.0000, 0.0000, 0.0000)$$

It explains that the necessity of having super slow steaming associated with *"GW1=serious"*, *"EFC3=recession"* and *"BFP1=high"* is {(*0.9206, strongly recommended*), (*0.0794, 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 Fig. 4.

In a similar way, the necessity of having super slow steaming associated with "GW_i *{i = 1 (serious), 2 (not serious)}*", "EFC_j *{j = 1 (booming), 2 (stable), 3 (recession)}*" and "BFP_k *{k = 1 (high), 2 (low)}*" is obtained as partially shown in Table 5.

Step 5: Results and discussions

Referring to each rule in Table 5, the posterior probability values of more than 50% will be considered as the selected option of the test case. Given Rule 1 as an example, the necessity of having super slow steaming associated with "*GW1=serious*", "*EFC1=booming*" and "*BFC1=high*" is (*0.9409, moderately recommended (SSS3)*). The result is straight-forward and easy to understand by shipping companies. Rules 5, 6, 7, 9, 10, 11 and 12 can be explained in a similar way as Rule 1.

In Rule 2, the necessity of having super slow steaming associated with "*GW1=serious*" and "*EFC1=booming*" and

Table 5: The outputs of necessity of having Super Slow Steaming.

Rules	Antecedent Attributes			Super Slow Steaming (SSS)				
No	GW	EFC	BFC	strongly recommended	recommended	moderately recommended	not recommended	strongly not recommended
1	serious	booming	high	0.0000	0.0148	0.9409	0.0443	0.0000
2	serious	booming	low	0.0000	0.0000	0.0796	0.4682	0.4522
3	serious	stable	high	0.0787	0.4336	0.4758	0.0119	0.0000
4	serious	stable	low	0.0000	0.1258	0.3887	0.3944	0.0911
5	serious	recession	high	0.9206	0.0794	0.0000	0.0000	0.0000
…	…	…	…	…	…	…	…	…
12	not serious	recession	low	0.0251	0.2659	0.5431	0.1616	0.0042

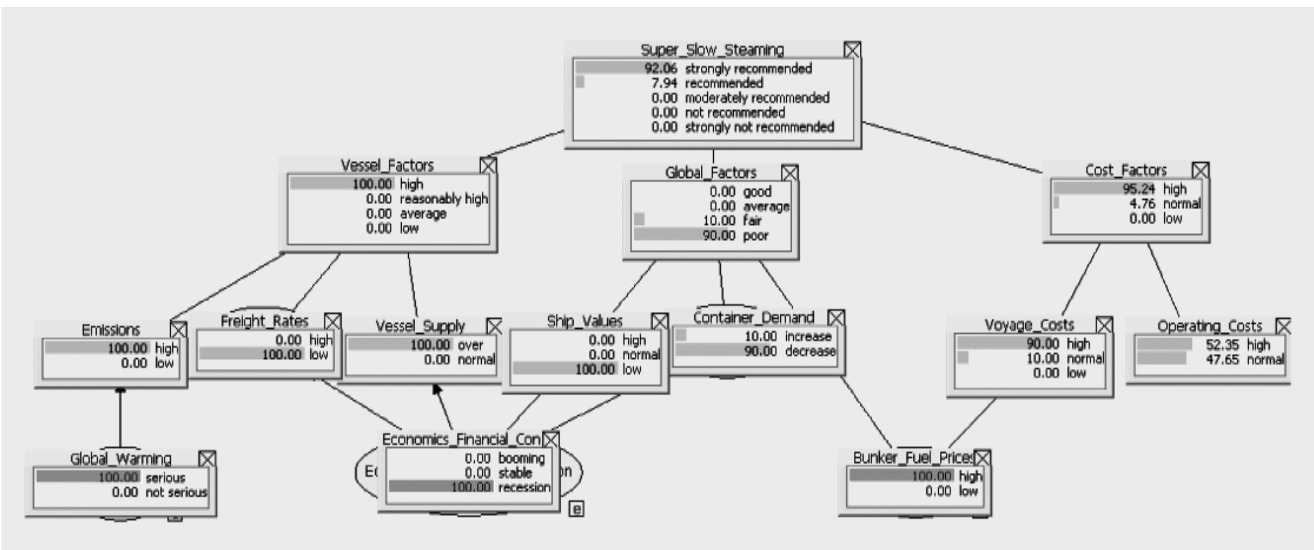

Fig. 4: The posterior probability value of the node "SSS" after giving evidence to nodes "GW", "EFC" and "BFC".

"*BFC2=low*" is {(*0.4682, not recommended (SSS4)*), (*0.4522, strongly not recommended (SSS5)*)}. The posterior probability values of both states are almost similar. As a result, the proposed *BN* model assists shipping companies in making a decision not to adopt super slow steaming speed in operating their vessels. Rules 3 and 8 can be explained in a similar way as Rule 2.

In Rule 4, the necessity of having super slow steaming associated with "*GW1=serious*" and "*EFC2=stable*" and "*BFC2=low*" is {(*0.3887, moderately recommended (SSS3)*), (*0.3944, not recommended (SSS4)*)}. Further investigation of this rule is needed in determining a final decision. This is because the posterior probability values of both states are comparatively large. Such two states are in different categories and shipping companies require more endeavour to decide a suitable steaming speed.

4. Conclusions

The research study carried out was fully conducted using a Rule-based Bayesian Reasoning method associated with the brainstorming and fuzzy set techniques. The qualitative dataset was obtained from the experts' judgement. This method is useful for assisting shipping companies in dealing with uncertain conditions. The outcomes produced can be used by shipping companies to determine the necessity of a super slow steaming speed in a dynamic operational environment. The novelties of this study are 1) the model development and 2) the application of all decision making methods described. An issue related to the results that can be used for future study is the uncertainty of the global situations. A process of identifying the most beneficial shipping business strategy in terms of cost saving, profit and service performance perspectives is needed.

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