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A Fuzzy Bayesian Belief Network Approach for Assessing the Operational Reliability of a Liner Shipping Operator

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***Abstract*— Container liner shipping is a highly competitive industry. With today's competitive environment, many liner shipping operators have acknowledged that having high operational reliability is a vital element for better overall performance and commitment to achieve a better competitive advantage. Operational reliability has become a key element for liner shipping operators to distinguish themselves from their competitors in the container liner shipping industry. This paper proposes a novel mathematical model for assessing operational reliability of a liner shipping operator using a combination of different decision-making techniques such as a symmetric model, Fuzzy Set Theory, and Bayesian Belief Network (i.e. Fuzzy Bayesian Belief Network). This assessment model is capable of helping liner shipping operators to conduct a self-assessment of operational reliability for enhancing their business performance in the container liner shipping industry.**

***Keywords* — Assessment model, operational reliability, liner shipping operator, symmetric model, fuzzy set theory, Bayesian belief network.**

I. Introduction

The importance of the container liner shipping industry (CLSI) for global and national economies is well recognised in the literature. The CLSI can be defined as container vessels operating on a regular scheduled service between groups of ports [1]. At present, a large proportion (i.e. 80%) of world commodities by volume are transported by seaborne trade and more than 62% of this seaborne trade is carried by the CLSI [2]. A recent study considering 157 countries over the 1962-1990 periods provided the empirical evidence that the CLSI is the driver of the 20th-century economic globalization [3]. Therefore, it is noteworthy to mention that the CLSI is remarkably acting as an artery in making contributions to the growth of the global economy.

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Competition among liner shipping operators (LSOs) continues to evolve with the result of structural changes within the industry. An operational reliability performance has become one of the significant concerns for LSOs to distinguish themselves from their competitors in the CLSI. On the other hand, shippers are increasingly looking for reliable LSOs and they are expecting for LSOs to offer them reliable global supply chain solutions and at the same time reductions in costs. In this paper, an operational reliability can be defined as the ability of an LSO's operations in delivering cargos in safely, securely, and timely manner.

The aim of this paper is to propose a novel mathematical model for assessing the value of operational reliability an LSO. This assessment model is capable of helping LSOs to conduct a self-assessment of operational reliability for enhancing business performance in the CLSI. In addition, with the help of the proposed methodology, shippers will be able to evaluate the reliability of LSOs in order to select the reliable ones for transporting their goods.

II. Literature Review

Recent developments in the maritime transportation have heightened the need for LSOs to enhance their operational reliability. Moreover, the global nature of today's supply chain networks has required LSOs to extend their geographical coverage and to offer high reliable services [4]. Operational reliability assessment have been widely discussed in many disciplines including energy supply, aviation, transportation, military, space, safety, healthcare, and education [5-9]. These studies have been primarily discussed under the concept of high reliability organization which covers management of hazards, theory of high reliability organization, resilience management, and safety culture. Most of these studies pay more attention in manufacturing industry, land transportation, and military rather than CLSI.

The impact of improper operation will cause financial losses [10]. Moreover, the unreliable operation will cause distrust that finally leads to loss of reputation among the shippers. Several studies have been conducted in the subject of operational risk and reliability in the maritime transportation [11-15]. None of them however deals with the operational reliability assessment for LSOs, which highlights a significant research gap to be fulfilled.

In this paper, four key reliability factors are carefully measured to assess the operational reliability of an LSO which are vessel reliability, container management, schedule reliability, and port reliability. It is well accepted that vessel reliability is a key factor for transporting cargos and crews in a safely, securely, and timely manner. Age of vessel, technology up-gradation, and ship staff reliability are three main indicators that signify the reliability of a vessel [14, 16]. Shippers are concern about the availability of their container at a port on-time. As a result, the effectiveness of container management needs to be highlighted in determining the operational reliability [17]. On the other hand, schedule reliability becomes a core factor for shippers when choosing the most reliable shipping lines in order to ensure their cargos arrive at destination as per scheduled [18, 19]. While the unreliability of a port (i.e. congestions) will continue to affect the operational reliability of LSOs, the need for LSOs to assess the reliability value of a port at their operational area is indispensable [18]. Based on the recommendation and adaptation of various studies in the literature, and further consultations with the domain experts, the most significant factors that are influencing the operational reliability of an LSO is illustrated in Fig. 1.

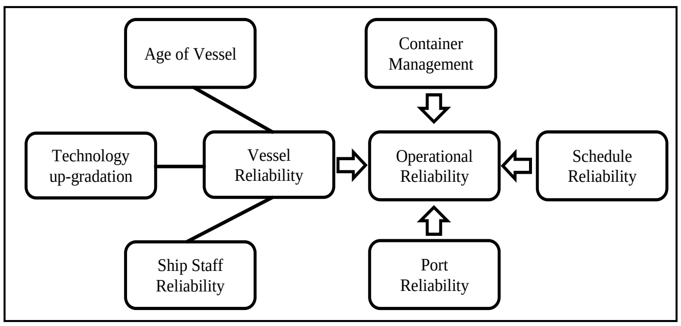

Figure 1. Operational reliability factors

A. *Bayesian Belief Network*

A BBN method was first developed by Bayes in 1761, later Bayes' Theorem was published in 1763 [20]. A BBN model is an artificial intelligence tool aimed to provide a decision-support framework for problems involving uncertainty, complexity, and probabilistic reasoning [21]. In addition, a BBN demonstrates the fundamental concept of probabilistic graphical models or probabilistic networks.

A BBN model is a Directed Acyclic Graph (DAG) consisting of a set of nodes, representing variables with a finite set of states, and arcs, representing the probabilistic causal dependence among the variables [12, 22]. *Nodes* represent random variables such as events that take values from the given domains, which may in principle be "discrete" or "continuous" [23]. *Arcs* are used to represent the direct probabilistic dependence relations among the nodes. The DAG represents the structure of causal dependence between nodes, and gives the qualitative part of causal reasoning in a BBN (i.e. unconditional probabilities). Thus, the relations between variables and the corresponding states of each variable give the quantitative part, consisting of a Conditional Probabilistic Table (CPT). A BBN structure is constrained to be acyclic. A BBN method is expected to produce a valuable result about assessing the operational reliability of an LSO as it provides an intuitive visual presentation with a sound mathematical calculation.

III. Methodology

In this paper, for assessing the operational reliability of an LSO, a combination of different decision-making techniques such as Analytical Hierarchy Process (AHP), symmetric model, Fuzzy Set Theory (FST) and Bayesian Belief Network BBN is used (i.e. FBBN). An AHP is employed to quantify the importance of attributes and is adapted into a deterministic weight vector [24]. A symmetric model is used to determine the conditional probabilities by synthesizing the AHP methodology [22]. An FST is used by exploiting a membership function for assessing quantitative and qualitative criteria in the assessment model [25]. Furthermore, a BBN is employed to demonstrate the fundamental concept of probabilistic graphical model and to calculate marginal probabilities by the help of Bayes chain rule [22, 26]. For the assessment of operational reliability of an LSO, as illustrated in Fig. 2, several steps are followed.

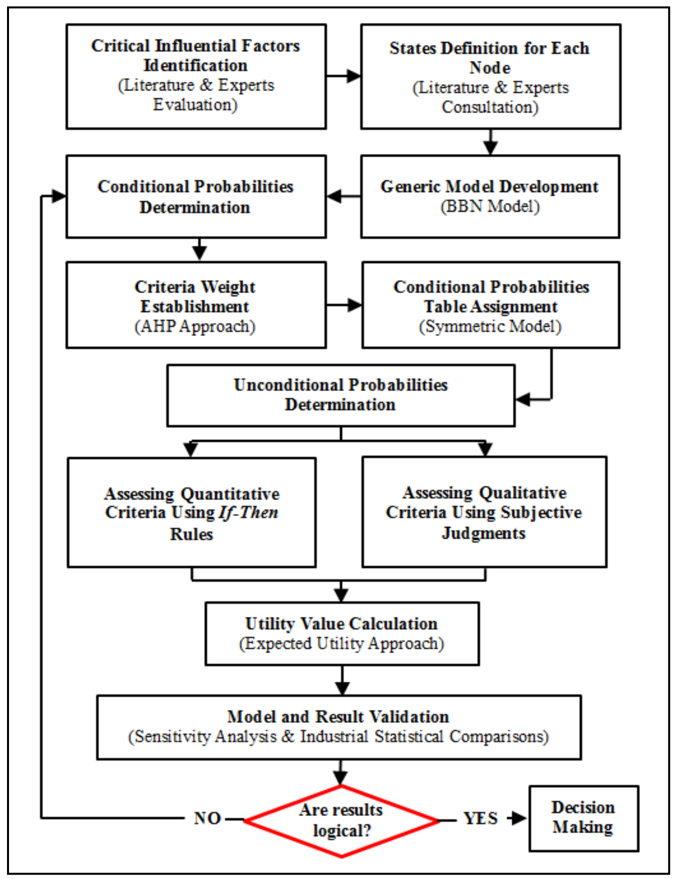

Figure 2. Framework for operational reliability assessment

A. *Identifying Critical Influential Factors and the Number of States of Each Node (Step 1 and 2)*

Identification of critical influential factors forms a visualization of the potential criteria and builds the foundations for the ensuing assessment process [27]. In this paper, an extensive literature review and consultation with domain experts have been used to identify the influential factors for assessing the operational reliability of an LSO. It is noteworthy to mention that the identified factors (i.e. Vessel reliability, container management, schedule reliability, and port reliability) are generic and they can be modified or adjusted based on a decision maker's preferences.

In step 2, a discrete fuzzy set membership functions can be applied to define states of each node. In this paper, three states for all nodes in the model have been defined as "high", "medium", and "low".

B. Development of a Generic Model of the Operational Reliability (Step 3)

The kernel of developing a generic model is that it can be modified or adjusted to be used for a particular firm or industry. In this paper, the identified factors as discussed in step 1 are used to develop a generic model of the operational reliability of an LSO. In step 3, a generic model of the operational reliability is constructed by using a BBN model as shown in Fig. 3 and the abbreviations are listed in Table 1.

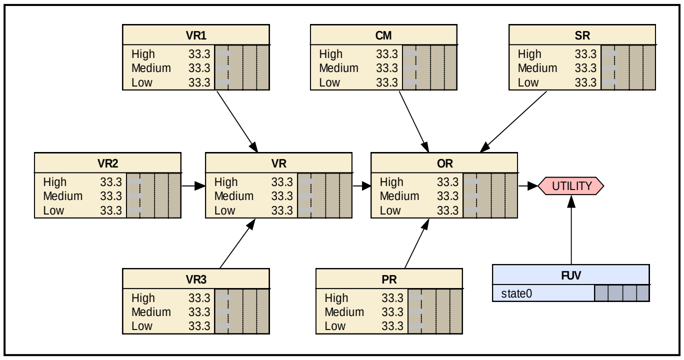

Figure 3. BBN model of the operational reliability of an LSO (without data)

TABLE I. TABLE OF ACRONYMS

Abbreviation	Description
VR	Vessel Reliability
CM	Container Management
SR	Schedule Reliability
PR	Port Reliability
VR1	Age of Vessel
VR2	Technology Up-gradation
VR3	Ship Staff Reliability
FUV	Final Utility Value

C. Determining the Conditional Probabilities (Step 4)

Conditional probability distributions are a set of distributions to represent the dependency of a child node to its parent node(s). In this paper, a weight is assigned to each parent node(s) by using an AHP technique. Then, the symmetric model is used to determine the conditional probabilities [22, 24]. The advantage of the symmetric model is that it can deal with the multi-state parents.

In the symmetric model, to determine the dependency of each child node to its associated parents, their normalized weights $(\omega_1, \omega_2, \ldots, \omega_n)$ need to be assigned. The kernel of the symmetric model can be described as follows:

In the normalized space, based on the influence of each parent node, the conditional probability of a child node *Y*, given each parent node, X_r, where $r = 1, 2, \ldots, n$, can be estimated as follows:

$$P(Y = present|X_1 = present) = \omega_1$$
$$P(Y = present|X_2 = present) = \omega_2$$
$$\vdots$$
$$P(Y = present|X_n = present) = \omega_n$$

$$\sum_{r=1}^{n} \omega_r = 1 \qquad (1)$$

Based on Eq. (1) in the situation of the symmetry model (i.e. normalized space), the probability of a child node *Y* conditional upon '*n*' parent nodes, X_r where $r = 1, 2, \ldots, n$, can be estimated as follows:

$$P(Y|X_1, X_2, \ldots, X_n) = \sum_{r=1}^{n} \tilde{\omega}_r \qquad (2)$$

$\tilde{\omega}_r = \omega_r$: If the state of the *"$r^{th}$ parent node"* is identical to the state of its child.

$\tilde{\omega}_r = 0$: If the state of the *"r^{th} parent node"* is different from the state of its child.

D. Determining the Unconditional Probabilities of Root Nodes (Step 5)

In step 5, for determining the unconditional probabilities, all assessment criteria (i.e. six root nodes) need to be evaluated. The assessment of the root nodes can be performed by internal team of an LSO (e.g. audit department) or shippers on monthly, quarterly, or annually basis.

While dealing with reliability assessment, quantitative data is a prime input. In this assessment model, *If-Then* rules are used to assess four quantitative criteria which are VR1, CM, SR, and PR. The measurement of each quantitative criterion is described as follows.

VR1: The year built of a vessel would indicate its performance as younger vessel would perform better at sea than the older ones [14]. Based on the domain experts' opinion, a vessel less than 10 years old can be assessed as high reliable, between 10 and 20 years old, and more than 20 years old, respectively, can be assessed as medium and low reliable. VR1 can be measured by using *If-Then* Rules as follows:

If a vessel is 10 (or less) years old, *then* the reliability is high.

If a vessel is between 11-20 years old, *then* the reliability is medium.

If a vessel is 21 (or more) years old, *then* the reliability is low.

For *n* vessels, if *k* of them are 10 (or less) years old, *l* of them are between 11-20 years old and *m* of them are 21 (or more) years old.

Then, $\frac{k}{n}$ = with high, $\frac{l}{n}$ = with medium, and $\frac{m}{n}$ = with low (3)

As an example, 10 vessels are currently operated in liner services under LSO 'A'. Age of all these vessels is between 11-20 years old. As a result, the reliability set for VR1 is calculated (i.e. 10/10 = 1 with medium reliable) and presented as:

VR1 = {(0, Low), (1, Medium), (0, High)}

By using the above technique, the other quantitative criteria (i.e. CM, SR, and PR) can be assessed.

CM: This criterion can be measured by calculating the difference between estimated arrival time (ETA) at a local port and the actual arrival time (ATA) [17]. If the difference between ETA and ATA is within one day or less, then CM can be assessed as high reliable. On the other hand, more than one and up to two days is assessed as medium reliable, and more than two days as low reliable.

SR: This criterion can be measured by calculating the difference between advertised vessel arrivals (AVA) at a destination port against ATA [17]. If the difference between AVA and ATA is within one day or less, then SR can be assessed as high reliable. On the other hand, more than one and up to two days is assessed as medium reliable, and more than two days as low reliable.

PR: This criterion can be assessed by evaluating container dwell times. Container dwell time is the amount of time container remains stacked at a local port while awaiting shipment for export or onward transportation [28]. If the container stacks at a local port is within four days or less, then the reliability of such port can be assessed as high reliable. On the other hand, more than four and up to seven days is assessed as medium reliable, and more than seven days as low reliable.

In a situation where there is a lack of existing data in the literature, imprecise information about past events and high uncertainty about future events, qualitative data can be obtained rather than quantitative data. There are various methods of qualitative data collection in a nature of information; one of them is through subjective judgments by experts. Qualitative data can be presented by linguistic variables (i.e. linguistic terms and their corresponding belief degrees). In this paper, three linguistic terms are used which are "high", "medium", and "low". As an example, linguistic variable for each qualitative criterion (i.e. VR2 and VR3) can be presented as follows:

$$\tilde{\Omega} = \{(\beta_1, \text{Low}), (\beta_2, \text{Medium}), (\beta_3, \text{High})\} \quad (4)$$

where β_1, β_2, and β_3 stand for belief degrees. The sum of belief degrees need to be equal to 1. After the values of conditional and unconditional probabilities have been obtained, the marginal probabilities of the child node(s) can be calculated by the help of the Bayes chain rule.

E. *Evaluation of the Utility Value (Step 6)*

The result of the assessment is presented by the three linguistic terms (i.e. high, medium, and low). To obtain a single crisp value for ranking the alternatives and comparison purposes the utility value approach is used [29].

$$u(H_n) = \frac{V_n - V_{\min}}{V_{\max} - V_{\min}} \quad (5)$$

$$U_v = \sum_{n=1}^{N} \beta_n u(H_n) \quad (6)$$

where $u(H_n)$ denotes the utility value of a considered linguistic term (i.e. H_n) and can be estimated using In Eq. (5). V_n is the ranking value of the linguistic term that has been considered (H_n); V_{max} is the ranking value of the highest linguistic term H_N; and V_{min} is the ranking value of the lowest linguistic term (H_1). In Eq. (6), the utility of the concerned criterion (i.e. goal) is denoted by U_v, and β_n stands for the belief degree associated with the n^{th} linguistic term of the concerned criterion.

F. *Validation of Model and Result (Step 7)*

Finally, sensitivity analysis (SA) is used to partially validate the result. SA is a process of analyzing how sensitive the result of a belief update (i.e. change in input belief degrees) is to variations of the parameters' value in the model. In order to ensure that the assessment methodology is consistent, SA must at least meet the following three Axioms:

Axiom 1: A slight increment or decrement in the degree of belief associated with any states of an input node will certainly result in a relative increment or decrement in preference degree of the model output.

Axiom 2: if the degree of belief associated with the highest preference state of an input node is decreased by l and m (i.e. simultaneously the degree of belief associated with its lowest preference state is increased by l and m ($1>m>l$)) and the utility values of the model are evaluated as U_l and U_m respectively; then U_l should be greater than U_m.

Axiom 3: If N and K ($K<N$) input nodes are selected and the degree of beliefs associated with their highest preference states are decreased by the same amount (i.e. simultaneously the degree of beliefs associated with their lowest preference states are increased by the same amount) and the utility values of the model output are evaluated as U_K and U_N respectively, then U_K should be greater than U_N.

SA is used for testing the logicality of the delivery of the analysis. Furthermore, it is used to calculate the impact of the change of a parameter on the model output.

IV. Conclusion

Evaluation of operational reliability of a liner shipping operator is vital and can help an LSO to enhance its performance. In this paper, a novel mathematical model based on the FBBN technique for assessing the operational reliability of an LSO, is proposed. In the proposed methodology, firstly, critical influential factors are identified. Secondly, the numbers of states of each node are identified. Thirdly, a BBN model for assessing the operational reliability of an LSO is developed. Fourthly, the conditional probabilities of each node are determined using the symmetric model. Fifthly, qualitative and qualitative data are obtained for determining the unconditional probabilities of each root node. Sixthly, the utility value of the model is evaluated by using an expected utility approach. Finally, the model and result are validated by using SA and industrial statistical analysis.

With the proposed assessment methodology, LSOs are able to conduct a self-assessment of their operational reliability. The operational reliability value can be used by an LSO to facilitate continuous improvement strategies for a better competitive advantage and market positioning in the CLSI.

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