

Enhancing Maritime Traffic Resilience via a Hybrid Model of Markov Networks and DBN: Evidence from LNGFV Navigation

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In order to comprehensively understand the internal operation mechanism and external interaction relationship during the navigation of coupled systems such as Liquefied Natural Gas-Fueled Vessels (LNGFV), this paper proposes a hybrid model that integrates the Causal Analysis based on System Theory (CAST) with Dynamic Bayesian Networks (DBN) to analyze the traffic resilience of LNGFV during navigation. Starting from the mechanism of system resilience, the study constructs a resilience evolution framework for LNGFV based on the Triple Protection Mechanism (TPM). The CAST method is employed to identify key influencing factors within the navigation safety control structure, and the integration of DBN with Hidden Markov Models (HMM) is used to quantify the dynamic characteristics of resilience. Through the analysis of LNGFV accident cases and environment data-driven simulations, the results indicate that the evolution of LNGFV traffic resilience follows a double U-shaped trend and is significantly positively correlated with the implementation effectiveness of TPM, demonstrating TPM's capability to maintain high resilience levels under external disturbances. This framework provides a systematic method and a new perspective for resilience assessment in complex shipping systems, supporting optimized decision-making for multi-level risk management.

1. Introduction

Maritime traffic is one of the important modes of transportation and plays a key role in economic development. Studying its resilience ensures that in the event of natural disasters and emergencies, the maritime traffic system can recover quickly and safeguard the flow of goods. In recent years, with the increase of climate change and environmental uncertainty, more and more new energy vessels have appeared in maritime traffic. Liquefied Natural Gas (LNG), as a clean and efficient energy source (Thomson et al., 2015), has played an increasingly significant role in the global energy landscape and maritime trade. Over the past decade, the application of LNG fuel propulsion technology in newly built ocean-going vessels has seen a substantial increase, driven by both market price advantages and the increasingly sophisticated LNG supply chain. In the next 3 to 5 years, with the continuous development of carbon neutrality and zero-carbon fuel technologies, LNG fuel technology will remain one of the primary technological pathways for green shipping (Iannaccone et al., 2020). As an alternative fuel for traditional vessel propulsion, LNG poses higher complexity in the navigation and operation of LNGFV due to its special physicochemical properties of flammability, explosiveness, and ultra-low temperature, combined with the unique operational mode of LNGFV (Livanos et al., 2014). It is further required to make advance response plans and reduce losses by studying resilience. Enhancing the resilience of maritime traffic system involved LNGFV operation remains a current research hotspot.

1.1 Maritime traffic resilience from the perspective of safety-II mode

Scholars have studied the theory of traffic resilience from different perspectives, including the stability, adaptability, and resilience of the system, and have formed a richer theoretical system to better understand the performance and coping strategies of traffic systems in the face of various disturbances.

Traditional models are developed from the perspective of analyzing the causality of accidents. Based on this, Hollnagel proposed the concepts of Safety-I and Safety-II Vanderhaegen et al. (2015). Safety-I aims to minimize the number of unsafe events and focuses on accident prevention based on the concept of safety management.

However, as systems become increasingly complex, traditional models face challenges: it is almost impossible to comprehensively predict all potential failures, and a pure reliance on accident causality analysis is no longer applicable. Conversely, Safety-II recognizes that systems are composed of highly complex activities that may change before their operational processes are described (Merandi et al., 2018). Safety-II complements Safety-I, it defines safety as "ensuring that everything goes right" and emphasizes the ability to succeed under different conditions defined in resilience engineering (van der Beek et al., 2015). The Safety-II perspective emphasizes that safety management needs to balance passive and active strategies, not only learning from accidents and failures but also encouraging proactive safety activities. This way, safety management can more effectively respond to complex and changing environments (Fan et al., 2022). Although the application of the resilience concept differs across disciplines, its three key characteristics are widely recognized and provide a foundation for assessing and quantifying resilient systems. System resilience is a fundamental attribute of system safety, and studying resilience is a crucial path to comprehensively understanding the safety-related attributes of complex systems (Wang et al. 2023).

1.2 Application of DBN in maritime traffic resilience assessment

Quantitative assessment of traffic toughness with the help of mathematical modeling and simulation has become a hot spot in research. For example, complex network theory is used to analyze the topology and anti-interference ability of the traffic network, and the toughness performance of the system is evaluated by simulating the traffic operation under different scenarios. LNGFV as a complex technological and societal system, the resilience can be quantitatively assessed. According to existing research literature, DBN is currently the mainstream technology for assessing the resilience of various complex systems and has been validated. (Yodo et al., 2017) By applying DBN to enhance the system's ability to withstand uncertainties and potential adverse operational environments, the resilience of typical complex systems is analyzed. (Cai et al., 2018) By considering time-dependent characteristics for system resilience assessment, the advantages of DBN have been further developed. Engineering systems have become a hot topic in discussions on DBN resilience assessment, as referenced in (Tong et al., 2020; Cai et al., 2021). (Vairo et al., 2021) develops a resilience framework using Bayesian inference and MCMC simulations to assess the safety of LNG bunkering processes. Additionally, DBN-based resilience assessment is also applicable to maritime-related infrastructure, which is crucial for the safe operation of maritime systems. In vessel's networks, ports are widely regarded as critical nodes, and their resilience has been studied from different perspectives using probabilistic DBN models. (John et al., 2016) Studied the resilience of seaport systems against disruptions and quantified the comprehensive resilience of deep-sea ports (Hosseini et al., 2016) and river ports (Hossain et al., 2019) by applying DBN. Furthermore, (Qiao et al., 2021) simulated Arctic traffic routes using fuzzy DBN for quantitative resilience analysis. (Li et al., 2022) proposes a DBN-based risk reasoning strategy for LNG ships in Arctic waters, integrating multi-source data and D-S evidence theory, validated by identifying key risks like icebergs and reefs. The interconnectivity of seaports has led to the development of supply chains, and their resilience assessment is also a hot issue, with (Ojha et al., 2018) and (Hosseini et al., 2022) using DBN to study it from the perspectives of risk propagation and disruption mitigation, respectively. Based on the above studies, this study selects DBN as the tool for resilience assessment of LNGFV.

2. Methodology

2.1 Traffic resilience for LNGFV system

According to the mathematical statement of the Maritime traffic resilience, the traffic resilience of LNGFV can be described as a comprehensive manifestation of the vessel's exposure to constantly changing external environment, the sensitivity issues arising from LNG fuel and involving its related fuel protection equipment, the adaptability of the vessel's subsystems to internal and external changes, as well as its emergency response status and self-recovery capabilities after being impacted.

The analysis of traffic resilience for LNGFV requires a description of the exposure, sensitivity, adaptability, and recoverability of the components of the maritime traffic system. Exposure focuses on the uncertain navigation surrounding conditions in which the vessel subsystem and LNG subsystem are located. Sensitivity primarily concerns the operational status of LNG fuel protection equipment. Adaptability addresses the state of the vessel under the combined influence of external environmental conditions and internal LNG fuel. The traffic resilience of LNGFV is the result of the combined and interactive effects of exposure factors to external environment, LNG sensitivity factors, vessel adaptability factors, and recovery factors. In summary, LNG traffic resilience is the comprehensive manifestation of the interaction among these four dimensions. By quantitatively analyzing the changes in the safety status of vessels under these four dimensions during traffic, the traffic system resilience can be assessed.

2.2 Model

2.2.1 CAST method

CAST, a causal analysis method based on system theory, incorporates a system engineering perspective into safety analysis. Starting from the control safety structure, it comprehensively considers the interactions among social, human, and design factors, believing that accidents are caused by the cumulative behavioral effects of unsafe states of risk factors. While the safety state of a single factor changes, it also has corresponding varying degrees of impact on other factors (Zhang et al., 2022).

2.2.2 Dynamic Bayesian network analysis method

The core theoretical foundation of BN can be illustrated using Equations (1) and (2). Equation (1) is Bayes' formula, used to describe the relationships between two conditional probabilities and to obtain the posterior probability of any node. Based on Bayes' formula, when new evidence is obtained for a parent node, the probabilities of intermediate and child nodes can also be updated. Equation (2) is derived from the total probability formula and represents the multivariate joint probability distribution.

$$P(X|Y) = \frac{P(Y|X) \cdot P(X)}{P(Y)} \quad (1)$$

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P(X_i | P_a(X_i)) \quad (2)$$

Where: $P(X|Y)$ and $P(Y|X)$ represent the posterior probabilities of variables X and Y (i.e., the conditional probabilities of X or Y given the occurrence of Y or X); $P(X)$ and $P(Y)$ represent the prior probabilities of variables X and Y ; $P(X_1, X_2, \dots, X_n)$ represents the joint probability of multiple variables; and $P_a(X_i)$ denotes the parent node of variable X_i .

Unlike static BN, traditional DBN consider Markov chain processes across time dimensions. By accounting for the uncertainty and variability of nodes over time, BN are extended into DBN with a time dimension to explicitly simulate system dynamics based on Markov processes. Therefore, the formula for DBN considering the time dimension is as follows:

$$P(X_1^t, X_2^t, \dots, X_n^t) = \prod_{i=1}^n P(X_i^t | X_i^{t-1}, P_a(X_i^t), P_a(X_i^{t-1}), \dots, P_a(X_i^0)) \quad (3)$$

However, for complex systems, there often exists the issue of unmeasurable parameters for some nodes, and traditional DBN have limitations in addressing this problem. In view of this, this study introduces the HMM method to improve the inference process of DBN. Assuming that the states of child nodes in the DBN are divided into four levels: S1, S2, S3, and S4, with n observable factors denoted as O1, O2, ..., and On, the markov transition process of the HMM-improved DBN is illustrated in Figure 1.

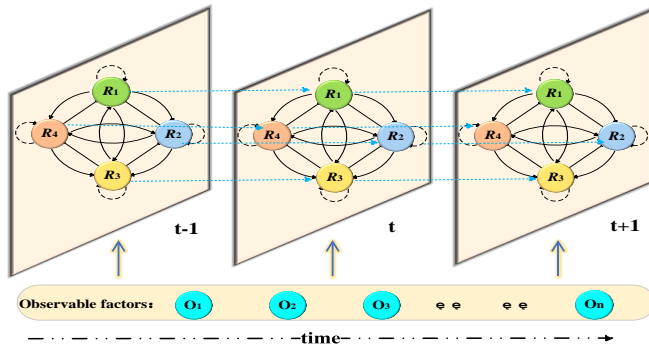


Figure 1: Markov transition process of HMM-Improved DBN

3 Case study

3.1 Application of the defined model

3.1.1 Establishing an evaluation index system for LNGFV traffic resilience

The resilience of LNGFV navigation is disturbed by various factors. The CAST method conducts a layer-by-layer analysis of the system from the physical layer to higher management layer. Additionally, combining resilience theory, resilience attributes such as adaptability, sensitivity, exposure, and recoverability are integrated into the CAST model. Based on the CAST method, a comprehensive analysis of the safety control structure of the LNGFV traffic system is conducted. Through the analysis results, the key causes of system accidents are identified, with a focus on analyzing the representation and determining metrics for LNGFV traffic

resilience. Subsequently, an evaluation index system for LNGFV traffic resilience is proposed, as shown in Table 2.

Table 2: Evaluation index system for LNGFV traffic resilience

Target system	Resilience attribute	Influencing factors
LNGFV traffic resilience	Adaptability factors	Vessel communication system (X1)
		Information perception system (X2)
		Vessel monitoring system (X3)
		Hull structure and condition (X4)
		Navigation assistance equipment (X5)
Sensitivity factors	Power system (X6)	
	vessel control system (X7)	
	Ventilation system (X8)	
	Security system (X9)	
	Personnel operation (vessel) (X10)	
	Propulsion devices and locations (X11)	
	Piping valves (X12)	
	Electronic control unit(ECU) (X13)	
	Physical containment system (X14)	
	Liquid and gas detection and alarm devices (X15)	
Exposure factors	LNG storage locations and tanks (X16)	
	LNG efficiency(Heat exchanger) (X17)	
	Personnel operation (LNG) (X18)	
	Traffic density (X19)	
	Route intersections (X20)	
Recovery factors	Wind (X21)	
	Current (X22)	
	Wave height (X23)	
	Visibility (X24)	
	Crew safety awareness (X25)	
	Captain's management level (X26)	
	Accident experience (X27)	
	Emergency drills (X28)	
Equipment redundancy (X29)		
Emergency plan Redundancy (X30)		
Emergency system (X31)		
Emergency shutdown (ESD) system (X32)		

3.1.2 Establishing the DBN structure

Based on the constructed resilience indicator system for the LNGFV system, the analysis results from CAST, and the information transmission paths within the safety control loop, a DBN rule-based network model is established, as shown in Figure 2.

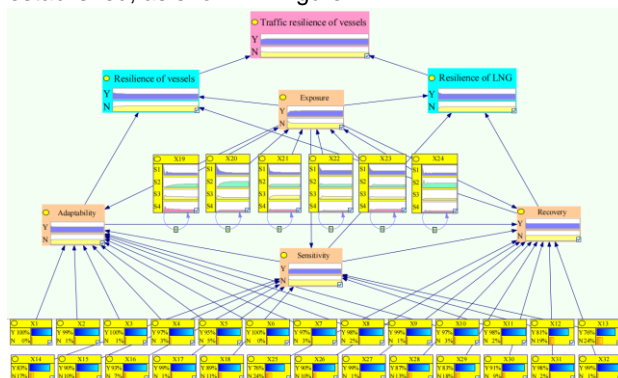


Figure 2: Information on inbound routes and vessel trajectories for LNGFV

The relevant attributes of nodes in the DBN model can be classified according to their different properties. For intermediate nodes, leaf nodes, and static root nodes, their states are divided into "Yes" and "No" represented by Y and N, based on whether an event might occur. For dynamic nodes, six nodes—traffic density, route intersection, wind, current, wave height, tides, and visibility—are classified into four risk status levels. The classification refers to (Li et al., 2021). For intermediate and leaf nodes, the model input is a conditional probability table. For dynamic environment nodes, the model input consists of a prior probability table and a state transition matrix.

3.2 Simulation results

Based on the duration of the accident, it is divided into 20 equal time slices. The relevant parameters of the trained DBN are input for DBN simulation to obtain the changes in LNGFV traffic resilience during this accident, as shown in Figure 3(a). The resilience performances of LNGFV navigation are simulated, with the results presented in Figure 3(b).

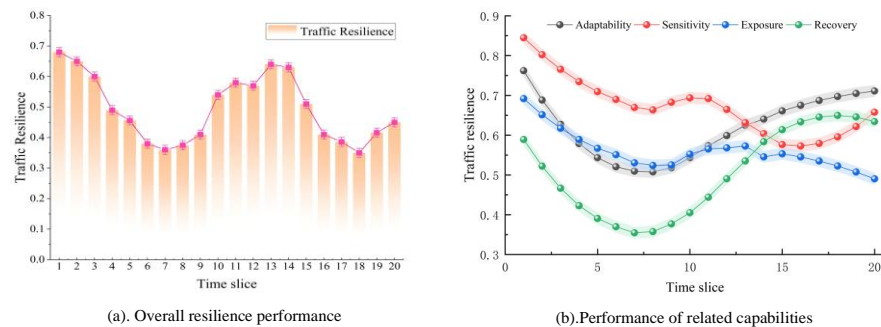


Figure 3: Simulation results of vessel traffic resilience during the accident process

The simulation results reveal the following:

(1) After the initial impact, LNGFV shows a rapid decline in resilience, followed by a gradual increase in the middle stage. In the mid-to-late stage, resilience levels again show a rapid decline, and at the end, they demonstrate an increasing trend. The overall evolution of traffic resilience throughout the accident follows a double "U"-shaped curve, which aligns with the actual situation where the LNGFV experienced two impacts during the accident.

(2) Adaptability, sensitivity, exposure, and recoverability exhibit significant dynamic changes within their respective time periods, highlighting the crucial roles of these key characteristics in the LNGFV traffic resilience system. The varying characteristics of these four resilience indicators reflect the vessel's resilience levels and response capabilities at different stages. In the early stage, the vessel is relatively safe and has strong response capabilities. In the middle stage, due to external environmental impacts and reduced sensitivity of protective equipment, adaptability and recoverability are challenged. In the later stage, through emergency measures and recovery processes, the vessel gradually restores its adaptability and emergency response capabilities. In summary, the LNGFV traffic resilience performance demonstrates a multi-layered risk management strategy and reflects the effectiveness of TPM in managing liquefied natural gas fuel leakage risks and enhancing the vessel's overall resilience.

(3) The ultimate goal of conducting CAST analysis is to propose countermeasures based on the analysis results. After analyzing the LNGFV accident case, it was determined that the accident was caused by a failure in the UPS within the vessel's power system, resulting in a loss of engine power and subsequent propulsion failure. During the navigation of LNGFV, the UPS is responsible for powering loads such as computer control systems, communication systems, and monitoring systems. Once the UPS fails, it can cause immeasurable losses to the entire system.

4 Conclusion

This study puts forward a complex system resilience analysis framework that combines CAST and DBN to explore the evolution of vessel traffic resilience. It establishes a safety control structure for the vessel traffic process, employs CAST analysis techniques to identify key causes impacting traffic resilience, and constructs an index system for vessel traffic resilience analysis, thereby building a DBN model for quantitative resilience analysis.

In combination with specific accident cases of LNGFV traffic process, the HMM method is introduced to infer unobservable parameters in the DBN. Through DBN simulation, the conclusion shows that the evolution mechanism of LNGFV traffic resilience presents a double "U"-shaped curve characteristic. The level of LNGFV

traffic resilience shows a high positive correlation with the effective operation of TPM. The effective implementation of TPM can ensure that the resilience of LNGFV remains at a more secure level. The maritime transportation resilience network is a complex system requiring a comprehensive hierarchical control structure to fully understand its elements and ensure accurate resilience evaluation. Simplifying this structure could hinder a thorough analysis and impact final results. Future research will focus on modeling this complex network using CAST's framework.

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