

Article

Resilience Assessment for the Northern Sea Route Based on a Fuzzy Bayesian Network

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Abstract: The safety level of the northern sea route (NSR) is a common concern for the related stakeholders. To address the risks triggered by disruptions initiating from the harsh environment and human factors, a comprehensive framework is proposed based on the perspective of resilience. Notably, the resilience of NSR is decomposed into three capacities, namely, the absorptive capacity, adaptive capacity, and restorative capacity. Moreover, the disruptions to the resilience are identified. Then, a Bayesian network (BN) model is established to quantify resilience, and the prior probabilities of parent nodes and conditional probability table for the network are obtained by fuzzy theory and expert elicitation. Finally, the developed Bayesian networkBN model is simulated to analyze the resilience level of the NSR by back propagation, sensitivity analysis, and information entropy analysis. The general interpretation of these analyses indicates that the emergency response, ice-breaking capacity, and rescue and anti-pollution facilities are the critical factors that contribute to the resilience of the NSR. Good knowledge of the absorptive capacity is the most effective way to reduce the uncertainty of NSR resilience. The present study provides a resilience perspective to understand the safety issues associated with the NSR, which can be seen as the main innovation of this work.

Keywords: northern sea route; resilience assessment; Bayesian network; fuzzy theory



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1. Introduction

Under the influence of global warming, a rapid decline in sea ice coverage and an increase in the depth of Arctic waters have been observed since 2000 Gascard et al., 2017 [1]. The potential commercial and political importance of arctic shipping routes has been the focus of various countries, shipping companies, and international organizations. Among the three shipping routes in Arctic waters, the arctic northeast route, also known as the northern sea route (NSR), is the most critical route because it greatly reduces the sailing distance between Asia, Europe, and North America compared with rational routes via the Suez [2]. According to [3], the reduced distance can be as much as 40%. As a result, shipping companies from Germany, China, Korea, Russia, Norway, and other countries have expressed interest in investing this route to obtain a competitive edge over competitors [4]. Although the opening and commercial operation of the NSR provide vast potential opportunities, Arctic waters still present major challenges for the shipping industry [5]. Harsh natural environments and fragile ecosystems make it difficult to maintain a satisfactory safety level for shipping operations along the NSR, which greatly increases the concerns of national and international parties. For example, the International Maritime Organization (IMO) issued the Polar Code in 2010 to ensure the safety level of shipping operations in Arctic waters [6]. In addition, the International Hydrographic Organization (IHO) has initiated a program to provide an accurate navigation chart for ships traveling along the NSR. Overall, the safety level of shipping operations within Arctic waters, particularly along the NSR, has garnered attention from various levels of companies at

the national and international scales. However, the safety level of the NSR is still far from satisfactory, and accidents associated with shipping operations still occur at times. Therefore, a great deal of work has been done to better understand how to improve the security capacity and mitigate the various risks along the NSR. Therefore, in the present study, the concept of system resilience is introduced to attempt to obtain knowledge about the security capacity, and an investigation is conducted to improve the system resilience of the NSR.

1.1. Literature Review

The risk management of arctic shipping operations seeks to minimize the risk level. One of the most important issues is to identify the causal factors that contribute to risk or accidents. Therefore, many studies have been conducted to investigate the risk factors based on accidents and the unique natural environment in Arctic waters; such methods involve applying various theories, models, and techniques. Fault tree analysis was utilized by [7] to investigate the risk factors involved in chemical tanker accidents in Arctic waters. Later, an integrated methodology including fault tree analysis and the Human Factor Analysis and Classification System (HFACS) model was developed by [8] to study the collision risk during icebreaker assistance. Records of navigational shipping accidents that occurred in the Northern Baltic Sea during 2007 and 2013 were collected and investigated by [9], who found that ridged ice of a certain thickness cannot be considered the main cause of accident occurrence. Ref. [10] investigated the risk factors associated with Arctic maritime accidents from 1993 to 2011 by performing root cause analysis. Ref. [10] summarized various navigational risk contributors when sailing along an Arctic route, and the corresponding numerical weights were also given by using fuzzy analytic hierarchy process (AHP) and expert elicitation. The risk factors can also be identified by the application of Bayesian networks. Later, a novel Bayesian network (BN) model was proposed by [11] to identify the shipping operation risk in Arctic waters. Some studies based on the perspective of navigators have been performed to evaluate the shipping operation risk in Arctic waters, and such studies include those of [12,13], who studied the navigation risk in icy waters in the Baltic Sea. Ref. [6] investigated the key factors that influence the operation of arctic shipping routes.

Resilience is widely regarded as a specified capacity factor pertaining to an organization or a system that reflects how well the organization or system can recover from a disrupted or destroyed state. The concept of resilience was first introduced by [14], who argued that resilience can enable an ecosystem to continue to operate after being disturbed. Later, many studies tried to define resilience [15–17]; however, there is currently no universal consensus on the definition of resilience. Based on its various definitions, resilience is widely used in different fields [18–21] due to its contribution to the development of the relationship between capacity and a disruption or disaster. Many important applications of system resilience are subject to infrastructure systems, such as urban infrastructure systems [22], electrical infrastructure systems [23], inland waterway ports [24], and full-service deep-water ports [25]. In addition, organizational resilience was defined by [17] as the ability of enterprises and other organizations to improve performance. Similarly, in the social domain, the resilience capacity is regarded as “the ability of communities to cope with external stresses and disturbances as a result of social, political, and environmental change” [26]. In past decades, substantial differences existed among various descriptions of system resilience; however, the quantification of system resilience has always been a common concern. Generally, system resilience can be regarded as a time-dependent variable, as shown in Figure 1. Initially, the system is stable in the original state; then, with the appearance of a disruptive event, the performance of the system deteriorates gradually, which can trigger system resilience to recover the system performance to the normal level. According to [27], system resilience can be decomposed into absorptive capacity, adaptive capacity, and restorative capacity, which can absorb the shocks caused

by a disruption, adapt the system to the new disrupted conditions, and restore the system to normal conditions as much as possible, respectively.

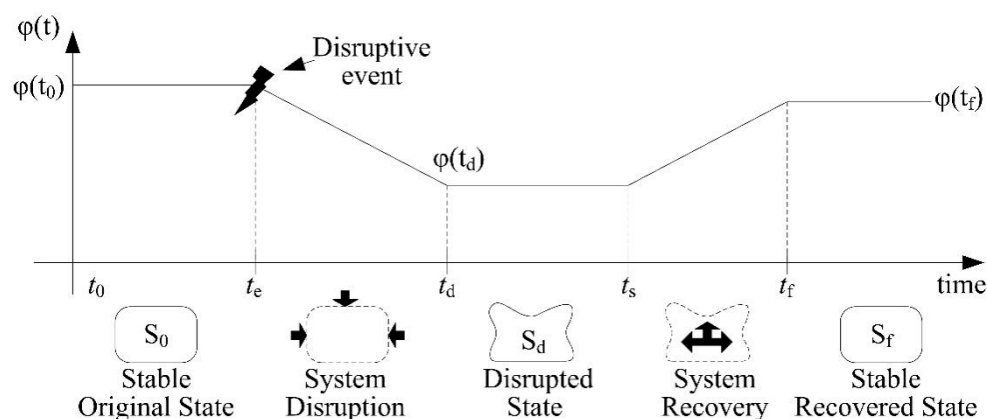


Figure 1. Resilience description associated with system performance and state transition [28].

Bayesian networks (BNs) are widely accepted as effective tools for conducting risk assessments and making decisions due to their notable advantage in easily updating information. Ref. [29] reviewed the applications of Bayesian inference for probabilistic risk assessment through 2007. Ref. [30] discussed different aspects of Bayesian network-based risk assessment. Actually, in engineering practice, BNs are usually integrated with other models, such as event trees [31], fault trees [32], bow-tie diagrams [33], HFACS [34], and so on. In addition to their successful application in risk assessment, BNs have been further utilized to evaluate the system performance and resilience capacity of specific systems. In the supplier selection BN model developed by [35], the resilience capacity was quantified in aspects of withstanding, adapting to, and recovering from a disruption. Moreover, [36] established a supply chain BN to forecast how risk factors affect the performance of the biomass supply chain network. Recently, in many studies, researchers have gradually explored the application of BNs in measuring system resilience. For instance, [37] established a comprehensive model for the resilience measurement of Systems of Systems (SoS) based on a BN. As a case study, the Littoral Combat Ship (LCS) was taken as an example, and conditional resilience metrics were proposed to assess the importance of individual sub-systems. Later, [38] proposed a BN model to quantify the system resilience of infrastructure and took an inland waterway port as an example to demonstrate the application of the model. Then, a resilience measurement model based on a BN was further extended to explore an interdependent electrical infrastructure system [23] and a full-service deep-water port [25].

1.2. Discussion of Existing Studies

Based on the literature review, extensive efforts have been made by international organizations and the relevant authorities to maintain the safety level of the NSR. Many studies on the NSR have been conducted, and safety issues for shipping operations that move through Arctic waters are still the main concerns globally due to the unavailability and uncertainty of information associated with navigation along the NSR. Improving the capacity to safeguard various ships transiting Arctic waters, especially the NSR, is a great challenge for the commercial operation of the NSR. The lack of safeguard capacity evaluations considering the safety of shipping operations along the NSR is a current gap in the literature. To address this gap, the present study proposes a comprehensive assessment model involving a fuzzy BN and information entropy to quantitatively measure the resilience of the NSR.

The present study mainly aims to pioneer the establishment of an integrated evaluation model based on fuzzy BN information entropy theory to measure the resilience of the NSR.

safeguard system and investigate the influence of contributing factors on system resilience. Under the framework of resilience, the disruptions to the NSR safeguard system were first identified by a literature review and expert elicitation. Then, resilience decomposition was performed to identify the contributing factors for system resilience, which were mapped into the BN structure together with the factors related to disruptions as the parent nodes in the BN. Experts with navigation experience or academic experience associated with the NSR were employed as consultants to quantify variables by using fuzzy theory. Finally, we ran the developed BN with GeNIe 2.3 software and generated conclusions. The main features of the present study are summarized as follows:

- A system resilience analysis framework is explored to improve the safeguard capacity of the NSR in mitigating various disruptions that affect safe transit along the NSR;
- A methodology is established to conduct a resilience assessment of the NSR based on the integration of fuzzy theory, a BN, and information entropy theory;
- The proposed fuzzy BN-based model can effectively cope with the uncertainty and unavailability of information associated with Arctic waters;
- The conduction of different types of analyses, such as forward and backward propagation, sensitivity, and information entropy analyses, helps us obtain a complete understanding of NSR resilience.

1.3. Organization

The remainder of the paper is structured as follows. Section 2 illustrates an overview of the proposed resilience measurement methodology, the employed techniques, and the relevant theory. In Section 3, a model aimed at measuring the system resilience of the NSR is established based on the fuzzy Bayesian network. The results and discussion of the present study are given in Section 4, and finally, the conclusion is presented in Section 5.

2. Proposed Resilience Measurement Methodology

The resilience level of a specified system is widely regarded as the measurement of the interaction between system resilience and disruptions exerted on the system. Thereinafter, disruption identification and resilience capacity decomposition are essential for resilience measurement, based on which some quantification technology can be applied to calculate the resilience level and investigate the resilience characteristic. In the present study, a methodology that includes five steps based on a fuzzy Bayesian network is proposed to evaluate system resilience, as illustrated in Figure 2.

Step 1—Identify the disruptions exerted on the system. The first step is to identify the potential disruptions that impacts the performance of the NSR resilience. A potential disruption may be caused by a severe nautical environment, the failure of equipment or facilities, and navigational service outages; these issues will be analyzed in detail based on expert elicitation and a literature review.

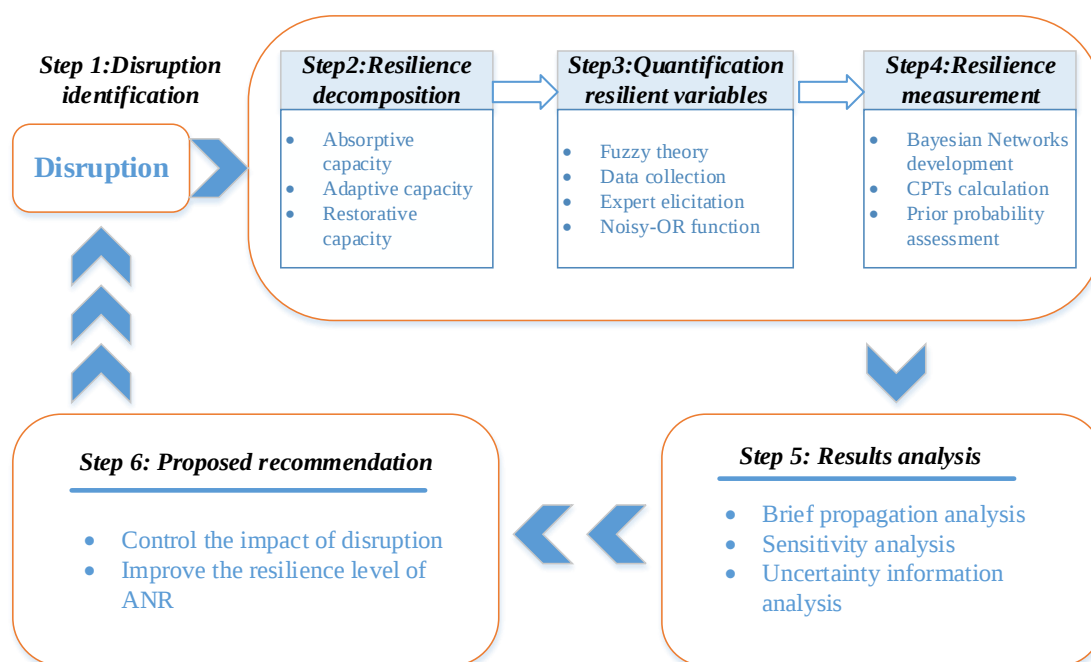
Step 2—System resilience decomposition. This step will focus on the design of the resilience capacity structure that fully relates to the different stages of disruption identified in Step 1. In this step, the system resilience capacities are primarily decomposed into three capacities: absorptive capacity, adaptive capacity, and restorative capacity.

Step 3—Quantification of resilient variables. It is critical for the resilience measurement to quantify the identified disruption and relevant capacities. Therefore, in this step, a methodology associated with the combination of fuzzy theory and expert elicitation is applied based on the present data concerning the NSR resilience. Additionally, the noisy-OR function is used, and it can be regarded as the input for the subsequent Bayesian network.

Step 4—System resilience measurement. The resilience level of the Arctic NSR is calculated through the establishment of a Bayesian network in which the prior probabilities of the nodes without parent nodes and the conditional probability table (CPT) for the child nodes with multiple parent nodes are obtained according to Step 3.

Step 5—Result analysis. Different techniques are employed in this step to gain insights based on the developed Bayesian network in Step 4. The techniques include forward propagation, backward propagation, sensitivity analysis, and information uncertainty analysis.

Step 6—Proposed recommendation. Some potential recommendations are proposed according to the abovementioned steps to improve the resilience level of the Arctic NSR to defend against disruptions from the environment.



Note: conditional probability table (CPT); Arctic northern sea route (ANR)

Figure 2. Proposed resilience measurement model for the northern sea route (NSR).

2.1. Fuzzy Theory

2.1.1. Fuzzy Number Selection to Design a Questionnaire

Since first proposed by [39], fuzzy set theory has been widely introduced in the analytic hierarchy process (AHP) because experts prefer to express fuzzy judgements rather than crisp comparisons. According to fuzzy set theory, we can define a fuzzy number, M , in the set of real numbers, R , where $F(R)$ represents the fuzzy sets; then, $M \in F(R)$. The concept of a fuzzy number can be expressed as [40]:

$$\left. \begin{aligned} \mu_M(x_0) &= 1 & x_0 \in R \\ A_\alpha &= [x, \mu_{A_\alpha}(x) \geq \alpha] & \alpha \in [0, 1] \end{aligned} \right\} \quad (1)$$

where μ is the membership function and α is a random real number. Generally, triangular and trapezoidal fuzzy numbers have been widely applied for the fuzzy judgements of experts in varied case studies. According to the definition of a fuzzy number, the membership function of the triangular fuzzy number can be expressed as:

$$\mu_M(x) = \begin{cases} \frac{x}{a_2 - a_1} - \frac{a_1}{a - 2a_1}, & x \in [a_1, a_2] \\ \frac{a_3}{a_3 - a_2} - \frac{x}{a - 2a_1}, & x \in [a_2, a_3] \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where the triangular fuzzy number is defined as $M(a_1, a_2, a_3)$ for $a_1 \leq a_2 \leq a_3$; a_1 and a_3 are the lower and upper values of fuzzy number, M , respectively; and a_2 is the modal value.

For the limit case of $a_1 = a_2 = a_3$, M is a nonfuzzy number. Similarly, for a trapezoidal fuzzy number, $N(a_1, a_2, a_3, a_4)$, the membership function is expressed as:

$$\mu_N(x) = \begin{cases} \frac{x}{a_2-a_1} - \frac{a_1}{a-2a_1}, & x \in [a_1, a_2] \\ 1 & x \in [a_2, a_3] \\ \frac{a_4}{a_4-a_3} - \frac{x}{a-4a_3}, & x \in [a_3, a_4] \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

To illustrate the operational rules of fuzzy numbers, two different triangular fuzzy numbers are taken as examples, $M_1(a_1, a_2, a_3)$ and $M_2(b_1, b_2, b_3)$, and the algebraic operation rules are:

$$M_1 \oplus M_2 = (a_1, a_2, a_3) \oplus (b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \quad (4)$$

$$M_1 \otimes M_2 = (a_1, a_2, a_3) \otimes (b_1, b_2, b_3) = (a_1 b_1, a_2 b_2, a_3 b_3) \quad (5)$$

$$\lambda \odot M_1 = \lambda \odot (a_1, a_2, a_3) = (\lambda a_1, \lambda a_2, \lambda a_3) \quad \lambda > 0, \lambda \in R \quad (6)$$

$$M_1^{-1} = (a_1, a_2, a_3)^{-1} = \left(\frac{1}{a_1}, \frac{1}{a_2}, \frac{1}{a_3}\right) \quad (7)$$

Generally, the linguistic expressions of experts are meaningful for handling complex circumstances and eliciting meaningful advice. However, it is difficult to directly quantify the qualitative expressions of experts; therefore, the application of fuzzy numbers can solve this problem. Several attempts have been made to transfer qualitative linguistic expressions into corresponding fuzzy numbers [41–43], and the technique proposed by [43] is widely accepted; this approach includes eight scales associated with verbal expressions. Later, [44] suggested that the estimation of human memory aptitude should include seven terms, plus or minus two patches, indicating that the number of verbal terms should be between five and nine for good expert elicitation.

In the present study, transformation scale six, which includes five verbal expressions [45], was selected to design the expert questionnaire, and fuzzy trapezoidal numbers were selected to express expert judgements. The reason for selecting scale six was mainly that the experts preferred to give their judgements through five verbal expressions. In addition, the reliability of scale six has been verified by its successful application in various fields, such as the oil and gas [46], medicine [47] and marine [48] fields. Table 1 illustrates the corresponding relationship between linguistic expressions and fuzzy numbers based on scale six. According to Equation (3), the expression of the membership function of the trapezoidal fuzzy is illustrated in Figure 3.

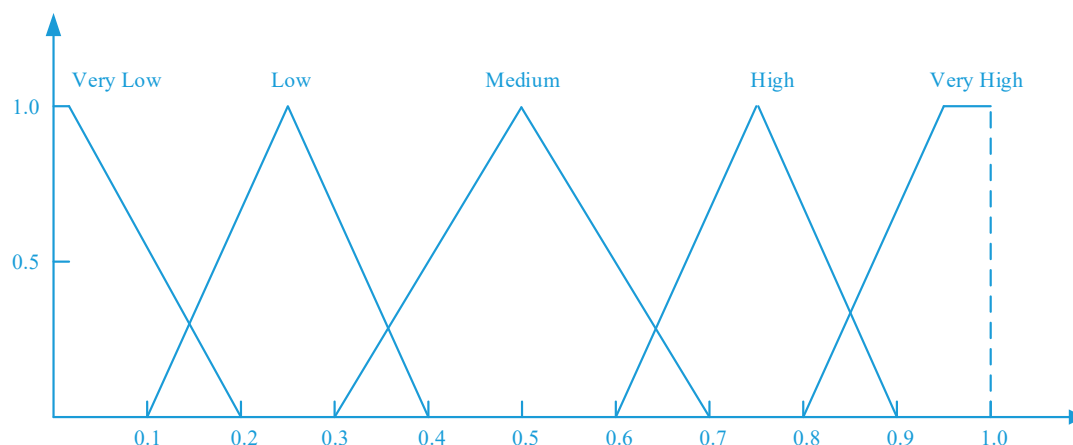


Figure 3. Scale six transformation [45].

Table 1. Linguistic expressions and their corresponding fuzzy numbers for scale six.

Linguistic Expressions	Fuzzy Trapezoidal Numbers
Very Low (VL)	(0,0,0.1,0.2)
Low (L)	(0.1,0.25,0.25,0.4)
Medium (M)	(0.3,0.5,0.5,0.7)
High (H)	(0.6,0.75,0.75,0.9)
Very High (VH)	(0.8,0.9,1,1)

2.1.2. Weight Determination for the Expert Capacity

With different professional positions, experience levels, education levels, and so on, the experts employed gave various judgements regarding the issues in the present study; therefore, it is necessary to weigh individual expert capacities to value the judgements made by high-level experts more than those from low-level experts. Before evaluating the expert capacity, indicators representing the expert capacities should be designed. Then, a score rating for each indicator should be developed to quantify various capacities. Next, pairwise comparison matrices can be established based on expert information. These matrices can be further processed as follows until the weight of an individual expert is calculated [49].

- With respect to fuzzy numbers in pairwise comparison matrices, the geometric mean technique is applied to obtain the synthetic pairwise comparison matrix, $\tilde{B} = [\tilde{b}_{ij}]$, as follows:

$$\tilde{b}_{ij} = \left(\widetilde{a^{(1)}}_{ij} \otimes \widetilde{a^{(2)}}_{ij} \otimes \cdots \otimes \widetilde{a^{(k)}}_{ij} \right)^{\frac{1}{4}} \quad (8)$$

where $\widetilde{A^{(k)}} = [\widetilde{a^{(k)}}_{ij}]$ is the pairwise comparison matrix of the K th indicator for the expert capability evaluation.

- The fuzzy weights of the criteria for each expert can be calculated by the following equation:

$$\tilde{r}_i = \left(\tilde{b}_{i1} \otimes \tilde{b}_{i2} \otimes \cdots \otimes \tilde{b}_{in} \right)^{\frac{1}{n}} \quad (9)$$

where the fuzzy weight of the i th expert is indicated by $\tilde{r}_i$.

- The fuzzy weights for each criterion are defined as follows:

$$\tilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \cdots \oplus \tilde{r}_n)^{-1} \quad (10)$$

where $\tilde{w}_i(lw_i, mw_i, uw_i)$ denotes the fuzzy weight of the i th criterion, for which lw_i , mw_i , uw_i indicate the lower, middle, and upper values of the fuzzy weights of the i th criterion, respectively.

- The weight of each expert is computed by employing the center of area technique, as follows:

$$P(E_i) = \left(\frac{1}{3} \right) [(uw_i - lw_i) + (mw_i - lw_i)] + lw_i \quad (11)$$

2.1.3. Expert Viewpoint Aggregation

To eliminate any cognitive biases, it is necessary to aggregate expert opinions. Suppose that each expert, $E_i (i = 1, 2, 3, \dots, n)$, states his or her personal viewpoints about a certain issue by utilizing a predefined set of linguistic expressions. These linguistic variables can then be transferred into corresponding triangular or trapezoidal fuzzy numbers, which can be processed further until defuzzification is achieved.

(1) Calculation of the degree of similarity. $S_{uv}(\tilde{E}_u, \tilde{E}_v)$ is defined as the degree of agreement for different opinions among experts. Suppose $\tilde{E}_u(a_1, a_2, a_3)$ and $\tilde{E}_v(b_1, b_2, b_3)$

represent two standard triangular fuzzy numbers ($u \neq v$); then, the degree of agreement between $\tilde{E}_u$ and $\tilde{E}_v$ can be obtained by:

$$S_{uv}(\tilde{E}_u, \tilde{E}_v) = 1 - \frac{1}{J} \sum_{i=1}^J |a_i - b_i| \quad i = 1, 2, 3 \quad (12)$$

where J is the number of fuzzy set members; e.g., $J = 3$ is for standard triangular fuzzy numbers and $J = 4$ is for standard trapezoidal fuzzy numbers. Additionally, the greater the values of $S_{uv}(\tilde{E}_u, \tilde{E}_v)$ are, the greater the similarity between experts E_u and E_v .

(2) Calculation of the average agreement (AA) degree for each expert viewpoint.

$$AA(E_u) = \frac{1}{U-1} \sum_{u \neq v, v=1}^U S_{uv}(\tilde{E}_u, \tilde{E}_v) \quad (13)$$

where U is the total number of experts.

(3) Calculation of the relative agreement (RA) degree between two kinds of experts. The value of $RA(E_u)$ for the u th expert can be obtained by:

$$RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^U AA(E_u)} \quad (14)$$

(4) Estimation of the consensus coefficient (CC) for each expert. The value of $CC(E_u)$ for the u th expert can be obtained by:

$$CC(E_u) = \beta \times P(E_u) + (1 - \beta) \times RA(E_u) \quad (15)$$

where the coefficient β ($0 \leq \beta \leq 1$) is introduced to represent the importance of $P(E_u)$ over $RA(E_u)$, namely, the greater β is, the more important $P(E_u)$ is. Actually, when $\beta = 0$, no weight is distributed to $P(E_u)$, indicating that a homogenous group of experts is employed; for another limit case, $\beta = 1$, the consensus degree among the various expert viewpoints is adequately high.

(5) Calculation of the aggregated results of the expert viewpoints. The aggregated results denoted by $\tilde{R}_A$ can be computed by:

$$\tilde{R}_A = CC(E_1) \otimes \tilde{E}_1 \oplus CC(E_2) \otimes \tilde{E}_2 \oplus \cdots \oplus CC(E_U) \otimes \tilde{E}_U \quad (16)$$

(6) Defuzzification of the aggregated results. The defuzzification of fuzzy numbers is critically important for the application of fuzzy set theory. The center of area (CoA) method is widely used for the defuzzification operation, and it is expressed as:

$$X = \frac{\int \mu_M(x) x dx}{\int \mu_M(x) dx} \quad (17)$$

where X represents the defuzzification result and $\mu_M(x)$ indicates the aggregated membership functions defined in (1) and (2) for fuzzy triangular and trapezoidal numbers, respectively. Therefore, the fuzzy numbers of the aggregated results, denoted as $\tilde{R}_A(c_1, c_2, c_3)$ for fuzzy triangular numbers and $\tilde{R}_A(c_1, c_2, c_3, c_4)$ for fuzzy trapezoidal numbers, can be defined by (18) and (19), respectively.

$$R_A = \frac{\int_{c_1}^{c_2} \frac{x-c_2}{c_2-c_1} x dx + \int_{c_2}^{c_3} \frac{c_3-x}{c_3-c_2} x dx}{\int_{c_1}^{c_2} \frac{x-c_2}{c_2-c_1} dx + \int_{c_2}^{c_3} \frac{c_3-x}{c_3-c_2} dx} = \frac{c_1 + c_2 + c_3}{3} \quad (18)$$

$$R_A = \frac{\int_{c_1}^{c_2} \frac{x-c_1}{c_2-c_1} x dx + \int_{c_2}^{c_3} x dx + \int_{c_3}^{c_4} \frac{c_4-x}{c_4-c_3} x dx}{\int_{c_1}^{c_2} \frac{x-c_1}{c_2-c_1} dx + \int_{c_2}^{c_3} dx + \int_{c_3}^{c_4} \frac{c_4-x}{c_4-c_3} dx} = \frac{1}{3} \frac{(c_4 + c_3)^2 - (c_2 + c_1)^2 - c_4 c_3 + c_1 c_2}{c_4 + c_3 - c_2 - c_1} \quad (19)$$

2.2. Bayesian Network Theory

A Bayesian network is a multielement graphical model involving a set of variables and their conditional dependencies via a directed acyclic graph [50]. With the advantages of a flexible structure and probabilistic reasoning function, BNs are widely applied in the field of safety evaluation [32,51]. Series of nodes and edges are necessary for a basic BN to represent system variables and association rules, respectively. Each node in a BN is assigned a probability distribution, and each edge is affiliated with a direction, which is directed from parent node to child node. The nodes with multiple parent nodes should be assigned conditional probabilities that are included in the conditional probability tables (CPTs). The CPTs are based on the type and strength of the causal relationships between parent and child nodes.

Considering the conditional dependencies of the variables, a BN represents the joint probability distribution of a set of variables, $V = \{Z_1, \dots, Z_n\}$, as in [52]:

$$P(V) = \prod_{i=1}^n P(Z_i | P_a(Z_i)) \quad (20)$$

where $P_a(Z_i)$ is the parent set of variable Z_i . The probability of variable Z_i can be obtained by:

$$P(Z_i) = \sum_{Z_{j,j \neq i}} P(V) \quad (21)$$

Based on Bayes' theorem, a BN can update the prior probability of events under newly given observations, called evidence, to yield the posterior probability. The posterior probability can be calculated by:

$$P(V|E) = \frac{P(V, E)}{P(E)} = \frac{P(V, E)}{\sum_V P(V, E)} \quad (22)$$

where $P(V|E)$ is the desired posterior probability and E represents the evidence.

2.2.1. Prior Probability Calculation for Nodes without Parents

The prior probability for nodes without parents in the Bayesian network can be quantified by the integration of fuzzy theory and the aforementioned expert elicitation. The calculation can be conducted following the steps described below.

Step 1—The questionnaire is designed to obtain expert viewpoints according to the approach described in Section 2.1.1.

Step 2—The capacities of experts employed in the present study are weighted and scored to compensate for any cognitive biases and aggregate expert opinion based on the calculation process mentioned in Section 2.1.2.

Step 3—The fuzzy aggregation of expert opinions obtained from Step 1 is implemented by applying the calculation methods expressed in Section 2.1.3.

2.2.2. Conditional Probability Table Calculation with the Noisy-OR Function

The calculation of the CPT is crucial for reliable model inference. However, the CPT is generally regarded as complicated, especially for the case of a large BN with many nodes. Therefore, many studies have focused on CPT calculations, of which expert elicitation associated with fuzzy theory has been widely employed [34,53,54]. Based on expert elicitation, the Noisy-OR model [55] is utilized to calculate the CPT with the following

assumptions (suppose a child node Y has n parents, $X_1, X_2, \dots, X_i, \dots, X_n$, as shown in Figure 4a):

- (1) All the nodes in the proposed Bayesian network can be regarded as Boolean variables; that is, the nodes have binary states, true or false, representing positive or negative outcomes, respectively;
- (2) The causes (parent nodes) of $X_1, X_2, X_3, \dots, X_n$ are mutually independent;
- (3) The probability that Y is true when only one causal factor, X_i , is true while all other factors except X_i are false can be expressed as:

$$P_i = P(Y|\overline{X_1}, \overline{X_2}, \dots, X_i, \dots, \overline{X_n}) \quad (23)$$

where P_i represents the connection probability between the parent node, X_i , and the corresponding child node, Y . The connection probability can be derived by:

$$p_i = \frac{p(Y|X_i) - p(Y|\overline{X_i})}{1 - p(Y|\overline{X_i})} \quad (24)$$

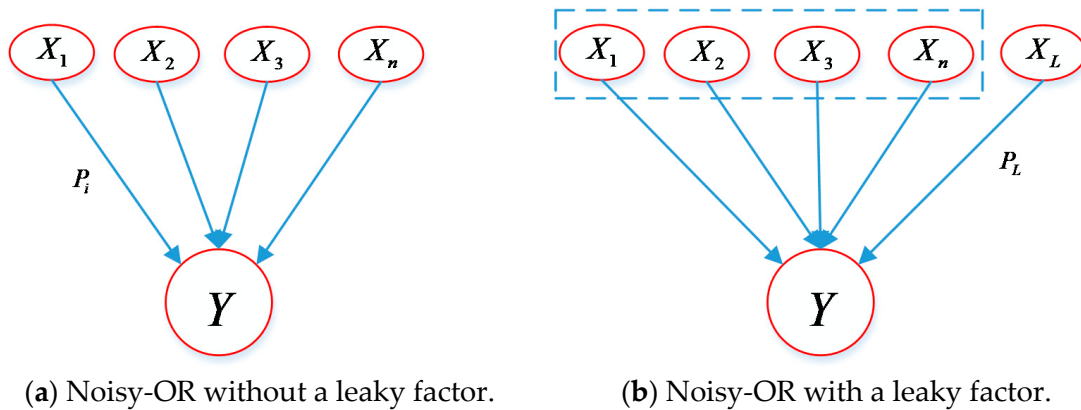


Figure 4. Typical Noisy-OR model.

Suppose every causal factor, X_i , in Figure 4a is a member of the set $\{X_p\}$ and all the causal factors with a “true” state label belong to $\{X_T\}$. Additionally, the causal factors with a “false” label are members of $\{X_F\}$. Then, the CPT of Y can be obtained by

$$p(Y|X_p) = 1 - \prod_{X_i \in X_T} (1 - p_i) \quad (25)$$

For the limit case in which $\{X_T\}$ is a null set, that is, the states of all the causal factors are “false”, then $p(Y|X_p) = 0$. However, it is almost impossible for the probability, $p(Y|X_p)$, to equal zero. In practice, the subsequent event, Y , may occur even if all the causal factors are “false” because some unknown causal factors may still exist beyond the identified causal factors. Therefore, the leaky Noisy-OR model (illustrated in Figure 4b) is introduced to handle the unknown causal factors; in this case, the conditional probability of Y can be calculated by:

$$p(Y|X_p) = 1 - \prod_{X_i \in X_T} (1 - p_i)(1 - p_L) \quad (26)$$

where P_L represents the connection probability between Y and the leaky causal factors X_L .

2.3. Information Entropy Theory

Currently, the Arctic NSR is not a well-developed commercial waterway; as a result, some information associated with the NSR may be absent, which makes it difficult to

quantify the uncertainty of the unknown information. To improve the reliability of the underlying information, information entropy theory is applied in the present study. In the framework of information entropy, the uncertainty of a variable can be measured by a probability distribution. Suppose X is a discrete random variable with the probability distribution P , where P_i represents the probability of $x_i \in X$. Then, the information pertaining to a specific value, x_i , for this random variable can be defined as:

$$I(x_i) = -\log(P_i) \quad (27)$$

where the base in the logarithm is usually taken as 2 or; in the present study, the base is 2.

The information function theoretically controls the volume of information conveyed by the specific state, such as x_i . The information entropy function can be defined as the expectation of the information, which is expressed as:

$$H(X) = E[I(X)] \quad (28)$$

The information entropy function can be further processed mathematically as:

$$H(X) = \sum_{i=1} P_i \cdot I(x_i) = -\sum_{i=1} P_i \cdot \log_2(P_i) \quad (29)$$

For the discrete random variable, X , the Function (29) can be expressed as:

$$H(X) = -\sum_{x \in X} P(x) \log_2 P(x) \quad (30)$$

where $0 \leq P(x) \leq 1$ and $\sum_{x \in X} P(x) = 1$. The higher the value of the information entropy is, the more uncertainty the variable contains. The entropy can reach the maximum when the probability distribution is uniform, i.e., $P(x)$ is equal for all x .

Suppose X is a target variable and Y is a contributing factor, similar to the relationship between the child node and parent node in the Bayesian network. If the target variable X is conditionally dependent on the dependent variable Y , then we have:

$$H(Y|X) = \sum_i P(Y_i) \cdot H(Y_i|X_i) \quad (31)$$

where i denotes the number of states, $i = 2$ for a Boolean variable, and $H(Y|X)$ represents the conditional entropy of target X given the contributing factor Y . Then, the mutual information between the target variable X and the contributing factor Y can be defined as:

$$I(X, Y) = H(X) - H(Y|X) \quad (32)$$

3. Model Established for NSR Resilience Measurement

3.1. Scenario Development

The Arctic NSR is characterized by a special nautical environment and unique location compared to other national and international waterways. Traditionally, the NSR depicted in Figure 5 is made up of five legs: the Barents Sea, the Kara Sea, the Laptev Sea, the East Siberian Sea, and the Chukchi Sea. The presence of sea ice, including drifting icebergs, has made this route almost inaccessible for marine transportation [56]. The area of ice-covered waters within the NSR is shown in Table 2. It is widely accepted that the navigating period for the NSR can be continuous from September to March of the following year.



Figure 5. The Arctic Northeast Route [11].

Table 2. Average ice-covered waters in the marginal seas of the NSR region [57].

Sea	March (Million km ²)	September (Million km ²)	Seasonal Changes
Barents Sea	0.855	0.128	85%
Kara Sea	0.830	0.266	68%
Laptev Sea	0.536	0.196	63%
East Silerian Sea	0.770	0.516	33%
Chukchi Sea	0.595	0.196	67%

With the difficulties associated with communication and data acquisition in the NSR region, the safety issues and environmental risks related to NSR transport are traditionally managed based on empirically determined rules and regulations, which can be useful for shipping activities characterized by low traffic density with small ships [58]. However, the ships sailing along the NSR are becoming increasingly large in size, and there is a lack of relevant empirical data on which mitigation of the hazards with respect to the NSR can be based [59]. Therefore, safety issues concerning the NSR are an urgent problem that must be solved.

3.2. Disruption Identification

A disruption of the system resilience, also known as a potential threat, can be beneficial for the improvement of the resilience level of the system. Only if a disruption is identified effectively can the resilience be quantitatively measured; however, the disruptions are different from risks and causal factors contributing to accidents. Actually, only part of a disruption is able to ultimately cause accidents, with evolution to risk and causal factors. Therefore, it is difficult to identify all disruptions practically. In the present study, the disruptions identified from safety meetings, accident reports, interviews, and literature reviews are listed in Table 3.

Table 3. Descriptions of the disruptions to the NSR resilience.

No.	Disruption	Description
1	Weather forecast inaccuracy	The weather along the Arctic Northeast Route is complex and variable, making it difficult to predict; as a result, the NSR security system suffers from information uncertainty associated with weather forecasts [60]
2	Sea chart incomplete	The navigation chart for the NSR is still incomplete due to complex factors such as the geological conditions, lack of hydrographic ship information, and political intervention [61]
3	Communication/positioning unavailable	According to the database for maritime accidents (DAMA of Det Norske Veritas), missing safety instructions and defective communication can impact the safety level of navigation in Arctic waters [62]
4	Malfunction of power plant	Based on the comments from experts of the Canadian Transport Agency, the malfunction of power plants, such as engine failure and power and back-up power failures, are the primary causes of ship collisions, foundering, and grounding along the NSR [11]
5	Damaged propeller/steering gear	The propeller and steering gears of ships that use the NSR can be severely damaged by icebergs, which cause considerable disruptions to the NSR safety [60]
6	Malfunction of deck machinery	In the case of extremely low temperatures, some deck machinery may malfunction, thus impacting normal ship operation along the NSR [61]
7	Restricted function of nav. instruments	The navigation instruments on ships may not work properly due to the influence of high latitudes, which can put the ship at risk [63]
8	Low temperature	Low temperatures can easily affect the performance of security-related equipment such as the hull, windlass, and mooring winch [64]
9	Iceberg/floating ice	The existence of sea ice, such as icebergs, floating ice, and old ice, is the main feature that distinguishes the NSR from other sea lanes globally; the impact of ice on the safety of ships is continuous and inevitable [65]
10	Poor visibility	Poor visibility caused by steam fog, ice fog, blowing snow, and other processes along the NSR is frequently encountered and limits the watchkeeping of navigation officers [64]
11	Rough sea	Most of the currents in the NSR are along the coast of a shallow-water continental shelf, and the currents in the narrow straits between the islands are strong, thus creating challenges for polar navigation [66]
12	Magnetic storm	Magnetic storms can greatly disturb the NSR security system in the field of communication and influence navigation instruments [35]
13	Obstacles other than ice	Underwater obstacles such as reefs, beaches, and unknown explosives are potential disruptions that threaten the effectiveness of the NSR precautions [67]
14	Seafarer competency	Seafarers on ships sailing along the NSR are faced with considerable ship handling and emergency challenges, which can potentially affect the function of the NSR precautions [61]
15	Geopolitics	The ships sailing along the NSR have to consider different laws and regulations, including those at the local, national, and international level; additionally, sometimes political considerations are involved, making the decision-making process very complex. [68]

As shown in Table 3, 15 kinds of disruptions were identified in the present study. Subsequently, a safety meeting was conducted. After consulting experts, such as experienced mariners, senior scholars, and safety managers associated with the Arctic NSR, all disruptions were finally divided into four groups: navigation services out of order ($N = 3$), malfunction/failure of machinery ($N = 4$), harsh nautical environment ($N = 5$), and other disruptions ($N = 3$). The classification results are presented in Figure 6. Furthermore, classifying all the disruption factors into different groups can facilitate the calculations for the CPT of the Bayesian network in Section 3.4.

3.3. Resilience Capacity Decomposition for the Arctic Northeast Route

The resilience capacity can be defined as the capacity of a certain system to absorb, adapt to, and recover from any shock due to a disruption [23]. It is widely accepted that resilience capacities are classified as the absorptive capacity, adaptive capacity, and restorative capacity for a specified system [25,27]. In the present study, the underlying factors pertaining to these three kinds of capacities for the Arctic NSR resilience are identified, as illustrated in Figure 7. All the factors presented in Figure 7 will be included in the developed BN.

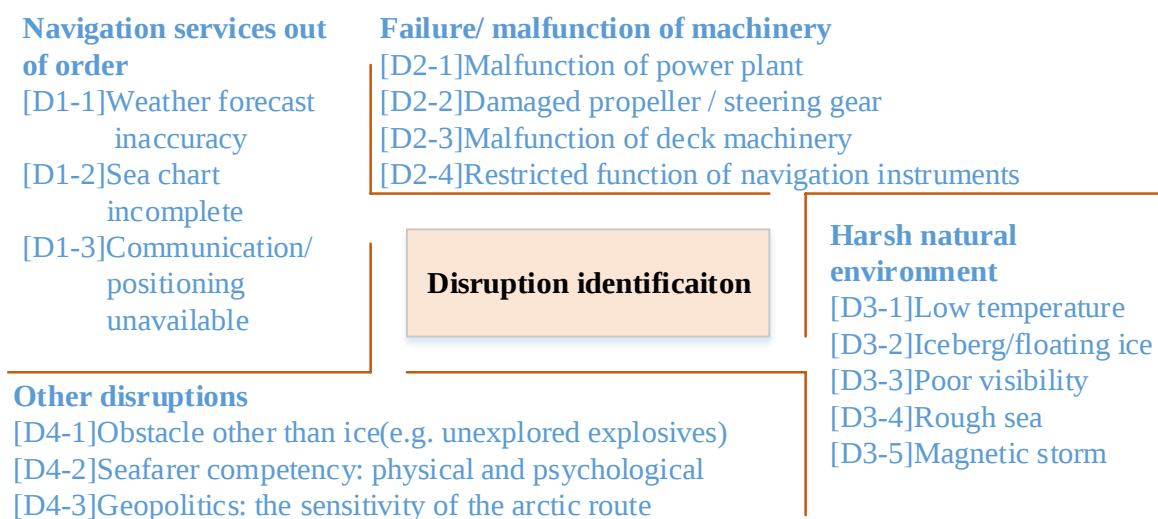


Figure 6. Disruptions to safe navigation along the NSR.

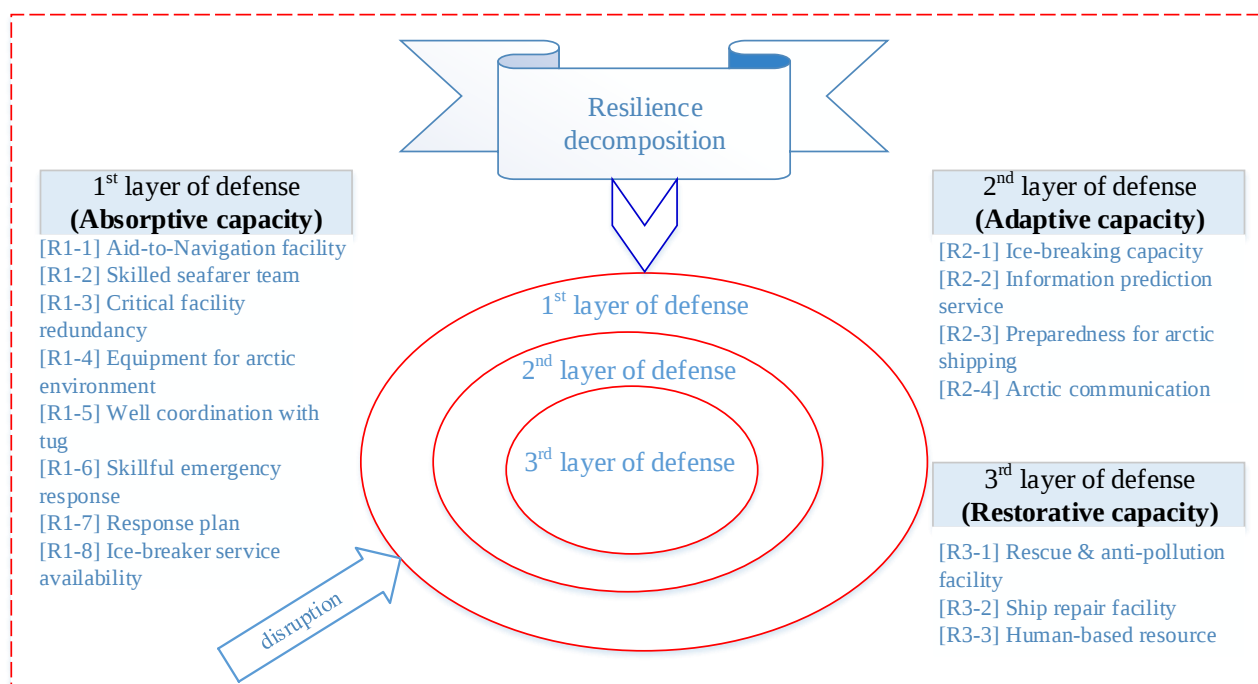


Figure 7. Resilience decomposition designed for the NSR.

3.3.1. Absorptive Capacity

The absorptive capacity can be defined as the extent to which the Arctic Northeast Route security system is able to automatically defend against shocks due to disruptions. As shown in Figure 6, the absorptive capacity is considered the first line of defense to resist the adverse impact of the disruption. Inspired by the “inherent resilience” theory proposed by [69], the absorptive capacity can be further divided into the defense capacity under ordinary circumstances and the emergency response capacity under crisis conditions. Finally, a list of seven contributing factors for the absorptive capacity of the Arctic Northeast Route security system was obtained, and it is presented in Table 4.

Table 4. Absorptive capacity of NSR resilience.

Features	Description
Aid-to-navigation facility	The aid-to-navigation (A-to-N) facilities, including visual and audible A-to-N facilities, racons, radar marks, and shore-based Automatic Identification System (AIS) stations, are critical for navigating safely along the NSR. There are approximately 1240 coastal visual signs and 300 floating markers associated with the NSR [68].
Skilled seafarer team	Compared with conventional shipping route, the NSR is characterized by lots of special risks. The skilled seafarer team can swiftly evaluate the situation and take effective countermeasures with teamwork to deal with potential risks. In addition, a skilled seafarer team can develop a harmonious atmosphere in which everyone can limit the defense risk.
Critical facility redundancy	The redundant critical facilities, such as those that provide emergency power backup, high power conservation, extra positioning techniques, and backup navigation instruments, are able to strengthen the robustness of the security system and restrict the consequences of disruptions.
Equipment for arctic environment	The equipment designed for the arctic environment can effectively defend against or absorb the risks caused by weather condition, such as low temperatures, frost, and moisture, especially the equipment allocated on deck, including cranes, mooring winches, and windlasses, which are exposed to the external environment.
Coordination with icebreaker	Icebreaker assistance operations play an essential role in ice-covered waters to reduce the risk of accidents, such as ice collisions and propeller or rudder damage. In addition, the case of trapped vessels by ice can also be avoided, and the disruption introduced by large amounts of floating ice can be absorbed [8].
Ice pilots/navigators	The assistance provided by ice pilots or navigators can defend against or attenuate various risks caused by disruptions; this approach is suitable for the case in which a shipmaster has little experience navigating in ice along the NSR. The organizations providing ice pilot services can be obtained from the NSRA [68].
Skilful emergency response	Under unpredictable situations related to heavy fog, floating ice, and strong wind in the NSR region, a proficient emergency response group can establish counteractive measures to response to the threats. Besides, a skilled seafarer can fully utilize the available resources, which are essential for mitigating various risks [27].
Response plan	A detailed response plan corresponding to various predictable disruptions and risks encountered along the NSR is useful for guiding seafarers or operators to take appropriate actions during disruptions, thus keeping the disruption or risk controllable.
Navigational publications	Navigational publications refer to charts and other navigational publications, such as those used for guidance in arctic navigation, lists of radio signals, and notices to mariners; ice charts, which are useful for monitoring the risk related to sea ice, are particularly important [67,70]

3.3.2. Adaptive Capacity

The adaptive capacity can be defined as the level to which a system self-organizes itself and takes dynamic measures to restrict and control the severe impact of a disruption. Compared with the absorptive capacity, the adaptive capacity requires flexible and dynamic efforts [71] and mitigates a disruption as a “second line of defense”, as presented in Figure 6. It is also regarded as part of the “post-accident strategy”. The features contributing to the adaptive capacity of the NSR resilience are described in Table 5.

Table 5. Adaptive capacity of NSR resilience.

Features	Description
Ice-breaking capacity	The ice-breaking capacity allows the vessels to adapt to a risk or disruption caused by floating ice in ice-covered waters along the NSR. The ice-breaking capacity can be improved by strengthening the hull to bear ice loads for safe navigation in ice fields [70].
Information prediction services	Information prediction services include those for sea ice coverage, thickness, and motion, as well as weather conditions [1]. Under the conditions of predictable information, in the case of a disruption, seafarers and operators can take action in advance, for example, by anchoring to avoid a disruption or risk, changing the designed route, or requesting assistance from an icebreaker.

Table 5. Cont.

Features	Description
Preparedness for arctic shipping	Before navigating into ice-covered waters, vessels must be fully prepared, including obtaining extra fuel reserves, psychological preparation, understanding all the regulations that must be observed, preparing for low temperatures, etc.; in case of a disruption, the vessel can make some changes based on their preparations to adapt to the new situation caused by the disruption [70].
Arctic communication	Arctic communication, including radar, radio, and International Maritime Satellite Organization (INMARSAT) communication, can coordinate operations from ship to ship and ship to icebreaker to adapt to the harsh environment and sailing conditions along the NSR [67]; additionally, Arctic communication helps vessels in the NSR region get assistance and guidance during disruptions, thus making risks controllable.

3.3.3. Restorative Capacity

The restorative capacity can be defined as the extent to which a specified system is able to recover from or repair a destroyed or failed function due to the impact of a disruption. Based on Figure 6, the restorative capacity acts as the last line of defense for the system to resist a disruption; that is, in the case that the absorptive and adaptive capacities fail to tolerate the impact caused by a disruption, the restorative capacity remains. Generally, it takes a relatively long time for the restorative capacity to recover the normal function of the system, and various human resources, services, tools, and so on are essential. Three aspects of the restorative capacity pertaining to the Northeast Route security system are described in Table 6.

Table 6. Restorative capacity of NSR resilience.

Features	Description
Rescue and anti-pollution facility	Rescue and anti-pollution facilities are utilized to restore the shipping capacity of the NSR after natural disasters and accidents. Currently, there are three rescue and research centers established temporally along the NSR from July to October. In addition, the rescue and anti-pollution capacities of the ports (20 approximately) along the NSR need to be improved for the quick restoration of the damaged route.
Ship repair facility	Ship repair facilities, such as yards, docks, gate operations, cranes, and warehouses, are essential for vessels that experience hull damage, machinery malfunctions, and propeller damage. Notably, the restorative capacity aimed at damaged ship repair will be limited if the stakeholders have little interest in investment.
Human-based resources	The restorative capacity associated with human-based resources includes service restoration and technology restoration, which are substantial parts of the post-disaster strategy. Restoration may include communication, navigation, pilot service, ice-breaker assistance, and weather and hydrology information systems.

3.4. Resilience Measurement Using the Fuzzy Bayesian Network

In this section, a Bayesian network is established to quantify the resilience of the Arctic Northeast Route security system. Based on the identified disruptions and the resilience capacity decomposition in Sections 3.2 and 3.3, the visual structure of the proposed Bayesian Network described in Figure 8 is developed using GeNIe 2.3 software.

3.4.1. Reliability Quantification for the Employed Experts

Expert elicitation is useful and valuable in most situations when available resources are lacking or limited by physical circumstances [72], and the Arctic NSR is one of these cases. However, the competence of the employed experts is essential for scientific conclusions. According to the study of [34], the selection criteria used for capable experts in this research can be described as follows:

- A heterogeneous group of experts is usually preferred to a homogenous group. In a heterogeneous group, the individual experience of each expert receives considerable attention;
- With respect to the education and experience of the experts in a field, the longer they have focused on a subject (academic or practical subject), the more accurate their intuitionistic judgement is;
- With respect to expert familiarity with a subject, especially through practical experience, an experienced specialist can theoretically master every detail of the subject.

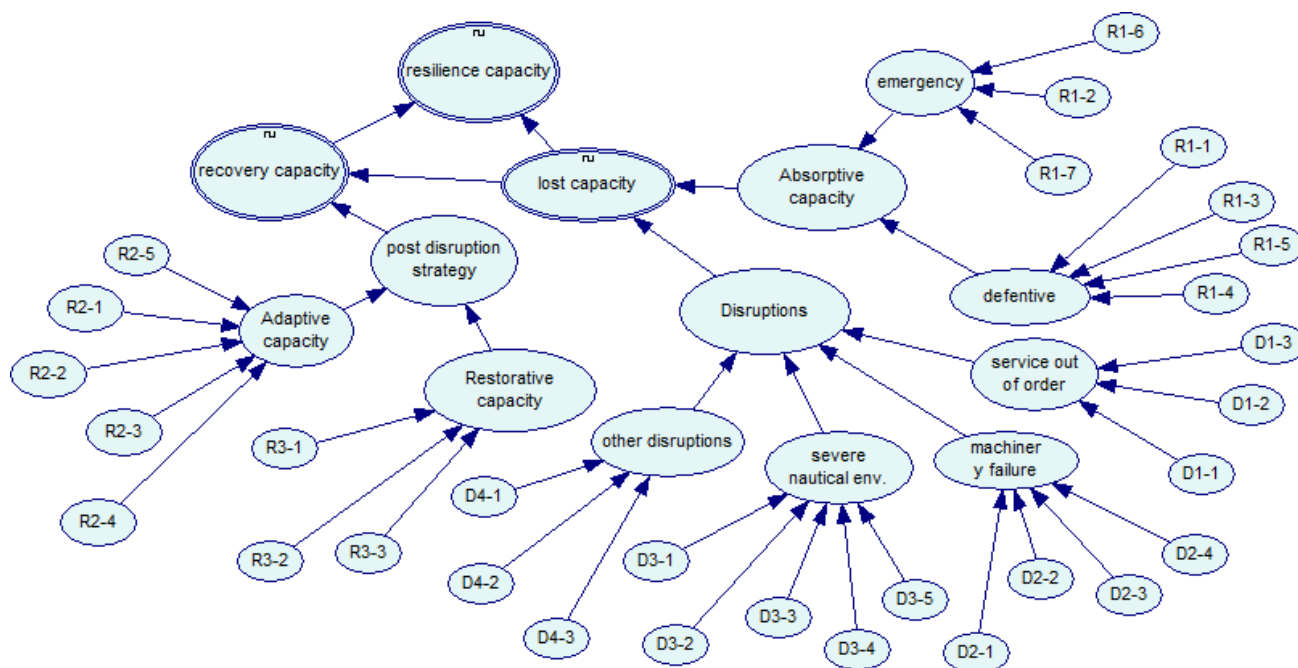


Figure 8. Bayesian network (BN) established for measuring the resilience of the NSR.

Based on the abovementioned criteria, a heterogeneous group of five experts (their information is listed in Table 7) was developed to comment on the various disruption and resilience capacities associated with the Arctic NSR.

Table 7. Details of the experts.

Item	Age	Occupation	Educational Level	Certificate Rank	Job Tenure
Expert 1 (E1)	53	Senior seafarer	Bachelors of navigation	Senior Captain	He has been working on board a ship for nearly 25 years; as a senior captain, he sailed the Arctic Northeast Route recently.
Expert 2 (E2)	50	Senior seafarer	Bachelors of navigation	2nd Officer	He has been working on board a ship for nearly 15 years; currently, he is certified as a Chief Officer working on a ship capable of navigating the NSR.
Expert 3 (E3)	48	Professor	Ph.D. of navigation	Senior Captain	He has been working on board ships since 1991 and obtained the certificate of senior captain; currently, he is an associate professor focusing on Arctic sea transport.

Table 7. Cont.

Item	Age	Occupation	Educational Level	Certificate Rank	Job Tenure
Expert 4 (E4)	41	Associate professor	Masters of marine engineering	Chief engineer	He has been working on ships since 2001, beginning as a cadet and eventually becoming a chief engineer; currently, he is an associate professor focusing on risk assessments of Arctic transport.
Expert 5 (E5)	43	Safety manager	Masters of navigation technology	Chief officer	He has been working on board ships since 2001, eventually becoming a chief officer; he is familiar with marine operation and equipment management for ships transiting Arctic waters.

The weight for each expert was assessed based on their education level, expertise, professional position, work experience, and age [46,73–75]. In addition, the competency certificate level of the selected experts was also regarded as an important indicator. Finally, the rating criteria were developed, as presented in Table 8.

Table 8. Scores of indicators for expert evaluation.

Indicator	Classification	Score	Indicator	Classification	Score
Professional position	Senior academic	5	Experience (2)	6–9	2
	Junior academic	4		≤5	1
	Engineer	3	Education level	Ph.D.	5
	Technician	2		Masters	4
Age	Worker	1		B.S. or B.E.	3
	≥50	4		Junior college	2
	40–49	3		School level	1
	30–39	2	Certificate rank	Senior Cap. or C/E	5
	≤30	1		Cap. or C/E	4
Experience (1)	≥30 years	5		C/O or 2/E	3
	20–29	4		Operational Officer/engineer ratings	2
	10–19	3			1

Based on the information from the employed experts shown in Table 7, the capacity was first scored by every individual expert according to the rating criteria presented in Table 8; then, pairwise comparison matrices were derived. Finally, the weight for each expert was obtained by applying Formulas (8)–(11), as summarized in Table 9.

Table 9. Evaluation results of expert capabilities.

Expert	Position	Experience	Education	Age	Certificate	Weight
Expert 1	Senior seafarer	30	Bachelors	53	Senior Captain	0.189
Expert 2	Senior seafarer	27	Bachelors	50	2nd Officer	0.121
Expert 3	Professor	18	Ph.D.	48	Senior Captain	0.300
Expert 4	Associate professor	22	Masters	41	Chief engineer	0.206
Expert 5	Safety manager	8	Masters	43	Chief officer	0.184

3.4.2. Calculation of the Prior Probabilities of the Nodes without Parent Nodes

Based on the qualitative analysis discussed in Sections 3.2 and 3.3, there are a total of 30 parent nodes included in the established Bayesian network illustrated in Figure 5. The prior probabilities of these parent nodes can be calculated according to the calculation

procedures mentioned in Section 2.2.1. The experts involved in this process are considered independently during decision making. The results of the aggregation and defuzzification of expert judgements are presented in Table 10.

Table 10. Aggregation results for each Boolean variable based on expert elicitation.

Item	Aggregated Value	Item	Aggregated Value	Item	Aggregated Value
D1-1	0.6528	D3-4	0.5325	R1-6	0.67
D1-2	0.4615	D3-5	0.5445	R1-7	0.6198
D1-3	0.7225	D4-1	0.4355	R2-1	0.5445
D2-1	0.7084	D4-2	0.7807	R2-2	0.7085
D2-2	0.6036	D4-3	0.6438	R2-3	0.5021
D2-3	0.7338	R1-1	0.5887	R2-4	0.6635
D2-4	0.7138	R1-2	0.8142	R2-5	0.8594
D3-1	0.6468	R1-3	0.4994	R3-1	0.7897
D3-2	0.7818	R1-4	0.5079	R3-2	0.6083
D3-3	0.6641	R1-5	0.7892	R3-3	0.6097

3.4.3. Calculation of the Condition Probability Table for the Network

To obtain the conditional probability table for the nodes with multiple parents, the leaky Noisy-OR function is applied considering that the states of child nodes may be false even if all the parent nodes are true. Based on the calculated connection probability, P_i , for each parent node, the Leaky Noisy-OR function can be expressed as:

$$\text{NoisyOR}(P_1, X_1, P_2, X_2, \dots, P_n, X_n, l) \quad (33)$$

where l represents the leaky factor, indicating the degree to which the missing causal factors contribute to a consequence being true. Generally, the leaky factor is a nonzero probability, even if all the causal factors are false. Therefore, the leaky factor represents a probability that implies that the child node will be true if the parent nodes are false, as expressed below.

$$l = P(Y = \text{true} | X_1 = \text{false}, X_2 = \text{false}, \dots, X_n = \text{false}) \neq 0 \quad (34)$$

In the present study, five experts with attributes described in Section 3.4.1 were employed to give their judgements regarding the conditional probabilities of nodes with multiple parent nodes in the form of linguistic expressions. The expert insights were further processed based on the fuzzy methodology proposed in Section 2.1, after which the conditional probabilities for child nodes can be expressed by the Noisy-OR function as follows:

$$P(\text{Nav. service out of order}) = \text{Noisy-OR}([D1-1], 0.6277, [D1-2], 0.5870, [D1-3], 0.3626, 0.05)$$

$$P(\text{equipment failure}) = \text{Noisy-OR}([D2-1], 0.49, [D2-2], 0.26, [D2-3], 0.80, [D2-4], 0.58, 0.032)$$

$$P(\text{severe nautical env.}) =$$

$$\text{NoisyOR}([D3-1], 0.43, [D3-2], 0.38, [D3-3], 0.87, [D3-4], 0.61, [D3-5], 0.39, 0.011)$$

$$P(\text{other disruptions}) = \text{NoisyOR}([D4-1], 0.24, [D4-2], 0.57, [D4-3], 0.33, 0.218)$$

$$P(\text{restorative capacity}) = \text{NoisyOR}([R3-1], 0.84, [R3-2], 0.68, [R3-3], 0.69, 0.016)$$

$$P(\text{adaptive capacity}) =$$

$$\text{NoisyOR}([R2-1], 0.94, [R2-2], 0.88, [R2-3], 0.17, [R2-4], 0.71, [R2-5], 0.92, 0.02)$$

$$P(\text{defensive capacity}) = \text{NoisyOR}([R1-1], 0.41, [R1-3], 0.57, [R1-5], 0.21, [R1-6], 0.96, 0.009)$$

$$P(\text{emergency capacity}) = \text{NoisyOR}([R1-2], 0.90, [R1-7], 0.89, [R1-8], 0.67, 0.04)$$

The conditional probability table for the proposed Bayesian network can be induced by combining the Noisy-OR function of child nodes with Equation (26). To concisely represent the computing process for the CPT, the node “service out of order” (Y) with three

parent nodes (X_1, X_2, X_3) was taken as an example, and the exhaustive information is given in Table 11.

Table 11. Calculation process for the conditional probabilities of the node “nav. service out of order”.

Expert Judgement					
$Y \leftarrow X_1$:	M	H	H	M	H
$Y \leftarrow X_2$:	M	L	L	M	VH
$Y \leftarrow X_3$:	VH	H	M	H	H
Aggregation of expert judgement (the same method as adopted for the aggregated value in Table 10)					
$P(Y \leftarrow X_1) = 0.6528$ $P(Y \leftarrow X_2) = 0.4615$ $P(Y \leftarrow X_3) = 0.7225$					
Conditional probability calculation by the Noisy-OR model					
$P(Y \leftarrow X_1, X_2) = 1 - (1 - P(Y \leftarrow X_1)) * (1 - P(Y \leftarrow X_2)) = 0.8130$					
$P(Y \leftarrow X_1, X_3) = 1 - (1 - P(Y \leftarrow X_1)) * (1 - P(Y \leftarrow X_3)) = 0.9037$					
$P(Y \leftarrow X_2, X_3) = 1 - (1 - P(Y \leftarrow X_2)) * (1 - P(Y \leftarrow X_3)) = 0.8506$					
...					
Conditional probability table for the node “nav. Service out of order” (Y)					
$P(Y \leftarrow X_1, \overline{X_2}, \overline{X_3}) = 0.6528$ $P(Y \leftarrow X_1, X_2, \overline{X_3}) = 0.8130$					
$P(Y \leftarrow X_2, \overline{X_1}, \overline{X_3}) = 0.4615$ $P(Y \leftarrow X_1, \overline{X_2}, X_3) = 0.9037$					
$P(Y \leftarrow X_3, \overline{X_1}, \overline{X_2}) = 0.7225$ $P(Y \leftarrow \overline{X_1}, X_2, X_3) = 0.8506$					
$P(Y \leftarrow \overline{X_1}, \overline{X_2}, X_3) = 0.0519$ $P(Y \leftarrow X_1, X_2, X_3) = 0.9481$					

3.5. Resilience Quantification

Many studies have been performed to evaluate the resilience of a specified system, and different models have been proposed to quantify system resilience. In the present study, the model developed by [28] is utilized to measure the resilience of Arctic Northeast Route security. Specifically, resilience is defined as the ratio of the recovery capacity to the loss capacity of the system, which can be expressed by:

$$R = \frac{\text{recovery}}{\text{loss}} \quad (35)$$

In the present study, the loss capacity variable of the system is conditioned based on three variables, namely, the probability of disruption occurrence (PDO), the absorptive capacity, and the actual security capacity (ASC). In practice, the loss capacity is greatly dependent on the degree to which the absorptive capacity is capable of withstanding the system shocks caused by disruptions; that is, the probability of the absorptive capacity being in a true state. If the state of the absorptive capacity is true (the probability is 100%), then the loss capacity will be zero. The actual security capacity is set as a constant in the present study because both the absorptive capacity and recovery capacity are associated with the actual security capacity in the expression of the resilience measurement. Therefore, the loss capacity can be obtained according to Table 12.

Table 12. Conditional calculation of the loss capacity.

State of the Absorptive Capacity	True	False
Expression	$\text{PDO} \times \text{ASC}$	0

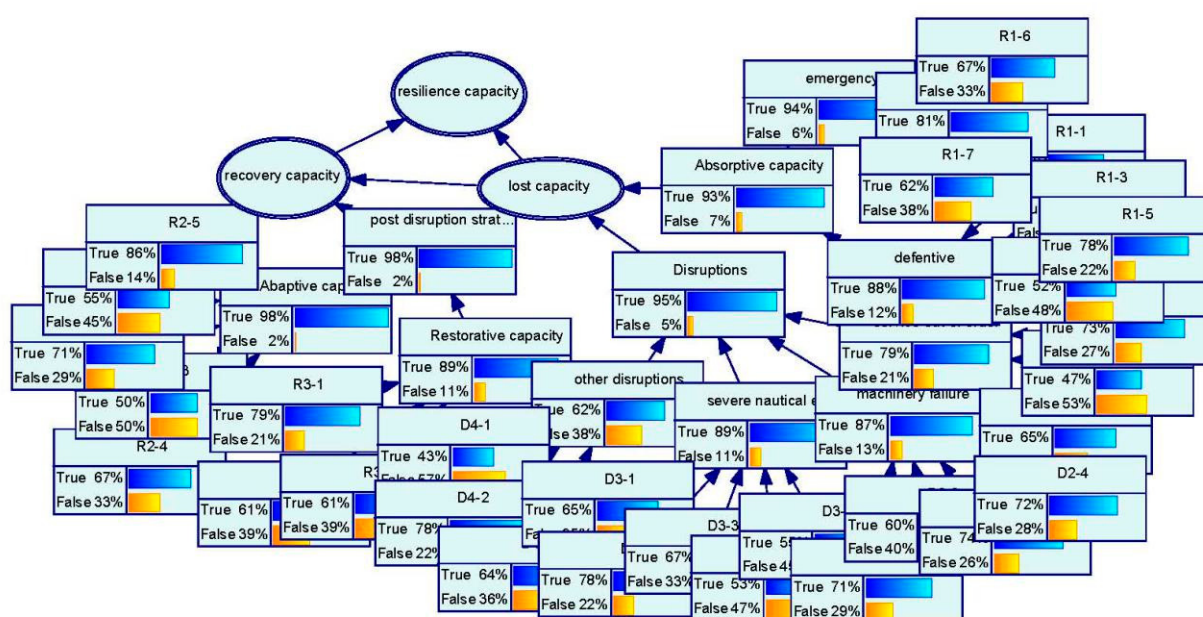
The recovery capacity of the system is dependent on the effectiveness of the post-disruption strategy (the combination of the adaptive capacity and restorative capacity) and the degree of the Loss Capacity (LC). If the post-disruption strategy is fully effective, that is, the state of the post-disruption strategy is true, the security system will recover 85% of the loss capacity; otherwise, the value will be zero. Therefore, the recovery capacity can be calculated according to Table 13.

Table 13. Conditional calculation of the recovery capacity.

State of the Post-Disruption Capacity	True	False
Expression	$LC \times 0.80$	0

4. Results and Discussion

The resilience level of the developed Arctic Northeast Route security system can be evaluated quantitatively based on the fuzzy Bayesian Network, and the expected resilience is 78.5%, as shown in Figure 9. In this section, we will conduct various types of analyses, such as belief propagation, sensitivity, and uncertainty analyses, based on the Bayesian network structure, as depicted in Figure 9.

**Figure 9.** The base model of BN used to measure the resilience of the NSR.

4.1. Belief Propagation Analysis

Bidirectional reasoning and probabilistic inference can be performed in the Bayesian network by updating evidence formation, which is called “propagation analysis” [76]. Generally, propagation analysis in Bayesian networks includes forward-propagation analysis and backward-propagation analysis. The former is basically a cause-to-effect analysis in which the parent nodes measure their impact on the child nodes, and the latter is widely applied to update the probability distribution of the parent nodes for certain specified states of the target nodes.

As with forward-propagation analysis, three disruptive scenarios are defined to observe the corresponding impacts on system resilience and the decomposed capacities. The scenario description and BN inference results are presented in Table 14. In Scenario 1, it is observed that there is a lack of skilled seafarer teams (the state of (R1-2) is *false*), which reduces the absorptive capacity of system resilience from 93.4% to 89.2%; eventually, the resilience of the system descends to 78.1% from 78.5% in the base model. Scenario 2 simulates the case of two contributing factors in which the skilled seafarer team and the information prediction service are unavailable (the states of (R1-2) and (R2-2) are set as *false*). The results show that both the adaptive capacity and system resilience are reduced, the former from 98% to 94% and the latter from 78.5% to 77.8%, respectively. In Scenario 3, another contributing factor is considered on the basis of Scenario 2, that is, the state of a new factor, namely, the rescue and anti-pollution facility (R3-1) is further defined as *false*.

After simulating the developed BN model, the results indicate that the resilience of the NSR suffers from the most notable effect, decreasing to 75.9%, while the restorative capacity is lowered to 65.7% from 88.2%. A general insight obtained from the forward-propagation analysis indicates that all individual capacities are critical for the development of the resilience of the NSR.

Table 14. Different scenario sets for forward-propagation analysis.

Scenario	R1-2	R2-2	R3-1	Absorptive Capacity (%)	Adaptive Capacity (%)	Restorative Capacity (%)	Resilience (%)
Base	–	–	–	93.4	98.0	88.2	78.5
1	false	–	–	89.2 (↓)	98.0	88.2	78.1 (↓)
2	false	false	–	89.2	94.8 (↓)	88.2	77.8 (↓)
3	false	false	false	89.2	94.8	65.7 (↓)	75.9 (↓)

Note: ↓ denotes a reduction in a certain variable value in the defined scenario compared with the value in the base case.

4.2. Sensitivity Analysis

Sensitivity analysis is one of the characteristic features of the application of BNs in identifying the most important independent variable(s) based on a particular dependent variable under a given set of conditions [77]. Herein, GeNIe 2.3 software is applied to simulate the established BN model and investigate the extent to which the parent nodes differ from the target nodes.

In the present study, the fuzzy ratio of variation (RoV) associated with the prior and posterior probabilities is calculated according to Equation (33) to evaluate the desired probability level of the contributing variables.

$$RoV(X_i) = \frac{\tilde{\zeta}(X_i) - \zeta(X_i)}{\zeta(X_i)} \quad (36)$$

where X_i denotes the i th contributing factor and $\tilde{\zeta}(X_i)$ and $\zeta(X_i)$ represent the posterior and prior probabilities of X_i , respectively. Actually, all the parent nodes in the Bayesian network can theoretically be analyzed.

As discussed in Section 3.3, the NSR system resilience is mainly represented by the absorptive capacity, adaptive capacity, and restorative capacity. Therefore, in this section, we will set these individual capacities as the target nodes to investigate the corresponding effects of the contributing factors. Deductive reasoning is applied to update the probabilities of the contributing factors for the resilience related to the occurrence of the individual capacity (absorptive capacity, adaptive capacity, or restorative capacity), and then the value of the ratio of variation can be obtained by Equation (33). Finally, the results of the sensitivity analysis are illustrated in Figure 10.

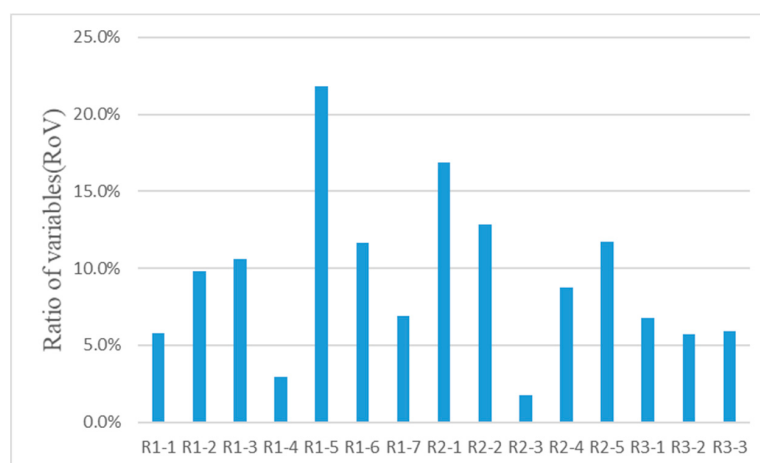


Figure 10. Sensitivity analysis for the absorptive capacity.

Figure 10 shows the effects of individual contributing factors on the corresponding capacity. For the absorptive capacity, when the state is set as “true”, it is obviously found that the contributing factor “skilful emergency response” (R1-5) has the most important influence on the desired absorptive capacity; moreover, the “well-coordinated with tugs” (R1-4) has the lowest impact on the improvement of the absorptive capacity. When the state of the adaptive capacity is set as “true”, after updating the probabilities of parent nodes, we can obtain the values of RoV for the contributing factors, as shown in Figure 7, from (R2-1) to (R2-5). Similarly, the results indicate that the “ice-breaking capacity” has the highest influence on the expected adaptive capacity, and the “information prediction service” ranks second; however, the effect of the “preparedness for arctic shipping” on the adaptive capacity is almost negligible. For the restorative capacity, there is no evident difference among the three contributing factors, and the “rescue and anti-pollution facility” (R3-1) may be characterized as the most potential influence on the restorative capacity.

4.3. Uncertainty Analysis Based on Information Entropy Theory

Based on the discussion in Section 3.3, theoretically, the NSR security system is conditionally dependent on the absorptive capacity, adaptive capacity, and restorative capacity, which can be illustrated as shown in Figure 11. Actually, there is no direct and obvious causal relationship between system resilience and the decomposed capacities based on the analysis of the fuzzy Bayesian network. The system resilience and its supporting capacities are connected by the dotted line in Figure 8.

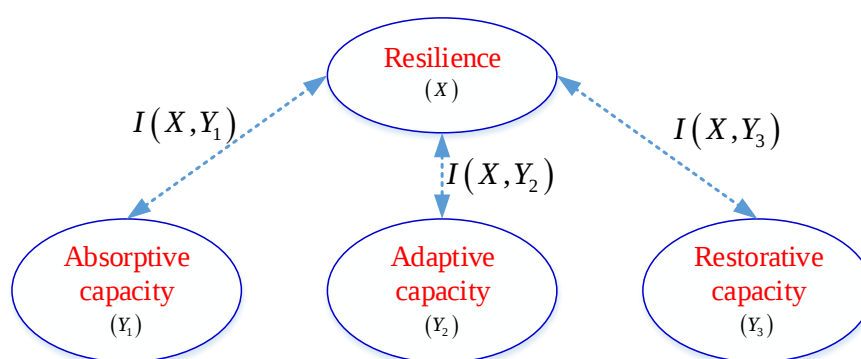


Figure 11. Mutual information links between resilience and the corresponding decomposed capacities.

As shown in Figure 11, the system resilience is set as the target variable X , and the decomposed absorptive capacity, adaptive capacity, and restorative capacity are regarded as Y_1 , Y_2 , and Y_3 , respectively. In this section, Y_1 , Y_2 , and Y_3 are set as the predictive variables (predictor) associated with system resilience X . The predictive importance of each predictor can be determined by calculating the entropy and mutual information $I(X, Y_i)$, and the most important predictor will provide maximum information gain for system resilience.

The prior probability of system resilience can be obtained by simulating the developed Bayesian network as:

$$P(X = \text{true}) = 0.785, P(X = \text{false}) = 0.205 \quad (37)$$

Then, the entropy of system resilience can be calculated by:

$$H(X) = - \sum_{i=1}^2 P_{x_i}(X) \cdot \log_2 P_{x_i}(X) = 0.785 \times \log_2(0.785) + 0.205 \times \log_2(0.205) = 0.743 \quad (38)$$

$$H(X|Y_1) = \sum_{i=1}^2 P_{x_i}(X) H_i(X|Y_1) = P(X = \text{true}) \cdot H(X = \text{true}|Y_1 = \text{true}) + P(X = \text{false}) \cdot H(X = \text{false}|Y_1 = \text{false}) \quad (39)$$

where the conditional entropies $H(X = \text{true}|Y_1 = \text{true})$ and $H(X = \text{false}|Y_1 = \text{false})$ are unknown terms to be solved according to the developed Bayesian network. Notably, the state of the absorptive capacity in the network is set as “true” and “false”, and the BN is simulated with GeNIe 2.3 software; the conditional entropy can be calculated as:

$$H(X = \text{true}|Y_1 = \text{true}) = -[0.805 \times \log_2(0.805) + 0.185 \times \log_2(0.185)] = 0.304 \quad (40)$$

$$H(X = \text{false}|Y_1 = \text{false}) = -[0.298 \times \log_2(0.298) + 0.692 \times \log_2(0.692)] = 0.89 \quad (41)$$

By substituting the results of Equations (37), (40) and (41) into Equation (39), we are able to obtain the conditional entropy of $H(X|Y_1)$ by:

$$H(X|Y_1) = 0.785 \times 0.304 + 0.205 \times 0.888 = 0.421 \quad (42)$$

Finally, the mutual information between X and Y_1 can be evaluated based on the results of Equations (38) and (42) by:

$$I(X, Y_1) = H(X) - H(X|Y_1) = 0.743 - 0.421 = 0.322 \quad (43)$$

In the framework of information entropy, the result obtained from Equation (40) indicates that the absorptive capacity can reduce the uncertainty of system resilience by approximately 32.2%; that is, if we have good knowledge associated with the absorptive capacity, the extent of uncertainty of the system resilience can be reduced by 32.2%. Similarly, the conditional entropy and mutual information of the adaptive capacity and restorative capacity can also be calculated. Finally, the results for all three capacities obtained from information entropy theory are listed in Table 15.

Table 15. Summary of the information entropy analysis.

Capacity Type (Y_i)	Conditional Entropy $H(X Y_i)$	Mutual Information $I(X, Y_i)$	Implication of Mutual Information
Absorptive capacity (Y_1)	0.421	0.322	The uncertainty of system resilience can be reduced by 32.2% in the case of a good knowledge of absorptive capacity
Adaptive capacity (Y_2)	0.440	0.303	The uncertainty of system resilience can be reduced by 30.3% in the case of a good knowledge of adaptive capacity
Restorative capacity (Y_3)	0.542	0.201	The uncertainty of system resilience can be reduced by 20.1% in the case of a good knowledge of restorative capacity

Based on the information presented in Table 15, by comparing the values of mutual information between system resilience and its three supporting capacities, it can be observed that the absorptive capacity of system resilience is able to reduce the extent of uncertainty regarding the resilience level of the NSR, and the restorative capacity is the least valuable in reducing the uncertainty of the resilience level. Generally, the results of the present study agree with the general belief that the absorptive capacity is complex and expandable and that the restorative capacity is not as difficult to identify. The result of $I(X, Y_1) > I(X, Y_2) > I(X, Y_3)$ can be used by the related authorities and organizations to focus on the absorptive capacity with regard to obtaining a better understanding of NSR resilience because the uncertainty of resilience is mainly related to the absorptive capacity.

5. Conclusions

The present work attempts to propose a comprehensive framework by which the safety level of the NSR can be improved. The safety level of the NSR is a common concern for mariners, authorities, and related organizations. Although huge endeavors have been

made, the safety level of the NSR is still far from being satisfied. In the present study, system resilience is introduced to analyze the NSR safeguard capacity. Based on the existing studies about system resilience, the resilience capacity of the NSR is decomposed into three capacities: absorptive capacity, adaptive capacity, and restorative capacity. Then, we identify the contributing factors pertaining to these capacities. Moreover, the disruptions to the NSR are also identified. Next, all the identified disruptions, contributing factors, and capacities are regarded as nodes in the BN and, as a result, a BN model is developed. The prior probabilities for the nodes without parents and the CPT for the network inference are obtained by the fuzzy methodology proposed by [34]. Finally, the established BN model is simulated with GeNIe 2.3 software, and a sensitivity analysis and an information entropy analysis are conducted with regard to the results obtained from the simulation. Overall, the present study provides a resilience perspective to understand and evaluate the NSR safety issue, which can be seen as the main innovation of this work. The analysis framework proposed in the present study can improve our understanding of the system resilience of the NSR and aid in mitigating disruptions to the NSR.

Although the framework proposed in the present study is demonstrated to effectively quantify and interpret the resilience of the NSR, the structure of the proposed BN can be optimized based on additional information from experts and stakeholders. In addition, the resilience level of the system is generally regarded as a variable that changes over time; therefore, in the future, potential work can be devoted to improving the performance of resilience modelling for the NSR based on the framework given in the present study. The work associated with the abovementioned issues remains in progress.

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