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Research Article

Safety Risk Analysis of Unmanned Ships in Inland Rivers Based on a Fuzzy Bayesian Network

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Risk factor identification is the basis for risk assessment. To quantify the safety risks of unmanned vessels in inland rivers, through analysis of previous studies, the safety risk impact factor framework of unmanned vessels in inland rivers is established based on three aspects: the ship aspect, the environmental aspect, and the management and control aspect. Relying on Yangtze River, a fuzzy Bayesian network of the sailing safety risk of unmanned ships in inland rivers is constructed. The proposed safety risk model has considered different operational and environmental factors that affect shipping operations. Based on the fuzzy set theory, historical data, and expert judgments and on previous works are used to estimate the base value (prior values) of various risk factors. The case study assessed the safety risk probabilities of unmanned vessels in Yangtze River. By running uncertainty and sensitivity analyses of the model, a significant change in the likelihood of the occurrence of safety risk is identified, and suggests a dominant factor in risk causation. The research results can provide effective information for analyzing the current safety status for navigation systems of unmanned ships in inland rivers. The estimated safety risk provides early warning to take appropriate preventive and mitigative measures to enhance the overall safety of shipping operations.

1. Introduction

With the rapid development of science and technology, artificial intelligence has penetrated all aspects of human life more and more deeply. As an important branch of its development, driverless technology has had a major impact on social and economic development and national defense construction; it has become one of the hotspots in the AI (artificial intelligence) field today. Due to the fast development of driverless technology and the shortage of labor faced by the shipping industry, the shipbuilding industry is still in the stages of structural adjustment, upgrading, and overcapacity. Shipowners are very eager for "smart, green, safe, and efficient" ships, and unmanned ships are coming at a faster than expected speed. With the birth of Massterly, the world's first unmanned shipping company, unmanned ships began to enter the commercial era after a time of being mere concepts. As early as the 1960s, remotely controlled unmanned fleets were widely used in the military field. In recent years, there has been a quick development of technologies such as automatic control, Internet of Things, and big data; environmental awareness technologies and communication and navigation technologies related to ships have also been widely improved, providing a broad technical feasibility for the development of smart ships/unmanned ships.

Inland navigation has an important position in the national economic system because of its large volume, low cost, convenience, and flexibility. Since its reform and opening up, inland navigation has developed rapidly. Especially in recent years, not only has economic growth accelerated, but environmental awareness has increased; however, the country has strengthened channel regulations of the inland waterway, which has led to a rapid increase in the volume of inland rivers, a large increase in the number of inland vessels and an increasing density of navigation. For example, during the first half of 2017, there were 140 waterborne traffic accidents in the Yangtze River Maritime Administration area, including 58 collision accidents, which accounted for 41.4% of the total accidents. According to research, human factors are often the triggering factors of water traffic accidents, and they are dominant among the various factors. According to recent surveys of waterway traffic accidents, the main causes of marine accidents are human factors, such as decision-making errors, operational errors, and improper emergency response. According to a report released by Allianz Insurance in 2012, 75–96% of marine accidents are the result of human error. Surveys of Canada and the United Kingdom show that the proportions are 75% and 60%, respectively. In the design of the unmanned ship, the maneuvering of the ship is mainly operated on the shore with better working conditions through the expert decision-making system and the remote-controlled system; this fundamentally reduces the influence of human factors on navigation safety of the ship, which can reduce the probability of waterway traffic accidents. Autonomous systems may bring smarter and more efficient operations as well as emerging risks, due to lack of knowledge and operational experience with automated systems, and challenges related to verification of safety performance [1]. While paying attention to the safety of traditional ships, we will study the new risks brought by ship-shore integration on ship safety. Therefore, it is very important to study the navigation safety of unmanned vessels in inland rivers. In view of the navigation safety problem of unmanned vessels in inland rivers, this study proposes a study on the safety risk analysis of unmanned vessels in inland rivers.

The main contributions of this paper are as follows:

(1) Establishment of a safety risk indicator system for unmanned ships in inland rivers.

(2) Construction of the risk assessment model of unmanned ships in inland rivers based on fuzzy Bayesian network.

2. Literature Review

The concept of risk was first proposed in the seventeenth century. The nautical terminology from Spain was explained by the American scholar Haynes at the end of the 19th century. He explored the nature of risk, categorized risks, and points out the possibility that the term "risk" represents loss in economics or other academic fields [2]. According to the theory of accident causation, any navigation risk is a description of the effect of the cause factor on the ship's navigation process [3]. At present, the relevant theories of risk management have been relatively mature, and its application range covers many industries, from manufacturing to shipping to financial industry. In particular, the term risk originated from navigation at the beginning, and the process of ship navigation was full of risks. In view of this, risk management research in the field of ship navigation is extremely rich; risk assessment is an extremely important part of risk management, so many scholars have studied it.

Xia et al. [4] establish a risk ranking ANFIS model of a ship safety navigation system to accurately achieve risk assessment on sailing ships. Taking uncertainty into consideration, Fu et al. [5] assessed the risks of major ship accidents in the Arctic waters through the use of the copula-based fuzzy event tree analysis approach. Chai et al. [6] evaluated the risk of ships being involved in ship collisions according to a quantitative risk assessment (QRA) model. Literature [7] used "Fuzzy based risk assessment" to assess cargo vessel accidents at the coasts and open seas of Turkey. Baksh et al. [8] proposed Bayesian Network (BN) to investigate the possibility of marine accidents such as collision, foundering, and grounding in the Northern Sea Route (NSR). Thieme et al. [9] adopt a Bayesian Belief Network (BBN) to estimate the Performance of Human Autonomy Collaboration (HAC) which as a part of risk model for AUV operation.

In the safety risk assessment of unmanned ships, the following scholars have conducted the following studies. Ter Brake et al. [10] discussed the latest developments and plans for the unmanned ship simulation project, MARIN developed a real-time dynamic risk index which would be integrated into Dolphin to monitor the safety of all ships and focus on unmanned ships. Rødseth et al. [11] pointed out that the MUNIN project was conducting a feasibility study for unmanned bulk carriers on intercontinental voyages. MUNIN adopted a risk-based design approach to develop technical and operational concepts, and used scenario analysis to identify risks and simplify the scope of operations, using system hazard identification to identify critical security risks and how to address them [11]. Wróbel et al. [12] developed a list of potential hazards associated with unmanned ships. According to the high uncertainty of the potential risk model, the Bayesian network model structure was given. Xiang et al. [13] analyzed the risk of URV used in the adaptive learning and fuzzy reasoning capabilities of Mamdani Fuzzy Neural Network (MFNN). Wróbel et al. [14] conducted a preliminary assessment of the impact of unmanned ships on maritime safety by 100 maritime incident reports. A hypothetical analysis framework enhanced by the Human Factors Analysis and Maritime Accident Classification System (HFACS-MA) was used. The purpose of the analysis was to assess whether an accident occurs when the ship is unmanned, once an accident occurs - the consequences are different. Wróbel et al. [15] used Systematic Theoretic Process Analysis (STPA) to identify and study the most likely safety control structures of the remotely merchant ship system. Gerigk [16] proposed a performance-oriented risk-based approach to estimate the risk of unmanned ship.

According to the presented literature review, we can see that most studies that have tried to assess and analyze the risk of ship safety. Most of these studies consider risk analysis of traditional ships; a few studies are qualitative research on unmanned ship risk. Using the Fuzzy Bayesian Network, this study is the first study which has focused on assessing quantitatively the risk for an inland unmanned ship. The premise of risk assessment is to identify risk factors. Scholars have many achievements in the identification of traditional ship navigation safety risk factors. According to the literature, 50 risk criteria related to shipping safety, are identified. Detailed criteria have been listed in Table 1.

3. Methodology: Fuzzy Bayesian Network

3.1. Bayesian Network. The Bayesian Network, namely the reliability network, is an extension of the Bayes method. It was proposed by Judea Pearl in 1986 and is a type of inference-based

Table 1: Most used risk criteria related shipping safety.

Target	Level indicators	Secondary indicators	Three-level indicator	References
Factors of shipping risk	Human factor	Human errors	Skill-based errors	[17–25]
			Decision errors	[17–20, 23, 24, 26, 27]
			Perceptual errors	[17–20, 24, 27]
		Violations	Routine violations	[18, 20, 21, 23, 25, 28]
			Exceptional violations	[18, 20, 21, 24, 25, 29]
		Quality and experience of crew	Post adaptability of crew	[19, 22, 30–32]
			Situation awareness	[18, 27]
			Psychological factor	[20, 22, 24, 27, 30, 33, 34]
			Physiological factor	[22, 24, 27, 28, 30, 33]
			Technical factor	[20, 22, 25, 29, 30, 33]
			Experience	[19, 20, 31]
	Ship factor	Static information	Tonnage	[31, 35–37]
			Ship/vessel age	[20, 30, 31, 33, 35, 37]
			Ship type	[20, 31, 38]
			Ship size	[19, 39]
			Ship equipment, radar and other equipment configurations	[18, 20, 26, 27, 29, 33, 40]
			Maintenance issues	[41]
			Structural strength	[12, 19, 25, 29, 30, 39, 42]
			Watertightness	[39]
			Buoyancy	[12]
		Dynamic information	Technical faults	[17, 26]
			Speed and heading	[31]
			Vessel draught	[31, 39]
			Ship maneuvering performance	[43, 44]
			Ship Seaworthiness	[19, 20, 31]
		Stowage of goods	Ship stability	[12, 19, 39, 42]
			Nature of the carried cargo	[19, 29]
	Environmental factor	Natural environment	Wind speed and direction	[31, 35, 37, 39, 42, 45–47]
			Visibility	[18, 20, 30, 31, 33, 35, 46–48]
			Weather condition	[20, 38, 44]
			Water current affects/stream	[18, 20, 30, 31, 33, 46]
			Wind and waves	[19, 20, 30, 35, 39, 43, 46, 49]
		Navigation environment	Traffic volume	[38, 50]
			Channel traffic conditions	[20, 47, 50–53]
			Bridge	[30, 33, 54]
			Channel dimension	[31, 39]
			Channel width affects	[20, 30, 33, 39, 47]
			Send radius of the waterway	[20, 47]
			Completeness of navigation aids	[20, 26, 27, 30, 31, 33]
			Restricted river depth	[20, 39, 55, 56]
			Occurrence of ice	[55]
			Shipwreck	[19, 30, 33]
	Management factor	External supervision	Completeness of maritime management laws and regulations	[20, 30, 31, 33]
			Equipment completeness of maritime monitoring system	[25–27, 30, 31]
			Adequacy of the supervision and management	[20, 24, 30, 32]
			Supervise violations or not	[18, 20]
		Internal management	Safety culture	[20, 24, 25, 27, 30, 57, 58]
			Correct problem timeliness	[18, 20]
			Organizational errors	[17, 18, 25]
			Completeness of emergency facilities on board	[34]

network based on probability uncertainty, and variability. It is suitable for expressing and analyzing various uncertainties and probabilistic events. The network is applied to decisions that conditionally depend on multiple control factors; it can use proper reasoning from knowledge or information that is completely low, less accurate, or less certain. The Bayesian network, due to its unique uncertainty knowledge expression form, rich probabilistic expression ability and incremental learning characteristics of comprehensive prior knowledge, has been used in many fields. Especially in the field of traffic safety, the Bayesian network has been successfully applied to traffic disaster cause analysis, traffic safety warning, and traffic safety assessment and so on. In the field of ship navigation safety management, some countries have long applied Bayesian networks to risk analysis. Since the IMO's general implementation of the FSA method in the field of ship navigation safety, many scholars have nested Bayesian networks into the FSA method to conduct a comprehensive assessment of ship navigation safety. In addition to being nested in the FSA method, Bayesian networks are currently being used separately for various types of waterway safety research [59–63].

The Bayesian network based on Bayesian inference to quantify risk, but in the process of reasoning, the distribution of prior probability is needed. At present, the occurrence probability of basic events in many research projects is demonstrated by using certain values. In the inland navigation, corporate organization, human factor management and other events have strong uncertainties, and the historical data that can be used is limited. It is difficult to express the probability of occurrence with a certain value. Therefore, the expert knowledge can be fully utilized, mainly by the semantic variables of expert evaluation, and the event probability of conceptual and fuzzy language description is transformed into triangular fuzzy number or trapezoidal fuzzy number. After defuzzification, the Bayesian network is adopted to reasoning to predict the shipping safety risks probability. In the literature [64], the Bayesian Network and fuzzy set theory is used to diagnose the causes for high railway traffic, but our field of research is safety risk analysis of unmanned ships in inland rivers.

3.2. Probabilistic Analysis Based on Fuzzy Set Theory. A fuzzy set is used to represent a set of things with specific properties whose boundaries are ambiguous. The basic idea is to obscure the absolute membership in the classical set. The language using the feature function can be expressed as: the membership of the element to the set is no longer limited to taking 0 and 1, but can take any value between 0 and 1.

3.2.1. Fuzzy number processing for expert language description. The advantages of using the fuzzy method are: it is difficult to give or obtain a specific value in the fuzzy state, and the linguistic variable can be introduced in order to more intuitively represent the expert's evaluation result. Wickens [65] believes that the occurrence probability of events can be divided into seven different levels of semantic values: very high (VH), high (H), faint high (FH), medium (M), faint low (FL), low (L), and very low (VL); the fuzzy number form and λ-cut set are shown in Table 2.

To more accurately use the fuzzy number to quantify the occurrence probability of the entire event, it is necessary to combine the evaluation results of multiple experts. In this paper, the arithmetic average method is used to synthesize the evaluation results of many experts. The comprehensive evaluation of n experts can be expressed as [64]:

$$P(i) = \frac{f_{i1} \oplus f_{i2} \oplus \ldots \oplus f_{im}}{n}, \quad i = 1, 2, \ldots, m. \tag{1}$$

In Equation (1), $P(i)$ is the fuzzy occurrence probability of the ith event, f_{ij} is the fuzzy value of the ith event judged by the jth expert, m is the number of events, and n is the number of experts [64].

3.2.2. Ambiguity Resolution Method. In fuzzy sets, ambiguity resolution is a process that takes relative representatives of the single value of the entire fuzzy set. The methods of ambiguity resolution include full integral value algorithm, center of gravity method, extreme left maximum method, extreme right maximum method, average maximum method, weighted average method, and membership degree limiting element averaging method. The results obtained by different ambiguity resolution methods are also different. In theory, the center of gravity method is more reasonable, but the calculation process is more complicated. The integral value method can use the λ-cut set operation to process the fuzzy number, which is easy to understand and simple to calculate. Therefore, this paper adopts this method and uses the optimization index ε to reflect the opinions of the decision makers. It is assumed that P is an L-R type fuzzy number, and the calculation formula of the ambiguity resolution value of the fuzzy number P is as follows:

$$I(P) = (1 - \varepsilon) I_R(P) + \varepsilon I_L(P). \tag{2}$$

In Equation (2), $\varepsilon \in [0, 1]$ is the optimistic coefficient. When $\varepsilon = 0$ and $\varepsilon = 1$, $I(P)$, respectively correspond to the upper and lower bounds of the ambiguity resolution value of the fuzzy number P. When $\varepsilon = 0.5$, $I(P)$ is the representative value of the ambiguity resolution value of the fuzzy number P. $I_R(P)$ and $I_L(P)$ are the integral values of the inverse function of the left membership function and the right membership function of the fuzzy number, respectively. For triangular fuzzy numbers, $I_R(P)$ and $I_L(P)$ can be represented by λ-cut sets, i.e., [64]

$$I_R(P) = \frac{1}{2}\left[\sum_{\lambda=0.1}^{1} \lambda_R(P)\Delta\lambda + \sum_{\lambda=0}^{0.9} \lambda_R(P)\Delta\lambda\right], \tag{3}$$

$$I_L(P) = \frac{1}{2}\left[\sum_{\lambda=0.1}^{1} \lambda_L(P)\Delta\lambda + \sum_{\lambda=0}^{0.9} \lambda_L(P)\Delta\lambda\right]. \tag{4}$$

In Equation (3) and (4), $\lambda_R(P)$ and $\lambda_L(P)$ are the upper and lower bounds of the λ-cut set of the fuzzy number P; $\lambda = 0, 0.1, 0.2, \cdots 1; \Delta\lambda = 0.1$.

3.2.3. Probability Distribution of Fuzzy Bayesian Network Nodes. A fuzzy Bayesian network is a node variable that introduces fuzzy node variables into a Bayesian network. For a finite set of nodes, it can be fuzzified into a fuzzy random

Table 2: Fuzzy Number Form and λ-cut Set [64].

Language description	Fuzzy number form	λ-cut set
Very low (VL)	$f_{VL} = (0.0,\ 0.1,\ 0.2)$	$f_{VL}^{\lambda} = [0.1\lambda + 0,\ -0.1\lambda + 0.2]$
Low (L)	$f_{L} = (0.1,\ 0.2,\ 0.3)$	$f_{L}^{\lambda} = [0.1\lambda + 0.1,\ -0.1\lambda + 0.3]$
Faint low (FL)	$f_{FL} = (0.2,\ 0.3,\ 0.4,\ 0.5)$	$f_{FL}^{\lambda} = [0.1\lambda + 0.2,\ -0.1\lambda + 0.5]$
Medium (M)	$f_{M} = (0.4,\ 0.5,\ 0.6)$	$f_{M}^{\lambda} = [0.1\lambda + 0.4,\ -0.1\lambda + 0.6]$
Faint high (FH)	$f_{FH} = (0.5,\ 0.6,\ 0.7,\ 0.8)$	$f_{FH}^{\lambda} = [0.1\lambda + 0.5,\ -0.1\lambda + 0.8]$
High (H)	$f_{H} = (0.7,\ 0.8,\ 0.9)$	$f_{H}^{\lambda} = [0.1\lambda + 0.7,\ -0.1\lambda + 0.9]$
Very high (VH)	$f_{VH} = (0.8,\ 0.9,\ 1.0)$	$f_{VH}^{\lambda} = [0.1\lambda + 0.8,\ -0.1\lambda + 1]$

variable u_i and u_i inherits all possible states of x_i. Then, the fuzzy set of x_i is:

$$U_i = \left\{\widetilde{X}_{i1}, \widetilde{X}_{i2}, \ldots, \widetilde{X}_{in}\right\}. \tag{5}$$

$\widetilde{X}_{ij}$ represents the jth fuzzy state of u_i, and $\widetilde{X}_{ij}$ can be expressed as:

$$\widetilde{X}_{ij} = \left\{x,\ \mu_{ij}(x)|x \in X_i\right\}. \tag{6}$$

$\mu_{ij}(x)$ indicates that the variable x in X_i belongs to the degree of membership of the jth fuzzy state $\widetilde{X}_{ij}$ in u_i, and the conditional probability of $\widetilde{X}_{ij}$ for a given x condition can be expressed as:

$$\mu_{ij}(x) = P\left(\widetilde{X}_{ij}|x\right), \tag{7}$$

$$0 \le \mu_{ij}(x) \le 1, \quad \sum_{j=1}^{r_i} \mu_{ij}(x) = 1. \tag{8}$$

Further assume that the causal dependence of variables in U is represented by a directed arc:

$$L = \left\{\left(u_i, u_j\right)|i \ne j, i, j = 1, 2, ..., n\right\} \subset U \times U. \tag{9}$$

The probability of its dependence can be expressed by a conditional probability table:

$$P = \left\{P\left(u_i \gamma_{u_i}^{+}\right)|i = 1, 2, \ldots, n\right\}, \tag{10}$$

where $\gamma_{u_i}^{+}$ represent the set of parent nodes of the fuzzy variable u_i. The fuzzy evidence of the fuzzy variable u_i can be expressed as:

$$E(\mu_i) = \left(\mu_{i1}, \left(x_i^0\right), \mu_{i2}, \left(x_i^0\right), ..., \mu_{in}, \left(x_i^0\right)\right). \tag{11}$$

The trust degree $B(u_i)$ of the fuzzy variable u_i is:

$$B(\mu_i) = P(\mu_i|E) = (B(\widetilde{x}_{i1}), B(\widetilde{x}_{i2}), \ldots, B(\widetilde{x}_{in})), \tag{12}$$

where: E represents the set of evidence on the set U of fuzzy variables.

In general, the result of the inference decision is to know the maximum possible state of the continuous variable x_i corresponding to the fuzzy variable u_i. For a fuzzy Bayesian network, the node u_i is given a probability vector corresponding to all possible states after the inference. Conversely, the defuzzification method can be used to determine the maximum probability that the continuous variable x_i is in continuous state x_i^0. By synthesizing all the fuzzy states, a unique fuzzy set $\widetilde{X}_i$ can be determined. The unique continuous point x_i^0 can be located by the centroid method.

$$\mu_{\widetilde{X}_i}(x) = \sum_{j=1}^{r_i} \mu_{ij}(x) B\left(\widetilde{X}_{ij}\right), \tag{13}$$

$$x_i^0 = \frac{\int_{x_i}^{x} \mu_{\widetilde{X}_i}(x)dx}{\int_{x_i}^{\mu} \widetilde{x}_i(x)dx}. \tag{14}$$

Let $q(x \to x')$ be the probability of transitioning from state x to state x', which defines the Markov chain in the state space. Let $\pi(x)$ be the probability that the system is in state x at time t, and the definition of the Markov chain reaching steady state distribution is:

$$\pi(x') = \sum_{x} \pi(x) q(x \to x'). \tag{15}$$

When the expected flow in any direction between any two states is comparable, it can be called a detailed balance:

$$\pi(x) = q(x \to x') = \pi(x') q(x' \to x). \tag{16}$$

X_i is used to represent the sampled node, and $\overline{X_i}$ is the hidden variable except for X_i. The values of X_i and $\overline{X_i}$ in the current state are x_i and $\overline{x}_i$. Now, for a new value x_i' of X_i to be conditionally sampled on all other variables (including evidence variables), there is:

$$q(x \to x') = q((x_i, \overline{x}_i) \to (x_i', \overline{x}_i)) = p(x_i', \overline{x}_i, e). \tag{17}$$

Given a Markov coverage, the probability of a variable and the probability of the parent node are proportional to the product of the probability of the corresponding child node:

$$p\left(\frac{x_i'}{mb(X_i)}\right) = ap\left(\frac{x_i'}{\text{parents}(X_i)}\right) \times \prod_{Y_i \subset \text{Children}(X_i)} p\left(\frac{y_i}{\text{parents}\left(Y_j\right)}\right). \tag{18}$$

Table 3: Node table at each level of Inland river unmanned ship navigation safety risk status.

Target node	Intermediate node	Sub-node	Evidence node
Inland river unmanned ship navigation safety risk status	Ship factor	Ship stowage	Full load rate
			Ship balance
			Hazardous nature of cargo
			Cargo fastening degree
		Tonnage and age	Tonnage
			Age
		Structure and performance	Buoyancy reserve
			Speed of ship
			Initial stability height
		Equipment and maintenance	Integrity rate of outfit
			Ship maintenance
	Environmental factor	Weather condition	Fog
			Rain
			Wind
			Illumination
		Channel condition	Channel width
			Keel clearance
			Sailing restrictions
			Obstructed building
			Channel traffic density
		Hydrological condition	Flow rate
			Flow state
		Parking condition	Berth utilization
			Anchorage condition
		Interference factor	Floating objects hinders navigation
			Speed and direction of interference boat
	Management and controlling factor	Human-related	Human error
			Technical failures
			Situation awareness
			Information overload
		Reliability and security of control device	Remote operation reliability
			Power device stability
			Cyber security
			Information transmission security
		Emergency response capability	Emergency rescue capability
		Safety supervision	Security check strength
			Fault maintenance timeliness

When changing the value of each variable X_i, the number of multiplications required is equal to the number of child nodes of X_i.

Through the above calculation, the posterior probability of a single node can be obtained, and the probability of the target node risk can be finally obtained, which is the comprehensive shipping risk probability of the unmanned ship in the inland river.

4. Influencing Factors of Navigation Safety Risk of Unmanned Navigation Vessels in Inland Rivers

4.1. Overview of Influencing Factors of Unmanned Ship Navigation Risk of Inland River. In fact, the ship itself factor, environmental factor and supervision and management factor, for example, like ship full load rate, ship balance, ship tonnage, ship age, ship stability, ship buoyancy, ship speed, ship maintenance, visibility, wind speed, water current, channel traffic, channel width, restricted river depth, inadequate supervision, planned inappropriate operation, failure to correct known problem, supervisory violations, and so on, these safety risk factors between unmanned ship and traditional ship are similar. According to the presented literature review on the safety risk of unmanned ships, we can clarify the following issues: while paying attention to the safety of traditional ships, we must study the new risks brought by ship-shore integration to shipping safety.

Is it possible to eliminate human factors in the sailing safety of unmanned ships when compared to traditional

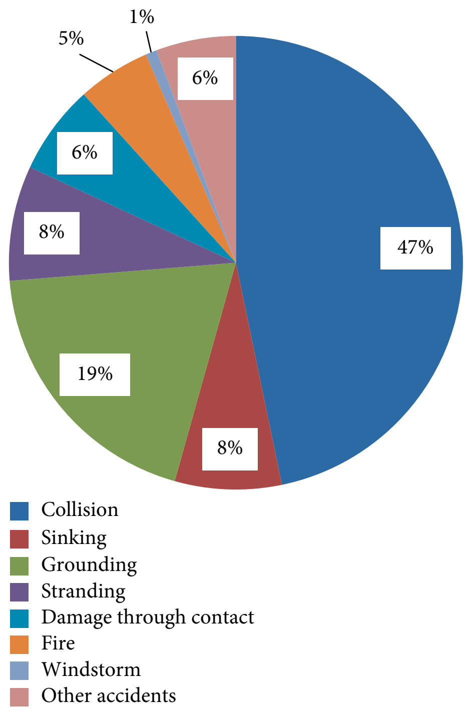

Figure 1: Yangtze River trunk line accident classification between 2010 and 2017.

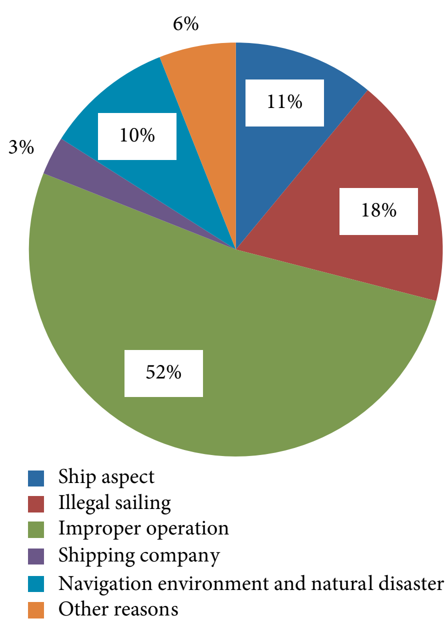

Figure 2: Analysis of the proportion of the Yangtze River trunk accident causes.

manned ships? In response to this question, the following scholars' research gives us an answer. The MUNIN project demonstrates the unmanned ships technology is feasible, and also shows the unmanned system is as safe as a traditional manned system. It is a seriously misunderstand to say an unmanned system will eliminate human error. Unmanned vessels do not mean eliminating human factors. On the contrary, there is a need to pay more attention to human factors in developing and maintaining high-level situation awareness in dynamic systems [67]. Technical failures can play an important role at the outset, as in most newly systems; as experience increases, they can be expected to be overcome. But human error would continue to be a huge challenge for unmanned ships [67–69]. The shore-based control of the ship contains new safety issues and an interesting question will be the interaction of manned and unmanned vessels in the same traffic zone. The design and rules of each control algorithm and rules for the internal decision logic of the autonomous ship are coded by human software engineers. Maintaining situational awareness is also critical to the safe and effective control of ships [70]. When the operator takes over the ship control subsystem to solve the problem, it means that the possibility of human error is not eliminated, but instead it is transferred to a control center hundreds of miles away [14].

Some engineering-related issues may affect the unmanned shipping safety [12]. The problem of normal operation of various engines on board may be the cause and result of navigational accidents. For example, stranding may be caused by a malfunction of the steering device. On the other hand, if the ship is stranded, it will cause serious damage to the rudder. In addition, the loss of electricity can cause most of the ship's systems to fail, including propulsion, steering, communication and ballast. Poor system design, such as poor consideration on ergonomics and maintainability of the system/components will put the ship in danger.

Ship handling is considered a complex task. On a traditional ship, crewmembers handling vessel rely on navigational instruments (e.g., radar or ECDIS) and visual information from the environment (e.g., available wave or water direction). The spatial movement of ships (e.g., rolling, slamming, pitching, or heaving) and the inertial performance of ships with relation to maneuverability are all contribute to the decisions made regarding vessel handling [68]. However, when the unmanned ship concept is introduced, it will be a big difficulty to maintain a high-level of situation awareness [67]. Information overload and automation awareness issues will affect ship handling. Automation and remote operations involve the ship being equipped with and loading multiple sensors, and the operator may be exposed to too much information to understand the situation. If one monitors several ships, the problem may expand; moving the focus from one ship to another may be a potential disaster point. Delay and cognitive horizons may also be potential influencing factors. Signals are transmitted by satellite or other means, which means there is always a delay in remote operation. Too much wait time can suppress the actual task implementation, i.e., if the distance/wait time is too long; it may exceed the "cognitive range" in remote operations.

Reliability and maintenance management are essential for unmanned ships. Traditional ships seem to rely heavily on the crew on board as on-site resources to recover from failures at sea and to perform preventive maintenance programs online during maritime navigation. The lack of permanent crew on board will greatly reduce the ability to monitor site conditions and prevent and correct manual maintenance tasks during maritime navigation. This means that systems that are essential for operation need to be designed for remote maintenance or

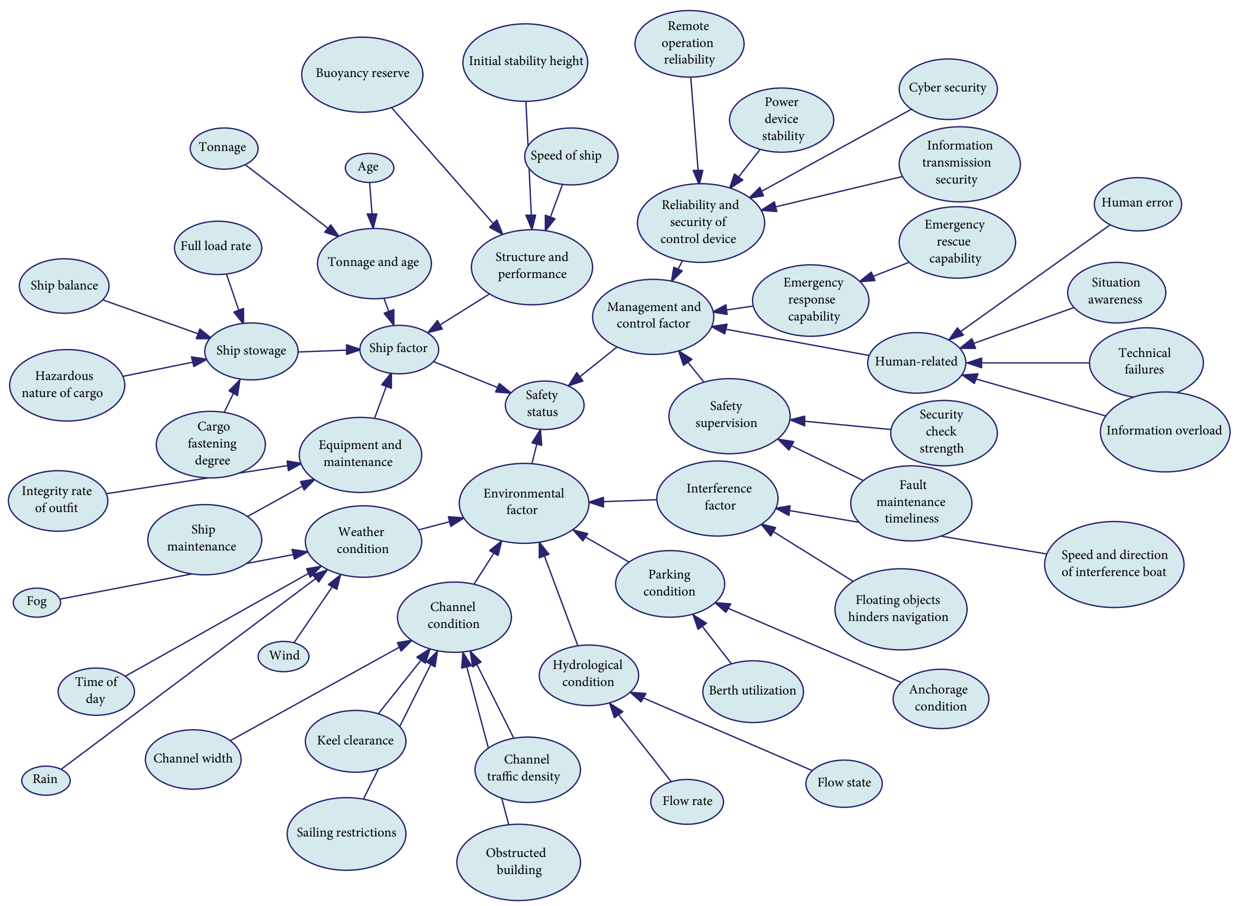

Figure 3: Bayesian network for risk of safety status of inland river unmanned ship.

for flexibility and extended maintenance intervals. The lack of permanent crew members also puts higher demands on the maintenance arrangements for port stays.

In the context of autonomous and remotely operated vessels, concerns about cyber security are further increased, with the system's connectivity further extended to allow the vessel to operate in autonomous mode or remotely. This means that, in principle, anyone who is skilled and capable of entering the ICT system can control the ship and change its operation according to the hacker's goals. In addition to intrusion systems, the operation of automated vessels may also be threatened by intentional interference or spoofing of AIS or GPS signals or data communications between the ship and the land control center.

For unmanned vessels sailing in inland rivers, it is also necessary to consider the impact of space constraints in navigational waters [43]. The following pose a potential collision hazard to sailing vessels: the scale of the channel being limited, the river channel changing frequently, the water level fluctuating with the season, the shape of the water flow being complex and variable, the channel being narrow and curved, the ship sailing density being high, and the number of bridges and the increasing number of buildings across the river becoming limitations, and obstacles for the navigation of inland vessels. Therefore, the primary factor for analyzing the collision risk of unmanned ships in inland rivers is the restriction of inland waterways. When inland river vessels are to avoid collisions, in addition to passing and clearing obstacles or the coming ship, it is also necessary to consider that any collision avoidance decisions taken should not be too close to the boundary of the channel or the shore wall; limiting the impact of navigable water space is a prerequisite for making safe and effective collision avoidance decisions. Because of the limitation of the width of the channel, inland vessels often travel along the coast, which may cause difficulties due to the influence of water flow and shore suction, resulting in collision and grounding risks.

Based on the limitation of the navigation channel scale, the influence of the ship's maneuverability is very obvious, which has a direct impact on the ship collision risk [43, 66]. Maneuverability of a ship mainly refers to the performance of the ship to maintain or change its speed, heading and position. Ship handling performance mainly includes the ship's heading stability, rotation, and heading. When an obstacle or ship is found, the ship should change the course or speed in time to avoid collision. If the steering is used alone, the ship is required to have good rotation and heading. Therefore, for ships with better maneuverability, the collision risk with obstacles or the incoming ships will be smaller than it is for ships with poor maneuverability. This is because ships with poor maneuverability have difficulty in quickly following the driver's commands to control the ship course or speed, and the collision

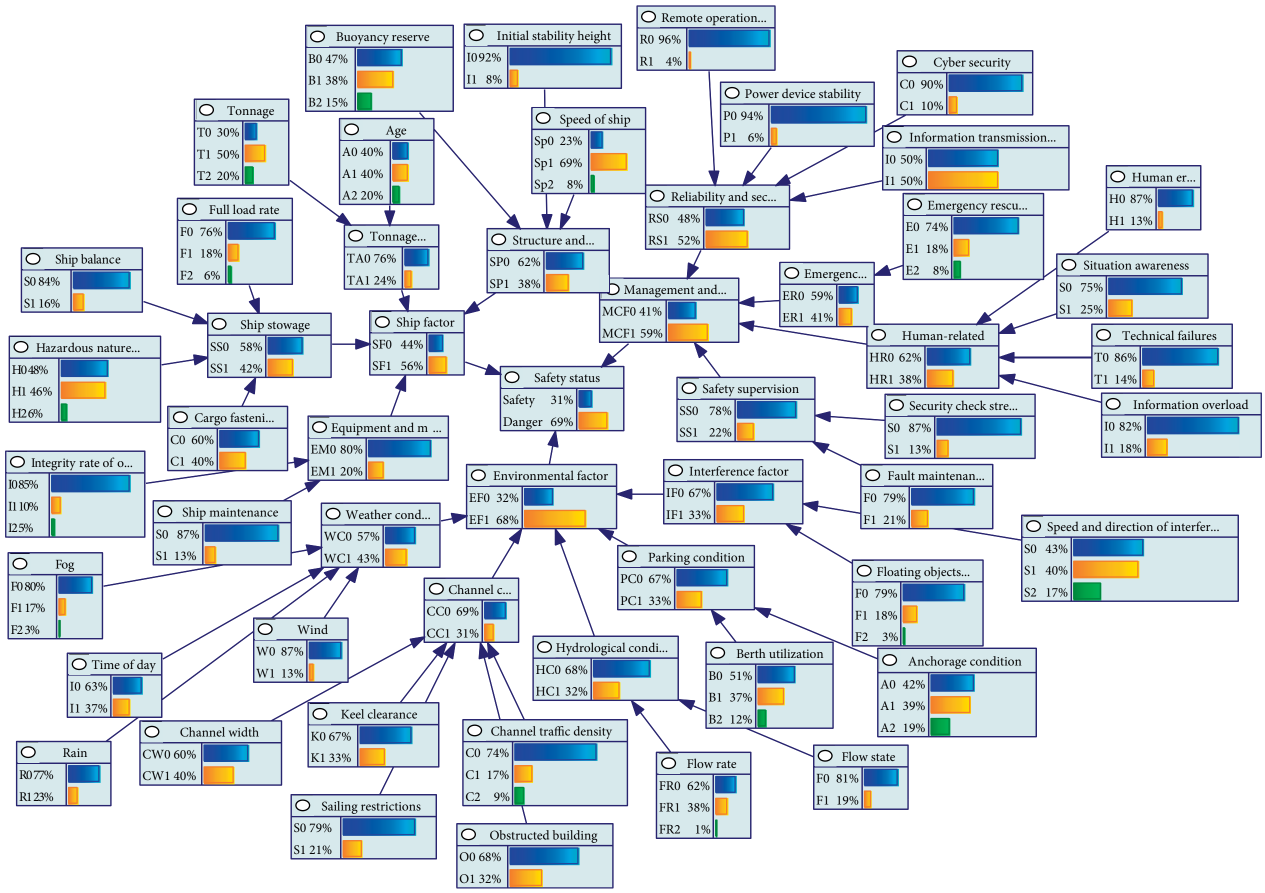

FIGURE 4: Distribution probabilities for primary causes of shipping safety of inland river unmanned ship.

risk when confronted with obstacles or incoming ships is also much greater. Ships should take reasonable collision avoidance measures according to their handling performance. Therefore, the maneuverability of the ship is a very important factor for the collision risk of the ship.

4.2. Bayesian Network Node Composition of Unmanned Ship Navigation Risk of Inland River. The inland water network is densely distributed, and the traffic volume of channel is large; the types of accidents are diverse, and the social environment around the channel is complex, including public areas such as bridges, commercial areas, and residential areas. In the event of collisions, fires, etc., it will cause heavy casualties and property loss. Therefore, studying the sailing safety risks of inland unmanned vessels has great significance. Factors affecting ship risk continuously change with time and environment. Therefore, detailed risk identification of ships should not only consider static risk factors related to ship safety; it should also take under consideration many dynamic factors such as meteorology, hydrology, and traffic flow, as well as factors which vary with the movement of the ship's position, such as the width of the channel and the curvature of the channel. In view of the complexity and diversity of ship navigation risks, the combination of objective analysis and subjective judgment is adopted, which is based on the principle of risk factor selection and combined with literature and expert opinions from various fields to analyze ship navigation risk factors.

The ship field expert group 1 contains 10 researchers and staff from China Shipbuilding Industry Corporation, China Ship Research Institute and China Maritime Safety Administration. Each expert has more than eight years of work experience and has profound knowledge in the field of ship navigation safety. The research team conducted a questionnaire survey for this group of experts, initially identified the main sources of risk, conducted a literature review, expanded the risk source framework, and used the Delphi method to organize experts to analyze the ship navigation risk factors and obtain preliminary analysis results. The expert group 2 consists of 10 professors and associate professors from the Institute of Shipbuilding Industry Management and Institute of Systems Engineering affiliated to universities. This group of experts reviews the results of the preliminary analysis of risk sources to test their scientific basis, comprehensiveness, and operation. If the review is passed, the risk assessment framework can be constructed based on the results of the analysis. Otherwise, the above operations are repeated on the basis of the comments of the members of expert group 2. Using the above steps to complete 4 times iterative process analysis, more complete risk factor analysis results can be obtained.

Based on Table 1, through the literature review 50 risk criteria had been identified, including 11 human criteria, 16 ship criteria, 15 environmental criteria, and 8 management criteria. According to the frequency of repetitions in literatures, sailing characteristics of unmanned ships, characteristics of inland

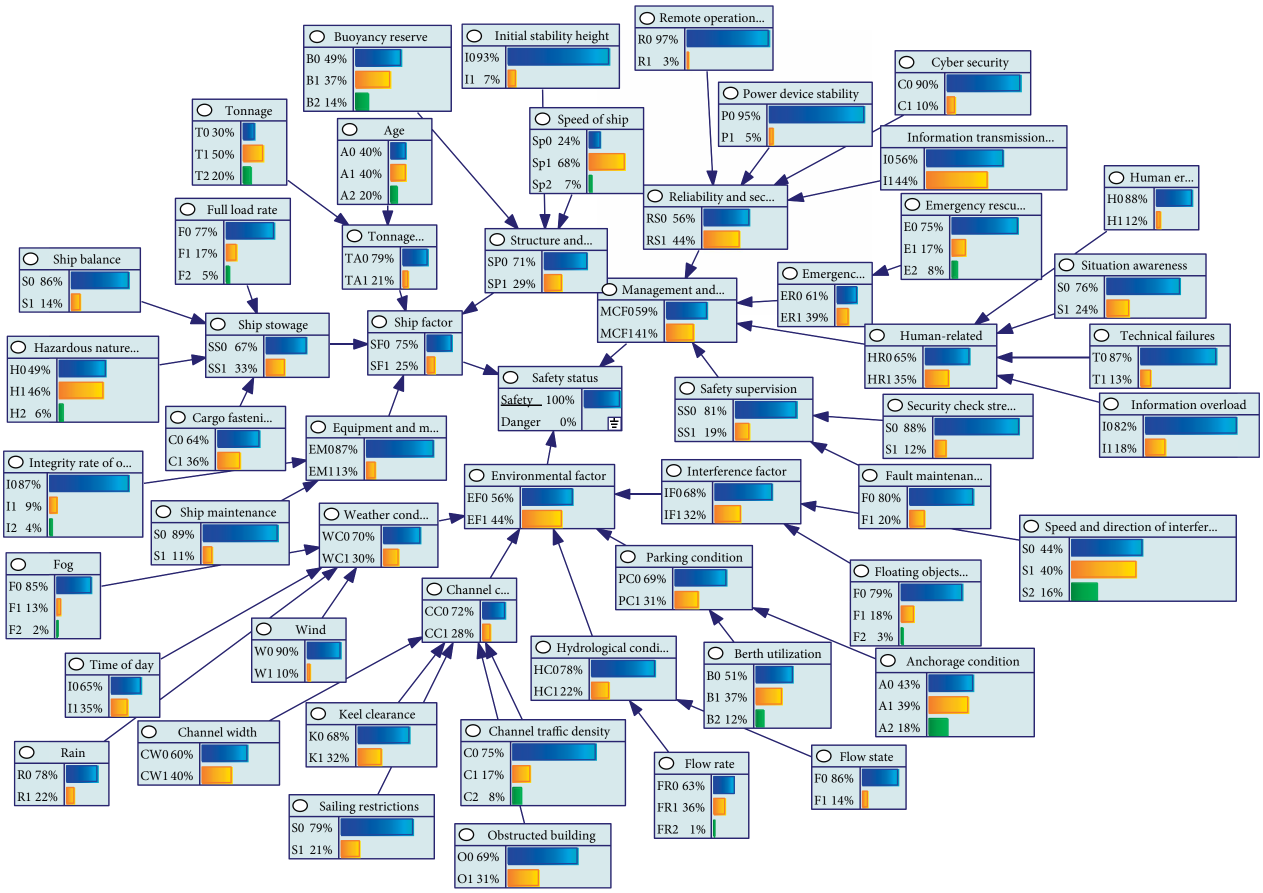

Figure 5: Reverse reasoning learning result.

waterways, similarity and correlation of criteria, available data and suggestions of experts, were considered to select the final criteria. Based on these conditions, the academic experts and ship field experts were asked to specify which of the criteria should be considered. Then, by analyzing the suggestions of experts, the project team divided the navigation risk factors of unmanned ships into three aspects: ship aspect, environment aspect, and management and control aspect. Each risk element was a node of the Bayesian network. The target node (also known as the root node) was the "safety risk status of inland navigation for unmanned ships," and the three categories of "ship," "environment" and "management and control" were used as intermediate nodes. According to the attributes of specific influencing factors, it is further divided into 13 subnodes. Finally, the project team considered 11 ship factors, 15 environmental factors, and 11 management and control factors, which provided a total of 37 factors to serve as evidence nodes that directly affect the navigation risk of inland unmanned vessels. The nodes at each level are shown in Table 3.

5. Application of the Methodology: Case Study

5.1. Navigation Accident Analysis of Unmanned Ships in Yangtze River. The Yangtze River Basin is one of the most developed areas in China's industry, agriculture, commerce, cultural education, and science and technology. The Economic Belt of the Yangtze River covers an area of 400,000 square kilometers, accounting for 4% of China's land area, but its population and GDP account for 18% and 25% of China's population. Its population density, economic density, and per capita GDP are 4.5 times, 6.2 times, and 1.4 times of China's average level, respectively. It occupies an important position in China's national economy. The Yangtze River shipping volume accounts for 41% of China's total inland shipping. Therefore, it is reasonable to study the safety mechanism of inland navigation based on the Yangtze River shipping. According to the current statistical caliber, the types of shipping accidents are generally divided into: collision, sinking, grounding, stranding, damage through contact, fire, windstorm and other accidents. According to the information provided by the Yangtze River Maritime Safety Administration, the proportion of the various types of accidents on the Yangtze River trunk line between 2010 and 2017 is shown in Figure 1. It can be seen that the most common occurrences are collision accidents, followed by grounding accidents.

According to the information provided by the Yangtze River Maritime Safety Administration, the project team reached the following conclusions through analysis: the causes of the waterway traffic accidents on the Yangtze River can be divided into ship aspect, crew aspect, shipping company aspect, navigation environment and natural disaster and other

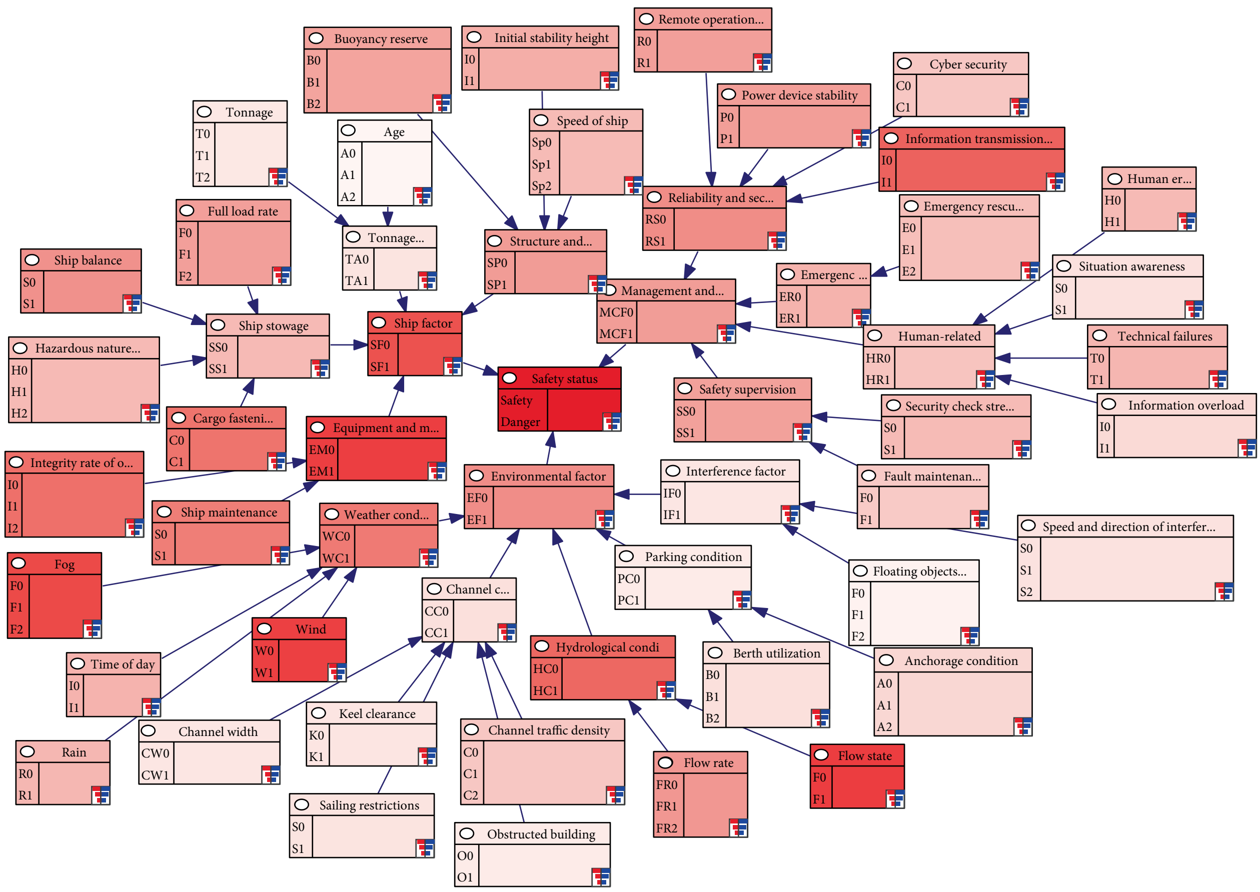

FIGURE 6: Sensitivity analysis of the Bayesian network.

reasons. Among them, the crew aspect is divided into illegal sailing and improper operation. Through analysis of the causes of grade accidents in recent years, we found that the main cause of accidents was the crew's improper operation, accounting for 52%, and accidents caused by the crew's illegal sailing accounted for 18%, this reveals that 70% of the accidents were caused by crew factors. Ship factors and navigational environments and natural disasters are the objective causes of accidents. Figure 2 reflects the frequency of various accidents.

5.2. Determining the Probability Distribution of Fuzzy Bayesian Network Nodes. The Bayesian network structure model can be constructed by software such as Matlab, GeNIe2.3, and Netica. Although Matlab software can perform network structure learning by loading Bayesian network packets, its disadvantage is that it requires a lot of programming and cannot sensitively reflect the change relationship between various risk factors. GeNIe2.3 and Netica software can visually reflect the structural changes through visualized pages. Therefore, this paper uses the widely used GeNIe2.3 software to construct the Bayesian network model. The relationships among all nodes are established, and the final graphical structure of Bayesian Network model is shown in Figure 3.

Based on the statistical data of ship accidents on the Yangtze River trunks collected by the Yangtze River Maritime Safety Administration, the research team classified and ranked the navigation accidents of the Yangtze River trunks from various risk factors, and distributed the statistical results to the expert group. Based on the statistical results of the classification, the expert group gave the language description of the fuzzy probability value. We assumed that the weights of the experts are the same. According to Table 2 and Equations (1) to (4), adopting the arithmetic mean method and the defuzzification method, we obtained the prior probability of each node. The distribution probabilities for primary causes of shipping safety of inland river unmanned ship are shown in Figure 4.

In this study, as shown in Figure 4, in the BN analysis demonstrates the probability of sailing safety status is only 0.31. The reason for the low probability is that compared with sailing in open water, unmanned ships are restricted by navigation channels in the inland river, plus the technology of unmanned ships is still immature, and various reasons have made the sailing security of unmanned vessels in Yangtze River greatly reduced.

5.3. Bayesian Network Reasoning. Based on the Bayesian network model, the Bayesian network forward and reverse causal reasoning techniques are used to conduct risk prediction and diagnosis, respectively. Managers can estimate the risk level of ship navigation safety based on prior knowledge, and can also predict risk level when the new evidence appears

Figure 7: Tornado diagram of sensitivity for "Safety_status = Safety."

continuously during the navigation process. Conversely, when the risk of an accident increases, the risk diagnosis can be based on the posterior probability, and then measures can be taken in a targeted manner.

When using GeNIe2.3 software for reverse reasoning, setting the first state of the safety status to 100%, the key risk influencing factors under this risk level can be inferred inversely. The inference results are shown in Figure 5.

As shown in Figure 5, the first state of the end node is set to 100%, and the probability change value of each node is reversely inferred. From the analysis results, the probability values of the first state of almost all nodes are improved. The changes in the three secondary indicators are significant, dating back to the third-level indicators, the probability of the first state for weather condition has risen by 13%, and hydrological condition, ship stowage, structure and performance, reliability and security of control device, equipment, and maintenance have risen by about 9%; during the forth-level indicators, the probability of the first state for information transmission security, fog, flow state, cargo fastening degree, wind, and tonnage have risen by about 4%. This shows that the safety of inland river shipping can be improved by improving the conditions corresponding to the above evaluation indexes.

5.4. Sensitivity Analysis. Sensitivity analysis of the Bayesian network indicates the effect of small changes in the model's local parameters or evidence on the target node. Minor changes in sensitive factors can lead to significant changes in the evaluation results, while changes in nonsensitive factors have little effect on the results of the evaluation. The greater the sensitivity of the node, the more sensitive it is to the safety risk level of the unmanned ship. It should be taken as an important parameter and structure of the complex system. Through sensitivity analysis, key risk impact factors affecting the navigation safety of inland river unmanned vessels can be identified, and parameters that need further improvement are identified. Sensitivity analysis is one of the statistical decisions that provides new ideas for risk analysis. In this paper, the GeNIe 2.3 model is used to directly set the navigation safety risk of the inland river unmanned ship as the target node. Based on the Bayesian network, survey data and online learning results, sensitivity analysis of other influencing factors can be directly performed to identify key risk factors in the target. According to the reverse reasoning of the previous section, the sensitivity analysis of the Bayesian network is performed using GeNIe2.3, as shown in Figure 6.

Figure 6 shows the sensitivity analysis results of the Bayesian network model with the importance of the safety evaluation index of inland river unmanned ship. The deeper the red color indicated by the box indicates the more sensitive it is to the overall risk impact. Therefore, the more sensitive sailing safety risks are mainly concentrated in the risk of equipment and maintenance, weather condition, hydrological condition, and reliability and security of control device.

A sensitivity analysis was performed to assess the sensitivity of the Bayesian network to some of the most critical variables. The tornado diagram can more accurately reflect the impact of these more sensitive factors on the overall risk. From Figure 7, we can find ten top ranked indicators. Taking Figure 7, the state probability of "Safety_status" in state "Safety" as an example, the first histogram shows that when other factors are constant, the variation of the probability of "Equipment_and_maintenance" in state "EM0" corresponds to that the probability variation range of target node (Safety status) in state "Safety" is [0.3046, 0.3223], that is, the maximum probability variation range of "Safety_status" in state "Safety" under this condition. From the analysis, it can be seen that a significant change in the probability of each node can make a difference to the probabilities of "Safety_status" in state "Safety". A 10% increase in the initial probability of each node can make significant changes to the corresponding risk probability. From the tornado diagram, it can be seen that "Equipment and maintenance," "Wind," "Flow state," "Fog," and so on, impact significantly on "Safety status." The above sensitivity analysis allows designer and manager of unmanned ship to improve the unmanned ship safety by narrowing down major factors.

6. Conclusion

Inland river channels are often curved and hydrologically complex, and inland navigation safety accidents often occur. According to the characteristics of unmanned ships and paying attention to the safety issues of traditional ships, it is also necessary to study the new risks brought by ship-shore integration to ship safety. Therefore, it is of great significance to study the navigation safety of unmanned vessels in inland rivers. In this paper, first based on the analysis of previous studies and a literature review, the influencing factors of navigation risk of unmanned navigation vessels are determined: ship aspect, environment aspect, management, and control aspect. From these three aspects, we have established a framework for influencing factors of navigation safety risks for unmanned ships in inland navigation.

Since the application of unmanned ships has just started, the statistical data and related reports of safety accidents are rare. Fuzzy mathematics analysis methods were used, along with expert evaluation and the statistical analysis of the traditional ship safety accident data of the Yangtze River trunk line, in the early stages of the project. Using the fuzzy Bayesian model, based on GeNIe 2.3, the sailing risk probability of unmanned ships in inland river represented by the Yangtze River trunk line is predicted. The Bayesian network analysis demonstrates the probability of sailing safety status is only 0.31. The reason for the low probability is that compared with sailing in open water, unmanned ships are restricted by navigation channels in the inland river, plus the technology of unmanned ships is still immature, and various reasons have made the sailing security of inland river unmanned vessels greatly reduced. From the reverse reasoning and subsequent sensitivity analysis, it is clear that some of the evidence nodes are the dominant factors towards the safety status. From the tornado diagram, it can be seen that a significant change in the probability of each node can make a difference to the probabilities of "Safety_status" in state "Safety." A 10% increase in the initial probability of each node can make significant changes to the corresponding risk probability. It can provide effective information for analyzing the current safety status of the navigation systems of unmanned ships in inland rivers. The proposed approach can be helpful for decision makers and safety experts to estimate the probability of unmanned ship safety considering the factors most contributing to the existing environmental and operational conditions.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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