Quantitative Risk Analysis of Collisions of Maritime Autonomous Surface Ships

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Abstract: Maritime Autonomous Surface Ships (MASS) are being developed globally, and their safety is of paramount importance in the realization of MASS. The fundamental concept is the Operational Design Domain (ODD), which refers to the operational limits regarding internal and external conditions that must be properly operated autonomously. If internal and external conditions exist within the ODD, MASS are operated autonomously. Previous studies have obtained the failure probability of collision avoidance of MASS using Bayesian Network and Fault Tree; however, these studies did not consider the ODD concept. Based on this background, this study estimated the failure probability of collision avoidance of MASS by developing a Bayesian Network (BN) model that considers the ODD. A sensitivity analysis was performed, and the nodes sensitive to the failure probability of collision avoidance in the developed BN were identified. In addition, the failure probability of collision avoidance when each system was duplicated was calculated, and the most effective system for reducing the failure probability of collision avoidance was revealed.

Keywords: Maritime Autonomous Surface Ships (MASS), Operational Design Domain (ODD), Collision, Bayesian Network

1. INTRODUCTION

Maritime Autonomous Surface Ships (MASS) are being developed worldwide, and the International Maritime Organization (IMO) is in the process of creating a non-mandatory goal-oriented MASS Code, which is expected to be finalized in 2024, to ensure the safety of these ships. The safety of MASS is of the utmost importance, and risk analysis is a technique that considers the safety of the target system. Risk is typically defined as the product of the likelihood of an accident and the severity of the accident.

Risk analyses can be broadly categorized into qualitative and quantitative approaches. In quantitative risk analysis, risk is handled numerically, allowing for a more in-depth examination of the safety of the target system than in qualitative risk analysis. While there have been numerous studies on qualitative risk analyses of MASS, there are only a few studies that focus on quantitative risk analyses of MASS. Quantitative risk analysis of MASS collisions is crucial for the following reasons: the objective of the currently developed MASS is the automation of the navigation function, and ship collisions are one of the most common types of maritime accidents among conventional ships.

To determine the risk of collision, it is necessary to estimate the collision frequency. This frequency can be estimated as the product of the geometric number of collision candidates if no evasive maneuvers are made and the probability of failing to avoid a collision [1]. Generally, the geometric number of collision candidates is calculated using ship traffic data, while the probability of collision avoidance failure is estimated using probability calculation technologies such as Event Tree (ET), Fault Tree (FT), and Bayesian Network (BN).

References [2]-[4] provide the collision frequency of various MASS. For instance, Reference [2] reported the collision frequency of a small autonomous ferry operating in the Trondheim Canal in Norway by estimating the geometric number of potential collision scenarios from ship traffic data and the probability of failing to avoid a collision (hereinafter, "failure probability of collision avoidance") using BN. Reference [3] estimated the failure probability of collision avoidance for MASS using FT analysis. Reference [4] obtained the failure probabilities of collision avoidance for MASS under four different operation scenarios based on various weather and illumination conditions using FT.

MASS operates autonomously when internal and external conditions are within the Operational Design Domain (ODD). The ODD is defined as "design range that Automated Operation System or Remote Operation System can work properly" in [5]. If the conditions fall outside of the ODD, manual operation is performed. Previous studies [2-4] have not addressed the importance of the ODD concept in calculating the collision avoidance failure probability of MASS. Therefore, this study developed a Bayesian Network (BN) model that considers the ODD to estimate the failure probability of collision avoidance for MASS. A sensitivity analysis was conducted, and the nodes sensitive to the failure probability of collision avoidance in the BN model were identified. Additionally, the failure probability of collision avoidance was presented when each system was duplicated, considering system redundancy as a safety measure. The most effective system for reducing the failure probability of collision avoidance was also revealed.

The rest of this paper is organized as follows. Section 2 explains the target ship used in this study. Section 3 presents the method used to estimate the failure probability of collision avoidance for MASS and shows the developed BN model and input probabilities. Section 4 presents the calculation results for the failure probability of collision avoidance and provides a discussion. Finally, conclusions are presented in Section 5.

2. TARGET SHIP

2.1. Target Function and Degrees/Levels of Autonomous

Although ships generally have several functions, such as navigation, cargo management and energy management, the primary objective of this study is to focus on a ship with automated navigation functions. In terms of autonomous navigation, there are various degrees/levels of autonomous that can be considered. However, for the purposes of this study, the following degrees/levels of autonomous has been assumed:

- The crew is present on the bridge; however, they can perform tasks other than those for the navigation function. They are not allowed to drink alcohol or sleep.
- If the MASS deviates from its ODD, the system will request human intervention, and the crew will switch the operation mode to manual.

Although switching to manual operation may carry the risk of failure, this study assumes success for the sake of simplicity. Additionally, it is assumed that a long-term voyage plan has been appropriately established; therefore, the failure to plan the voyage is beyond the scope of this study.

2.2. System Composition

The target ship operation consists of two main processes.

a) Comparison between current internal and external conditions and the ODD and determination of whether the operation mode is autonomous.
b) Planning a collision-avoidance route and acting as track control along the planned route.

This study assumed a system composition to conduct these processes, as depicted in Figure 1. The system composition was not that of an actual ship; however, we developed it by referring to the MASS system for demonstration tests in Japan [6-15] and the concepts of MASS in the literature [4, 16]. Hence, we believe that this can be one typical system composition of MASS.

3. METHOD

3.1. Bayesian Network

A Bayesian network is a graphical model to represent probabilistic relations among variables of domain [17]. Formally, a BN can be defined as a directed acyclic graph with the following properties [18]:

- Each node represents a random variable.
- Each node representing a variable A with parent nodes representing variables B_1, B_2,…, B_n is assigned a conditional probability table (CPT) of $P(A|B_1, B_2, \ldots, B_n)$.

The nodes represent random variables, and the edges represent probabilistic dependences between variables. These dependences are quantified through a set of CPTs. Each variable is assigned a CPT of the variable given its parents. For variables without parents, this is an unconditional (also called a marginal) distribution.

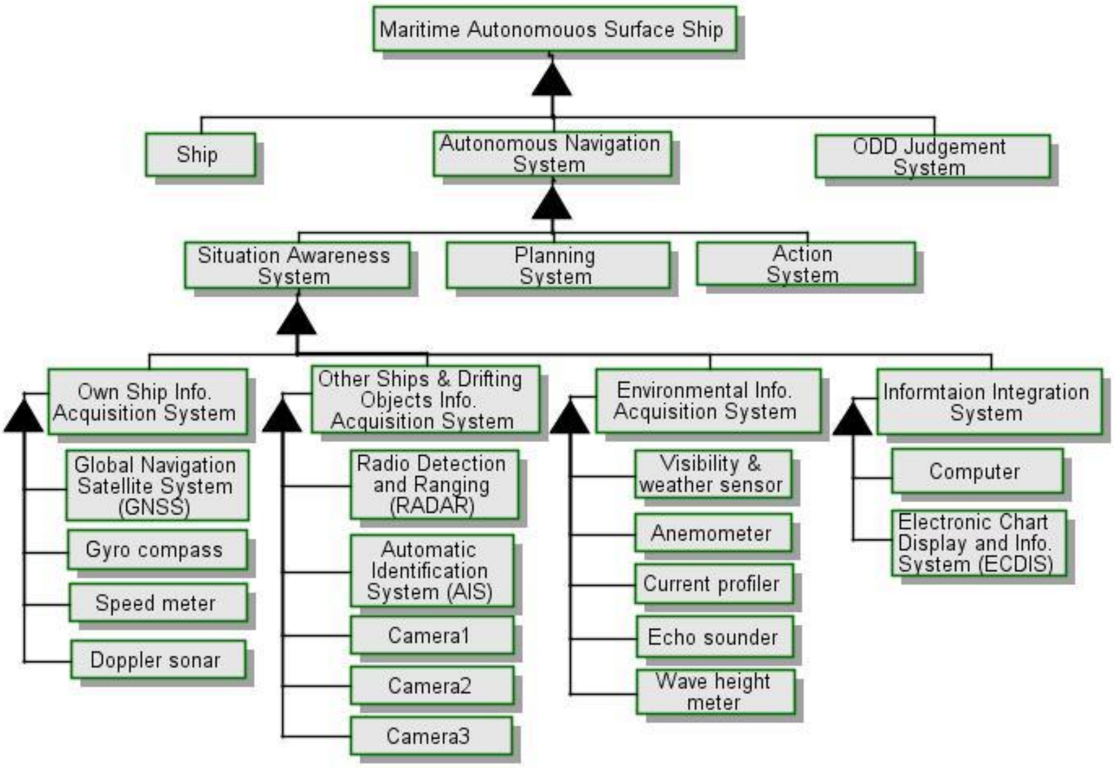

Figure 1. System composition of the target ship.

In this study, a BN was utilized to calculate the failure probability of collision avoidance for MASS. To accomplish this, we employed Hugin Developer 9.5, a software tool designed for working with BNs, and the RHugin package [19], which is a Hugin API for the R environment. R is a free software environment for statistical computing and graphics [20].

3.2. Construction of Structure

We applied the Naturalistic Decision-Making (NDM) model [21] to develop a BN model structure, as several previous studies [17, 22-23] have successfully utilized the NDM model for collision risk analysis of conventional ships. The NDM model is a model to describe a process of decision-making and contains three cognitive phases, that is, “Situation Awareness,” “Decision” and “Performance of Actions.” These correspond to the ANS subsystems. We assume that each failure of these three cognitive phases directly results in collision avoidance failure.

In addition, the developed BN model incorporates nodes for *Failure of ODD judgment* and *Mode of operations* to account for the ODD concept, as previously mentioned. Figure 2 illustrates the constructed BN model. The relationships between the nodes, the states of the nodes and the edges are explained in below.

(1) Situation awareness

- A node labeled *Failure of Situation Awareness* represents failures related to the following areas:
  - Information acquisition of own ship,
  - Information acquisition of other ships and drifting objects,
  - Information acquisition of environmental conditions,
  - Information integration.
- If the state of the *Failure of Situation Awareness* node is *Yes*, the state of the *Failure of Collision Avoidance* node is also *Yes*, regardless of the state of the *Mode of operations* node.

(2) ODD judgement and mode of operations

- If the state of the *Failure of Situation Awareness* node is *No*, the states of the *Failure of ODD judgment* and *Mode of operations* nodes are considered. These nodes are relevant to the following tasks:

- Comparing acquired information with ODD values and determining whether autonomous operation should be maintained:
    i. If the current situation is outside the ODD, the *Mode of operations* is changed to *Manual*,
    ii. If the current situation is within the ODD, the *Mode of operations* is maintained as *Autonomous*.
- Regarding the *Failure of ODD Judgment*, there are two types of failures that are taken into account: one, the computer misjudges the mode of operations must be changed to *Manual* when the actual situation is within the ODD; the other, the computer misjudges the mode of operations can remain as *Autonomous* when the actual situation is outside the ODD. In the first case, the state of the node *Failure of Collision Avoidance* is *No* because manual operation is conducted; in the second case, the state of the node *Failure of Collision Avoidance* is *Yes* because autonomous operation is conducted even though the current situation is outside the ODD.

(3) Collision avoidance
- If the state of the node *Failure of Situation Awareness* is *No* and the state of the node *Mode of Operations* is *Manual*, the state of the node *Failure of Collision Avoidance* is *No*, which is independent of the states of the nodes *Failure of Planning* and "*Failure of Action*.
- If the state of the node *Failure of Situation Awareness* is *No* and the state of the node *Mode of Operations* is *Autonomous*, the state of the node *Failure of Collision Avoidance* is *Yes* when the state of one of the nodes *Failure of Planning* and *Failure of Action* is *Yes*; the state of the node *Failure of Collision Avoidance* is *No* when the states of both nodes *Failure of Planning* and *Failure of Action* are *No*.

(4) Hardware and software failures
- *Hardware Failures* and *Software Failures* are considered factors of *Failure of Situation Awareness*, *Failure of ODD Judgment*, *Failure of Planning*, and *Failure of Action*. The state of the corresponding node is *Yes* when the state of one of the nodes *Hardware Failures* and *Software Failures* is *Yes*.

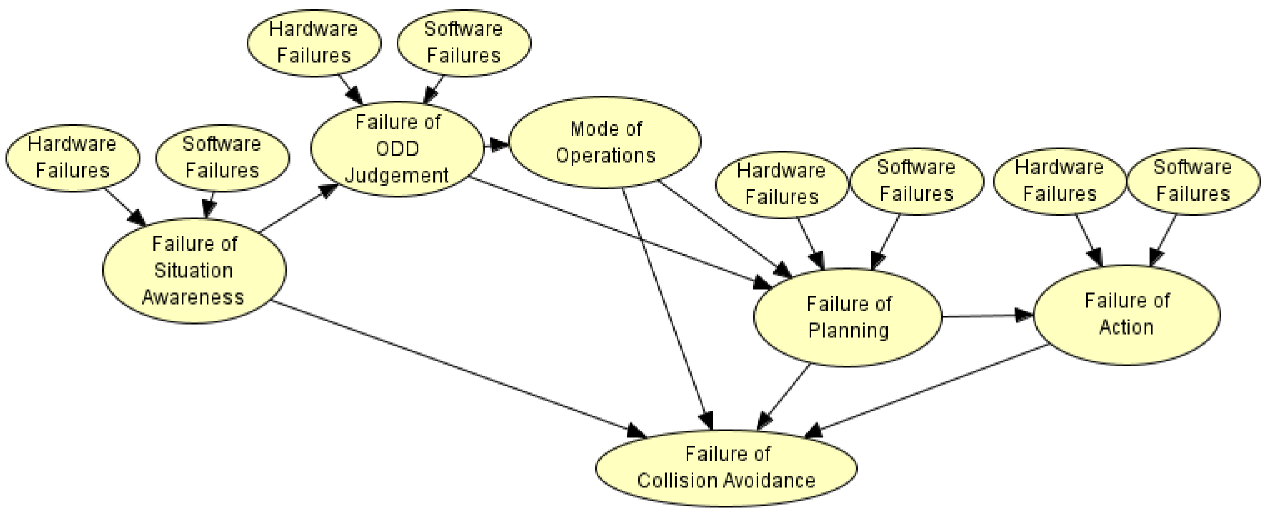

Figure 2. BN model on failure of collision avoidance.

3.3. Probability Inputs

3.3.1 Conversion of Failure Rate to Probability

The probability values for the nodes *Hardware Failures* and *Software Failures* in Figure 2 were obtained from the literature. In the literature, the failure rate and/or the mean time between failures (MTBF) are typically reported for hardware and software failures, rather than the probability. Consequently, we assumed an exponential probability distribution and converted the failure rate to the probability of failure using Equation (1) [24]:

$$P(t) = 1 - e^{-\lambda t}, \tag{1}$$

where $P(t)$ represents the probability of failure at time t, λ denotes the failure rate, and t indicates the operating time. When only the MTBF was reported in the literature, it is converted to the failure rate using: .

$$\lambda = \frac{1}{T_{MTBF}}, \tag{2}$$

where T_{MTBF} denotes the MTBF[24].

3.3.2 Failure Rate of Series Systems

Situation awareness systems are composed of multiple subsystems, as illustrated in Figure 1. This study assumed that autonomous navigation would be feasible as long as none of these subsystems failed. In other words, the Situation Awareness System operates as a series system. The failure rate of the series system can be calculated using Equation (3) [24].

$$\lambda = \sum_{i=1}^{n} \lambda_i , \tag{3}$$

where λ_i represents the failure rate of i-th subsystem and n signifies the number of subsystems.

3.3.3 Utilized Failure Rate Values

Table 1 lists the failure rates of the hardware of the subsystems of situation awareness system. Table 2 lists the failure rates of the hardware and software failures of autonomous navigation system and ODD judgement system. If multiple references are cited in Tables 1 and 2, the failure rates were calculated as the average of those reported in the references. With regard to the action system, it is important to consider the failures of the engine/rudder/propeller as well as the control system's failure. However, the probabilities of failure for these components are relatively low according to reference [3], and thus, they were not considered in this study.

3.3.4 Conditional Probability Tables

The conditional probability of the *Mode of Operations* node is elaborated upon. The conditional probability table (CPT) is illustrated in Table 3. The CPT was established in light of the absence of available data. Specifically, in the event that the ODD judgement failure is *Yes*, it is assumed that the possibility of the operation mode being judged as *Autonomous* or *Manual* is equal. In the event that the ODD judgement failure is *No*, the probability of the autonomous operation can be considered as a percentage of the time that internal conditions and external situations are within the ODD of the total voyage time. A larger percentage indicates a wider range of conditions/situations that can be operated autonomously, that is, a higher value of the MASS. Given that the development of MASS is currently underway, the percentage was set at a small value. The probability was set at 0.2.

The configurations of the other nodes' CPTs were adjusted to align with the explanations provided in the previous section.

4. RESULTS & DISCUSSION

4.1. Model Validation

The case was calculated for an operating time of 730 hours, which is equivalent to one month, to validate the BN model. The derived failure probability for collision avoidance was 0.559. In comparison, the failure probability of collision avoidance for MASS was calculated using a Fault Tree (FT) in [3-4] with an operating time of 730 hours. The calculated failure probabilities in [3] and [4] were 0.412 and 0.114 to 0.318, respectively, and varied depending on the operation situations. Despite differences in system compositions, factors considered in the collision model, techniques used (BN and FT), and input failure rates between this study and

Table 1. Failure rates on hardware of situation awareness system.

System		Failure rate (1/hour)	References
Own Ship Info. Acquisition System	GNSS	1.21×10^{-5}	[25], [26], [27]
	Gyro compass	1.41×10^{-4}	[27]
	Speed meter	1.25×10^{-5}	[27]
	Doppler sonar	4.00×10^{-4}	[28]
Other Ships & Drifting Objects Info. Acquisition System	RADAR	2.04×10^{-4}	[4], [27], [29], [30]
	AIS	1.00×10^{-5}	[31]
	Camera1	4.29×10^{-5}	[2], [3], [4], [27], [32]
	Camera2	4.29×10^{-5}	
	Camera3	4.29×10^{-5}	
Environmental Info. Acquisition System	Visibility & weather sensor	1.04×10^{-5}	[3], [33]
	Anemometer	7.61×10^{-6}	[34]
	Current profiler	4.44×10^{-6}	[4]
	Echo sounder	6.15×10^{-5}	[27], [35], [36]
	Wave height meter	1.15×10^{-6}	[37]
Information Integration System	Computer (Hardware)	7.57×10^{-6}	[27], [38], [39], [40]
	ECDIS	2.52×10^{-5}	[41]

Table 2. Failure rates of autonomous navigation system and ODD judgement system.

System				Failure rate (1/hour)	References
Hardware failure	Autonomous Navigation System	Situation Awareness System		1.03×10^{-3}*	-
		Planning System	Computer (Hardware)	7.57×10^{-6}	[27], [38], [39], [40]
		Action System	Computer (Hardware)	6.23×10^{-6}**	[42]
	ODD Judgement System	Computer (Hardware)		7.57×10^{-6}	[27], [38], [39], [40]
Software failure	Autonomous Navigation System, ODD Judgement System		Computer (Software)	4.50×10^{-5}	[40], [43], [44]

* Sum of the failure rates shown in Table 1.
** It is assumed that the failure rate of action system is equivalent to that of heading control system.

Table 3. Conditional probability table of *Mode of Operations*.

	Failure of ODD judgement	
	Yes	No
Autonomous mode	0.5	0.2
Manual mode	0.5	0.8

[3-4], the calculated failure probabilities of collision avoidance are of the same order. This indicates that the constructed BN model was appropriate.

4.2. Results

The calculation results for the case where the operating time is 24 hours are shown below. Table 4 displays the results of the probabilities of failure for collision avoidance, situation awareness, ODD judgment, and action. According to the table, the probability of failure for collision avoidance is 2.66×10^{-2}, and among the other four failure probabilities that are associated with the failure of collision avoidance, the highest probability of failure is for situation awareness.

Table 4. Calculation results of failure probability for each node per 24 hours.

	Probability
Failure of collision avoidance	2.66×10^{-2}
Failure of situation awareness	2.55×10^{-2}
Failure of ODD judgement	1.26×10^{-3}
Failure of planning	8.82×10^{-4}
Failure of action	1.23×10^{-3}

4.3. Sensitivity Analysis

A sensitivity analysis was executed. The objective of sensitivity analysis is to pinpoint the variables responsible for the failure probability of collision avoidance. In this investigation, the failure probability of collision avoidance was determined by changing the failure probability of each node to zero or one. Figure 3 depicts the outcomes of the sensitivity analysis in the form of a tornado chart. The vertical line illustrates each node, and the horizontal line demonstrates the failure probability of collision avoidance when the failure probability of each node was either zero or one. The green and red components for each node represent the increase and reduction, respectively, of the failure probability of collision avoidance from the baseline value. As illustrated in Figure 3, the hardware and software failures of the situation awareness system exhibit high sensitivity to the failure probability of collision avoidance. Specifically, hardware failure of the situation awareness system is noteworthy; if the probability diminishes, the failure probability of collision avoidance is diminished.

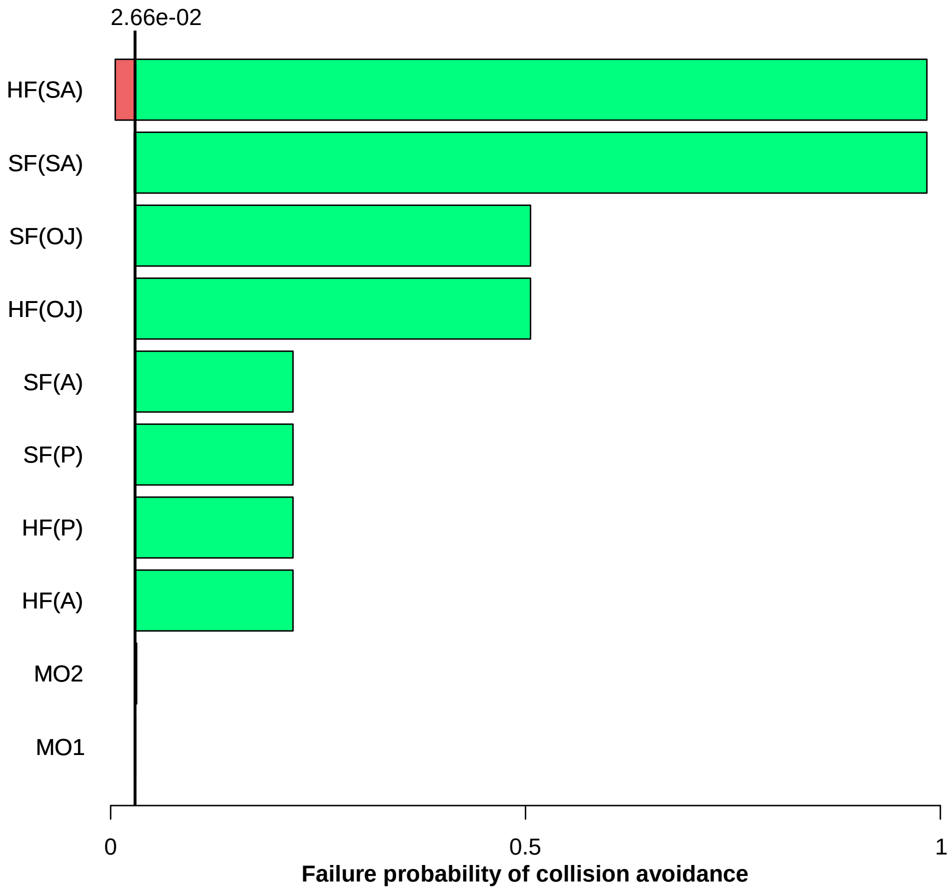

Figure 3. Result of sensitivity analysis.
(HF(SA): Hardware failure of situation awareness system, SF(SA): Software failure of situation awareness system, HF(OJ): Hardware failure of ODD judgement system, SF(OJ): Software failure of ODD judgement system, HF(P): Hardware failure of planning system, SF(P): Software failure of planning system, HF(A): Hardware failure of action system, SF(A): Software failure of action system, MO1: Mode of operations is autonomous when the failure of ODD judgement is yes, MO2: Mode of operations is autonomous when the failure of ODD judgement is no.)

4.4. Evaluation of Redundancy

Redundancy is an approach used to address hardware failures. To evaluate the effectiveness of this approach, we conducted an analysis to estimate the decrease in the probability of failure for collision avoidance when each subsystem of the situation awareness system was duplicated. The results of this analysis are presented in Table 5. As indicated in Table 5, the subsystem that experienced the greatest reduction in failure probability was doppler sonar, followed by RADAR.

Table 5. Estimation results of effectiveness of redundancy of each subsystem of situation awareness system.

Duplicated subsystem	Failure prob. of collision avoidance	Ratio to original one	Duplicated subsystem	Failure prob. of collision avoidance	Ratio to original one
GNSS	2.62×10^{-2}	0.99	Camera3	2.55×10^{-2}	0.96
Gyro compass	2.32×10^{-2}	0.87	Visibility & weather sensor	2.62×10^{-2}	0.99
Speed meter	2.62×10^{-2}	0.99	Anemometer	2.63×10^{-2}	0.99
Doppler sonar	1.72×10^{-2}	0.65	Current profiler	2.64×10^{-2}	0.99
RADAR	2.17×10^{-2}	0.82	Echo sounder	2.50×10^{-2}	0.94
AIS	2.62×10^{-2}	0.99	Wave height meter	2.65×10^{-2}	1.00
Camera1	2.55×10^{-2}	0.96	Computer (Hardware)	2.63×10^{-2}	0.99
Camera2	2.55×10^{-2}	0.96	ECDIS	2.59×10^{-2}	0.97

4.5. Future Task

This study made several assumptions about the developed BN model. Further research should be done to consider the following:

- The likelihood of manual operation failing to be switched to, although this study assumed successful manual operation.
- The relationships between each item of ODD and failures of situation awareness, planning, and action. Although this study ignored these relationships, they should be considered. For example, the following relationships should be handled in the conditional probability table for each node:
  - In the case of dense fog, the failure probability of situation awareness is high,
  - In the case of high congestion, the failure probability of planning is high,
  - In the case of rough seas, the failure probability of action is high, etc.

5. CONCLUSION

This study aimed to estimate the likelihood of collision avoidance failure for the MASS by developing a BN model that takes into account the ODD. The BN model was validated by comparing its results with those of previous studies, and it is determined that the constructed BN is appropriate. A sensitivity analysis was also conducted, revealing that the hardware and software failures of the situation awareness system are highly sensitive to the failure probability of collision avoidance. Additionally, the failure probability of collision avoidance was presented when each subsystem of the situation awareness system was duplicated, and it is found that the doppler sonar had the greatest reduction, followed by the RADAR as the second highest. In our future work, we will improve the developed BN model to consider more complex situations, considering the abovementioned points.

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