UNDERSTANDING AND MANAGING SAFETY CHALLENGES IN SMALL FISHING BOATS IN REMOTE COMMUNITIES

By

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Dedication

To God Almighty, the Regional Maritime University, and my brother, Mr. David Cudjoe Domeh.

You have always worked for my good.

ABSTRACT

This thesis studied the development of probabilistic safety assessment (PSA) tools and methodologies for small fishing boats (SFB) use. The tools and methodologies developed were applied to case study scenarios, and they showed high prospects in identifying safety challenges when SFBs are fishing. Because, in most cases, SFBs in remote fishing communities lack adequate safety equipment to prevent accidents at sea, the PSA tools and methodologies are primarily aimed at these communities.

The SFB size in the marine environment, amidst harsh sea conditions, endangers fishers' safety during fishing voyages. Lapses that may be present in the SFB safety regulation and monitoring at individual country levels allow some SFBs not to have onboard the appropriate equipment to understand, monitor, and manage the safety challenges encountered. These safety challenges are rooted in the accidents SFBs encounter.

Although man or person overboard, main propulsion system failure, loss of situational awareness, and loss of stability were frequent in most SFB accident and incident databases, the research on these mostly led to only uncovering their causation factors. Linking these factors and their incidents to yield PSA tools capable of explaining how the incidents occur was yet to be done. The quantitative risk analysis (QRA) and Bayesian network (BN) modelling were identified through a literature review as rigorous methods for developing PSA tools and methodologies, so they were applied accordingly to the named accidents and incidents.

The novel contributions the thesis made to the body of knowledge in SFB safety and maritime research, in general, are (1) the development of a unique methodology called the goal-directed risk identification technique (Goal-DRIT) for listing risk factors in highly complex systems; (2) naïve

Bayes' application to fill conditional probability tables (CPT) with probability scores; (3) development of a rule-based system for guiding subject-matter experts in probability elicitation exercises, to minimise variability in experts scores and (4) development of independence of causal influence model using De Morgan gates for both qualitative risk analysis and probabilistic risk analysis.

The thesis study is recommended for the fishing industry (particularly the SFB sector), national and international maritime administrations, and SFB safety researchers.

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NOMENCLATURE

AFI	Artisanal fishing industry
B	Centre of buoyancy
B1	Centre of buoyancy
BN	Bayesian network
BT	Bow-tie
CFI	Commercial fishing industry
CPT	Conditional probability tables
DMS	Data management system
ETA	Event tree analysis
FAO	Food and Agriculture Organisation of the United Nations
FTA	Fault tree analysis
FTD	Fault tree diagram
G	Centre of gravity
GBP	Great Britain Pounds
GM	Transverse metacentric height (m)
GZ	Righting lever or arm (m)
GDTA	Goal-directed task analysis
Goal-DRIT	Goal-directed risk identification technique
GRT	Gross registered tonnage
HRCO	Hierarchical risk control option
ILO	International Labour Organisation
IMO	International Maritime Organisation
ISO	International Organisation for Standardisation
K	Keel
KG	Centre of gravity height above the keel (m)
LFV	Large fishing vessel
LoS	Loss of stability
LRF	Lower risk factor
M	Transverse metacentre
m	Metre
MAS	Mission abort strategies

MES	Mutually exclusive scenario
MFV	Medium fishing vessel
MIS	Mutually inclusive scenario
MIT	Maintenance interval time
MOB	Man overboard
MOP	Man overboard occurrence probability
MPC	Most probable configuration
MPS	Main (or marine) propulsion system
OCS	Operational conditions at sea
OOBN	Object-oriented Bayesian network
OOP	Object-oriented programming
OOW	Officer-of-the-watch
OREDA	Offshore reliability data handbook
P(A)	Probability of the event, "A" in the bracket
PRA	Probabilistic risk assessment
PSA	Probabilistic safety Analysis/Assessment
QBN	Qualitative Bayesian network
QRA	Quantitative risk assessment/analysis
RAC	Risk acceptance criteria
RA_w	Risk awareness
RBM	Risk-based maintenance
RCA	Risk control analysis
RCG	Risk control group
RF	Risk factor
RIF	Risk influencing factors
RM	Righting moment (tonne-m)
SA	Situation (or situational) awareness
SEA	Systems engineering approach
SFB	Small fishing boat
SFV	Small fishing vessel
SGISc	Second Generation of Intact Stability Criterion
SME	Subject matter expert

SOLAS	Safety of life at sea
SSF	Small-scale fisheries
STCW	Standards of Training, Certification, and Watchkeeping Convention
UK	United Kingdom
URF	Upper risk factor
US$	United States Dollars
WL	Waterline
$\bar{A}$	Complement of A
b_1, b_2	BARRIER gates
c_1, c_2	CAUSE gates
Con	Consequence impact
$Cost_B$	Breakdown repair cost
$Cost_C$	Cost of damages done by the failure to items and residential buildings
$Cost_{clean}$	Cost to cleanup the damage
$Cost_D$	Cost of damage to the environment due to the failure
$Cost_d$	Per hour cost for equipment downtime
$Cost_E$	Environmental impact cost
$Cost_H$	Cost due to health loss
$Cost_{h1}$	Cost of being unwell
$Cost_{h2}$	Cost of ill health
$Cost_{h3}$	Cost of hospitalisation
$Cost_{h4}$	Cost of disability
$Cost_{h5}$	Cost of life
$Cost_I$	Inspection cost
$Cost_{ip}$	Inspection cost per hour
$Cost_{lfh}$	Per hour rate for not fishing
$Cost_M$	Maintenance cost
$Cost_p$	Cost due to loss of fishing
$Cost_{plant}$	Cost of plant items damaged
$Cost_R$	Cost for restoring the environment to the original state
$Cost_{Res}$	Cost of residential buildings damaged
e	Child node probability in De Morgan gates
F_r	Factor relating to the cleanup time

i_1, i_2	INHIBITOR gates
$life_{h1}$	Number of people unwell
$life_{h2}$	Number of people ill
$life_{h3}$	Number of people hospitalised
$life_{h4}$	Number of people with disabilities
$life_{h5}$	Number of people lost
M_{staff}	Per hour charge for maintenance
N_{CPT}	Number of probabilities expected for a child node
n_p	Number of parent nodes connected to the child node
P_1	Probability of the event, "being unwell" occurring
P_2	Probability of the event, "ill health" occurring
P_3	Probability of the event, "being hospitalised" occurring
P_4	Probability of having someone disabled
P_5	Probability of losing a human life
P(A|B)	Probability of "A" given that event "B" has occurred
P_{clean}	Probability of spillage of contamination occurring
P_{plant}	Probability of plant items being damaged
P_{Res}	Probability of damaging a residential building
P_R	Prior failure probability
P(t)	Annual failure probability
P_U	Updated failure probability
r_1, r_2	REQUIREMENT gates
S_e	Cost for specialised equipment or personnel hired
S_p	Cost for spares and replacement parts
t	Time in years
T_{insp}	Inspection time

T_{repair}	Time to repair faulty equipment	$\cap$	Intersection	λ	Failure rate
		$\cup$	Union		

CHAPTER 1

1.0.General Introduction

1.1. Background to the Thesis Study

Small fishing boats (SFB), also called small fishing vessels, are the marine vehicles the small-scale fisheries (SSF) sector uses for fish harvesting, whether inland or in territorial marine waters. It could be said, then, that the recent successes the SSF sector has been seeing are primarily driven by SFB operations [1—4]. In Ayilu et al. [5] and Mills et al. [6], the SSF produces nearly one-fourth of the world's fish consumption needs. Additionally, the SSF employs approximately 88% of the global workforce in the commercial fishing industry. In most developing countries, the annual fish production by SSF is more significant than that from the large-scale fisheries sector [6]. Also, in these developing countries, the SSF dominates over large-scale fisheries when considering inland water fishing [6]. A significant portion of the SSF workforce is involved in operating SFBs. Therefore, it can be inferred that SFB is a vital member of the SSF sector and contributes significantly to its growth.

In addition, Figure 1.1 shows other popularly known benefits the SSF sector gives [1—6]: earns foreign exchange for nations through the sale of fish and fish products, empowers women by making them the key partners, and improves the standard of living in fishing communities amidst helping eradicate poverty among the community inhabitants.

SFBs, which are the backbone of the SSF sector, vary in the broad areas shown in Figure 1.2. Typically, the length overall of SFBs, as discussed in many fishing industry literatures, including Zytoon and Basahel [7] and Mendo et al. [8], do not exceed 12 m. However, length overalls of up to 15 m and 18.50 m were reported by Scarponi [9] and Kim and Yeo [10]. Also, because the 1966

Load Lines and 1976 Safety of Life at Sea (SOLAS) Conventions (including their revisions) of the International Maritime Organisation (IMO) only regulate fishing vessels with a length overall of at least 24 m, some literature classifies fishing vessels of less than 24 m length overall as SFBs. While these variations in the length present challenges when one wants to define an SFB based on the length, the main observation to be made here is that the length measurements indicate that the SFB is a small marine vessel operating in the vast ocean.

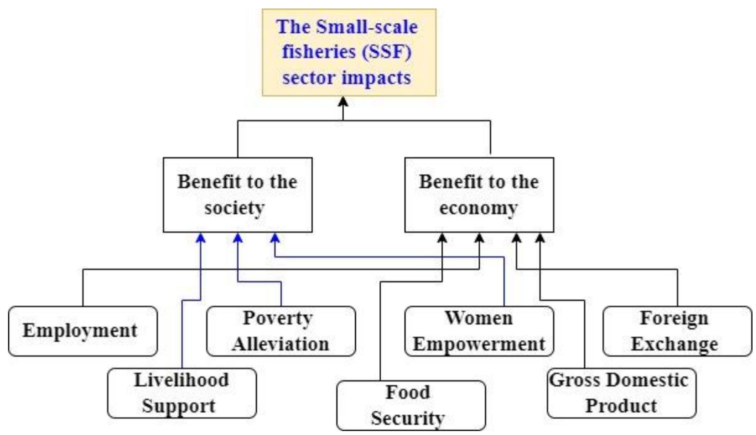

Figure 1.1. Some well-known benefits derived from small-scale fisheries [1—6].

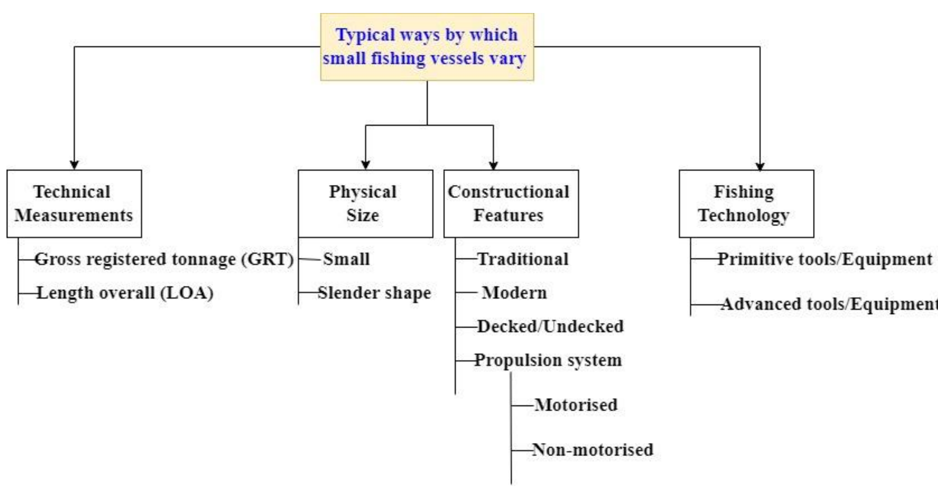

Figure 1.2. Main areas of variation in small fishing boat types [7—14].

The gross registered tonnage (GRT) measures a vessel's internal space capacity. For an SFB, usually, GRT is just a few hundred tons [11—14]. Hence, fishers' boats are quickly filled up, especially in times of abundant harvest. In such harvest periods, the tendency to overload the boat is also high, judging from the small GRT of the SFB. When overloading happens, the crew risks capsizing or sinking their boat. Despite the limitations imposed on SFBs due to the small-size GRT and length overall, the Food and Agriculture Organisation (FAO) of the United Nations estimated that as of 2020, at least 81% of the 4.1 million fishing vessels existing globally were SFBs [15]. These SFBs' had overall length less than 12 m, showing that, apart from being a key SSF sector driver, SFB also dominate the commercial fishing industry.

From a constructional design perspective, SFBs may be modern or traditional, as shown in Figure 1.2. In modern SFBs, scientific principles govern the design and construction of boats [16, 17]. On the other hand, traditionally built SFBs rely on boat-building experience handed over to fishers by their forefathers. The lack of application of scientific methods when SFBs are built traditionally makes these boats liable to accident scenarios at sea. Sometimes, water seeps through holes in the underwater hull into the boat, resulting in flooding, which could lead to sinking or capsizing.

Most traditionally built SFBs do not have a top covering to protect fishers from adverse weather conditions [18—20]. Flooding is most likely to occur in such boats when it rains heavily during fishing expeditions. In spite of these and other similar safety challenges, building SFBs by the traditional approach continues, especially in remote fishing communities. The main reason behind the choice of traditionally made SFBs in such communities is affordability. The cost of modern SFBs is too expensive for fishers in these communities. As a result, they prefer the traditionally built SFBs, which are believed to be less costly than the modern SFBs.

The non-decking nature of most traditionally built SFBs, typically the artisanal fishing boat class, presents further safety challenges. Any damage to the hull immediately exposes the boat's content and crew to the marine environment [18—20]. The consequences could be grave since person-overboard, hypothermia, and drowning are possible. Traditionally built SFBs, despite their shortcomings, form a significant portion of the 4.1 million estimated fishing vessels globally. They are vital members of the SSF sector, especially in the coastal West African sub-region and fishing communities of other developing countries [15, 21].

Another distinguishing factor among SFBs is the propulsion power used. As Yaakob et al. [11] and Zhao and Jia [22] noted, some SFBs use outboard motors or small-size inboard engines to propel their movement in the water, and so are called motorised SFBs. Other SFBs, however, especially those operating close to the shore in the artisanal fishing fleet, are usually unmotorised [21, 23]. Such SFBs are propelled manually by the fishers using oars. Manual propulsion can be strenuous, especially in rough sea-state, negatively impacting fishers' health and safety. In that case, the motorisation of SFBs is advantageous. However, the outboard motors or inboard engines must be maintained regularly to keep them operational. When engines malfunction, the propulsion system fails, leaving an SFB stranded at sea. Propulsion system failures resulting in a boat being stranded, environmental pollution, and sometimes vessel capsizing or sinking are common in SFBs [24—29].

Lastly, inferring from Figure 1.2 again, it is also possible to differentiate among SFBs based on the tools and equipment—fishing technology—employed by fishers for harvesting fish. Broadly, the fishing technology aboard fishing vessels may be classified as primitive and advanced. Primitive tools and equipment for harvesting fish are simple to operate and usually include fishing nets, hooks and lines, and simple traps set to catch fish. Advanced fishing technology, however, can be complex due to the sophisticated machinery or equipment employed in harvesting fish. For example, while a fishing crane (an advanced fishing technology) may be operated to haul in fishing gear, the primitive technology would require fishers to manually pull the gear with fish into the

SFB. Advanced technology is used aboard modern SFBs, while some traditionally built SFBs rely solely on primitive tools for fish harvesting.

Meanwhile, Uğurlu et al. [30] have shown that fishing tools and equipment have injured fishers irrespective of the vessel or fishing technology type. In some cases, accidents related to fishing equipment and tools are so severe that fishers are hospitalised or die [31]. Common accidents in this category are struck by fishing gear and caught up in fishing gear [31—33]. With the appropriate fishing tools and equipment (also called fishing gear), fishers use various methods to harvest fish. The FAO identifies the fishing gear types in Table 1.1 as the nine fishing methods in practice for fish harvesting [34]. When a fishing vessel is observed closely, whether SFB (modern or artisanal) or large fishing vessel, the way the fishing gear aboard is operated would fall under one of these nine areas. The operating procedures of the fishing gears are described briefly in Table 1.1; a detailed description can be found in FAO [34]. Here, the objective is to highlight that fishing gears are crucial to studying SFB safety. This is because Roberts [31], Uğurlu et al. [30], and Özaydın et al. [33] recorded fisher injuries and deaths caused by engaging fishing gears in the ways described in Table 1.1.

It can be inferred from the earlier paragraphs that differentiating among SFBs using the parameters in Figure 1.2, can be challenging. The fishing gear types and how they are used for fish harvesting do not vary much among SFBs and large fishing vessels too. Therefore, FAO [34] encourages fishing vessels to be differentiated into falling gear, trawl, seine net, gillnet and entangling net, hook and line, lift net, surrounding net, trap, and dredge operated vessel, as described in Table 1.1. The different ways of categorising SFBs have also shown that when regulating or managing safety in SFBs, the areas of consideration are broad and must include limiting the load carrying capacity, suitable constructional features, machinery maintenance requirements, safe operation of fishing gears, and the boats' adaptability to the marine environment.

Table 1.1. Fishing gear classifications and brief operational description.

Number	Gear type	Brief description of gear operation
1	Surrounding net	The gear is a long net framed by ropes and harvests fish by encircling a group of schooling fish.
2	Seine net	Similar to the surrounding net, only that seine net can be cone-shaped, and have both head-and-foot ropes; also catches fish by encircling and herding.
3	Trawl	It is a cone-shaped netting that is towed by one or two boats, to harvest fish by herding and sieving.
4	Dredge	It is cage-like, with a scraper blade, which is moved to scoop up fishes on the sea bottom for harvesting into the cage.
5	Lift net	A type of net built onto a frame; when lowered into the water, fishes entre the area above, and when the net is lifted, the fishes a trapped and harvested.
6	Falling gear	Like a basket, this gear is push down to harvest fish under it.
7	Gillnet and entangling net	These are long rectangular wall netting used to harvest fish by entrapping, gilling, snagging, or wedging.
8	Trap	A stationary structure mounted on the seabed into which fishes are pushed by sea current or guided for trapping and harvesting.
9	Hook and line	The use of baited hooks to catch fish; a hook-and-line gear may have one or many hooks on the line.

The present section of the thesis introduction situated the SFB within the SSF sector. As the driver of the sector, SFB has helped SSF to deliver various benefits: food security [35, 36, 37], socio-economic growth in fishing communities [35, 38], increase in gross domestic product [36—39], job creation and employment [40, 41], and poverty alleviation [35, 40]. The present section also discussed the variations in SFBs based on size, fishing gear, fishing method, constructional features, and boat propulsion system mechanism. This discussion was done alongside the safety challenges that emerge when the variations are examined, considering the vast marine environment, harsh sea conditions, human behaviours, and technical systems malfunctions.

In every industry, regulations provide firsthand control measures to tackle safety challenges. The MSC.1/Circ.1182/Rev.1 and SOLAS III/17-1 of the IMO entreats vessels to have onboard the human and technological capacities to address safety challenges. Additionally, the Standards of Training, Certification, and Watchkeeping (STCW-F) Convention of IMO urge fishing vessel masters to conduct familiarisation tours of the safety systems and emergency procedures aboard their vessels for crew members as another measure towards keeping safety challenges under check. Moreso, the International Labour Organisation's (ILO) Code, "Accident Prevention on board ship at Sea and in Port", and the International Organisation for Standardisation's (ISO), ISO/PAS 211195:2018 (en) (specifying the minimum requirement expected of shipboard equipment) gives further measures that ensure safety challenges in line with shipboard equipment are kept minimum, if not avoided entirely.

Although all these regulations also apply to fishing vessels, only those of length 24 m or more are targeted [31, 33]. Hence, internationally, SFBs appear to be under-regulated. Individual nations have their own regulations to keep safety challenges in SFBs under check since these vessels operate in territorial waters. Based on the discussions, the following observations are evident:

1. The SFB plays a central role in the flourishing of the SSF sector.
2. Some safety challenges in SFB are systemic. The challenges are infused during the design and construction phases, especially in the traditionally built SFB.
3. Typically, accidents aboard SFBs are caused by incidents such as the ones below;
    - Machine failure—e.g., the outboard motor is faulty at sea;
    - Human factor—e.g., boat sinking due to hauling in an overload of harvested fish;
    - The marine environment—e.g., boat flooded from rainwater due to the absence of top cover for the boat.

1.2.The Research Problem

This section of the thesis discusses the safety problems in SFBs to answer the following questions: (1) What are the major accidents confronting SFBs, (2) Which SFB accidents or incidents have not been addressed adequately, and (3) What are the safety challenges underpinning typical fishing incidents?

Roberts [31] and McGuinness et al. [32] identified SFBs as one main area contributing significantly to the high fatal rates attributed to the commercial fishing industry. Between 2000 and 2009, it is mentioned in Myers et al. [42] that 116 SFB fishers died due to fishing accidents in the Gulf of Mexico. The 116 deaths come to approximately one fisher death per month. A similar situation was realised for the Spanish-flagged SFBs between 2004 and 2007. Out of 46 fishers, 32 died (or were missing) due to SFB capsize, as recorded in Mata-Álvarez-Santullano and Souto-Iglesias [43, 44].

More recent data collected from the Global Integrated Shipping Information System, the Marine Accident Investigation Branch, the European Maritime Safety Agency, the Australian Transport Safety Bureau, and the Transportation Safety Board of Canada by Uğurlu et al. [30] revealed 126 fisher deaths out of 83 SFB accidents between 2009 and 2018. Apart from the deaths, there were 87 cases of vessel loss too. SFB fisher-injury incident is also on the rise by 25 to 50 times more than onshore workers in some European and North American countries, as Jensen et al. [45] discovered.

The conclusion one could draw from the above discussions is that safety challenges are still present aboard SFBs. The safety challenges are characterised by different accidents, which in general terms, are either vessel-related (i.e., when the accident occurs to the SFB structure or onboard machinery, like, capsize or collision) or person-related, the accident occurs directly to a fisher [30, 31]. The discussion from the earlier paragraphs shows that these safety challenges lead to fisher deaths, injuries, and vessel losses, making the fishing profession aboard SFB dangerous and life-threatening, as Jezewska et al. [46] recounted.

Previous fishing safety research prioritised safety challenges mitigation aboard SFBs. However, the majority of these studies focused on boat capsize [42], sinking [45], grounding [47], and collision [30]. Although the grave consequences of these accidents justify their attention, other similarly dangerous accidents are yet to be addressed. The man overboard (MOB), a person-related accident type, is known to have caused many fisher deaths in SFBs, making it a dangerous SFB accident [30]. A MOB is said to occur when a shipboard crew unintentionally falls from the ship into the sea or ocean, leading to the conduction of a search and rescue operation [30, 33, 48]. Feraru et al. [48] mentioned that in the year 2016 alone, 284 fishers became MOB victims in a fisheries sector.

Özaydın et al. [33] addressed some person-related accidents in Turkish fishing vessels. The study showed that MOB is a safety challenge, particularly for SFBs. This is because MOB frequency was the highest among the investigated accidents—Jamming (i.e., fisher stuck or entangled in a fishing gear), "Hit by an object", and MOB—for vessels under 24 m in length overall. The "Hit by an object" instead occurred more in large fishing vessels. The MOB (66 accidents) appeared highest again, when Özaydın et al. [33] analysed the data for both SFB and large fishing vessel types in the Turkish fishing industry. It was followed by "Hit by an object" (65 accidents) and jamming (42 accidents), last. That notwithstanding, the ratio of seven fisher deaths to ten MOB accidents can be estimated from the study undertaken by Uğurlu et al. [30] for SFB accidents investigated between the 2008 and 2018 fiscal years.

The above statistics show that MOB is a prime safety challenge. Yet studies such as Katsamenis et al. [49], Feraru et al. [48], and Mou et al. [50] aimed at alleviating MOB, focused on emergency recovery systems design, developing technology for identifying a MOB victim in seawater, and performing search and rescue operations. Although these methods are MOB mitigation measures, because they are only active after a person has fallen into the water, they are primarily post-accident mitigation methods. Such methods, even though good at avoiding some accident consequences, particularly fisher death, lack proactiveness and cannot identify safety challenges ahead of time, to prevent the accident from happening foremost.

Like MOB, the main propulsion system (MPS) failure is another common accident occurring in SFBs but has not received much attention by way of prevention. When MPS failure occurs in SFBs, the fishers onboard are left at the mercy of the sea state, which may cause a boat to drift to unknown destinations quickly due to the small size of such boats [51]. The situation often evolves into "fisher lost at sea" cases or boat capsize and drowning accidents [52, 53], which presents a danger to the SFB fisher's life. Weng and Yang [51] and Li et al. [52] identified machinery faults as the causality for MPS failure, with around a 37.6% occurrence rate in most ship accident databases. Behrendt and Rajewski [53] and Jezewska et al. [46] recount the 225 MPS failures in the Polish fishing fleet operating in the Baltic Sea from 1999 to 2007. More than forty-two of the 225 MPS failures occurred in SFBs and were due to faults from machinery within the MPS: main engine, auxiliary systems, shafting, and the propeller. MPS failure refers to the inability to propel or move a ship while underway due to a fault or faults from a piece of machinery within the ship's propulsion system.

While it is obvious that proper maintenance of the MPS would resolve the failure incident, the challenge is that SFB fishers are always fishing, making it difficult for them to set aside time to do regular maintenance work. Often, the fishers do well at maintaining their fishing gear promptly, but the same cannot be said for the MPS due to the limited budget for maintenance works. As Wang et al. [54] and Jezewska et al. [46] noted, the situation has left some SFBs stranded before at sea, and in adverse sea state, the situation has evolved into collision and capsize accidents. Fishers have lost their lives due to these occurrences caused primarily by MPS failure.

To address the safety challenge with MPS maintenance, an optimised maintenance plan must be developed for SFBs. The maintenance plan must consider the various MPS machinery and their components and the economic as well as other interests of fishers that conflict with maintenance needs in SFBs. Ultimately, the optimised maintenance plan must suit the allocated maintenance budget and offer minimal or no interruption to fishing expeditions.

The loss of situation (or situational) awareness is another safety challenge researchers have noticed as a contributing factor to the prevalence of accidents in SFBs. Situation awareness (SA), as defined by Sharma et al. [55], is the universal terminology to describe a person's continuous comprehension of an ongoing incident. Hence, in the event the person is unable to follow up with the incident's evolution, a loss of SA has occurred. Roberts [31] and Uğurlu et al. [30] mentioned that the loss of SA has resulted in many SFB accidents. Meanwhile, preventing the loss of SA requires using equipment to gather the necessary information [55]. As mentioned in Section 1.2, ship safety legislations and regulations from the IMO strictly apply only to vessels of 24 m in length or more. The vessels are mandated to have the necessary equipment to facilitate their SA while at sea. Due to this, virtually all large fishing vessels and shipping vessels have onboard appropriate instrumentation to collect the information needed for SA monitoring.

Unfortunately, since SFB operations are not supervised directly by IMO, some SFBs (especially the traditionally built ones) are not adequately equipped with the necessary instrumentation to avoid loss of SA. Thorvaldsen [56] discussed how SFB fishers use their "common sense" judgement to prevent the loss of SA and make decisions on safety when fishing. The fishers, undoubtedly, know about sea conditions and how it affects their fishing operations. However, "common sense" used to create awareness of ongoing situations can prove unreliable, especially when competing goals are at stake. In such instances, SFB fishers may experience loss of SA [55], leading to an accident. Therefore, loss of SA is a safety challenge in SFBs, and preventing its occurrence during fishing expeditions, is essential to mitigating accident occurrences at sea. Pre-accident monitoring tools development could be helpful since tools like that would assist in tracking SA of accidents, thereby avoiding a loss of SA and encouraging proactive assessment of a fishing accident occurrence likelihood.

Davis et al. [57] also identified the loss of stability as another safety challenge requiring redress. The loss of stability is the inability of a heeled ship to return to the upright position due to a reduction in metacentric height [43, 44, 57]. Loss of stability is a precursor to vessel capsizing, a major SFB sector accident. Then, when the loss of stability is well understood and adequately controlled, that will be a significant step towards remedying vessel-capsize accidents. In the risk analysis literature [30, 43, 44, 57], it is common to see the loss of stability mentioned as a root or intermediate cause of SFB accidents. However, when critically examined, loss of stability is an incident with several risk influencing factors (RIF) due to the direct impact that loads (both onboard and in the marine environment) have on ship stability.

Not much is known in the risk assessment literature regarding studying the loss of stability as a top incident to uncover the root causes involved. A risk-based tool developed for the loss of stability, as was done by Uğurlu et al. [30] for fishing vessel sinking and collision, would assist in consolidating the RIFs of the incident and probabilistically, estimate the likelihood of loss of stability when an SFB is on the voyage. Earlier paragraphs mentioned the inadequacy of safety monitoring equipment aboard some SFBs. Hence, developing such risk-based tools could assist in addressing the safety challenges posed by the non-availability of such equipment, especially in traditionally built SFBs.

In concluding this thesis section, let's answer the questions asked at the beginning. The incidents, vessel capsize, sinking, grounding, fire and explosion, collision, MOB, MPS failure, loss of SA, and loss of stability, are some significant accidents confronting SFBs. Among these incidents, the present section discussion points to the MOB, MPS failure, loss of SA, and loss of stability, as the incidents needing further redress due to their continuous occurrence and the opportunities that exist to improve their safety management further, as illustrated in Figure 1.3. The figure summarises the incidents needing further attention, their safety challenges and the mitigation strategies proposed to address the incidents. The methods and procedures followed in developing the proposed mitigation strategies are introduced in the next section.

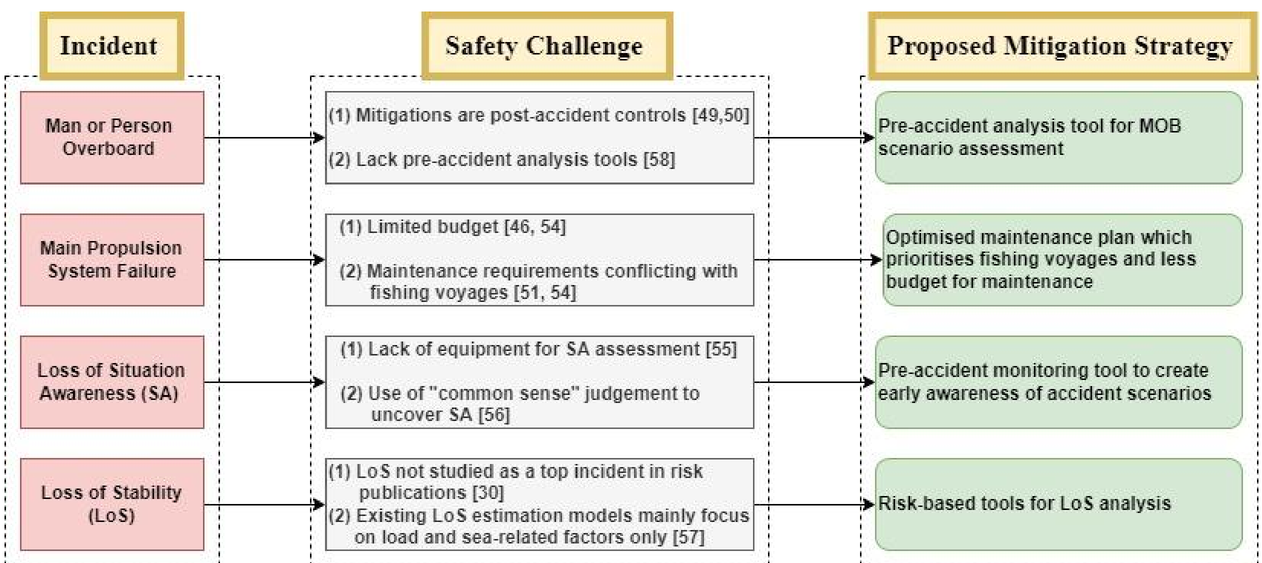

Figure 1.3. The incidents identified for SFB safety assessment and management.

1.3. The Research Aim, Objectives, and Questions

With the incidents of interest identified (see Figure 1.3), the purpose of the thesis research is to develop probabilistic safety assessment (PSA) tools through the method of quantitative risk analysis (QRA) in aid of understanding how these incidents occur and the management of the associated safety challenges. A PSA tool is a pre-accident analysis tool that probabilistically captures an incident's risk influencing factors (RIF) for the incident's likelihood estimation [59]. As a result, a PSA tool is also a data-driven decision-making tool. It can learn the causal scenarios under which the incident has a higher chance of occurrence [59, 60].

The QRA, discussed in more detail in the next section, is the method to develop a PRA tool [61, 62]. Both QRA and PRA have applications in the maritime [61—64] and fishing [30, 33] industries but limited applications in SFB particularly. Therefore, the thesis research sought to demonstrate how valuable QRA and PRA could be to the SFB, especially in safety tools development, since the discussions in Section 1.2 point strongly to inadequate safety equipment for use in these boats. An area within the SFB sector that suffers most from the issue of inadequate safety equipment is the remote fishing communities. The boat types these communities use, and the fishers' education level pose challenges in installing state-art-of-the-art safety systems and equipment aboard [21, 56, 57]. Hence PSA tools development would be of great use to such communities. To achieve the research purpose, the following specific objectives were tackled:

1. Risk analysis of man overboard scenario is a small fishing vessel;
2. A novel methodology to develop risk-based maintenance strategies for fishing vessels.
3. An operational risk awareness tool for small fishing vessels operating in harsh environments;
4. Loss of stability risk analysis in small fishing vessels.

The main steps followed in tackling the objectives are (1) define the appropriate RIFs for the incident under study; (2) use the total probability theorem, conditional probability theory, joint probability distribution, and Bayes' theory to probabilistically capture the RIFs into building the PSA tool; (3) using the tool, perform the following analyses: (a) forward analysis to estimate the incident's likelihood score, (b) sensitivity analysis to identify the RIFs contributing most to the likelihood score, (c) backward analysis through probability updating to know the new state scores for root RIFs when the incident's likelihood score is 100%; and (4) develop risk control strategies to mitigate and manage the dangerous RIFs and accident scenarios realised through the analysis. The research questions guiding the thesis study are as follows:

1. What are the RIFs for the incidents under study?
2. How must RIFs be arranged to form a coherent accident network for PSA tool development?
3. How is uncertainty in data-driven models like the PSA tool handled?
4. How could the variability in scores produced by subject-matter experts during PSA tools development be minimised?
5. Which maintenance plan would be flexible towards increased fishing voyages while avoiding abrupt maintenance problems with limited budget requirements?
6. How could one select, among several risk control measures, the most effective for accident scenario mitigation?
7. How could fishers' knowledge of the observations at sea be synthesised to produce a PSA tool adaptable to SFB fishers' ability to monitor accident scenarios during fishing expeditions proactively?

8. When is the risk estimate from a PSA tool small (so the envisaged danger could be ignored) or large and needs immediate redress?
9. How can the probability elicitation task to fill conditional probability tables (CPT) with scores be made less burdensome during PSA tools development?
10. What quality checks must be done to assure the validity of results from a PSA tool?

1.4. Research Methodology

The current section presents a high-level description of the methods applied in achieving the thesis purpose and specific objectives. The section broadly discusses QRA and Bayesian network (BN), the two main methods the thesis applied. The QRA provided the general research framework for the thesis, and the BN is the method followed to develop the PSA tools.

1.4.1. Introduction to quantitative risk analysis

A QRA is a rigorous quantitative assessment method that gives an accident or incident under study a numeric value called risk, defining the degree of danger the accident or incident poses. The estimated risk is the product of the probability of occurrence and the consequence impact, should the incident or accident happen. Qualitative risk analysis is closely related to QRA, where the assessment uses descriptive measures instead [36, 64, 65]. Although both assessment methods are for analysing an incident's risk, the QRA is more detailed than the qualitative one. The reason is that in QRA, numeric measurements are required for the incident occurrence probability and its consequence should an accident occur [61, 62, 66]. In qualitative risk analysis, however, the numeric values are replaced with descriptive scales such as high, medium, or low risk.

The numeric risk in QRA then provides objectivity, although that comes with more computational work and a longer time for the analysis. Meanwhile, because the objectivity and detailed work involved boost confidence when communicating risk and improve decision-making capability, QRA is worth doing [63, 67]. It is often chosen over qualitative risk analysis, especially in cases of uncertainty measurement. In PSA, uncertainty exists as epistemic and aleatory. Epistemic uncertainty in PSA tools is due to insufficient numeric data for the incident's RIFs, and the lack of knowledge about the complete RIFs to describe the incident in totality [68, 69]. On the other hand, aleatory uncertainty refers to the uncertainty in the result of the tool caused by the probabilistic variations in the random events influencing the incident being studied [68, 70].

A PSA tool must address these uncertainties sufficiently well if the tool is to give adequate information for decision-making purposes. Therefore, qualitative risk analysis is usually preferred for smaller projects or less complex incidents with known hazards [64].

1.4.2. The conceptualisation of quantitative risk analysis

There are various ways to conduct QRA, but when examined carefully, all the steps could be categorised into the core activities of hazard assessment, risk analysis, and risk management. The variety in methods for QRA also adds to its admiration as a flexible approach to safety engineering. Figure 1.4 is a framework for the QRA approach adopted by the thesis study. In addressing the specific objectives the thesis defined, Figure 1.4 played a pivotal role. In the framework, the core QRA activities mentioned earlier are in rectangles, the typical tasks to achieve each activity are in rounded rectangles, and circles show the target goal for each step in the QRA.

For one to consider a QRA study, a dangerous situation or safety challenge, generally called a hazard, has been noticed or is being perceived. Hence, the first step to kick start a QRA study is to assess the hazard for known and unknown accidents, scenarios, and root causes. That way, the incident(s) to focus on will be defined.

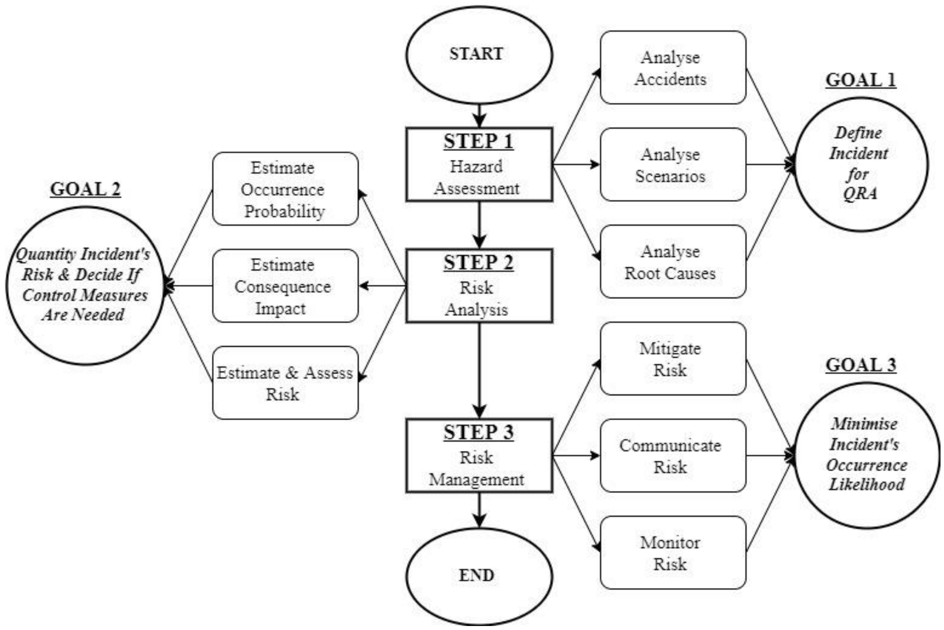

Figure 1.4. The proposed framework to do quantitative risk analysis (QRA).

The choice incident, among others, could be selected because it occurs too frequently, the economic burden or accident consequences associated with its occurrence are unbearable, or the uncertainty it has is too high. After the first goal is achieved, it is time to estimate the incident's chances of happening and the numeric value of the consequences should the incident happen. Equation (1.1) is used next to combine the occurrence likelihood and the consequence estimates into the risk.

$$Risk = occurrence\ probability \times consequence\ impact \tag{1.1}$$

The risk must be assessed to know whether there is a need for risk mitigation to prevent the incident from happening, Goal 3. In mitigating risk, control measures are needed, as well as creating risk awareness through risk communication and monitoring. These three tasks constitute the risk management phase for the incident under consideration. All things being equal if the phases tasks are executed and the expected outcomes achieved, safety would likely be assured. In Chapters two to five, the typical methods and procedures employed to tackle the tasks in the rounded rectangles are presented and discussed in detail.

1.4.3. Methods for quantitative risk analysis

QRA requires various methods and resources to execute. Fault tree analysis (FTA), event tree analysis (ETA), bow-tie (BT) analysis, and BN are the frequently used methods for estimating the occurrence probability and consequence impact in QRA studies. The FTA is a deductive method for identifying the causes of incidents and accidents [71, 72]. However, the ETA is an inductive method showing an initiating event's various possible accident outcomes [73]. Therefore, in QRA studies, FTA is used to estimate the occurrence probability, while ETA is used for consequence impact estimation. The BT analysis was developed to combine the capabilities of FTA and ETA into a single method [74]. That makes the BT analysis superior to FTA or ETA since it estimates the risk directly.

The FTA, ETA, and BT analyses have limitations that must be considered when using them. Being graphical methods, depending on the number of RIF defining the concerned incident, the diagrams involved could be enormous, especially for complex incidents [75]. This translates into more time for drawing and computations. Although software exists to reduce the drawing and computational burden, even at that, doing FTA, ETA, or BT analysis for vast and complex incidents is still challenging. The assumptions of events independence and mutually exclusive states for events is another limitation in FTA and, by extension, in BT too. As Khakzad et al. [75] explained, these assumptions are not always valid because, practically, interactions exist among RIFs. Also, not all RIFs have hard-evidence states (i.e., failure or success) only; others have soft-evidence states (e.g., a leaking valve), resulting in some uncertainty about mutual exclusivity. An ETA, too, would yield several consequences, creating uncertainty in attributing a consequence of interest solely to an incident. The BT has this limitation too.

While all graphical methods for QRA, including BN modelling, have the challenges of diagramming and computational burdens, the BN allows for creating dependencies among RIFs and dealing with the computational uncertainties that arise during risk estimation. As a result, in recent times, most research publications in QRA [30, 71, 76] employ BN modelling but not FTA, ETA, or BT analysis. BN is a directed acyclic graphical model for representing incidents, RIFs, and consequences in one whole [30, 75], like the BT. When data is given to the root causes, a BN will compute the occurrence probability, consequence impact rate, and the risk for a given incident. For complex incidents that, when modelled, would result in a huge BN, the complexity and model size could be managed by transforming the BN into the object-oriented Bayesian network (OOBN) as described in Obeng et al. [71].

1.4.4. Bayesian network modelling for QRA

In BN, dependencies are formed using CPTs. Then, computations for occurrence probability, consequence impact rate, and risk are done using the total probability theory illustrated in Equation (1.2). The uncertainties in the incident and its RIFs, are handled by Bayes' theorem, Equation (1.3), through probability updating.

$$P(A) = P(A|B = b) \times P(B = b) + P\left(A\middle|B = \bar{b}\right) \times P(B = \bar{b}) \tag{1.2}$$

where, "A" is the incident; "B" is a risk factor for "A" to occur; "b" and "$\bar{b}$" are the occurrence and nonoccurrence states of "B", respectively; $P(A)$ is the probability or likelihood of "A" happening; $P(A|B = b)$ is the probability of "A" happening given that "B" is in state "b"; $P(B = b)$ is the prior probability of "B" happening; $P\left(A\middle|B = \bar{b}\right)$ is the probability of "A" happening given that "B" did not occur; and $P(B = \bar{b})$ is the prior probability of "B" not happening.

$$P(A|B) = \frac{P(B|A) \times P(A)}{\sum_{\cup} P(B)} \tag{1.3}$$

where, “A” and “B” are two dependent events, $P(A|B)$ is the posterior probability, $P(B|A)$ is the likelihood or conditional probability, $P(A)$ is the prior probability, and $\sum_{\cup} P(B)$ is the total probability.

In Equation (1.3), the posterior probability is the new or updated probability for “A” given that it is certain “B” has happened (i.e., evidence). That way, the uncertainty of not knowing what the probability of “A” would be when “B” occurs has been addressed. The total probability considers all the possible ways an event (e.g., “A”) can happen, and the estimation is done using Equation (1.2). The CPT represents the likelihood probability. Consider the example BN model in Figure 1.5; the incident, “A”, and its root causes, “C, D, and E”, are called the leaf and root nodes or child and parent nodes, respectively, with their occurrence and nonoccurrence states in brackets.

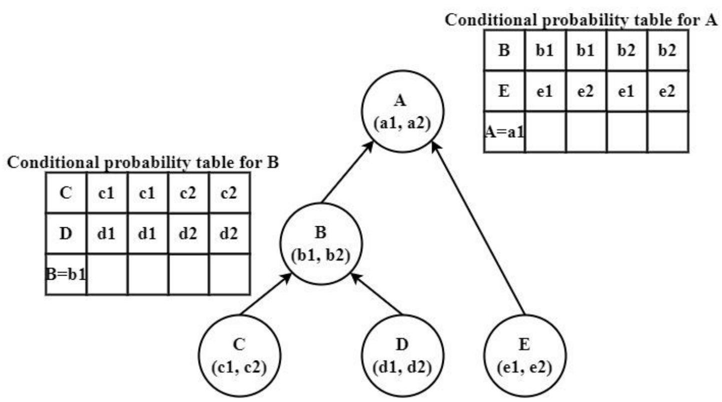

Figure 1.5. A BN model with leaf (A), intermediate (B), and root (C, D, and E) nodes.

The node, “B”, between the incident and root nodes, is called the intermediate node. It will be a child node to any node connecting to it, but a parent node to a node it is connecting (i.e., “A”). Parent nodes can transfer information (or data) to child nodes but not vice-versa, which makes BN an acyclic graphical model. The two tables in Figure 1.5 are the CPTs establishing the dependency relationship between events “A”, “B”, and “E” and events “B”, “C”, and “D”. Each node’s states (e.g., “a1” and “a2” for “A”) are treated as two mutually exclusive events and collectively exhaustive too. Therefore, when the occurrence state (e.g., “a1” for “A”) is known, Equation (1.4) is used to compute the nonoccurrence state probability.

$$P(A|a1) + P(A|a2) = 1 \quad (1.4)$$

where, “A” is an event with the occurrence and nonoccurrence states, “a1” and “a2”, respectively; P(A|a1) is the probability of the event “A” happening; and P(A|a2) is the probability of the event “A” not happening.

Subject-matter experts provide probabilities for CPTs. The use of expert judgement has resulted in the introduction of subjectivity challenges into BN modelling. The issue is a major one in PRA. The challenges are in the consistency and reliability of experts’ judgement approach when eliciting probabilities for CPTs. As Sonal and Ghosh [77] and Elidolu et al. [78] showed, multiple experts providing probability scores for the same CPT produce different datasets per expert. The variability in resulting datasets raises questions about consistency in the conditional probability elicitation approach and the reliability of the output result from BN. The thesis study contributed to addressing the subjectivity challenge by proposing the use of objective scales having pre-determined probability scores, from which experts can select their choice score based on a set of rules. In practice, this objective scale will vary from incident to incident or industry to industry, reflected in the selected scores. Thus, for a given incident or a particular industry use case, the scale will be objective for all experts to apply; but when compared with another for a different incident or industry use case, differences may exist. The choice scores must be selected using proper engineering judgement to suit a use case or the incident under study. The approach was demonstrated through case studies in chapters three and four for the main propulsion system failure and the loss of SA incidents.

With the CPTs filled, it is left with prior probabilities (i.e., c1, d1, and e1) for the root nodes (i.e., C, D, and E) so that the BN model can estimate the occurrence probability, "a1", for the incident, "*A*". Prior probabilities are occurrence likelihood scores for root nodes, which are the basic or structural variables of the incident under study. These variables are also known as active failures, whose occurrence would lead to the incident. Prior probabilities are typically sourced from historical data on the root nodes. Expert judgement can be used to estimate prior probability scores if historical data is unavailable.

1.4.5. Some applications of BN in QRA and SFB, and the knowledge gaps

Accident occurrences aboard SFBs are a long-known challenge in the fishing industry. Research in the past focused on identifying the various accidents and their RIF. Publications ensuing created awareness of the various accidents in the industry and events leading to their occurrences [7, 30—32,42—45, 56, 57, 66]. The data from these discoveries serve as a good foundation for future research to focus on developing PSA tools for pre-accident analysis. With such tools, hazardous incidents would be proactively identified and corrected to prevent them from becoming accidents, thereby promoting safety in SFBs.

Examples of published research using such data to demonstrate how to develop pre-accident analysis tools through BN modelling for SFBs abound. Recently, using BN modelling, Özaydın et al. [33] developed a PSA tool to study the risk posed by various occupational accidents in the Turkish SFB industry. QRA by BN has also been done for SFB capsize, sinking, and human error in Obeng et al. [71], Uğurlu et al. [30], and Obeng et al. [76], respectively.

Despite the popularity of BN modelling in fishing industry studies, very little exist in the literature about BN used in developing PSA tools for the four incidents the thesis study identified as important for SFB safety management. The publications by Gonel and Cicek [79], Ahn et al.

[80], and Tsekenis et al. [81] are among the most recent publications on MOB; however, when carefully studied, they present post-accident methods and tools for treating MOB. la Fata et al. [82] study of reliability and risk management for the propulsion system of fishing vessels is among the closest publications to the thesis objective two study. However, la Fata et al. [82] is interested in classifying failure modes into predefined and ordered risk categories to explain the uncertainty and vagueness in the input data. Their study did not address maintenance planning needs for SFB.

Moreso, the studies of Fu et al. [83], Adumene et al. [84], and Murray and Perera [85] show that the loss of SA is still a topical issue in QRA and the maritime sector. Meanwhile, their studies and similar ones did not address the challenge for fishing vessels and the SFB, in particular. Lastly, although the loss of stability and its association with vessel capsize accidents continue to be discussed in QRA studies [71, 86], it is hardly studied as a standalone incident for probabilistic risk analysis. The loss of stability is often treated in BN modelling as a root or intermediate node when it is an incident caused by some latent and active failures.

From the above discussions, it is evident that the specific objectives in Section 1.3 had not been sufficiently addressed before the present thesis was undertaken. The choice of BN modelling to develop PRA tools for the MOB scenario, main propulsion system failure, loss of SA, and loss of stability is also appropriate because similar tools have been developed in existing literature for accidents such as vessel capsize, sinking, and grounding. Chapters two to five discuss the detailed work done to achieve the thesis objectives.

1.5. Research Outcomes and Significance

Broadly, the thesis outcomes are in two parts, (1) PSA tools developed for gaining insight into the safety challenges confronting SFBs, and (2) proposed strategies for managing safety challenges in

SFBs. Figures 1.6 and 1.7 present summary descriptions of the achievements within the two broad outcome areas. Details on these tools and management strategies can be found in chapters two to five.

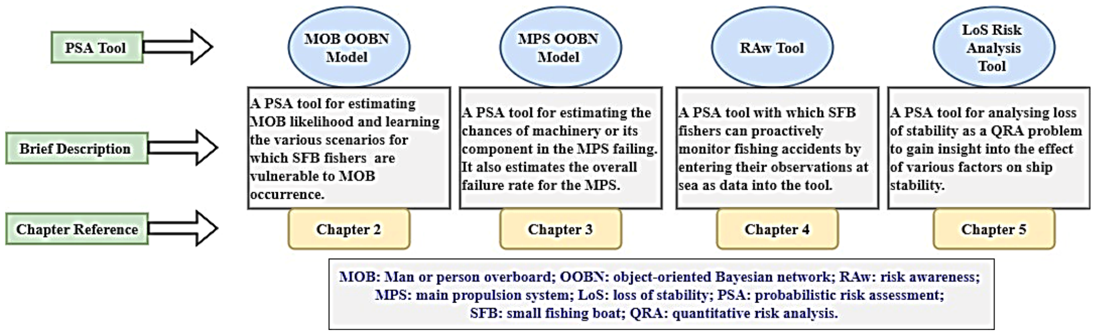

Figure 1.6. PSA tools developed to gain insight into safety challenges in fishing boats.

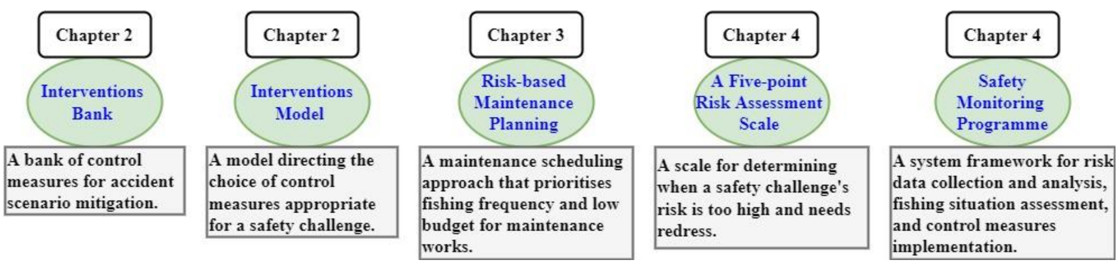

Figure 1.7. Strategies proposed for managing safety challenges in fishing boats.

Apart from the above contributions, three journal publications have been made in the first three specific objectives. A manuscript on the fourth objective is currently undergoing review with the Ocean Engineering Journal. The thesis outcomes will benefit boat owners and operators in the commercial fishing industry, governmental and non-governmental organisations overseeing fishing activities, and researchers interested in fishing safety. Novel aspects of the thesis research making it significant in the field of safety and risk engineering are as follows:

1. ***The Goal-directed risk identification technique, Goal-DRIT (see chapter three):*** a unique method for listing RIFs in highly complex systems;

2. ***Naïve Bayes' approach to eliciting scores for CPTs (see chapter three):*** BN models with parent node occurrence conditioned on the child node are built and used to elicit scores for CPTs (see chapter three and Appendix B3 in the supplementary material for details);
3. ***Probabilities elicitation scale (see chapter four):*** a predetermined scores scale proposed for guiding subject-matter experts when eliciting probabilities for CPTs. The scale, together with the naïve Bayes' approach, offers a methodology that helps to minimise variability in experts' scores and boost reliability and trust in BN model results;
4. ***De Morgan gates infusion in BN model (see chapter five):*** although a BN model is capable of qualitative analysis because it is a graphical tool, when De Morgan gates are incorporated, the analysis is enhanced with further descriptive measures: (i) REQUIREMENT gate—the RIF must be present for the incident to occur, (ii) CAUSE gate—the RIF's presence increases the incident's likelihood, (iii) BARRIER gate—the RIF's presence decreases the incident's likelihood, and (iv) INHIBITOR gate—the RIF prevents the incident from happening.

1.6. The Scope and Limitations of the Research

The thesis research scope and limitations are as follows:

- SFBs being considered in the study are those undertaking sea or ocean fishing expeditions, irrespective of size, but use low technology for navigation, safety management, and fishing operations. These vessels typically are less than 24 m in length overall and are not governed directly by the IMO regulations for marine vessels.
- The sourcing of RIFs for the SFB incidents studied, and data for the PSA tools operationalisation was done by literature survey. The literature for the survey was sourced

from governmental fishing accident databases and credible scientific journals in the subject area. The databases searched include the Global Integrated Shipping Information System, the Marine Accident Investigation Branch, the European Maritime Safety Agency, the Australian Transport Safety Bureau, and the Transportation Safety Board of Canada. As a result, the RIFs used in developing the PSA tools may be limited.

- Although the thesis study was determined to substitute the expert judgement approach for filling CPTs with a completely objective process, it cannot be said that this goal was achieved absolutely. The probability scoring scale developed in chapter four to objectively assign scores in CPTs has inherent subjectivity. Another risk analyst can decide to use different scores to construct the scale. However, in a given industry, when a conclusion is reached on the scores to be on the scale, objective decisions can be made to fill CPTs with probabilities.
- In developing the loss of stability tool in chapter five, misinterpreting De Morgan gates' meanings could occur, resulting in inaccurate modelling and computational outcomes. This will widen the uncertainty (i.e., aleatory and epistemic) gap in the incident representation and the risk estimate ensuing. One way to deal with the misinterpretation is to involve a person who understands the incident well enough during the modelling phase of the study.

1.7. The Thesis Organisation Structure

The present thesis is organised into six chapters using the manuscript style. The current chapter is the first and provides an overview of the study. Then, the thesis-specific objectives were addressed as separate manuscripts in chapters two to five. These chapters have been published in the journals named in Figure 1.8. The literature particular to each objective is presented separately in each chapter. Likewise, the detailed discussion of the QRA methodology peculiar to the objective is also presented in the separate chapters.

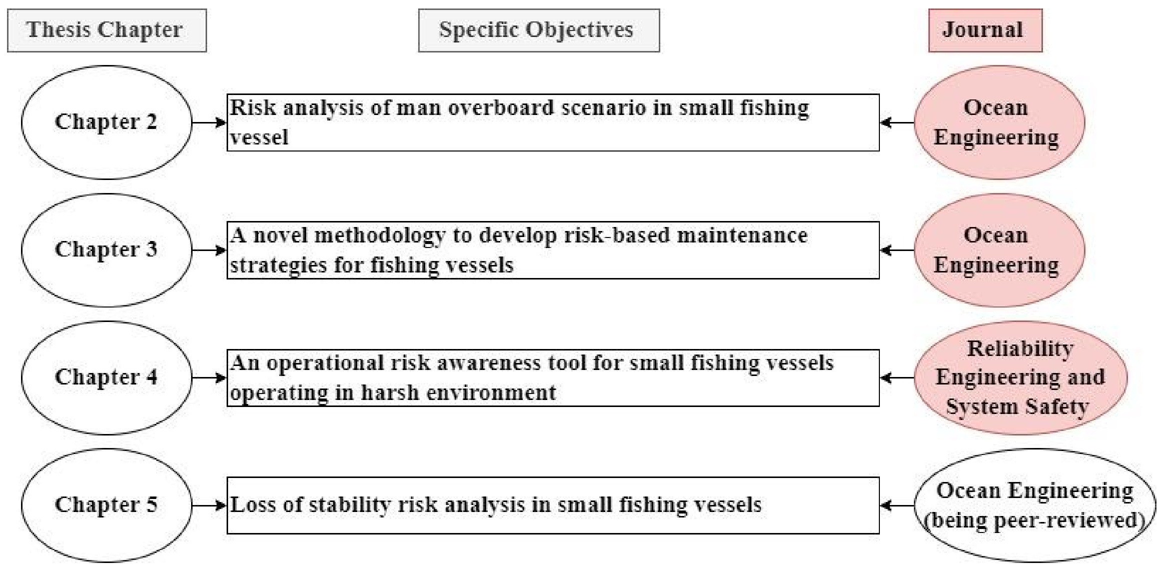

Figure 1.8. Journals in which thesis objectives were published.

Chapter 2 is the first publication and addresses the need for pre-accident analysis tools and methodologies to mitigate MOB scenarios aboard SFBs. A PSA tool, the MOB OOBN model, was developed in the chapter for pre-accident analysis. The model can identify the RIFs for a potential MOB case when engaged. Then control measures to address the identified RIFs, are selected from the developed interventions bank based on the guidance of the MOB-intervention model also developed in the chapter. The innovation the chapter study brings to the subject of MOB is the viewpoint of proactive management of events to avoid an actual MOB.

Chapter 3 is the second publication in the thesis study and achieved the second specific objective. Through literature review, it was revealed that apart from capsizing, sinking, and fire and explosion, the abrupt damage of shipboard machinery is another major vessel-related accident in the SFB sector. The risk is particularly high when the faulty machinery is within the main propulsion system. This chapter, therefore, developed a risk-based maintenance approach tailored to the maintenance needs of the marine propulsion system aboard SFBs. The PSA tool developed in the chapter can estimate the likelihood of the propulsion system failing and predict the associated RIFs. The chapter sought to communicate the innovation of using the PSA tool to facilitate risk-based maintenance planning for fishing vessel main propulsion system.

Chapter 4 is the third publication, addressing thesis-specific objective three. Because safety monitoring is instrumental in managing RIFs in SFBs, the chapter developed the risk awareness tool for pre-accident analysis. The tool allows fishers to input into it, their observations at sea as data. Using this data, the tool predicts the probable fishing accidents fishers need to watch out for. In addition, the tool predicts the accident scenarios in favour of the identified fishing accidents as conducive conditions. The tool's development and subsequent engagement is the innovation the chapter sought to communicate to potential beneficiaries. The tool's application presents a proactive approach to monitoring accidents in SFBs to promote safety in the commercial fishing industry.

Chapter 5 tackled the last specific objective. It is the fourth publication currently undergoing review in the journal, Ocean Engineering. In the chapter study, the loss of stability incident is approached using QRA. Because RIFs for loss of stability are vast, a systems engineering approach was used to capture high-level risk factors for the PSA tool developed to estimate stability loss in SFB. Although developed in a BN environment, the tool is unique because, unlike similar studies that employ "NoisyOR" and "NoisyAND" gates to model the independence of causal influence among RIFs, the present tool uses De Morgan gates instead. This enhances qualitative analysis in BN.

Chapter 6 finally summarises the thesis study by emphasising on key outcomes, recommendations for industry, research, and policymaking, and brief discussion of future research.

References

[1] ILO. International Standard Classification of Occupations: ISCO-88. Geneva. 1990.

[2] G. Burella, L. Moro, and B. Neis, "Is onboard noise putting fish harvesters' hearing at risk? A study of noise exposures in small-scale fisheries in Newfoundland and Labrador," *Saf. Sci.*, vol. 140, no. April, p. 105325, 2021, doi: 10.1016/j.ssci.2021.105325.

[3] M. Gleason, C. Cook, M. Bell, and E. Feller, "Editorial: Are we missing the boat? collaborative solutions for North American fish wars," *Conserv. Biol.*, vol. 23, no. 5, pp. 1065–1067, 2009, doi: 10.1111/j.1523-1739.2009.01315.x.

[4] F. Maynou, L. Recasens, and A. Lombarte, "Fishing tactics dynamics of a Mediterranean small-scale coastal fishery," *Aquat. Living Resour.*, vol. 24, no. 2, pp. 149–159, 2011, doi: 10.1051/alr/2011131.

[5] R. K. Ayilu, M. Fabinyi, and K. Barclay, "Small-scale fisheries in the blue economy: Review of scholarly papers and multilateral documents," *Ocean Coast. Manag.*, vol. 216, no. September 2021, p. 105982, 2022, doi: 10.1016/j.ocecoaman.2021.105982.

[6] D. J. Mills, L. Westlund, G. de Graaf, Y. Kura, R. Willman, and K. Keller, "Under-reported and Undervalued: Small-scale Fisheries in the Developing World," in *Small-scale Fisheries Management: Frameworks and Approaches for the Developing World*, 2011, pp. 1–15.

[7] M. A. Zytoon and A. M. Basahel, "Occupational safety and health conditions aboard small- and medium-size fishing vessels: Differences among age groups," Int. J. Environ. Res. Public Health, vol. 14, no. 3, 2017, doi: 10.3390/ijerph14030229.

[8] T. Mendo, S. Smout, T. Photopoulou, and M. James, "Identifying fishing grounds from vessel tracks: Model-based inference for small scale fisheries," *R. Soc. Open Sci.*, vol. 6, no. 10, 2019, doi: 10.1098/rsos.191161.

[9] Matteo Scarponi, "Use of the Wolfson stability guidance for appraising the operational stability of small fishing vessels," in Proceedings of the 16th International Ship Stability Workshop, 2017, pp. 5–7.

[10] D. J. Kim and D. J. Yeo, "Estimation of drafts and metacentric heights of small fishing vessels according to loading conditions," International Journal of Naval Architecture and Ocean Engineering, vol. 12, pp. 199–212, Jan. 2020, doi: 10.1016/J.IJNAOE.2019.11.001.

[11] O. Yaakob, F. E. Hashim, and M. R. Jalal, "STABILITY, SEAKEEPING AND SAFETY ASSESSMENT OF SMALL FISHING BOATS OPERATING IN SOUTHERN COAST OF PENINSULAR MALAYSIA Heat treatment of Ballast Water using shipboard waste heat View project Combined Ocean Renewable Energy system (CORES) View project," 2015. [Online]. Available: https://www.researchgate.net/publication/356665880.

[12] A. Halim et al., "Developing a functional definition of small-scale fisheries in support of marine capture fisheries management in Indonesia," Mar Policy, vol. 100, pp. 238–248, Feb. 2019, doi: 10.1016/j.marpol.2018.11.044.

[13] J. W. Yu, M. K. Lee, Y. I. Kim, S. B. Suh, and I. Lee, "An optimisation study on the hull

form and stern appendage for improving resistance performance of a coastal fishing vessel," Applied Sciences (Switzerland), vol. 11, no. 13, Jul. 2021, doi: 10.3390/app11136124.

[14] B. Lin, C. Y. Lin, and T. C. Jong, "Investigation of strategies to improve the recycling effectiveness of waste oil from fishing vessels," Mar Policy, vol. 31, no. 4, pp. 415–420, Jul. 2007, doi: 10.1016/j.marpol.2007.01.004.

[15] FAO, "Fishing fleet." https://www.fao.org/3/cc0461en/online/sofia/2022/fishing-fleet.html (accessed Feb. 04, 2023).

[16] H. K. Fox, T. C. Swearingen, A. C. Molina, and C. M. Kennedy, "Oregon recreational fishers' knowledge, support, and perceived impacts of marine reserves," Ocean Coast Manag, vol. 225, no. 106241, pp. 1–10, May 2022.

[17] A. Papadopoulos, K. Touloumis, E. Tziolas, and D. Boulamatsis, "Evaluation of Marine Recreational Fisheries and Their Relation to Sustainability of Fisheries Resources in Greece ," Sustainability , vol. 14, no. 3824, pp. 1–15, Mar. 2022.

[18] D. M. de Freitas and P. R. A. Tagliani, "The use of GIS for the integration of traditional and scientific knowledge in supporting artisanal fisheries management in southern Brazil," J Environ Manage, vol. 90, no. 6, pp. 2071–2080, May 2009, doi: 10.1016/j.jenvman.2007.08.026.

[19] L. García-Flórez et al., "A novel and simple approach to define artisanal fisheries in Europe," Mar Policy, vol. 44, pp. 152–159, 2014, doi: 10.1016/j.marpol.2013.08.021.

[20] G. Longin et al., "When subsistence fishing meets conservation issues: Survey of a small fishery in a neotropical river with high biodiversity value," Fisheries Research , vol. 241, no. 105995, pp. 1–9, May 2021.

[21] F. K. E. Nunoo, B. Asiedu, J. Olauson, and G. Intsiful, "Achieving sustainable fisheries management: A critical look at traditional fisheries management in the marine artisanal fisheries of Ghana, West Africa," 2015.

[22] X. Zhao and P. Jia, "Towards sustainable small-scale fisheries in China: A case study of Hainan," Mar Policy, vol. 121, Nov. 2020, doi: 10.1016/j.marpol.2020.103935.

[23] H. Robotham et al., "Contribution to the study of sustainability of small-scale artisanal fisheries in Chile," Mar Policy, vol. 106, Aug. 2019, doi: 10.1016/j.marpol.2019.103514.

[24] M. L. V. Barbosa-Filho, G. B. G. de Souza, S. de Faria Lopes, R. A. Hauser-Davis, S. Siciliano, and J. da Silva Mourão, "Artisanal Fisher Knowledge and Attitudes Concerning Compressor Fishing in a North-Eastern Brazilian Marine Protected Area," Hum Ecol, vol. 48, no. 3, pp. 357–366, Jun. 2020, doi: 10.1007/S10745-020-00156-2.

[25] M. L. Adeleke and M. Wolff, "Adaptation of the Artisanal Fisher Folks to Climate Change in the Coastal Region of Ondo State, Nigeria," Climate Change Management, pp. 177–193, 2016, doi: 10.1007/978-3-319-25814-0_13.

[26] M. Luiz, V. Barbosa-Filho, R. Ann, H.-D. Fundação, and O. Cruz, "Artisanal fisher perceptions on ghost nets in a tropical South Atlantic marine biodiversity hotspot:

Challenges to traditional fishing culture and implications for," Elsevier, doi: 10.1016/j.ocecoaman.2020.105189.

[27] P. Lousã, F. Moreira, L. S.-2018 16th International, and undefined 2018, "Micro-VMS: a VMS mobile unit for artisanal fishing vessels," ieeexplore.ieee.org, Accessed: Nov. 18, 2022. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8566888/.

[28] D. A. Willette et al., "Characterizing Industrial and Artisanal Fishing Vessel Catch Composition Using Environmental DNA and Satellite-Based Tracking Data," mdpi.com, 2021, doi: 10.3390/foods10061425.

[29] C. P. Ortiz-Ojeda and V. F. Rázuri-Esteves, "Baseline study to determine the implementation area of an oily waste management system for artisanal fishing vessels," Environ Monit Assess, vol. 193, no. 2, Feb. 2021, doi: 10.1007/S10661-021-08845-1.

[30] F. Uğurlu, S. Yıldız, M. Boran, Ö. Uğurlu, and J. Wang, "Analysis of fishing vessel accidents with Bayesian network and Chi-square methods," Ocean Engineering, vol. 198, Feb. 2020, doi: 10.1016/j.oceaneng.2020.106956.

[31] S. E. Roberts, "Britain's most hazardous occupation: Commercial fishing," Accid Anal Prev, vol. 42, no. 1, pp. 44–49, Jan. 2010, doi: 10.1016/j.aap.2009.06.031.

[32] E. McGuinness, H. L. Aasjord, I. B. Utne, and I. M. Holmen, "Fatalities in the Norwegian fishing fleet 1990-2011," Saf Sci, vol. 57, pp. 335–351, Aug. 2013, doi: 10.1016/j.ssci.2013.03.009.

[33] E. Özaydın, R. Fışkın, Ö. Uğurlu, and J. Wang, "A hybrid model for marine accident analysis based on Bayesian Network (BN) and Association Rule Mining (ARM)," Ocean Engineering, vol. 247, Mar. 2022, doi: 10.1016/j.oceaneng.2022.110705.

[34] P. He, F. Chopin, P. Suuronen, R.S.T. Ferro, and J. Lansley. 2021. *Classification and illustrated definition of fishing gears*. FAO Fisheries and Aquaculture Technical Paper No. 672. Rome, FAO. https://doi.org/10.4060/cb4966en.

[35] U. Tietze. Circular and undefined 2016, "Technical and socio-economic characteristics of small-scale coastal fishing communities, and opportunities for poverty alleviation and empowerment," *search.proquest.com*, Accessed: Nov. 20, 2022. [Online]. Available: https://search.proquest.com/openview/72e02c4d532ae5760e1481415b405b1b/1?pq-origsite=gscholar&cbl=237324.

[36] R. Pomeroy, K. Nguyen, H. T.-M. Policy, and undefined 2009, "Small-scale marine fisheries policy in Vietnam," Elsevier, Accessed: Nov. 21, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0308597X08001498?casa_token=wu7PPDoRfM8AAAAA:hOJ1Uou8gHxkEJDHBsNLtBu2X89RSk6TomnDxTd-DqWwmvaMK_pc269ogCeNG5t7DNyxl1WOIzCq.

[37] A. Said and R. Chuenpagdee, "Aligning the sustainable development goals to the small-scale fisheries guidelines: A case for EU fisheries governance," Mar Policy, vol. 107, Sep. 2019, doi: 10.1016/j.marpol.2019.103599.

[38] J. N. Kittinger, "Human dimensions of small-scale and traditional fisheries in the asia-pacific region," Pacific Science, vol. 67, no. 3. pp. 315–325, Jul. 2013. doi: 10.2984/67.3.1.

[39] R. Chuenpagdee et al., "The global information system on small-scale fisheries (ISSF): A crowdsourced knowledge platform," Mar Policy, vol. 101, pp. 158–166, Mar. 2019, doi: 10.1016/j.marpol.2017.06.018.

[40] M. Sowman, J. Sunde, S. Raemaekers, and O. Schultz, Fishing for equality: Policy for poverty alleviation for South Africa's small-scale fisheries," Mar Policy, vol. 46, pp. 31–42, May 2014, doi: 10.1016/j.marpol.2013.12.005.

[41] D. Belhabib, U. R. Sumaila, and D. Pauly, "Feeding the poor: Contribution of West African fisheries to employment and food security," Ocean and Coastal Management, vol. 111, pp. 72–81, Jul. 2015, doi: 10.1016/j.ocecoaman.2015.04.010.

[42] M. L. Myers, R. M. Durborow, and A. S. Kane, "Gulf of Mexico seafood harvesters: Part 1. Occupational injury and fatigue risk factors," Safety, vol. 4, no. 3. MDPI Multidisciplinary Digital Publishing Institute, 2018. doi: 10.3390/safety4030031.

[43] F. Mata-Álvarez-Santullano and A. Souto-Iglesias, "Stability, safety and operability of small fishing vessels," Ocean Engineering, vol. 79, pp. 81–91, Mar. 2014, doi: 10.1016/j.oceaneng.2014.01.011.

[44] F. Mata-Álvarez-Santullano and A. Souto-Iglesias, "Fishing effort control policies and ship stability: Analysis of a string of accidents in Spain in the period 2004-2007," Mar Policy, vol. 40, no. 1, pp. 10–17, Jul. 2013, doi: 10.1016/j.marpol.2012.12.027.

[45] O. C. C. Jensen, G. Petursdottir, I. M. Holmen, A. Abrahamsen, and J. Lincoln, "A review of fatal accident incidence rate trends in fishing," International maritime health, vol. 65, no. 2. pp. 47–52, 2014. doi: 10.5603/IMH.2014.0011.

[46] M. Jezewska, M. Grubman-Nowak, I. Leszczyñska, and B. Jaremin, "Occupational hazards for fishermen in the workplace in Polish coastal and beach fishing-a point of view," Int Marit Health, vol. 63, pp. 40–48, 2012, [Online]. Available: www.intmarhealth.plwww.intmarhealth.pl.

[47] R. W. Byard, "Commercial fishing industry deaths-Forensic issues," *J. Forensic Leg. Med.*, vol. 20, no. 3, pp. 129–132, 2013, doi: 10.1016/j.jflm.2012.05.010.

[48] V. A. Feraru, R. E. Andersen, and E. Boukas, "Towards an Autonomous UAV-based System to Assist Search and Rescue Operations in Man Overboard Incidents," in 2020 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR), Nov. 2020, pp. 57–64. doi: 10.1109/SSRR50563.2020.9292632.

[49] I. Katsamenis, E. Protopapadakis, A. Voulodimos, D. Dres, and D. Drakoulis, "Man overboard event detection from RGB and thermal imagery: possibilities and limitations," in Proceedings of the 13th ACM International Conference on PErvasive Technologies Related to Assistive Environments, 2020, pp. 1–6.

[50] J. Mou, T. Hu, P. Chen, and L. Chen, "Cooperative MASS path planning for marine man overboard search," Ocean Engineering, vol. 235, Sep. 2021, doi: 10.1016/j.oceaneng.2021.109376.

[51] J. Weng and D. Yang, "Investigation of shipping accident injury severity and mortality," Accid Anal Prev, vol. 76, pp. 92–101, 2015, doi: 10.1016/j.aap.2015.01.002.

[52] H. Li, X. Ren, and Z. Yang, "Data-driven Bayesian network for risk analysis of global maritime accidents," Reliab Eng Syst Saf, vol. 230, Feb. 2023, doi: 10.1016/j.ress.2022.108938.

[53] C. Behrendt and P. Rajewski, "Analysis of propulsion system failures in the fishing fleet operating from Polish ports ," 2008.

[54] J. Wang, A. Pillay, Y. S. Kwon, A. D. Wall, and C. G. Loughran, "An analysis of fishing vessel accidents," Accid Anal Prev, vol. 37, no. 6, pp. 1019–1024, 2005, doi: 10.1016/j.aap.2005.05.005.

[55] A. Sharma, S. Nazir, and J. Ernstsen, "Situation awareness information requirements for maritime navigation: A goal directed task analysis," Saf Sci, vol. 120, pp. 745–752, Dec. 2019, doi: 10.1016/j.ssci.2019.08.016.

[56] T. Thorvaldsen, "The importance of common sense: How Norwegian coastal fishermen deal with occupational risk," Mar Policy, vol. 42, pp. 85–90, Nov. 2013, doi: 10.1016/j.marpol.2013.02.007.

[57] B. Davis, B. Colbourne, and D. Molyneux, "Analysis of fishing vessel capsizing causes and links to operator stability training," Saf Sci, vol. 118, pp. 355–363, Oct. 2019, doi: 10.1016/j.ssci.2019.05.017.

[58] A. Sevin, C. Bayilmiş, I. Ertürk, H. Ekiz, and A. Karaca, "Design and implementation of a man-overboard emergency discovery system based on wireless sensor networks," Turkish

Journal of Electrical Engineering and Computer Sciences, vol. 24, no. 3, pp. 762–773, 2016, doi: 10.3906/elk-1308-154.

[59] E. Castillo, Z. Grande, and A. Calviño, "Bayesian Networks-Based Probabilistic Safety Analysis for Railway Lines," Computer-Aided Civil and Infrastructure Engineering, vol. 31, no. 9, pp. 681–700, Sep. 2016, doi: 10.1111/mice.12195.

[60] M. Yazdi, A. Nedjati, E. Zarei, and R. Abbassi, "A novel extension of DEMATEL approach for probabilistic safety analysis in process systems," Saf Sci, vol. 121, pp. 119–136, Jan. 2020, doi: 10.1016/j.ssci.2019.09.006.

[61] S. Nguyen, P. S. L. Chen, Y. Du, and W. Shi, "A quantitative risk analysis model with integrated deliberative Delphi platform for container shipping operational risks," Transp Res E Logist Transp Rev, vol. 129, pp. 203–227, Sep. 2019, doi: 10.1016/j.tre.2019.08.002.

[62] A. L. Tunçel, E. Akyuz, and O. Arslan, "Quantitative risk analysis for operational transfer processes of maritime pilots," Maritime Policy and Management, 2022, doi: 10.1080/03088839.2021.2009133.

[63] H. Liwång, J. W. Ringsberg, and M. Norsell, "Quantitative risk analysis - Ship security analysis for effective risk control options," Saf Sci, vol. 58, pp. 98–112, Oct. 2013, doi: 10.1016/j.ssci.2013.04.003.

[64] A. J. Peel, M. Hartley, and A. A. Cunningham, "Qualitative risk analysis of introducing batrachochytrium dendrobatidis to the UK through the importation of live amphibians," Dis Aquat Organ, vol. 98, no. 2, pp. 95–112, Mar. 2012, doi: 10.3354/dao02424.

[65] B. Svilicic, J. Kamahara, M. Rooks, and Y. Yano, "Maritime Cyber Risk Management: An Experimental Ship Assessment," Journal of Navigation, vol. 72, no. 5, pp. 1108–1120, Sep. 2019, doi: 10.1017/S0373463318001157.

[66] S. L. Case, J. M. Lincoln, and D. L. Lucas, "Fatal Falls Overboard in Commercial Fishing — United States, 2000–2016," MMWR. Morb. Mortal. Wkly. Rep., vol. 67, no. 16, pp. 465–469, 2018.

[67] R. Flage and T. Aven, "EXPRESSING AND COMMUNICATING UNCERTAINTY IN RELATION TO QUANTITATIVE RISK ANALYSIS," 2009.

[68] X. W. Zheng, H. N. Li, and P. Gardoni, "Hybrid Bayesian-Copula-based risk assessment for tall buildings subject to wind loads considering various uncertainties," Reliab Eng Syst Saf, vol. 233, May 2023, doi: 10.1016/j.ress.2023.109100.

[69] E. Zaitseva, V. Levashenko, and J. Rabcan, "A new method for analysis of Multi-State systems based on Multi-valued decision diagram under epistemic uncertainty," Reliab Eng Syst Saf, vol. 229, Jan. 2023, doi: 10.1016/j.ress.2022.108868.

[70] Z. Wang, M. Daeipour, and H. Xu, "Quantification and Propagation of Aleatoric Uncertainties in Topological Structures," Reliab Eng Syst Saf, p. 109122, May 2023, doi: 10.1016/j.ress.2023.109122.

[71] F. Obeng, V. Domeh, F. Khan, N. Bose, and E. Sanli, "Capsizing accident scenario model for small fishing trawler," Saf Sci, vol. 145, Jan. 2022, doi: 10.1016/j.ssci.2021.105500.

[72] Ö. Uğurlu, E. Köse, U. Yıldırım, and E. Yüksekyıldız, "Marine accident analysis for collision and grounding in oil tanker using FTA method," Maritime Policy and Management, vol. 42, no. 2, pp. 163–185, Feb. 2015, doi: 10.1080/03088839.2013.856524.

[73] A. Raiyan, S. Das, and M. R. Islam, "Event tree analysis of marine accidents in Bangladesh," in Procedia Engineering, 2017, vol. 194, pp. 276–283. doi: 10.1016/j.proeng.2017.08.146.

[74] R. Ferdous, F. Khan, R. Sadiq, P. Amyotte, and B. Veitch, "Analysing system safety and risks under uncertainty using a bow-tie diagram: An innovative approach," Process Safety and Environmental Protection, vol. 91, no. 1–2, pp. 1–18, Jan. 2013, doi: 10.1016/j.psep.2011.08.010.

[75] N. Khakzad, F. Khan, and P. Amyotte, "Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches," Reliab Eng Syst Saf, vol. 96, no. 8, pp. 925–932, Aug. 2011, doi: 10.1016/j.ress.2011.03.012.

[76] F. Obeng, V. Domeh, F. Khan, N. Bose, and E. Sanli, "Analysing operational risk for small fishing vessels considering crew effectiveness," Ocean Engineering, vol. 249, Apr. 2022, doi: 10.1016/j.oceaneng.2021.110512.

[77] Sonal and D. Ghosh, "Impact of situational awareness attributes for resilience assessment of active distribution networks using hybrid dynamic Bayesian multi criteria decision making approach," Reliab Eng Syst Saf, vol. 228, Dec. 2022, doi: 10.1016/j.ress.2022.108772.

[78] G. Elidolu, S. I. Sezer, E. Akyuz, O. Arslan, and Y. Arslanoglu, "Operational risk assessment of ballasting and de-ballasting on-board tanker ship under FMECA extended Evidential Reasoning (ER) and Rule-based Bayesian Network (RBN) approach," Reliab Eng Syst Saf, vol. 231, Mar. 2023, doi: 10.1016/j.ress.2022.108975.

[79] O. Gonel and I. Cicek, “Multicriteria emergency decision for responding to man overboard casualties: A proposed procedure developed using Binary Logistics Regression and General Linear Models,” Ocean Engineering, vol. 265, Dec. 2022, doi: 10.1016/j.oceaneng.2022.112581.

[80] S. il Ahn, R. E. Kurt, and E. Akyuz, “Application of a SPAR-H based framework to assess human reliability during emergency response drill for man overboard on ships,” Ocean Engineering, vol. 251, May 2022, doi: 10.1016/j.oceaneng.2022.111089.

[81] V. Tsekenis, C. K. Armeniakos, V. Nikolaidis, P. S. Bithas, and A. G. Kanatas, “Machine learning-assisted man overboard detection using radars,” Electronics (Switzerland), vol. 10, no. 11, Jun. 2021, doi: 10.3390/electronics10111345.

[82] C. M. la Fata, A. Giallanza, R. Micale, and G. la Scalia, “Improved FMECA for effective risk management decision making by failure modes classification under uncertainty,” Eng Fail Anal, vol. 135, May 2022, doi: 10.1016/j.engfailanal.2022.106163.

[83] S. Fu, Y. Yu, J. Chen, Y. Xi, and M. Zhang, “A framework for quantitative analysis of the causation of grounding accidents in arctic shipping,” Reliab Eng Syst Saf, vol. 226, Oct. 2022, doi: 10.1016/j.ress.2022.108706.

[84] S. Adumene, M. Afenyo, V. Salehi, and P. William, “An adaptive model for human factors assessment in maritime operations,” Int J Ind Ergon, vol. 89, May 2022, doi: 10.1016/j.ergon.2022.103293.

[85] B. Murray and L. P. Perera, “Ship behavior prediction via trajectory extraction-based clustering for maritime situation awareness,” Journal of Ocean Engineering and Science, vol. 7, no. 1, pp. 1–13, Feb. 2022, doi: 10.1016/j.joes.2021.03.001.

[86] H. Wang, Z. Liu, X. Wang, D. Huang, L. Cao, and J. Wang, “Analysis of the injury-severity outcomes of maritime accidents using a zero-inflated ordered probit model,” Ocean Engineering, vol. 258, Aug. 2022, doi: 10.1016/j.oceaneng.2022.111796.

CHAPTER 2

2.0. Risk analysis of man overboard scenario in a small fishing vessel

Preface

A version of this chapter has been published in ***Ocean Engineering 229 (2021) 108979****. I am the primary author alongside co-authors Francis Obeng, Faisal Khan, Neil Bose, and Elizabeth Sanli. I developed the conceptual framework for the man-overboard (MOB) scenario, carried out the literature review, performed the engineering analysis, and prepared the first draft of the manuscript. Subsequent revisions of the manuscript based on co-authors' and peer review feedback were also done by me. Co-author Francis Obeng read the first draft of the manuscript and drew my attention to obvious areas of concern. Co-author Faisal Khan helped in the concept development and testing of the logic behind the MOB model, reviewing and revising the manuscript. Co-author Neil Bose provided fundamental assistance in validating, reviewing, and correcting the model and results. Co-author Elizabeth Sanli assisted in validating, examining the technical writing constructs and correcting the model results. The co-authors also contributed to the review and revision of the manuscript after receiving peer-review feedback from the journal.*

Abstract

One major accident scenario aboard fishing vessels is "man overboard" (MOB). Prevention of this accident scenario would reduce the high fatality rate in the fishing industry. Critical understanding of the risk factors is vital for a robust risk assessment of this accident scenario and to develop interventions. This paper presents the Objected-Oriented Bayesian Network (OOBN) application for risk assessment of the MOB scenario. The OOBN model is developed to probabilistically

capture the key accident influencing factors in fragmented structures. The proposed methodology is demonstrated in an accident scenario, and the model captures the dynamic dependencies and interdependencies among basic variables and establishes their degree of influence on the accident occurrence probability. The vulnerability path was identified, and a pre-and post-accident intervention plan was proposed to minimize the accident occurrence and its associated risk. Applying the methodology provides vital safety-based information that could be adopted for small vessel operation and maritime administration regulation.

Keywords: Man overboard; OOBN; Fishing vessel accident; Risk control analysis; Risk analysis.

2.1. Introduction

Man overboard (MOB) is a shipboard accident that occurs when a person onboard a marine vessel falls into the surrounding water and needs to be rescued [1—4]. The MOB is also called "fall overboard" [1] and "person overboard" [5]. Almost every type of marine vessel [2,3,6—9] has recorded MOB occurrence. On fishing vessels, however, Case et al. [10], Thomas et al. [11], and Lucas and Lincoln [1] have identified MOB as a significant accident (next to capsize, sinking, or vessel loss) to fishers and requires an immediate remedy. The National Institute for Occupational Safety and Health says that 23% of Alaska's total fisher deaths from 1990 to 1999 were due to MOB [12]. Similar death statistics have been mentioned for the commercial fishing industries in the United Kingdom, Norway, New Zealand, Canada, and other parts of the United States [10, 11]. Looking at the eras in which these researchers generated statistics for MOB, one is tempted to say that the accident only existed before the twenty-first century and no longer bothers the commercial fishing industry (CFI). Such presumption would be incorrect since a recent study by Uğurlu et al.

[13] shows that, between the 2009- and 2018-year period, 26 MOB accidents occurred and resulted in 20 fishers' death. Meaning, on average, one fisher died each time a MOB accident occurred.

The MOB, categorized as a person-related accident, though has a low occurrence rate compared to vessel-related accidents such as capsizing, sinking, grounding, collision, or fire and explosion, its fatality rate is as high as those for these accident types [1, 11, 12]. Again, among the leading person-related accidents (i.e., struck by gear or heavy seas, entangled in gear, fall into the dock, and asphyxiated by fumes), which happens on fishing vessels' main deck and directly to the fisher, MOB presents the highest fatality rate [4, 13]. MOB poses a severe danger to fishing safety and is increasingly recognized worldwide as the one person-related accident that, if mitigated, could reduce fishing fatality significantly [1, 10, 14].

The MOB death toll in the industry has been linked to the small fishing vessels [4,15]. Wang et al. [16] noted that the absence of a harmonized safety legislation from the International Maritime Organization (IMO) to regulate small fishing vessels' activities encourages dangerous fishing practices, which often result in various accidents, including MOB. Roberts [4] reported 160 fisher deaths in the United Kingdom (UK) fishing industry within the 1996- and 2005-year period. The medium fishing vessels (MFV) (i.e., fishing vessels with a length overall from 24 m to 36 m) and large fishing vessels (LFV) (i.e., fishing vessels with a length overall more than 36 m) caused 38 and 20 deaths, respectively, leaving small fishing vessels (SFV) (i.e., fishing vessels with a length overall not more than 24 m) with as much as 120 deaths. Furthermore, 32 out of the 160 deaths were due to MOB, resulting in the distribution: SFV (24 deaths), MFV (6 deaths), and LFV (2 deaths). Therefore, there is no doubt that SFVs harbor several safety risks and are vulnerable to MOB.

The need to intensify research activities on SFVs and MOB cannot be overemphasized from the discussion so far. Proactive measures to improve safety onboard SFVs through MOB prevention are needed. This calls for the development of proactive methods capable of quantifying the occurrence or non-occurrence of MOB during everyday shipboard operations. The previous studies [1, 4, 10—24] on MOB used post-accident and qualitative methods in analyzing the MOB scenario. These methods have produced numeric results, indicating a quantitative assessment of MOB, yet, the numbers cannot be used to predict the chances of MOB occurrence during in-service operations aboard a vessel.

The methods used in generating these numbers are non-probabilistic and only yield statistics on how often a MOB causality, the accident itself, or both, have happened for a given vessel, maritime administration, or country [1, 10—12, 21]. Nevertheless, the methods have successfully identified the risk factors associated with MOB accidents, though they cannot anticipate the occurrence or non-occurrence of MOB scenarios and the accident during everyday shipboard operations. As a result, though MOB has been approached by previous researchers as a quantitative risk analysis (QRA) [25] problem, the aspects of occurrence prediction or predispose assessment are yet to be covered.

The present study proposed a QRA methodology based on probability theory [26—28] to analyze the MOB scenario. Methodologies founded on probability theory, as explained in Khakzad et al. [26] and Goerlandt and Montewka [29], are excellent at handling accident prediction and predispose assessment of risk factors because they can: (1) provide a broad picture of the accident scenario based on actual happenings; (2) deal with the uncertainties that arise in accident occurrence prediction due to lack of sufficient data; (3) identify the underpinning logic in accidents/incidents and their risk factors; (4) use the logic understanding to develop analytical networks for the accident scenario modeling; and (5) provide percentages that measure the chances of occurrence or non-occurrence of an accident and its risk factors.

Another critical aspect of MOB not covered in previous research is the linkage of MOB risk factors. As shown in later sections, MOB occurrence risk factors are broad and diverse and comprise human, technical, and environmental factors [10—24]. The human factors feature errors made by persons aboard vessels, which resulted in the MOB. The vessel and onboard equipment inadequacies leading to MOB constitute the technical factors. In contrast, weather conditions (such as the intensity of sea waves, wind, snow, rainfall, etc.), which interfered with vessel operations and caused MOB to occur, are the environmental factors.

Although previous researchers [1, 4, 10—24] have identified these risk factors, none has studied linking all the factors together into a network structure for the development of pre-accident analysis tools. This places limitations on a comprehensive description of the MOB scenario and the study of dependency and interdependency relationships among risk factors. The result is that the MOB scenario is not adequately understood, and the most probable scenario to cause MOB for a given vessel or operational condition cannot be predicted.

The current study uses Object-oriented Bayesian network (OOBN) modeling [28,30] to probabilistically capture MOB influencing factors in fragmented structures and link them together. Then, the resulting model is used to dynamically analyze the dependencies and interdependencies among basic variables. The OOBN is a probabilistic modeling tool often preferred to Bayesian Network (BN) when handling massive accident scenarios due to vast influencing factors [26, 28]. Although OOBN modeling has been applied to several complex accident scenarios in the maritime industry [28, 31, 32], the literature search conducted suggests that OOBN has not been applied to MOB or fishing vessels before the present study.

MOB occurrence presents severe consequences including drowning [10,33], cold-shock responses [14, 33], hyperventilation aspiration [17, 33], hypothermia [14, 17], and muscle function deterioration [17, 33]. The studies of Pitman et al. [9] and Thomas et al. [11] showed that these post-MOB incidents are responsible for the high fisher deaths attributed to MOB. Considering the death risk posed by these incidents and noting that Lucas and Lincoln [1] and Ugurlu et al. [13] showed that MOB occurrence had not declined yet in commercial fishing, research efforts on MOB interventions promotion must be intensified. Such interventions must provide control measures targeted at both pre-and-post-MOB incidents.

Regulations provide firsthand control measures and are therefore taken seriously in every industry. The MSC.1/Circ.1182/Rev.1 [34] and SOLAS III/17-1 [35] of IMO entreats all vessels to have onboard the human and technological capacities to recover a MOB victim from the water. To that effect, the regulations strongly advise frequent MOB drills to ensure the shipboard crew is adequately prepared to handle MOB accidents. Additionally, the Standards of Training, Certification, and Watchkeeping (STCW) Convention [36] of IMO urges vessels' masters to conduct familiarisation tours of the safety systems and emergency procedures aboard their vessels' for a new crew member. Among other things, the new crew member must be told the procedures for MOB aboard.

Furthermore, the International Labour Organisation (ILO)'s Code [37], "Accident prevention on board ship at sea and in port", provides MOB control measures when carrying out overboard tasks (e.g., checking draught readings). The Code says the crew member involved must wear a fall protection system and a personal floatation device. It also advises that another crew member must standby and keep watch. Lastly, the International Organisation for Standardisation's (ISO) ISO/PAS 21195:2018 (en) [38] have specified the minimum requirement expected of shipboard equipment used for MOB interventions. Although the ILO Code offers some pre-MOB interventions, these regulations predominantly offer post-MOB control measures and, therefore, lack the ability to prevent MOB occurrence proactively.

These regulations were enacted with vessels of length, 24 m, or more in mind; for example, the ISO regulation was passed specifically for passenger vessels. Due to this, their enforcement on SFVs is difficult. Also, non-overboard tasks that are equally liable for MOB occurrence cannot be addressed by the ILO Code's control measures. Realizing the inadequacies in existing regulations targeted at MOB prevention aboard SFVs, researchers [1, 11, 20, 33] worked at developing control measures to that effect.

The control measures are broadly categorized into engineering controls, administrative controls, and personal protective equipment (PPE) use [1, 10]. Engineering controls require modifications to vessels' systems and equipment to prevent a fisher from becoming a MOB victim. Administrative controls are rules or working procedures onboard aimed at limiting the fisher's exposure to MOB incidents. The PPE use, such as wearing of life jackets, is encouraged to mitigate MOB consequences. The engineering controls and administrative controls are preferred to PPE use because they provide pre-MOB interventions and are proactive [1].

Typical examples of the engineering controls, administrative controls, and PPE suggested for MOB prevention and to mitigate consequences on SFVs, will be discussed in later sections of the present study. Meanwhile, Lucas and Lincoln [1] recommended that more control measures be sought and paired with specific MOB causality. Therefore, the literature survey and brainstorming sessions held in the present study sought additional engineering and administrative controls. Together with those of previous researchers, the discovered control measures were built into the

MOB interventions model. The model selects from a bank of control measures, appropriate engineering controls, administrative controls, and PPEs for a given MOB causality.

In summary, though the present study builds on previous research works, its primary purpose is to demonstrate how OOBN modeling could be used to develop a probabilistic safety assessment tool for MOB scenario analysis aboard fishing vessels. The present study is different from previous MOB research; the methodology proposed here can measure the likelihood of a MOB accident occurrence (and the causation) during everyday shipboard operations. Therefore, the study is novel in two ways: (1) first-time application of OOBN in fishing safety assessment and (2) dynamic prediction of MOB scenario in the maritime industry using probability theory.

The study presents a proactive assessment method and a pre-accident analysis tool (through the proposed QRA framework and the OOBN model) for MOB scenario analysis. These are useful resources that policy-makers for maritime accidents prevention, ship owners and shipping companies, and shipboard officers could employ to manage MOB scenarios and related shipboard hazards before the incidents degenerate into accidents. The present study sought to achieve the following specific objectives: (1) to develop a MOB OOBN model for small fishing vessels; (2) to use the model to support decision-making on the most influencing factors for MOB occurrence; (3) to conduct a risk control analysis using the model, so as to provide control options for MOB prevention and its consequence mitigation; and (4) to develop the MOB interventions model from which control measures can be selected to address identified top risk factors for MOB occurrence.

This paper consists of six sections. Section 2.2 is the next and describes the study framework and methods used to develop the MOB OOBN model. In Section 2.3, a small fishing vessel case study shows how the proposed methodology works in practice. Subsequently, the case study results are presented and discussed in Section 2.4. Section 2.5 discusses the limitations with the study. Finally, the summary and key message of the study are presented as conclusions in Section 2.6.

2.2. The Methodology to Develop an OOBN Model for MOB Scenario analysis

The QRA is an established methodology that gives quantitative estimates of risks associated with operations or processes [25, 28, 39]. By its nature, QRA combines hazard assessment with risk analysis to estimate the risk foreseen. Two estimation approaches are broadly followed in a QRA: probabilistic [28] and non-probabilistic [39]. Probabilistic estimates give values between 0 and 1, while the non-probabilistic yields other non-zero values based on a Likert scale score (typically, 1, 2, 3, 4, 5, and 6). The probabilistic, by far, is the choice approach because of its underlying probability theory and the rigorous estimation process [28, 29]. Therefore, the QRA framework (see Figure 2.1) proposed for the present study used the probabilistic estimation approach.

The framework has four phases: hazard identification, accident scenario modeling, occurrence probability estimation, and risk control analysis (RCA). Rectangles/squares denote task steps, and the diamond shape is for decision making. In each yellow ellipse, the specific technique(s) to carry out a task is written, and arrows give workflow direction. To operationalize the framework, start by identifying factors initiating MOB occurrence. Go on to the next tasks and end after assigning control measures. Each phase of the framework is presented in detail subsequently.

Phase 1-Hazard Identification: This is the first stage in the framework presented in Figure 2.1. Here, the risk factors to cause MOB occurrence were identified through a literature survey and what-if analysis. When much literature exists on an accident or incident, Sanni-Anibire et al. [40] have shown that a literature survey can help identify the accident’s cause(s). The academic databases used for the literature search were ScienceDirect, Emerald, IEEE Xplore Digital Library, ProQuest, SpringerLink, Taylor and Francis Online, EBSCOhost, Engineering Village, Federal Science Library, Google Scholar, and Fish, Fisheries and Aquatic Biodiversity Worldwide. These databases hold many publications on maritime accidents, particularly for the commercial fishing industry, where MOB accidents frequently occur [1, 10, 11].

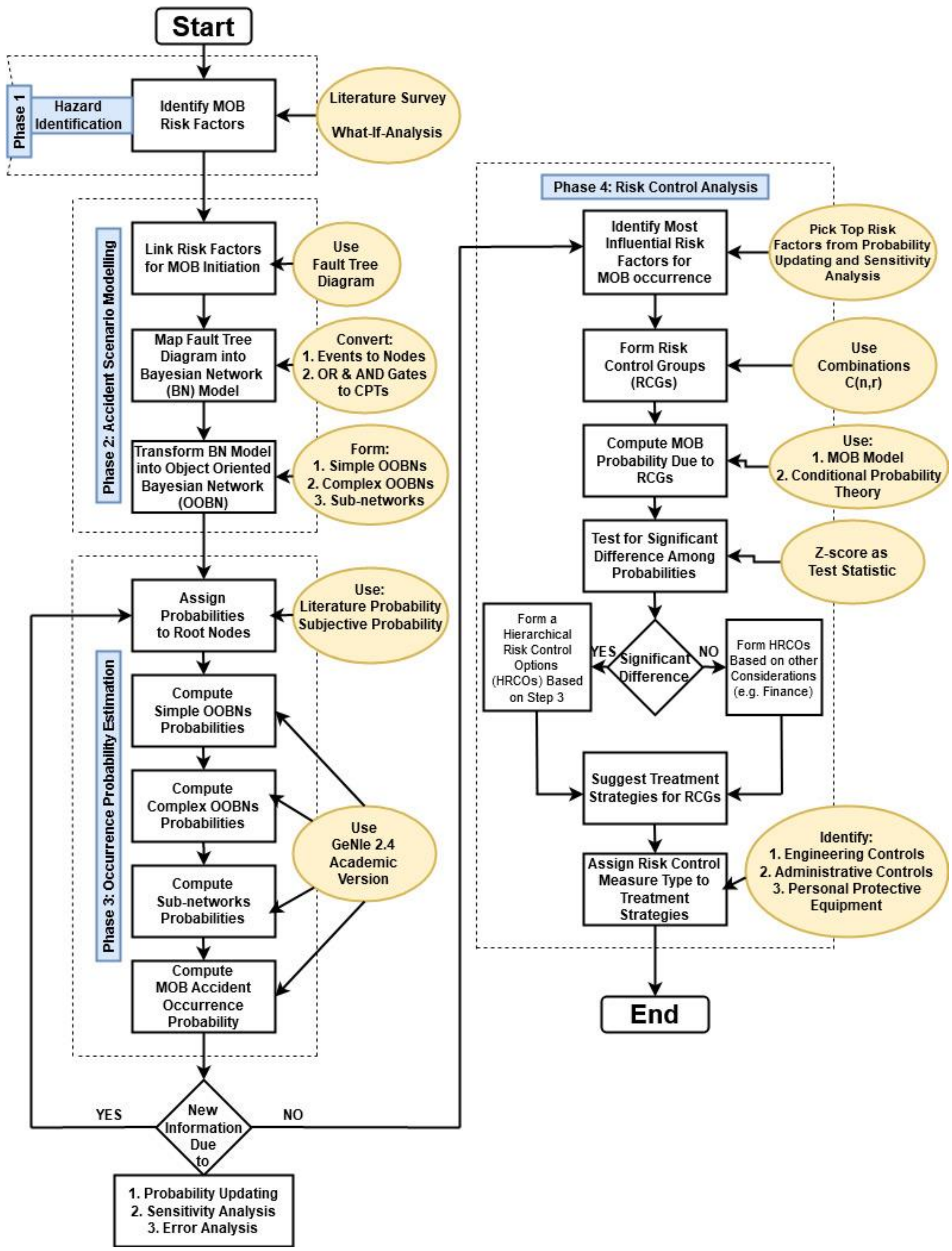

Figure 2.1. The proposed QRA framework for MOB scenario analysis.

The keywords “man overboard”, “person overboard”, and “fall overboard” were combined with “vessel”, “ship”, “marine”, “maritime”, “commercial fishing”, and “fishing accidents” to identify literature [1, 4, 10—24] relevant to the study. To avoid missing out on relevant risk factors, in addition to journal and conference papers, the study team carefully scrutinized MOB relevant contents in master’s and doctoral dissertations, textbooks, book chapters, technical reports, and working papers too.

This exercise ensured that the developed OOBN model captured the relevant aspects of MOB occurrence. Some identified risk factors for MOB occurrence needed further breakdown to identify root causes. The what-if analysis came in handy [41]. The what-if analysis yielded the additional risk factors needed through the study team’s brainstorming sessions to ask questions about possible undesired events. Finally, all risk factors identified were documented and saved on the computer and a backup storage device.

Phase 2-Accident Scenario Modelling: This phase was responsible for creating the accident network for MOB occurrence. Two assumptions were deemed critical for forming the network if a practical approach for MOB accident occurrence was to be modeled. First, follow a realism approach based on how events unfolded to describe MOB occurrence aboard vessels. Secondly, the dependency relationship between a group of risk factors can only be modeled as either mutually exclusive or mutually inclusive.

The first assumption calls for a thorough digest of accident investigation reports to understand the circumstances that led to MOB occurrence aboard vessels that fell victim to the accident. However, the second assumption calls for expert opinions on operational matters related to accident risk factors combination to cause the MOB accident. Therefore, the assumptions provide an opportunity to leverage lessons learned from past MOB accidents and experience gained in causality relationship development to build a robust accident network for MOB scenario analysis onboard marine vessels.

As Uğurlu et al. [13] explained, the accident network reveals the formation patterns of risk factors to result in the accident. To do this, first, a causality relationship was established among the risk factors identified in Phase 1 by following the three-tier stages in Figure 2.2. In establishing the causality relationship and the network, the brainstorming sessions focused on understanding how MOB occurs in reality. The accident investigations reports [1, 4, 10—24] studied during the sessions revealed how the risk factors identified unfolded to cause MOB accidents.

The study team discovered that regardless of the vessel type, the crew member was on the main deck for every MOB accident, not wearing a fall arrest system though close to the gunwale, and a significant unexpected vessel movement occurred too. That is the Tier I stage in the MOB scenario modeling (shown in Figure 2.2). At this stage, typical questions to be asked include, why was the crew on the main deck and not inside the accommodation structure (for vessels that have one), and what caused the unexpected vessel movement to occur.

To answer the questions, investigations about job-related tasks, personal behaviors, and vessel motion factors contributing to MOB occurrence followed as Tier II. Finally, to complete the risk factors arrangement, basic variables to Tier II factors were sourced next to constitute the Tier III stage. The Tiers I, II, and III together formed a hierarchical accident structure as shown in Figure 2.2, in which the MOB is positioned at the top as the incident. The broken lines in Figure 2.2 show that more causal factors may be sought in Tier II before defining Tier III's factors.

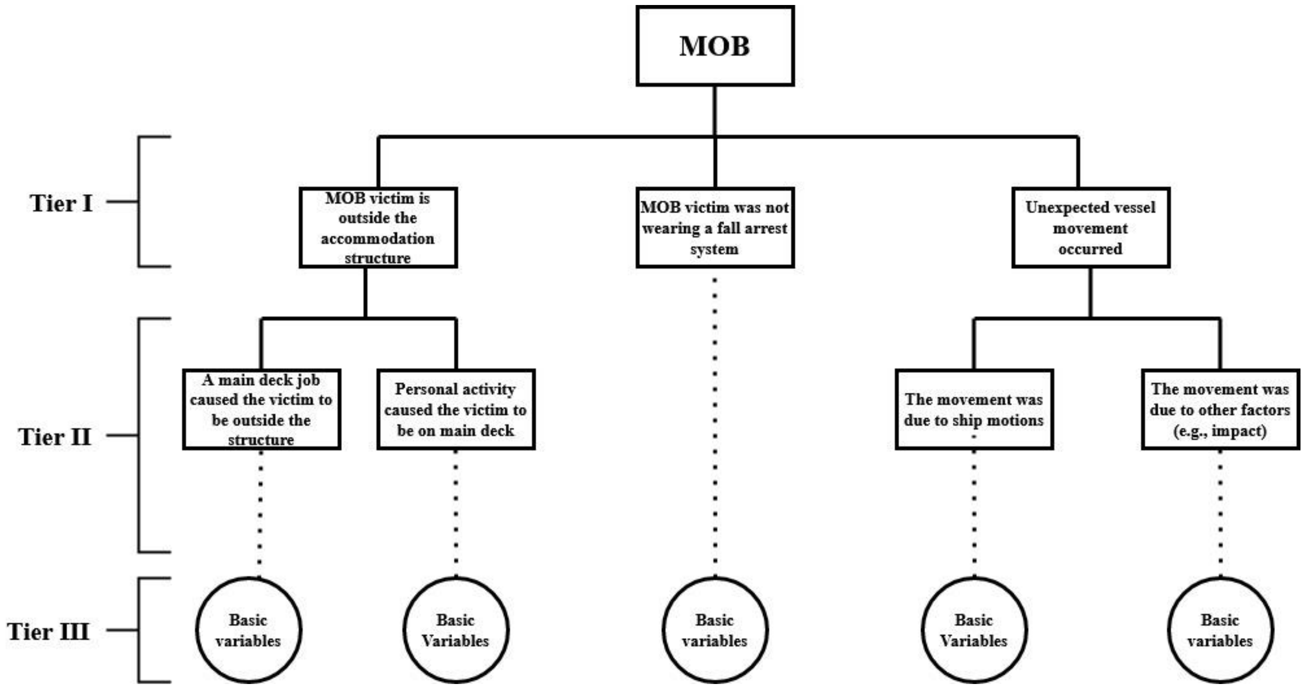

Figure 2.2. The hierarchical structure for developing the MOB accident network.

After establishing the hierarchical structure, the second step was to define the dependency relationship among the risk factors in the structure. The risk factors were assumed to be in mutually exclusive or mutually inclusive dependency relationship at each Tier. As a result, it was possible to transform the hierarchical structure in Figure 2.2 into a fault tree diagram (FTD). The FTD is a graphical risk modeling tool, excellent at representing accident scenarios as diagrams for easy comprehension [42, 43].

A group of risk factors modeled as mutually exclusive scenario (MES) require the occurrence of only one of the lower-risk factors (LRF) for the upper-risk factor (URF) to occur; this translates into an "OR Logic Gate" on the FTD for an MES. On the contrary, a group of risk factors exhibiting a mutually inclusive scenario (MIS) required all LRFs to occur before a URF would occur. Therefore, an MIS is represented by an "AND Logic Gate" on the FTD. The decision-making on forming MES and MIS was guided by published literature [1, 4, 10—24] on MOB accident investigations and expert opinions. The expert opinions were sought from senior researchers on the study team, who shared their knowledge on FTD formation based on previous experience. Kabir [43] also provides helpful guidance on FTD construction.

From the above discussion and bearing in mind the assumptions guiding the MOB accident network formation, Figure 2.2 was turned into an FTD in Figure 2.3. For a MOB to occur, the victim would be on the main deck, not wearing a fall arrest system while close to the gunwale, and an unexpected vessel movement would destabilize the victim, which most likely, could cause the victim to topple over and head for overboard. As a result, Tier I factors are LRFs, and together with MOB (as the URF), they are modeled as an MIS.

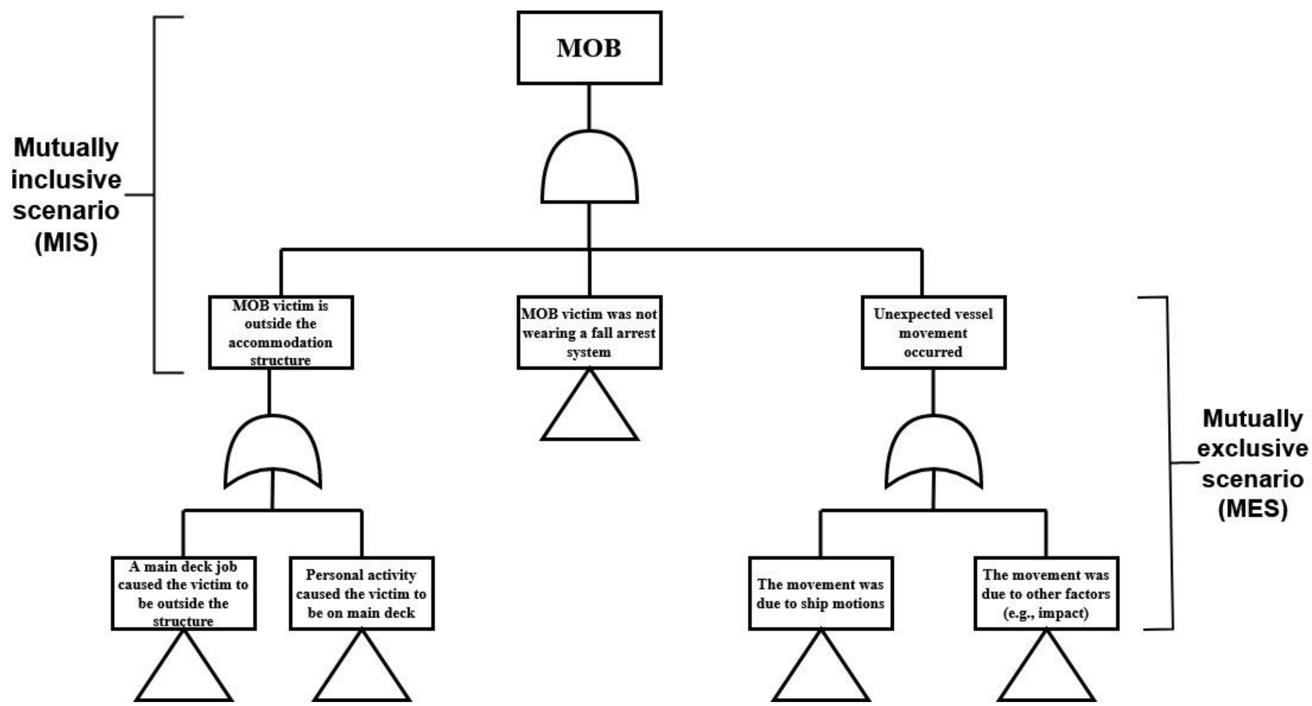

Figure 2.3. Fault tree diagram for MOB accident occurrence.

A MOB victim's reason for being on the main deck could be for job task execution or self-initiative (e.g., taking a stroll to enjoy the cool sea breeze). Likewise, vessel movements are either ship motions or some external factor (e.g., the impact from the iceberg or another ship) related. These LRFs in Tier II are mutually exclusive events, and so, when connected to their respective URF, an

MES evolves. The MES and MIS then combine to cause MOB accident, as illustrated in Figure 2.3.

Next, the FTD formed was converted into the MOB OOBN model, which is the accident network for MOB occurrence. As mentioned in the introduction section, the OOBN is excellent at handling accident scenarios whose modeling would result in vast and complex network structures viz-a-viz network learning requirements [26, 28], which was the case for the present study. The conversion was achieved by creating and linking simple OOBNs, complex OOBNs, sub-networks, and finally, the MOB OOBN model. While fundamentally, the OOBN combines the knowledge of object-oriented programming and Bayesian network [30], the simple OOBN and complex OOBN concepts introduced in Khan et al. [28], was applied to the present study.

A simple OOBN is a grouping of basic events/variables only, whereas groups of simple OOBNs only or simple OOBN(s) and basic event(s) constituted a complex OOBN. Subsequently, groupings of complex OOBNs formed sub-networks. Then, sub-networks were connected together to give the MOB OOBN model. Again, the formation and linking of simple OOBNs, complex OOBNs, sub-networks, and the MOB OOBN model, was guided by the earlier assumptions and the MIS and MES reasoning.

For computational purposes, MIS and MES are represented by conditional probability tables (CPTs). Following the procedure described in Yang et al. [44] for constructing CPTs and using "MOB" and "Unexpected vessel movement occurred" in Figure 2.3 as examples, Tables 2.1 and 2.2 describes the probability elicitation process for an MES and an MIS, respectively. Let the LRFs have binary decision states (i.e., "Yes" and "No", meaning occurrence and non-occurrence, respectively). Then, the number of probabilities to be entered in the CPTs for each URF was determined using Equation (2.1). Hence, the example MES and MIS required four and eight probability scores in their CPTs, as shown in Tables 2.1 and 2.2, respectively.

$$N_p = 2^n \tag{2.1}$$

where N_p is the number of probability scores needed in a conditional probability table for a URF and "n" is the number of LRFs describing the URF occurrence.

Table 2.1. An example conditional probability table for a mutually exclusive scenario.

The movement was due to ship motions	The movement was due to other factors (e.g., impact)	Unexpected vessel movement occurred
Yes	Yes	1
Yes	No	1
No	Yes	1
No	No	0

Table 2.2. An example conditional probability table for a mutually inclusive scenario.

MOB victim is outside the accommodation structure	MOB victim was wearing a fall arrest system	Unexpected vessel movement occurred	MOB
Yes	Yes	Yes	1
Yes	Yes	No	0
Yes	No	Yes	0
Yes	No	No	0
No	Yes	Yes	0
No	Yes	No	0
No	No	Yes	0
No	No	No	0

Finally, Phase 2 of the study framework (Figure 2.1) was completed by implementing the MOB OOBN model in a software environment. The academic version of GeNIe 2.4 software used by Yang et al. [44] was found suitable for the present study. Enabling the "submodel" feature in GeNIe 2.4 [45], the simple OOBNs, the complex OOBNs, the sub-networks, and the MOB OOBN model, were created as fragmented sub-models joined by their respective CPTs.

Phase 3-Occurrence Probability Estimation: With the MOB OOBN model (hereafter referred to as the model) developed and implemented in GeNIe, it is now possible to estimate MOB Occurrence Probability (MOP). This required all root-cause-risk-factors (hereafter referred to as root factors) to be assigned prior probabilities. Although historical databases [27] and expert elicitations [46] are the primary sources to acquire prior probability data, Animah and Shafiee [47] mentioned literature databases as another source of data for prior probability especially, at the initial stages of research. Therefore, the present study sought prior probabilities from the MOB literature during the Phase 1 task execution. To ensure a credible estimate for MOP, only prior probabilities from peer-reviewed papers in English and top-tier international journals and conference proceedings were used. The chosen prior probabilities for root factors were then put into the model, and GeNIe calculated probabilities (using the CPTs) for simple OOBNs, complex OOBNs, sub-networks, and finally, MOP.

The model also supports evidential reasoning and learning [30, 44]. When new information was discovered about a risk factor in the model, the calculation procedure was repeated to facilitate further analyses [26, 44]. Since the present study only aimed to use the model to predict the most probable MOB occurrence scenario and conduct RCA, further analyses were limited to probability updating and sensitivity analysis. Probability updating enabled the estimation of posterior probabilities for root factors given the occurrence of MOB. This was achieved by setting MOP to 100% in the model. GeNIe then recalculated new probabilities (i.e., posterior probabilities) for all the model factors.

The recalculation is based on Bayes' theory (see Equation (2.2)). From the equation, the model sought to calculate P(X|Y), meaning, the posterior (or new) probabilities of root factors given that MOP = 100 %.

$$P(X|Y) = \frac{P(Y|X) \times P(X)}{P(Y)} \tag{2.2}$$

where, X = a hypothesis (i.e., root factors); Y = the evidence obtained about the hypothesis (i.e., MOB occurrence); P(X) = prior probability and represent the probability of "X" before new evidence, “Y” became available (i.e., prior probabilities of root factors); P(Y|X) = likelihood probability and denote the probability of seeing the evidence “Y” if the hypothesis “X” is true (i.e., conditional probabilities in CPTs); P(Y) = total probability and denote the prior probability of Y under all possible hypotheses; and P(X|Y) = posterior probability and indicate the latest probability of “X” based on the new evidence, “Y” gathered (i.e., posterior probabilities of root factors given that MOP is 100 %).

After probability updating, the sensitivity analysis was next. As explained in Qian [48], sensitivity analysis measured the proportions of variability in the model’s output (i.e., MOP) attributed to root factors. In doing so, the contributions made by each root factor to the estimated MOP were known. Several techniques exist for sensitivity analysis [48]. However, the present study used the improvement index technique [26] because it allows for the model proposed to be involved in the conduction of sensitivity analysis. This way, the MOB OOBN model application in sensitivity analysis was demonstrated.

To determine the percentage contribution of a root factor, 0% was assigned to the factor, and GeNIe run for a new MOP. Subsequently, the percentage change in the old (or original) and new MOP values was computed using Equation (2.3). The procedure was repeated for the remainder of the root factors. The percentage changes recorded were ranked from the highest to the lowest as improvement indices. Higher scores made more contribution to MOB occurrence probability than lower scores.

$$\text{Improvement index} = \text{Percentage change} = \frac{\text{Original MOP} - \text{New MOP}}{\text{Original MOP}} \times 100\% \qquad (2.3)$$

Phase 4-Risk Control Analysis: This is the final stage of the framework. Its goal is to identify the most influencing root factors and then assign intervention measures to prevent or mitigate their occurrence. This would ensure MOB occurrence is prevented or minimized significantly. First, the list of most influencing root factors was created. All root factors that appeared top (e.g., first 3 or 5 factors) during the probability updating and sensitivity analysis were put on the list. Khakzad et al. [26] showed that risk factors could combine to cause the accident occurrence. Therefore, Equation (2.4) was used to form combinations of the single factors and added to the list to create risk control groups (RCG).

$$C(n,r) = \frac{n!}{r!(n-r)!} \tag{2.4}$$

where, C(n,r) = number of “r” groups out of “n”; n = total number of elements in the RCG set, and r = number of element combinations to be formed.

After creating RCGs, a new MOP was estimated given that an RCG has occurred (i.e., P(MOB|RCG)). The result was put into Equation (2.5), and subsequently, the joint probability of MOB and RCG (i.e., P(MOB, RCG)) was estimated. The procedure was repeated for other RCGs. Next, the most influential RCG was determined by the z-statistical test [49, 50]. The most influential RCG is the most probable configuration (MPC) [26] for MOB occurrence. The reason for doing the test is to check for a statistically significant difference among the RCGs, which would justify using RCGs to define the MPC. Finally, interventions were prescribed to the MPC by assigning control measures to each root factor involved.

$$P(MOB|RCG_i) = \frac{P(MOB, RCG_i)}{P(RCG_i)} \tag{2.5}$$

where P(MOB|RCG_i) = conditional probability, P(MOB, RCG_i) = joint probability, and P(RCG_i) = total probability.

2.3. Case Study Applications

It could be inferred from the introduction section that the commercial fishing industry and small fishing vessels are critical subjects when it comes to MOB occurrence. Therefore, applying the described methodology to case studies in these areas would be useful. In the broader sense, the case study serves two purposes: (1) demonstrating how to develop the MOB OOBN model for a specific sector of the maritime transport industry (e.g., CFI) and (2) showing how to use the MOB OOBN model to conduct MOB scenario analysis on a given vessel (e.g., a small fishing boat). The proceeding section presents the case study demonstrations.

2.3.1. MOB OOBN model development for the CFI

The MOB risk factors in the CFI were identified by implementing Phase 1 of the proposed framework (Figure 2.1). A total of 88 root factors (see Appendix A1) were realized and used in drawing the MOB occurrence FTD (see Appendix A2). Then, 22 simple OOBNs were formed from these root factors, and subsequently, complex OOBN (n = 19) and sub-network (n = 5) were formed.

The simple OOBNs, complex OOBNs, and sub-networks were finally linked together probabilistically (using the CPTs as explained in Tables 2.1 and 2.2), resulting in the MOB OOBN model (hereafter, referred to as the model). The model development, implementation, and computation analyses were done using the GeNIe 2.4 academic version. It must be noted that the summary description of procedures given here for the model development is based on the detailed explanation provided in Phases 1 and 2 of Section 2.2.

Figure 2.4 shows the model with its three (of the five) sub-networks (see Appendix A3) and root factors categorized into technical, environmental, and human factors (see Appendices A1 and A4). In Section 2.1 of this study, the bases for these categorizations were stated. Simple OOBNs in these categories were grouped under “T”, “E”, and “H”, respectively. They then combine as complex OOBNs in “M”, and their effects are extended as “F_A”, “F_B”, and “F_B” to form sub-networks by abstraction and encapsulation. See Figure 2.4 and Appendix A1 for illustrations. The developed model (Figure 2.4) described the possibility of MOB occurrence given that the crew member involved was on the main deck (Yes/No), not wearing a fall arrest system (Yes/No), and there was unexpected vessel movement (Yes/No). Sudden vessel movements or ship motions (Severely/Not severely) triggered the unexpected vessel movement.

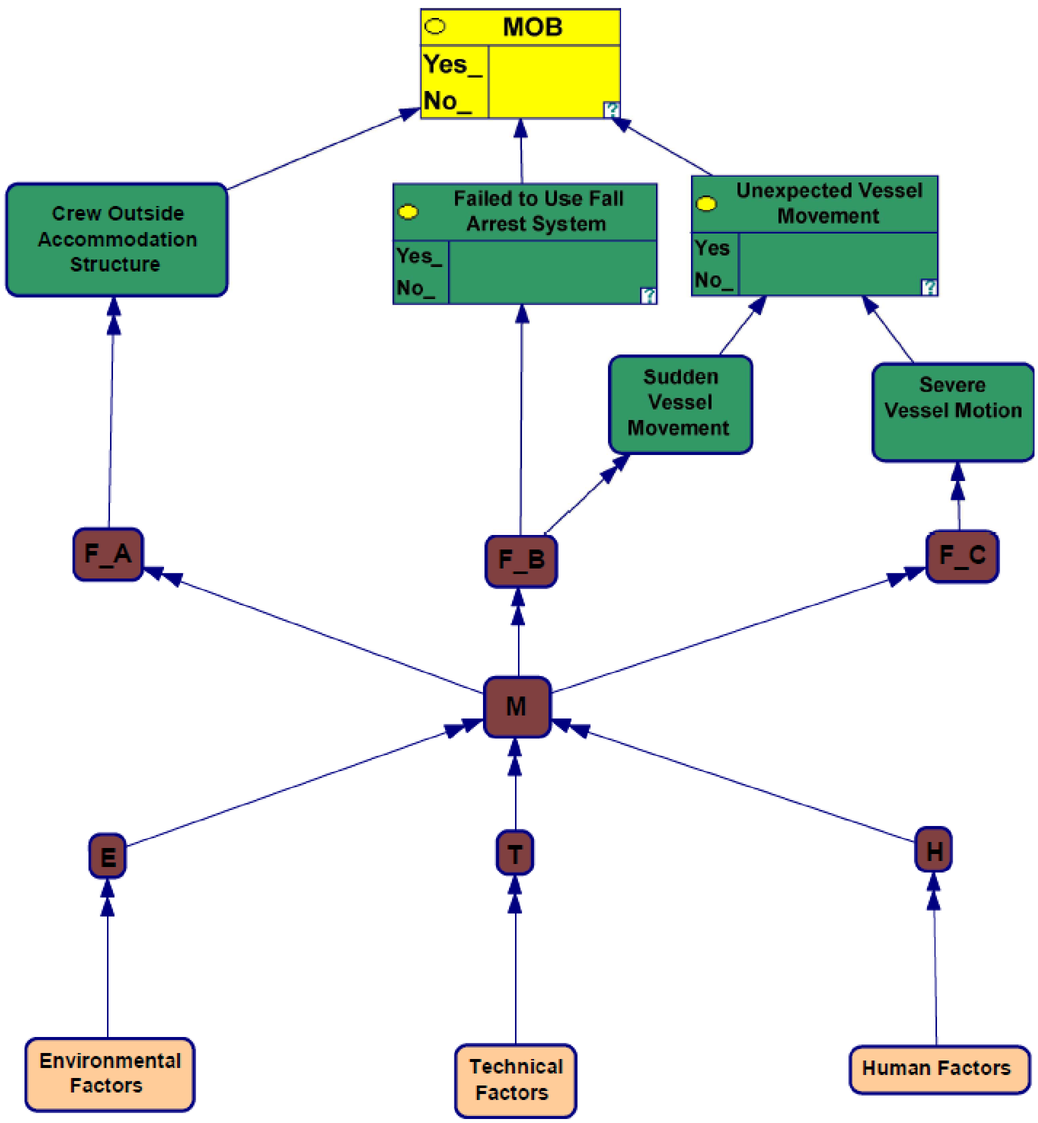

Figure 2.4. The developed MOB OOBN model.

2.3.2. MOB scenario analysis

The case study's first objective has been achieved with the MOB OOBN model developed for the CFI. Likewise, the foundation has been laid for the second objective, MOB scenario analysis, to be accomplished. A small fishing boat was employed as the case study vessel. Then, probability updating and forward, sensitivity, and risk control analyses were performed for the boat by following the procedures in Section 2.2, Phases 3 and 4. Further descriptives for the boat analyses follow next.

2.3.2.1. Case scenario description

The case study vessel is a hypothetical small fishing boat that uses pot gear and whose operational performances and environmental jurisdiction subjected it to the MOB risk factors identified earlier. Generally, a pot gear is a trap used to catch shellfishes such as lobsters, crabs, crayfish, octopus, and oysters [1, 33]. Fishing vessels employing this gear type ranges from small boats (used within territorial waters) to as large as 50 m in length vessels used on the high seas. For this study, the small boat type with a length overall not exceeding 24 m and capable of operating beyond territorial waters is the focus.

The vessel's suitability for demonstration comes from the fact that pot gear operation relies heavily on fishing lines [10, 33], which have been identified as the prime cause of gear entanglement [4] accidents leading to MOB occurrence. Also, among pot, gillnet, and longliner fishing gears, Lincoln and Lucas [1] reported 34 % (out of 71) fatal MOB occurrences on fishing vessels that used pot gear. This was the highest fatality by fishing gear type in Alaska from 1990 to 2005 [1]. Additionally, Thomas et al. [11] mentioned that out of 117 fishers hospitalized, the crab pot was the cause of the injury sustained by 53 of these fishers. Using prior probabilities (see

Appendix A5) sourced from literature and the model developed, a QRA was carried out on the case study vessel as detailed next.

2.3.2.2. Forward analysis

The goal of this section was to estimate MOP using the developed model (Figure 2.4). Therefore, probabilities for root factors were sought from literature, as described in Section 2.2, Phase 3, and entered into the model (see Appendix A4). GeNIe was run, and it yielded an estimate for MOP.

2.3.2.3. Probability updating

The goal and procedure for probability updating were discussed in Phase 3 of Section 2. Following the procedure described, the "Yes" decision state of the MOB node (yellow color) in Figure 2.4 was set to 100%, and GeNIe run to give posterior probabilities for root factors.

2.3.2.4. Sensitivity analysis

The sensitivity analysis was performed to determine each root factor's contribution to the estimated MOP. The "Failed to use fall arrest system (Yes/No)" in Figure 2.4 will be used to demonstrate the process. First, the MOP estimated in Section 2.3.2.2 was noted as the "original MOP". Then the "No" decision state of the "Failed to use fall arrest system" node was set to 100%; meaning, the node is excluded from the proceeding calculation. GeNIe was run, and a new MOP was estimated and called "new MOP". Finally, the "original MOP" and "new MOP" were plugged into Equation (2.3), and the node's percentage contribution to the "original MOP" was estimated as its improvement index. This process was repeated for the remaining 87 root risk factors.

2.3.2.5. Risk control analysis

The MPC for MOB occurrence was discussed in detail in Phase 4 of Section 2.2 and how to identify it using RCA. Here, a demonstration of the step-by-step procedures used is presented for the small fishing boat case study. Only three root factors were considered; for a detailed RCA, more root factors must be considered based on the results of sensitivity analysis and probability updating.

Step 1: The top three root factors for MOB occurrence were identified (see Appendix A5).

- Failed to use fall arrest system while on the main deck (R1)
- Working under alcohol influence (R32)
- Strolling/working close to low guardrails (R6)

Step 2: Risk control groups (RCG) were formed using Equation (2.4).

- Accident scenario triggered by a single risk factor: R1, R6, and R32.
- Accident scenario triggered by dual risk factors: (R1, R32); (R1, R6); (R6, R32).
- Accident scenario triggered by triple risk factors: (R1, R6, R32).

Step 3: The total probability for each RCG was estimated.

- For example, the total probability for R1 was computed as follows: $\mathrm{P(R1)} = [\mathrm{P(MOB = Yes|R1 = Yes)} \times \mathrm{P(R1 = Yes)}] + [\mathrm{P(MOB = Yes|R1 = No)} \times \mathrm{P(R1 = No)}]$. The model was used to evaluate $P(MOB = Yes|R1 = Yes)$ and $P(MOB = Yes|R1 = No)$ as done in Section 2.3.2.4, giving 0.715 and 0.000 for the conditional probabilities, respectively. Hence, $P(R1) = (0.715 \times 1) + (0 \times 0.285) = 0.715$, since $P(R1 = Yes) + P(R1 = No) = 1$.

Step 4: The joint probability for each RCG and MOB occurrence was estimated using Equation (2.5).

- For example, the joint probability of R1 and MOB occurrence was computed as follows: $P(MOB, R1) = P(MOB|R1) \times P(R1) = 0.715 \times 0.715 = 0.511$.

Step 5: Find out if significant differences exist between $P(MOB, RCG_i)$ values using the z-statistic [49,50].

- First, the null (H_o) and alternative (H_a) hypotheses were stated: H_o = all values of $P(MOB, RCG_i)$ are the same; H_a= at least one $P(MOB, RCG_i)$ value is different;
- Next, a significant level was set for the test (e.g., 5%);
- The z-score table was then used to estimate the areas under the graph corresponding to values of $P(MOB, RCG_i)_{i=1-7}$, for a two-tails or one-tail test;
- The estimated areas were then plotted on the standard normal distribution curve to find out which region (i.e., acceptance or rejection) did each fall;
- Lastly: (a) if all estimated areas fell in the acceptance region only or rejection region only, the null hypothesis was upheld true; (b) if the estimated areas are distributed in either region, the alternative hypothesis was upheld true instead.

Step 6: Establish hierarchical risk control options (HRCO) base on $P(MOB, RCG_i)$.

From the fifth point of Step 5, the following conclusions can be made:

- If (a) holds, then $P(MOB, RCG_i)$ values are not statistically different, and each RCG (in Step 2) has the same influence on MOB occurrence. In this case, no particular order is required to form HRCOs. Depending on other factors (e.g., finance or convenience), a specific RCG may be chosen first for redress towards MOB occurrence prevention and the mitigation of consequences.
- If (b) holds, then $P(MOB, RCG_i)$ values are statistically different, which means some RCGs have more influence on MOB occurrence than others. Therefore, a peculiar order is required to form HRCOs. The values of $P(MOB, RCG_i)$ were used to perform the ordering because MPC [26] refers to the combination of root factors to cause the accident, which is the joint probability. Higher values of $P(MOB, RCG_i)$ were top on the HRCOs list, while lower values were at the bottom.

In assigning interventions for MOB prevention or mitigation, RCGs with higher $P(MOB, RCG_i)$ values must be considered first. Those RCGs with lower $P(MOB, RCG_i)$ values may be tackled later since the earlier forestalls MOB occurrence.

The small fishing boat's RCA results and those of the forward analysis, probability updating, and sensitivity analysis, are presented and discussed in Section 2.4.

2.3.3. MOB interventions model

Once the MPC for MOB is known, control measures are needed to prevent or mitigate the root factors involved. To achieve this objective, the MOB interventions model (see Figure 2.5) was developed. This model assigns control measures from the interventions bank (see Appendix A6) to a given root factor. Effective accident prevention requires control measures to address both pre-accident and post-accident occurrences [1, 33, 51]. Therefore, in Figure 2.5, the MOB interventions model uses engineering controls and administrative controls to provide safety against pre-MOB occurrences. Then, PPE use is focused on post-MOB events to ensure a MOB victim does not drown but remains afloat to be rescued.

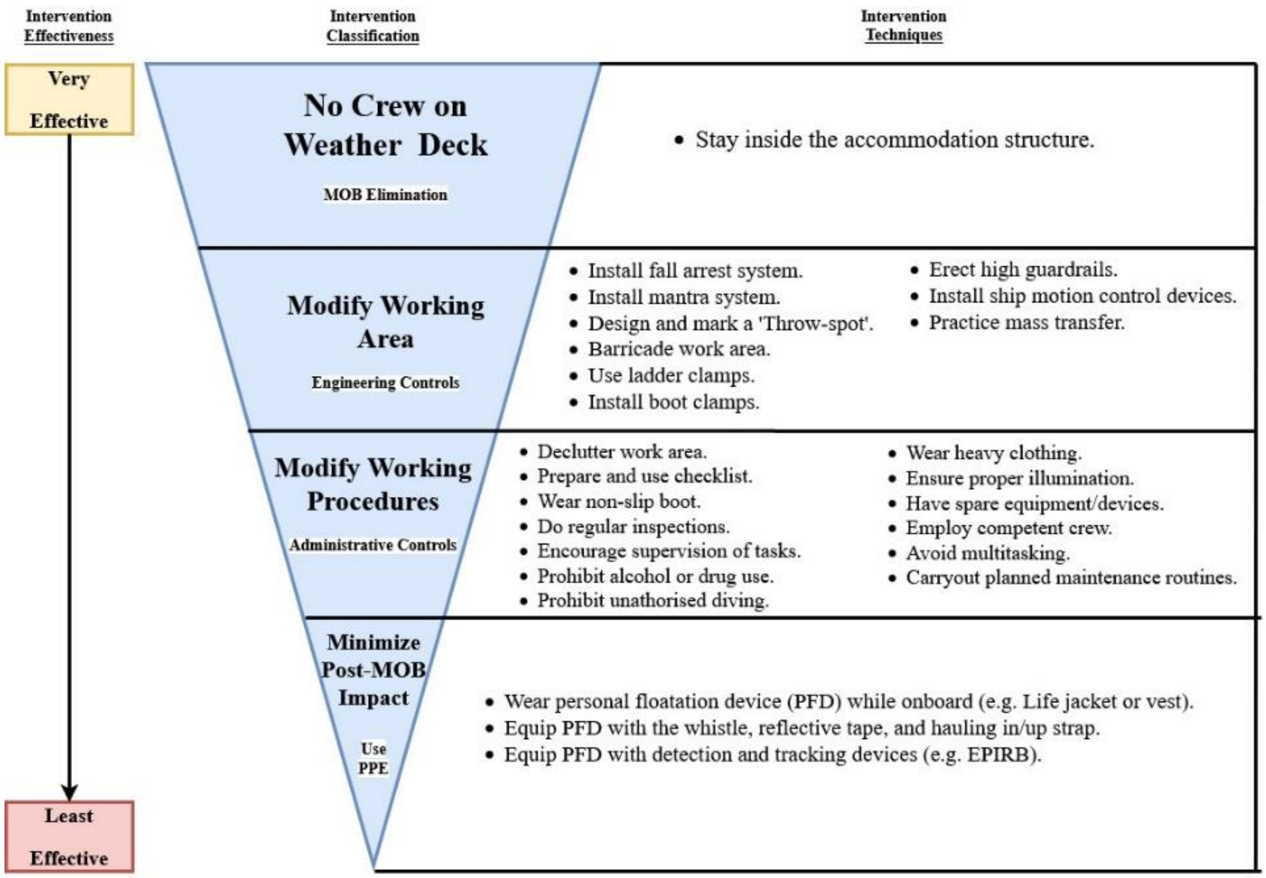

Figure 2.5. The MOB interventions model.

The safest protection for a seafarer against MOB accident is to stay inside the accommodation structure. However, that would mean no fishing activity can be performed for a fishing vessel, resulting in economic loss. Therefore, once a fisher is on the main deck, depending on the fishing task, appropriate engineering controls or administrative controls must be in place to ensure the fisher's protection against the MOB accident. These controls are intervention techniques retrieved from the interventions bank, with samples provided in Figure 2.5.

The interventions bank was formed by gathering MOB interventions mentioned in previous literature [1,4,10—24] and linking them to appropriate root factors. During the brainstorming sessions held (as described in Phase 1 of Section 2.2), new interventions for MOB prevention and the mitigation of the consequences were suggested, adding to the present study's novelty. Notable among them are using a mantra system on the bridge deck, compulsory use of the non-slip boot on the main deck while fishing, developing and implementing a checklist specifically for MOB, and designating a "Throw-spot" area on the main deck.

The mantra system [52] is becoming increasingly popular in scientific studies. Fundamentally, it is based on human meditation or concentration [53] and learning and information retention [54]. In the present study, the mantra is used to mean any system (mostly audio) capable of reminding a pilot or an officer-of-the-watch (OOW) on duty to continue focusing attention on the assigned task. This way, human errors that occur during vessel piloting and resulting in incidents (e.g., collisions) that could cause MOB occurrence are averted.

A non-slip boot would have soles that do not allow slipping; thus, slipping incidents culpable for MOB occurrence can be prevented. Also, the use of non-slip boots to avoid slipping related MOB occurrences is most likely to be a better economic choice than covering the entire main deck with non-slip flooring proposed by Lincoln and Lucas [1].

Checklists as decision aids have proven useful in the decision-making environment for curbing human error [55, 56]. During the brainstorming, the "Going-to-main-deck-checklist" and "Intoxication-level-checklist" specifically for MOB were proposed. Fishing vessels with accommodation structure will find the earlier checklist useful because it will define the acceptable condition for a fisher before being allowed on the main deck. The later checklist, which can be implemented on every fishing vessel type (using an appropriate mechanism), will be geared towards preventing fishers who are highly intoxicated by alcohol or drug from going on a fishing voyage.

A significant MOB fatality was recorded during the literature review for shooting and hauling fishing gears [1, 4, 10]. Designating an area on the main deck as a "Throw-spot" and encouraging fishers to do all shooting and hauling operations from there could have a positive impact on MOB accidents caused by such operations. The MOB interventions model was applied to the small fishing boat case study, and the outcome result is discussed in Section 2.4.

2.4. Results and Discussions

Table 2.3 shows the results from the forward analysis for the risk factors in Figure 2.4. Those for simple OOBNs, complex OOBNs, and sub-networks (not showing in Figure 2.4) can be found in Appendix A7. The values shown are occurrence probabilities for the risk factors involved. The improvement index results from sensitivity analysis are presented in column three of Table 2.4.

Next, the difference in prior and posterior probabilities due to probability updating performed on the case study vessel are presented in Table 2.4, column four. Only estimates for the top seven root factors are shown in Table 2.4 for both probability updating and sensitivity analysis. The remainder of the estimates is in Appendix A5. Finally, Table 2.5 shows the RCA results for the top three root factors from probability updating and sensitivity analysis.

Table 2.3. Occurrence probabilities from the forward analysis.

Number	Risk factor	Probability (Yes/Severely)
1	MOB	0.170
2	Failed to use fall arrest system	0.240
3	Crew outside accommodation structure	0.780
4	Unexpected vessel movement	0.910
5	Sudden vessel movement	0.880
6	Severe vessel motion	0.580

Table 2.4. Estimates for improvement index and the difference in prior and posterior probabilities.

Risk factor	Description	Improvement index (%)	Change in probability
R1	Failed to use fall arrest system	100.000	0.762
R32	Working under alcohol influence	27.059	0.135
R6	Strolling/working close to low guardrails	8.235	0.062
R33	Working under drug influence	5.882	0.050
R19	Working close to fishing gear	1.176	0.048
R84	Vessel veer about an obstacle	4.706	0.030
R86	Vessel required to stop suddenly	4.706	0.028

Table 2.5. Risk control analysis estimates using the top three root factors.

$RCG_{i=1-7}$	$P(RCG_i)$	$P(MOB\|RCG_i)$	$P(MOB, RCG_i)$	z-score	HRCOs
R1, R6, and R32	0.779	0.913	0.711	0.1292	1
R1 and R32	0.768	0.913	0.701	0.9992	2
R1 and R6	0.731	0.913	0.667	0.9992	3
R1	0.715	0.715	0.511	0.0055	4
R6 and R32	0.184	0.216	0.040	0.0002	5
R32	0.182	0.216	0.039	0.9992	6
R6	0.173	0.216	0.037	0.0002	7

While previous MOB research focused on identifying risk factors and their occurrence statistics, the present study primarily concerns the probabilistic linking of the risk factors to predict MOB scenarios aboard vessels. Very little was found in the literature on predicting a MOB scenario before it degenerated into an accident. Hence, the case study application in the commercial fishing industry has shown that by connecting associated risk factors in an Object-oriented Bayesian network environment, it is possible to develop a pre-MOB analysis tool for a given vessel.

Through the developed MOB OOBN model, endangering events culpable for MOB occurrence during shipboard operations can now be noticed ahead of time and appropriate steps taken to avoid their occurrence. This means, the MOB OOBN model could assist in the ongoing effort to reduce the frequency of MOB cases aboard fishing vessels and in the industry at large [1, 4, 10, 11, 13].

It is also worth noting that the 17% (see Table 2.3) MOB occurrence rate estimated by the model is comparable to some current statistics on the subject. Roberts [4], Thomas et al. [11], and Uğurlu et al. [13] have recorded similar values for smaller groups (e.g., fishing gear and communities). For country-specific estimations, the MOB occurrence rate stands between 23% and 33% of all fishing related accidents, often per 10 years period [1,10,14]. These findings suggest that the MOB OOBN model is giving reasonable assessment estimation. Furthermore, the model can be used beyond single vessel analyses: maritime administrations and fishing boat owners could use the model to investigate their local (e.g., vessels belonging to a group with a peculiar similarity), global (e.g., all the vessels of a fishing company), and cumulative (i.e., over a period; say, six months, one year, or a decade) MOB occurrence risk rates.

Rough weather was mentioned by Thomas et al. [11] as the cause for "Unexpected vessel movement (91%)", which then results in "Sudden vessel movement (88%)" or "Severe vessel motion (58%)". When these occur, and a crew member outside the accommodation structure (78%) did not wear a fall arrest system (24%), a MOB accident will likely happen. Thus, a fisher not wearing a fall arrest system while the vessel is in rough seas is the pre-existing condition to cause a MOB accident, since being outside the accommodation structure is unavoidable if fishing operations must continue. However, addressing the failure to wear a fall arrest system instead of rough seas, appears reasonable due to sea state variability. This viewpoint was also upheld by Case et al. [33].

Another question the present study sought to answer was which root factors contributed much to MOB occurrence and how to determine these factors before the accident (i.e., MOB) occurrence. Previous research works relied on eyewitness testimonies and other qualitative fact-finding methods to arrive at these factors [1, 4, 11, 33]. The main disadvantage of these methods is that they are only useful after the accident has occurred. Knowing that MOB consequences are grave, proactive strategies would be more desirable in identifying the critical root factors leading to the accident. Sensitivity analysis (by improvement index) and probability updating, as demonstrated in the works of Khakzad et al. [26] and Khan et al. [28], have proven useful in this regard.

After applying these techniques, the first seven most influencing root factors identified are shown in Table 2.4. These factors made the highest contributions to the 17% MOP estimated. Consequently, they are the most vulnerable events leading to MOB occurrence aboard the small fishing boat under study. Any resource allocation towards MOB occurrence prevention must be targeted first at these risk factors. As explained in Section 2.2, Phase 3, and Sections 2.3.2.3 and 2.3.2.4, the model developed facilitated sensitivity analysis and probability updating. Therefore, the model supports decision-making processes, and policy-makers in maritime accident prevention committees will find the model and the approach for vulnerable events identification useful when confronted with making decisions on which risk factors to target to mitigate MOB and related shipboard accidents. Likewise, the model and the approach could help vessel masters make decisions on daily proactive measures to avert MOB occurrence during shipboard operations.

Although knowing the individual critical factors (or vulnerable events) for MOB occurrence on a given vessel matters, it is equally important to define whether MOB occurs more often when these factors act in singles or combine. This way, control measures would be targeted at the worst-case scenario known as the MPC [26]. Hence, risk control analysis is necessary, and Table 2.5 shows the case study vessel's analysis results. The first column lists the RCGs and their root factors. Column 2 stands for total probability and provides a frequency measure for each RCG, under all the possible ways individual factors in an RCG could occur.

In calculating total probability, the non-occurrence probability of the factors involved is considered, making it impossible to use total probability to determine the MPC. Also, the conditional probability (column three), which gives the frequency measure for a MOB occurrence given that an RCG has occurred, cannot be used either. It does not quantify the combined impact of each root factor's occurrence and non-occurrence (within an RCG) on MOB occurrence. That is to say, it does not explore all the possible ways the factors in an RCG could lead to MOB occurrence. On the other hand, the joint probability can be used to decide the MPC because it estimates the possibility of MOB occurrence given the simultaneous occurrence of RCG factors and MOB.

From the above explanation, the results of column four (Table 2.5) show that the MPC for MOB occurrence considering the case study at hand is the simultaneous occurrence of all three root factors employed in the RCA. Before deciding to assign control measures, it is essential to inquire about statistical significance among the joint probability estimates for the sake of intervention prioritization and the creation of control options. The results for the z-statistics used are shown in column five of Table 2.5. At a 5% significance level for either one or two-tail test, all the z-scores are not in one region (acceptance or rejection). This means the joint probabilities are statistically different. Therefore, the hierarchy (i.e., last column of Table 2.5) for administering interventions was formed based on the joint probabilities.

As an optimum solution to prevent MOB occurrence for the case study vessel, interventions for all three risk factors must be prioritized. If, for example, because of budgetary limitations, all the three factors cannot be addressed simultaneously, HRCO 2, 3, and 5 (i.e., two factors combination) or HROC 4 and 6 (i.e., single factor) may be considered. Providing interventions to "Strolling/working close to low guardrails (i.e., R6)" is at the bottom, implying it is the last option of redress to be considered. That does not necessarily mean it is the least effective option. Depending on the intervention technique used, MOB occurrence could be prevented by focusing on R6. If the technique, "Erect high guardrails" (see Figure 2.5) is used, MOB occurrence may be aborted even if a fisher is not using a fall arrest system and is still close to the guardrail.

The interventions bank is shown in Appendix A6. It contains 119 control measures for the 88 root factors used in the case study model. The "Install and use a fall arrest system", "Prohibit alcohol or drug use", "Prepare and use the Go-to-main-deck and Alcohol-level-checklists", and "Wear lifejackets while onboard" are typical examples of control measures for MOB accident prevention and consequence mitigation for the case study vessel. The interventions bank will serve as an example for ship owners and fishing companies, guiding them on developing similar intervention measures for MOB (or other accidents) mitigation aboard their vessels.

2.5. Limitations of the Study

The present study has provided useful insight into probabilistic methods application for MOB scenario analysis. However, it can still be improved by addressing the following limitations:

- Due to the inconsistencies in literature data, which raises data inadequacy issues, the case study results may not reflect exact values. This could be improved by accessing historical data from the commercial fishing industry and going through the computational process described in Sections 2.2 and 2.3.
- Also, this study's methodology relied on hazard identification and analysis. Sanni-Anibire et al. [40] explained it is challenging (if not impossible) to enumerate all the incidents/events culpable of an incident. Therefore, the study is limited in the number of risk factors used. Meaning, it is likely, the model may not have captured all the possible dependency and interdependency relationships to trigger MOB accident aboard vessels. Thus, it is possible to enhance the analysis by considering more scenarios to identify additional risk factors, dependency and interdependency relationships for MOB occurrence, and then build a new MOB OOBN model.
- More control techniques can be researched in the same vein and added to the interventions bank to further equip it with tools for MOB prevention and the mitigation of the consequences.

- In following a practical approach to arrive at the model, the thought process involved in OOBN development may vary between researchers. Thus, a different thought process could be used to model the MOB accident scenario.

2.6. Conclusion

Man overboard (MOB) is the one shipboard accident identified globally as a leading cause of commercial fishing's high death rate. Would it, therefore, not be remarkable progress if a tool existed to predict MOB scenarios before they lead to the accident; this is the purpose the present study sought to achieve. Using the object-oriented Bayesian network (OOBN), MOB risk factors were captured in fragmented structures and linked together probabilistically to develop the MOB OOBN model. The model is capable of predicting scenarios culpable for MOB occurrence during everyday operations aboard fishing vessels. The model was applied to a small fishing vessel case study, and as a result, the following conclusions can be drawn:

- Given prior probabilities for basic variables, the model would estimate the percentage likelihood of MOB occurrence aboard a vessel; the estimate predicts the chances of MOB accident occurring at that instant.
- When used together with sensitivity analysis and probability updating techniques, the model could assist in decision-making about the vulnerable factors requiring control to prevent a possible MOB occurrence.
- During risk control analysis, the model can learn the most probable MOB occurrence scenario aboard a vessel.

- Not wearing a fall arrest system, strolling close to low guardrails, and working on the main deck under alcohol or drug influence, are the prime risk factors identified by the model as leading to MOB accident.

Apart from the MOB OOBN model, the study made other contributions to the body of knowledge on MOB. First, the study developed the MOB interventions model, from which engineering controls, administrative controls, and personal protective equipment (PPE) can be assigned to risk factors constituting the most probable MOB scenario. Second, the study proposed the design of a “Going-to-main-deck checklist” to ensure (for vessels with accommodation structure) every crew member leaving for the main deck is adequately equipped against becoming a MOB victim. Lastly, it was also proposed that a “Throw-spot area” (like the helideck area on some offshore supply vessels) be designated on the main deck of fishing vessels to curb MOB occurrences triggered by shooting and hauling of fishing gears, which was among the leading causes of MOB in fishing vessels.

The findings of the present study have important implications for MOB accident prevention and future research. When used together, the two models (i.e., the MOB OOBN model and the MOB interventions model) could serve as tools ship captains and superintendents can use to anticipate and correct probable MOB scenarios aboard their vessels while the crew engage in daily operational tasks. Hence, the models are recommended to fishing and shipping companies. Also, policy-makers in maritime administrations would find the MOB OOBN model helpful in decision-making on which MOB causality is the riskiest and deserves policy formulation to avoid MOB occurrences aboard vessels.

Further research in line with confidence interval prediction for MOB when using the MOB OOBN model is strongly encouraged. The artisanal fishing industry (AFI), a commercial fishing industry subsidiary, employs boats and traditional fishing methods, different from the case study application considered here. However, because those boats too operate in the same environment as the advanced ones, if a diligent study is carried out, a similar OOBN model could be developed for the AFI, which has also recorded significant MOB accidents. Additionally, a feasibility study targeted at the proposals, "Going-to-main-deck checklist" and "Throw-spot area" design, for curbing MOB accident, is needed; the feasibility study must be done alongside the efficacy.

The present study's key message is that using the object-oriented Bayesian network, a probabilistic model can be developed to predict man overboard scenarios aboard marine vessels before the accident occurs.

References

[1] D. L. Lucas and J. M. Lincoln, “Fatal falls overboard on commercial fishing vessels in Alaska,” *Am. J. Ind. Med.*, vol. 50, no. 12, pp. 962–968, 2007.

[2] A. Sevin, C. Bayilmis, I. Erturk, H. Ekiz, and A. Karaca, “Design and implementation of a man-overboard emergency discovery system based on wireless sensor network,” *Turkish J. Electr. Eng. Comput. Sci.*, pp. 762–773, 2016.

[3] E. Ortlund and M. Larsson, “Man overboard detecting systems based on wireless technology: An evaluation of wireless tracking systems in man overboard situations for the cruising industry,” Chalmers University of Technology, 2018.

[4] S. E. Roberts, “Britain’s most hazardous occupation: Commercial fishing,” *Accid. Anal. Prev.*, vol. 42, no. 1, pp. 44–49, 2010.

[5] A. Karvinen, “Person overboard rescue maneuver,” 2017.

[6] Z. Lusic, M. Marcic, M. Bakota, and D. Pusic, “Detecting a man in the sea,” in *8th International Maritime Science Conference*, 2019, pp. 560–570.

[7] T. Neale and P. Mirto, “How to prepare for a man overboard,” *BoatU.S. Magazine*, pp. 62–67, 2012.

[8] P.-H. Chen and P.-C. Chen, “Maritime fatal accidents and vessel disasters in Taiwanese fishing vessels, 2003 -2015,” *Occup. Environ. Med.*, vol. 76, no. Suppl 1, p. 1, 2019.

[9] J. S. Pitman, M. Wright, and R. Hocken, “An analysis of lifejacket wear , environmental factors , and casualty activity on marine accident fatality rates,” *Saf. Sci.*, vol. 111, no. July 2018, pp. 234–242, 2019.

[10] S. L. Yoo, “Network analysis by fishing type for fishing vessel rescue,” *Phys. A Stat. Mech. its Appl.*, vol. 514, pp. 892–901, 2019.

[11] T. K. Thomas, J. M. Lincoln, B. J. Husberg, and G. A. Conway, “Is it safe on deck? Fatal and non-fatal workplace injuries among Alaskan commercial fishermen,” *Am. J. Ind. Med.*, vol. 40, no. 6, pp. 693–702, 2001.

[12] NIOSH. 2002. Surveillance and prevention of occupational injuries in Alaska: A decade of progress, 1990–1999. Cincinnati (OH): National Institute for Occupational Safety and Health. Pub. No. 2002-15. 49 p.

[13] F. Uğurlu, S. Yıldız, M. Boran, Ö. Uğurlu, and J. Wang, “Analysis of fishing vessel accidents with Bayesian network and Chi-square methods,” *Ocean Eng.*, vol. 198, no. August 2019, 2020.

[14] P. Abraham, “International comparison of occupational injuries among commercial fishers of selected northern countries and regions.,” in *Proceedings of the International Fishing*

Industry Safety and Health Conference., 2002, pp. 455–465.

[15] E. Mcguinness, H. L. Aasjord, I. B. Utne, and I. Marie, "Fatalities in the Norwegian fishing fleet 1990 – 2011," *Saf. Sci.*, vol. 57, pp. 335–351, 2013.

[16] J. Wang, A. Pillay, Y. S. Kwon, A. D. Wall, and C. G. Loughran, "An analysis of fishing vessel accidents," *Accid. Anal. Prev.*, vol. 37, no. 6, pp. 1019–1024, 2005.

[17] A. Chochinov, "Alcohol 'on board,' man overboard - Boating fatalities in Canada," *Can. Med. Assoc. J.*, vol. 159, no. 3, pp. 259–260, 1998.

[18] D. H. Dickey, "Analysis of Fishing Vessel Casualties A Review of Lost Fishing Vessels and crew," 2008.

[19] D. Drudi, "Fishing for a Living is Dangerous Work," *Compens. Work. Cond.*, pp. 3–7, 1998.

[20] O. C. Jensen, G. Petursdottir, I. M. Holmen, A. Abrahamsen, and J. Lincoln, "A review of fatal accident incidence rate trends in fishing," *Int. Marit. Health*, vol. 65, no. 2, pp. 47–52, 2014.

[21] J. M. Lincoln and G. A. Conway, "Preventing commercial fishing deaths in Alaska," *Occup. Environ. Med.*, vol. 56, no. 10, pp. 691–695, 1999.

[22] J. M. Lincoln and D. L. Lucas, "Occupational fatalities in the United States commercial fishing industry, 2000-2009," *J. Agromedicine*, vol. 15, no. 4, pp. 343–350, 2010.

[23] S. M. Holen, I. B. Utne, I. M. Holmen, and H. Aasjord, "Occupational safety in aquaculture – Part 2 : Fatalities in Norway 1982 – 2015," *Mar. Policy*, vol. 96, no. July 2017, pp. 193–199, 2018.

[24] Ben-Yami and M., "Risks and dangers in small-scale fisheries : an overview," 2000.

[25] A. Brandsæter, "Risk assessment in the offshore industry," *Saf. Science*, vol. 40, pp. 231–269, 2002.

[26] N. Khakzad, F. Khan, and P. Amyotte, "Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches," *Reliab. Eng. Syst. Saf.*, vol. 96, no. 8, pp. 925–932, 2011.

[27] A. Aziz, S. Ahmed, F. Khan, C. Stack, and A. Lind, "Operational risk assessment model for marine vessels," *Reliab. Eng. Syst. Saf.*, vol. 185, no. February 2018, pp. 348–361, 2019.

[28] B. Khan, F. Khan, B. Veitch, and M. Yang, "An operational risk analysis tool to analyze marine transportation in Arctic waters," *Reliab. Eng. Syst. Saf.*, vol. 169, no. October

2017, pp. 485–502, 2018.

[29] F. Goerlandt and J. Montewka, "Maritime transportation risk analysis : Review and analysis in light of some foundational issues," *Reliab. Eng. Syst. Saf.*, vol. 138, pp. 115–134, 2015.

[30] H. Langseth and O. Bangsø, "Parameter learning in object-oriented Bayesian networks," *Ann. Math. Artif. Intell.*, vol. 32, no. 1–4, pp. 221–243, 2001.

[31] M. Afenyo, F. Khan, and A. K. Y. Ng, "Assessing the risk of potential oil spills in the Arctic due to shipping," in *Maritime Transport and Regional Sustainability*, 2020, pp. 179–191.

[32] M. Afenyo, F. Khan, B. Veitch, A. K. Y. Ng, Z. Sajid, and F. Fahd, "An explorative object-oriented Bayesian network model for oil spill response in the Arctic Ocean," *Saf. Extrem. Environ.*, vol. 2, no. 1, pp. 3–14, 2020.

[33] S. L. Case, J. M. Lincoln, and D. L. Lucas, "Fatal Falls Overboard in Commercial Fishing — United States, 2000–2016," *MMWR. Morb. Mortal. Wkly. Rep.*, vol. 67, no. 16, pp. 465–469, 2018.

[34] J. Wu, M. An, Y. Jin, and H. Geng, "Training safely , Training safety," *Int. J. Mar. Navig. Saf. Sea Transp.*, vol. 8, no. 3, pp. 423–427, 2014.

[35] T. Krilić, "News from IMO," 2012.

[36] I. T. W. Federation, *STCW: A guide for seafarers*. 2010, pp. 1–78.

[37] I. L. Organisation, *Accident prevention on board ship at sea and in port*. 1996.

[38] "ISO/PAS 21195:2018(en), Ships and marine technology — Systems for the detection of persons while going overboard from ships (Man overboard detection)." [Online]. Available: https://www.iso.org/obp/ui/#iso:std:iso:pas:21195:ed-1:v1:en. [Accessed: 09-Jun-2020].

[39] T. R. Qin, Q. Y. Hu, and J. Y. Mo, "Research on the risk assessment of man overboard in the performance of flag vessel fleet (FVF)," in *Navigational Systems and Simulators: Marine Navigation and Safety of Sea Transportation*, A. Weintrit, Ed. Taylor & Francis Group, 2011, pp. 201–205.

[40] M. O. Sanni-Anibire, A. S. Mahmoud, M. A. Hassanain, and B. A. Salami, "A risk assessment approach for enhancing construction safety performance," *Saf. Sci.*, vol. 121, no. September 2017, pp. 15–29, 2020.

[41] D. A. Crowl and J. F. Louvar, "What-If Analysis," in *Chemical Process Safety : Fundamentals with Applications.*, 2019, p. 482.

[42] Ö. Uğurlu, E. Köse, U. Yıldırım, and E. Yüksekyıldız, "Marine accident analysis for collision and grounding in oil tanker using FTA method," *Marit. Policy Manag.*, vol. 42, no. 2, pp. 163–185, 2015.

[43] S. Kabir, "An overview of fault tree analysis and its application in model based dependability analysis," *Expert Syst. Appl.*, vol. 77, pp. 114–135, 2017.

[44] Y. Yang, F. Khan, P. Thodi, and R. Abbassi, "Corrosion induced failure analysis of subsea pipelines," *Reliab. Eng. Syst. Saf.*, vol. 159, no. November 2016, pp. 214–222, 2017.

[45] Genie, "GeNIe Modeler," *Genie*, 2016.

[46] P. Sotiralis, N. P. Ventikos, R. Hamann, P. Golyshev, and A. P. Teixeira, "Incorporation of human factors into ship collision risk models focusing on human centred design aspects," *Reliab. Eng. Syst. Saf.*, vol. 156, pp. 210–227, 2016.

[47] I. Animah and M. Shafiee, "Application of risk analysis in the liquefied natural gas (LNG) sector: An overview," *J. Loss Prev. Process Ind.*, vol. 63, no. August 2019, p. 103980, 2020.

[48] G. Qian and A. Mahdi, "Sensitivity analysis methods in the biomedical sciences," *Math. Biosci.*, p. 108306, 2020.

[49] X. D. Zhang, "Illustration of SSMD, z score, SSMD*, z* score, and t statistic for hit selection in RNAi high-throughput screens," *J. Biomol. Screen.*, vol. 16, no. 7, pp. 775–785, 2011.

[50] J. Liang and W. S. Pan, "Testing The Mean For Business Data: Should One Use The Z-Test, T-Test, F-Test, The Chi-Square Test, Or The P-Value Method?," *J. Coll. Teach. Learn.*, vol. 3, no. 7, 2006.

[51] Barbara A. Plog & Patricia J. Quinlan, *Fundamentals of Industrial Hygiene (6th Edition)*. 2012.

[52] P. Guleria and M. Sood, "Yajna and Mantra Science Bringing Health and Comfort to Indo-Asian Public: A Healthcare 4.0 Approach and Computational Study.," in *Intelligent Learning Analytics in Healthcare Sector Using Machine Learning*, 2020, pp. 39–55.

[53] B. P. Harne, Y. Bobade, R. S. Dhekekar, and A. Hiwale, "SVM classification of EEG signal to analyze the effect of OM Mantra meditation on the brain," *2019 IEEE 16th India Counc. Int. Conf. INDICON 2019 - Symp. Proc.*, 2019.

[54] F. Marchetti, F. Becattini, L. Seidenari, and A. Del Bimbo, "MANTRA: Memory Augmented Networks for Multiple Trajectory Prediction," *IEEE Xplore*, pp. 7141–7150, 2020.

[55] M. N. Stienen, J. Fierstra, A. Pangalu, L. Regli, and O. Bozinov, "The Zurich checklist for safety in the intraoperative magnetic resonance imaging suite: Technical note," *Oper. Neurosurg.*, vol. 16, no. 6, pp. 756–765, 2019.

[56] M. Adya and G. Phillips-Wren, "Stressed decision makers and use of decision aids: a literature review and conceptual model," *Inf. Technol. People*, vol. 33, no. 2, pp. 710–754, 2019.

CHAPTER 3

3.0. A novel methodology to develop risk-based maintenance strategies for fishing vessels

Preface

A version of this chapter has been published in ***Ocean Engineering 253 (2022) 111281****. I am the primary author alongside co-authors Francis Obeng, Faisal Khan, Neil Bose, and Elizabeth Sanli. I developed the conceptual framework to study risk-based maintenance programming applications for fishing vessels' main propulsion system (MPS). I carried out the literature review, developed the MPS failure rate prediction model, performed the engineering analysis, and prepared the first draft of the manuscript. Subsequent revisions of the manuscript based on co-authors' and peer review feedback were also done by me. Co-author Francis Obeng read the first draft of the manuscript and drew my attention to obvious areas of concern. Co-author Faisal Khan helped in the concept development and testing of the logic behind the MPS model, reviewing and revising the manuscript. Co-author Neil Bose provided fundamental assistance in validating, reviewing, and correcting the model and results. Co-author Elizabeth Sanli assisted in validating, examining the technical writing constructs, and correcting the model results. The co-authors also contributed to the review and revision of the manuscript after receiving peer-review feedback from the journal.*

Abstract

Fishing vessels often encounter propulsion machinery faults, resulting in the main propulsion system (MPS) failure. MPS failure can lead to safety and economic loss. Maintenance programming is an effective way to mitigate MPS failures. Given the nature of the fishing business, corrective and preventive maintenance approaches are not best suited for fishing vessels' maintenance needs. This study presents a risk-based maintenance (RBM) methodology to develop a maintenance plan for fishing vessels. The methodology uses simple steps to design a tailormade maintenance plan for a given vessel. Central to the methodology is the "MPS OOBN model" that assists in estimating maintenance interval time for MPS subsystems and components needing maintenance. The study used a new method, the "Goal-directed risk identification technique (Goal-DRIT)", to define the risk factors employed in developing the "MPS OOBN model". The RBM methodology is benchmarked with the publicly available literature, and it demonstrates 24.78% savings in the budgeted maintenance cost, for an example fishing vessel operating in Ghana. The methodology and proposed models are recommended to the commercial fishing industry, chief engineers, and superintendents of marine vessels to aid their maintenance programme design needs.

Keywords: Ship propulsion, fishing vessel, maintenance planning, marine propulsion system, risk-based maintenance (RBM), probabilistic risk assessment.

3.1. Introduction

The proper functioning of a ship's propulsion system is a vital consideration in the ship operation business. That is because the ship's ability to move from one location to another principally ensures economic returns in ship operation – which is possible only when the propulsion system is always functional. Zhou et al. [1] identified the main (or marine) propulsion system (MPS) as the one essential ship system that must be maintained faultless always. Meanwhile, the reliability of the MPS is threatened by many factors, including its complexity [2, 3], the lack of redundancy for the main engine [4], machinery breakdowns[5—9], and the increased demand for ship transportation services [10, 11].

These factors introduce operational risks into the MPS performance and uncertainty in ship propulsion success. Thus, MPS failure is a major vessel accident in the maritime industry, especially aboard fishing vessels [12]. Kim [13] reported that the Korean Maritime Safety Tribunal recorded 2,397 MPS failure occurrences aboard the fishing fleet between the 2014 and 2018 fiscal years. The number represented 31.43% of all failure incidents within the period and became the incident type with the highest occurrences. Similarly, between 1995 and 2004, the study of Kujala et al. [14] showed that the 108 fishing vessel accidents (out of a total of 293 accidents) which occurred in the Arctic region had 71 MPS failure occurrences and were deemed the highest causality in the period.

MPS continued to be a topical area in research in the last ten years. The demand for shipping to reduce marine vessels' carbon footprints and improve their service performance has made studies on MPS matters important. The broad topical areas in MPS research include alternate drive solutions [15], subsystems fault diagnosis and treatment[9, 16—20], optimisation and simulation tools development [20—24], and condition-based maintenance approaches [16, 25, 26]. Typical methods used in these studies are, artificial neural network [9, 26], load distribution optimisation [17], failure mode and effect analysis [19], multi-criteria decision analysis [20], event tree analysis [16], fault tree analysis [16], bowtie [16], MATLAB/Simulink [21, 24], and Markov model [25]. Often, the case study vessel used in MPS studies is the tanker vessel [18, 23, 19], with some emphasis on fishing trawlers [21] when it comes to performance simulation.

MPS failures present economic, environmental, and life-threatening consequences [27, 28] and must be curbed. Being a mechanical system, maintenance programming is undoubtedly the way forward to mitigating MPS failure aboard marine vessels, especially fishing ones. Through the studies of Arunraji and Maiti [29] and Kumar and Maiti [30], methodologies available for maintenance programming, broadly, can be classified into two: corrective maintenance (i.e., fix the system only after a breakdown has occurred) and preventive maintenance (i.e., monitor the system for failure indicative signs to fix the problem before breakdown results). The earlier methodology was practiced up until around the 1950s [29], beyond which the latter took the mainstream in industry. The change was primarily due to the high uncertainty in machinery functionality caused by corrective maintenance practice, which did not favour the pace at which manufacturing was expanding after the end of World War II.

Kumar and Maiti [30] presented a preventive maintenance methodology with three main forms: condition-based maintenance (CBM), reliability-centred maintenance (RCM), and risk-based maintenance (RBM). The maritime industry, through the instruments of the International Maritime Organisation (IMO) (i.e., Safety of Life at Sea (SOLAS) [31], Chapter I/Regulations 7, 11, and 14, and Chapter V/Regulation 14), practices CBM by compelling ships to undergo maintenance in the dry-dock every five years and two years for cargo and passenger ships, respectively. However, according to Regulation 3 of SOLAS/Chapter I [31], fishing vessels were exempted, which has prompted maritime administrations worldwide to develop their own CBM guidelines for the vessels' maintenance inspection [32].

Manufacturers of ships' engine-room machinery also indicate running hours intervals at which systems and components are to be inspected and serviced. Thus, the CBM methodology is well known in marine transportation. On the other hand, RCM uses the failure rate to suggest maintenance planning needs for a system. Anantharaman et al. [25] studied the reliability of engine-room machinery using RCM; however, the concentration was on the turbocharger. The

RBM methodology is a step ahead of RCM because, in addition to the failure rate, the consequence of failure is also considered in suggesting a suitable maintenance plan for a system.

From the earlier discussion, coupled with the description of ship machinery maintenance practices by Lorencin et al. [26] and Anantharaman et al. [33, 34], it is evident that CBM and RCM continue to play maintenance roles in the MPS for ships. Meanwhile, these maintenance methodologies have limitations: (1) interruptions in business operations; (2) a piece of equipment could be found working perfectly, resulting in the loss of time and resources allocated for maintenance; (3) these maintenance methodologies increase operational expenditures; (4) they can lead to system failures when equipment is not fitted correctly after maintenance; and (5) the prescribed duration for maintenance to be done could be too long, and an equipment malfunction would occur earlier to trigger the system (e.g., MPS) failure.

The above challenges with CBM and RCM can be summarised as loss of system availability and high cost of maintenance. Coincidentally, the RBM is known for extending systems availability and reducing a firm's budgeted maintenance amounts. Hence, as revealed in Leoni et al. [35], Krishnasamy et al. [36], and Khan and Haddara [37], when RBM is implemented, the overall profitability of the firm is enhanced alongside avoiding machinery breakdowns and system failures. Mission abort strategies (MAS) too, such as those in Zhao et al. [38], Zhao et al. [39], and Shen et al. [40], have proven successful at increasing engineering systems availability, avoiding catastrophic situations due to failure of safety-critical components in the systems, and reduction of inspection costs. Meanwhile, little is known about using the MAS to facilitate maintenance schedules. The performance of such a schedule over the RBM schedule is also yet to be studied.

The study by Cullum et al. [41] presented the application areas of RBM methodology for marine transport management but did not apply RBM to the MPS nor fishing vessels' maintenance.

Meanwhile, the nature of the commercial fishing business causes fishing vessels to be at sea almost always, resulting in minimal time and attention for the MPS maintenance. As described in Wang et al. [12] and Weng and Yang [27], the situation is responsible for the high machinery failure rate in the commercial fishing industry. Hence the suitable methodology to resolve MPS failure aboard fishing vessels must favour minimal interruption to fishing performance while maintaining the operational integrity of the machinery involved. The RBM, therefore, was the choice methodology applied in the present study to develop a simple maintenance plan for the MPS of fishing vessels.

While the fault tree analysis-based RBM exists [36, 37], the present study adopted the Bayesian network (BN) approach by Leoni et al. [35] and Abbassi et al. [42] to ensure the uncertainties regarding data and information updating that arise in data-driven modelling [43—45], can be easily handled. The present study also employed the object-oriented Bayesian network (OOBN) and the six-sigma scale to build and assign conditional probabilities to the risk model developed for MPS failure risk assessment and the maintenance interval time estimation. The RBM, OOBN, and six-sigma have been used widely in research publications [27, 36, 46, 47] and have emerged as valuable tools for problem-solving in the maritime industry.

The primary purpose of the present study is to demonstrate how to utilise the potentials of the RBM, OOBN, and six-sigma methods, to develop a simple maintenance plan for the MPS of fishing vessels. The maintenance plan was aimed at the following goals: (1) be user-friendly (i.e., not complicated, easy to work with), (2) must capture MPS machinery and their components as the influential factors, (3) identify critical components for MPS failure, and (4) be able to minimise maintenance frequency and cost. As a result, the specific objectives addressed in the study are as follows: (1) to develop a model for MPS failure risk assessment, (2) to quantify MPS subsystems risks, and (3) to draw up the plan for fishing vessels' MPS maintenance. Objectives two and three were achieved using an example fishing vessel based on benchmarked data published by Aziz et al. [16] and Jeong et al. [20]. In summary, the present study made the following theoretical contributions:

(1) Although studies on risk assessment and reliability-centred maintenance are common for MPS subsystems [7, 16, 25], very little exist in the published literature about RBM for the MPS—the present study bridges this knowledge gap;

(2) The hybridisation of RBM, OOBN, and the six-sigma methods to develop a risk analysis tool, is another theoretical contribution by the present study;

(3) The proposal of the "Goal-directed risk identification technique (Goal-DRIT)"—a unique method for listing risk factors in extremely complex systems.

Practically, the present study has contributed to pioneering the development of an RBM plan for the MPS of fishing vessels. The study, when implemented, is expected to help the commercial fishing industry mitigate the frequent MPS failure occurrences mentioned by Wang et al. [12] and Kim [13]. The associated consequences, such as stranded or loss of a fishing vessel and fisher fatalities as reported by Weng and Yang [27], would also be curtailed. Fishing vessel owners and fleet superintendents could also apply the study to reduce operational costs by reducing maintenance budgets and frequency. Maritime administrations searching for MPS maintenance strategies to recommend to vessels under their supervision will also find the study helpful.

The present study is organised into four sections. The current section is the first and introduces the study with the background information, the MPS failure problem, and a brief description of the proposed solution. Section 3.2 will focus on the detailed description of the RBM framework followed to achieve the simple maintenance plan proposed for fishing vessels' MPS maintenance needs. The results of the RBM methodology following benchmarked data application in Section

3.2 are presented and discussed in Section 3.3. Finally, conclusions are drawn in Section 3.4 by highlighting the key message, findings of the study, and recommendations for future work.

3.2.The RBM Methodology Proposed

The present study methodology is founded on probabilistic risk assessment (PRA) [16, 48] and maintenance programming [29, 49]. The PRA was used to achieve the first and second objectives of the present study. Then by maintenance programming, the maintenance plan (i.e., objective three) was developed. Hence, through uniting PRA and maintenance programming, a new RBM methodology emerged and was used to develop the maintenance plan for addressing fishing vessels' MPS maintenance needs.

Maintenance programming, compared with PRA, has been in existence much longer. Arunraj and Maiti [29] and Cooke [49] reported that maintenance programming could be traced back to the 1940s. It has transitioned from the basic maintenance plan of "fix it when it breaks down" to the present logical ones built on risk management and resource allocation theory, as emphasised in Stamatelatos and Dezfuli [48]. The PRA, according to Stamatelatos and Dezfuli [48] and other studies [50, 51], is an established risk assessment method. PRA uses probability theory and probability distributions to assess accidents and incidents occurrence rates (i.e., frequency or likelihood) and the severity of the undesired consequences, should the accident or incident happen.

Maintenance programming, however, is a planning method that ensures machinery systems, subsystems, and components or parts, are properly scheduled for periodic inspection and maintenance work, as revealed in Mazidi et al. [52], Özcan et al. [53], and Pour et al. [54]. The PRA is an established method for resolving complex problems. It has become a useful method in research and field projects with "risk connotation" [16, 46, 48], of which maintenance programming is a typical example [36, 37, 41, 55].

When PRA and maintenance programming are merged, the RBM methodology is formed, and a suitable maintenance plan for a machinery's subsystems and components emerges. While the PRA aspect of an RBM methodology identifies the faulty subsystems and components, the maintenance programming part estimates the time interval for maintenance work to be done and the drawing of an appropriate schedule for periodic inspections. The detailed description of the RBM methodology applied in the present study is discussed next, starting with the study's assumptions.

3.2.1. The study's assumptions

Like other risk assessment studies [43, 44, 56], assumptions were made for the present study to give a reference frame for conducting the RBM planning. In doing so, the variability in MPS failure network development can be minimised substantially. Guided by the works of Stamatelatos and Dezfuli [48], Goerlandt and Reniers [44], Khorsandi and Aven [43], and Aven [45], the following assumptions, were applied to the present study:

- Apply the MPS configuration and operationality physics to aid in building a suitable risk model structure and identifying relevant risk factors. That way, a phenomenological understanding of ship propulsion is achieved, and aleatory uncertainty in the resulting model will be minimised.
- The uncertainties in the knowledge of the risk factors defined for MPS operability must be addressed by the developed model. Hence, the Bayesian network (BN) emerged as a suitable modelling tool for the present study.

- Structural variables (i.e., root nodes or basic variables) to the risk model are statistically independent, meaning that random failure occurrences in the MPS are appreciated. This assumption promotes "a what-if-scenario analysis", which would help analyse scenarios using the risk model developed.
- Structural variables have a constant failure rate; therefore, the exponential distribution function was used to estimate the time interval for maintenance planning in the present study.
- In structuring the risk model from the top (i.e., the leaf node) to the bottom (i.e., structural variables) by deductive approach, a structural variable is reached when the variable's occurrence probability can be calculated directly from data.
- The focus vessel type for risk factors identification, the MPS failure likelihood model development, and the RBM planning, is the fishing vessel. As mentioned in Section 3.1, the choice of vessel stems from the frequent machinery breakdowns recorded in the commercial fishing industry.

3.2.2. Description of the methodology framework

The framework in Figure 3.1 presents an overview of the proposed RBM methodology. The methodology comprises three phases in which rectangles and the diamond shape represent tasks to be accomplished and decision-making symbols, respectively. A circle on the right of each phase contains the methods and materials required to achieve the tasks in a phase. The framework is set in motion by first identifying the risk factors for MPS failure and then forming the failure occurrence scenario and network (i.e., Phase 1). That way, the MPS failure risk model was developed.

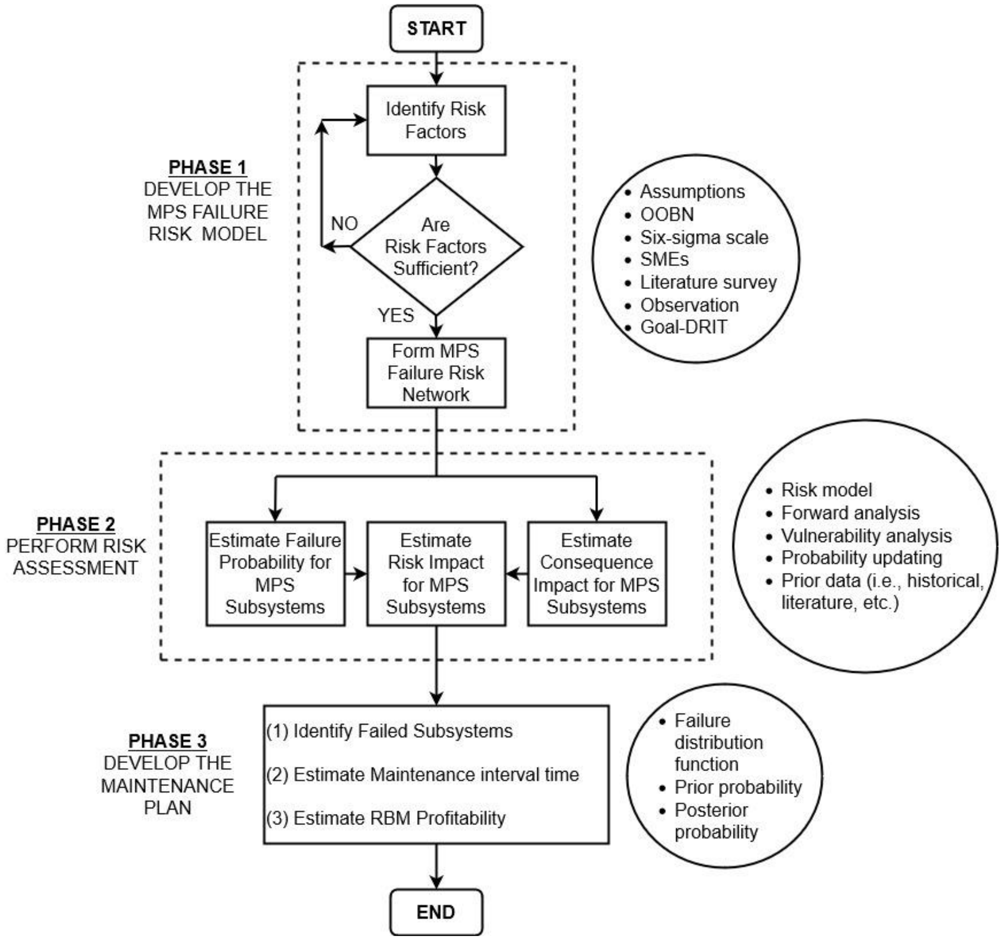

Figure 3.1. A framework developed for the RBM methodology proposed.

Before finalising the model structure, it is important to decide on the sufficiency of identified risk factors (i.e., the second step in Phase 1). In RBM methodology, risk assessment of the system and its subsystems are vital to developing a maintenance plan [35—37, 41, 42]. Thus, in Phase 2, failure occurrence probability, consequence impact, and posterior probability estimations were made for MPS and its subsystems using the benchmarked data [16, 20] and the risk model developed in Phase 1. Finally, Phase 3 used probability updating (of the failed subsystems) and the exponential probability distribution function to estimate the maintenance interval time (MIT), which enabled the maintenance plan to be developed as a tabular maintenance schedule. The three phases of the framework and the respective methods and materials used to achieve the set goals are explained in detail subsequently.

3.2.3. Description of Phase 1 of the RBM methodology

In Phase 1, the risk model named the "MPS OOBN model" was developed for estimating MPS failure occurrence likelihood. First, the risk factors (RF) for MPS failure were determined. Then the identified RF were linked together in a Bayesian network (BN) to realise the model. Through abstraction and encapsulation, BNs were consolidated into OOBN to create the model. A detailed description follows next.

3.2.3.1.Identifying risk factors for MPS failure

The risk factors for MPS failure were sought first, under three levels: high, mid, and initiating. Usually, risk factors are determined by the traditional hazard analyses methods (i.e., fault tree analysis, event tree analysis, hazard and operability analysis, and hazard identification study) [16, 36, 37]. However, a unique method, the "Goal-directed risk identification technique (Goal-DRIT)", is proposed for MPS failure risk factors enumeration in the present study. The Goal-DRIT is a significant contribution from the present study to the field of hazards identification methods.

The method was developed mainly for highly complex systems or complicated scenarios. The inspiration for developing the Goal-DRIT was drawn firstly from consideration of the several factors in ship propulsion and the decision-making about what to include or exclude during risk factors identification for the MPS. Then, secondly, the effectiveness of the "Goal-directed task analysis", which is popular in situation awareness studies as demonstrated in Sharma et al. [57]. In Goal-DRIT, risk factors are identified by defining the risk, hazard, or system under study; setting goals; and creating scenarios. Therefore, using Figure 3.2, goals were set at each level in the process of risk factors enumeration for the MPS. Only one goal is required to define high-level

RF, but several goals are needed for mid-level RF and initiating-level RF identification. Goals were set with recourse to the study purpose and assumptions mentioned in Section 3.2.1.

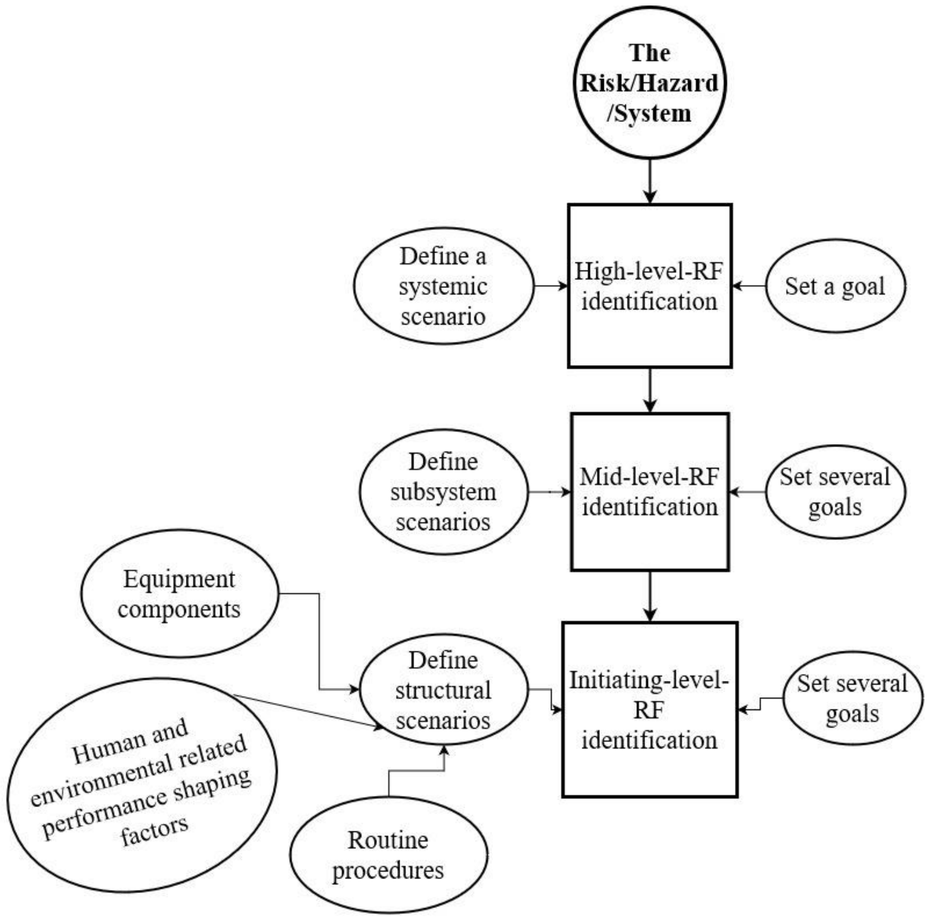

Figure 3.2. The Goal-DRIT framework for risk factors identification.

Scenarios that suit the goal were then defined. From these scenarios, risk factors were enumerated from high to initiating levels. Three types of scenarios, in line with the high, mid, and initiating levels (and goals), respectively, were employed: systemic, subsystem, and structural scenarios. The systemic scenario is only one and addresses the high-level goal; subsystem scenarios are many and address the similarly several goals in the mid-level. The structural scenario is also many and targeted at defining the basic variables that influence the subsystems of an MPS.

Scenarios must be physical systems, processes, arrangement layouts, or theoretical frameworks. They must be realised through the combination of individual items. The Goal-DRIT was applied to the MPS, and Table 3.1 emerged. See Appendix B1 for a detailed description of the Goal-DRIT process.

Table 3.1. Risk factors defined for the MPS.

Number	High-level-RF	Mid-level goal	Subsystem scenario	Mid-level-RF	Reference
1	Main engine	Identify the individual systems that enable the main engine to function	Four-stroke medium speed operation cycle	(1) Automation and control system (2) Four-stroke cycle operation (3) Freshwater cooling system (4) Fuel oil supply system (5) Lubricating oil system (6) Scavenge air system (7) Seawater cooling system (8) Starting air system	[58, 59]
2	Gearbox	Define the various groups into which gearbox components can be placed	PRM120 marine gearbox	(1) Gears (2) Plates (3) Shafts (4) Spiders	[9, 60]
3	Generator	Identify the two categories of generators aboard	Shipboard electrical power generation system	(1) Auxiliary generator (2) Emergency generator	[58, 59]
4	Propeller	Define separate group names for components peculiar to controllable-pitch propeller and those common to both fixed-and controllable-pitch propellers	Fixed-and-controllable-pitch propellers	(1) Controllable-pitch propeller parts (2) Fixed-pitch propeller parts	[59, 61]
5	Shaft line	Define separate group names for the shaft kinds involved in the shaft line and their attachments	Main propulsion layout	(1) Shaft types (2) Shaft line accessories	[5, 58, 59, 62]
6	Thrust block	-	-		[58, 59]

In all, by applying the Goal-DRIT to the MPS, six high-level RF, eighteen mid-level RF, and 143 initiating-level RF (i.e., root causes; see Appendix B2) were defined as the associated risk factors for modelling the MPS failure likelihood. Next, these factors were linked together in BN to form the "MPS OOBN model".

3.2.3.2.The MPS OOBN model development

The current section describes the formation of the "MPS OOBN model", which is the risk analysis tool for quantifying the likelihood of MPS failure aboard a fishing vessel. The two primary steps involved are described below:

- ***Step 1: link the RF to form the model***

Guided by Figure 3.3, the high-level network was formed first, then the mid-level network, and finally, the initiating-level network. Each network makes use of the respective risk factors identified in Section 3.2.3.1.

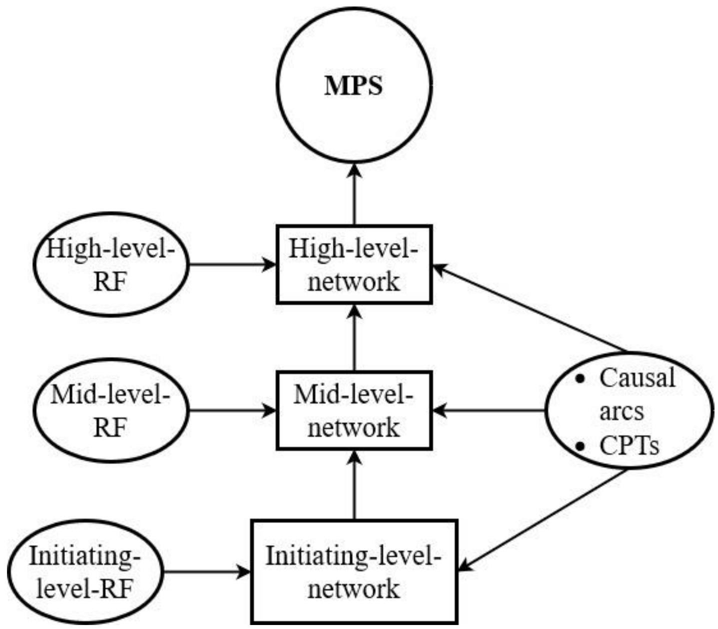

Figure 3.3. Stages in the MPS OOBN model development.

The networks were developed using BN to ensure the study's assumption two was adhered to. As mentioned in Khakzad et al. [63] and other studies [35, 64], BN can handle the epistemic uncertainty present in numerical models. With 167 nodes, it was envisaged that the resulting BN would be large and cumbersome. As a result, the BN was transformed into an OOBN. See Khan et al. [46] and Domeh et al. [47] for the step-by-step procedure on OOBN formation. Accordingly, the "MPS failure likelihood model" became known as the "MPS OOBN model" (hereafter referred to as the model). It is important to note that, in BN or OOBN models, RF become nodes (i.e., parent and child nodes).

The model is shown in Figure 3.4 and its individual BNs in Appendix B2. Thus, by combining separate BNs, an OOBN was developed for quantifying the failure probability of the MPS in operation. The root factors of the model are the MPS subsystems components. Once these components (i.e., initiating-level RF) fail, the MPS subsystems (i.e., high-level RF and mid-level RF) will fail, and as a result, the MPS (i.e., the system) is going to fail. Aboard marine vessels, it is common practice to note down systems and subsystems failures and which components failed to cause the malfunctions. Therefore, data on the frequency of components failures are readily available (say, from the engine-room logbook). Consequently, failure probabilities can be quantified and entered into the model (i.e., Figure 3.4) to estimate the MPS failure likelihood.

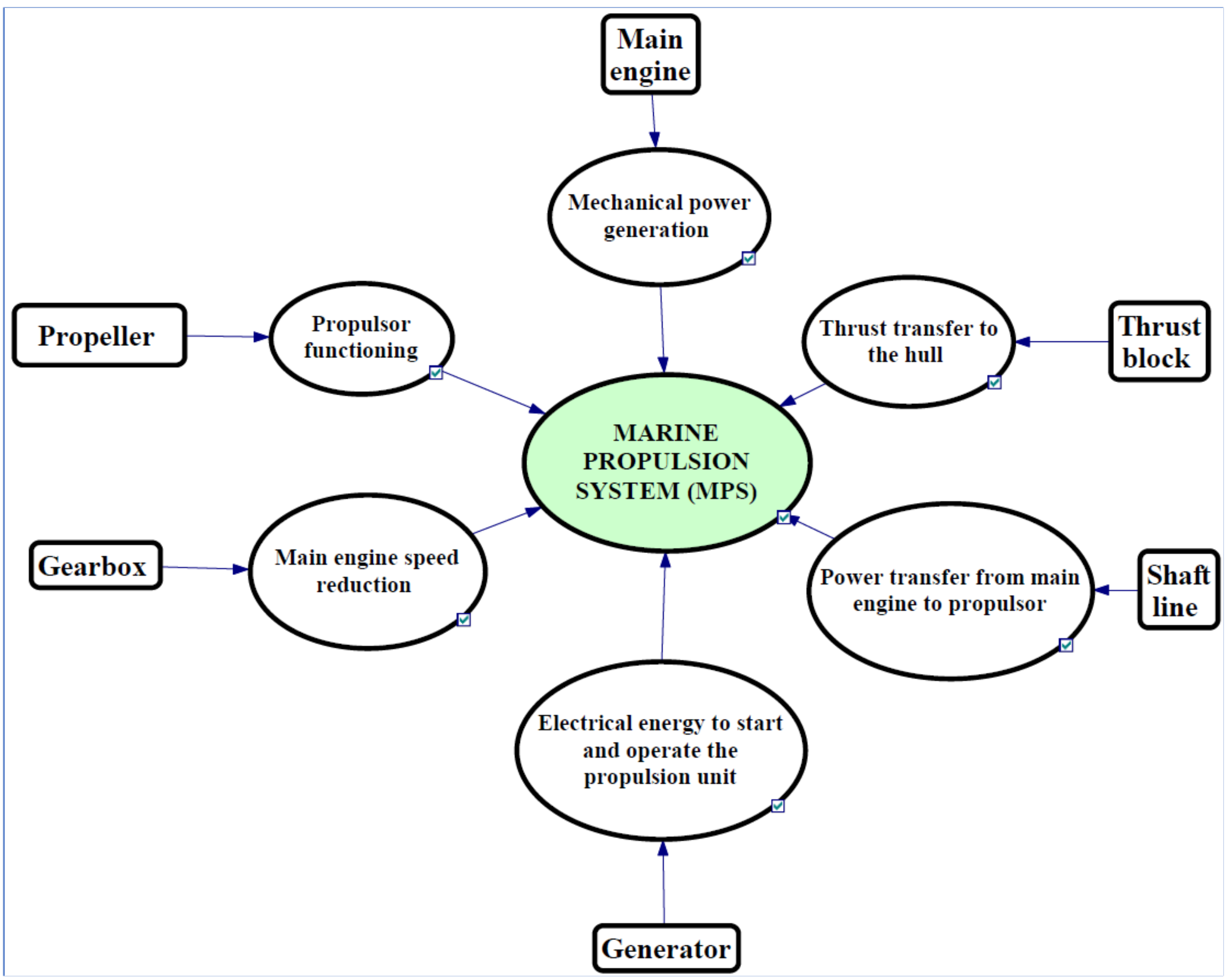

Figure 3.4. The MPS OOBN model.

- ***Step 2: fill the model's conditional probability tables***

Conditional probability tables (CPT) are required at each child node in the model to describe probabilistically the relationship between the child node and parent node. Once the causal arc connects the child and parent nodes, GeNIe software [65] automatically generates the CPT. What is left, therefore, is filling the CPTs with probabilities. The present study used a hybrid of subject matter experts (SME) elicitation, BN, hypotheses testing, and the six-sigma [66] methods to produce the probabilities for the CPTs after building a naïve Bayes' model specific to a CPT. Before eliciting probabilities for CPTs, the states for each node in the model must be defined. In the present study, each node in the model had only two states; the first state defined a node's "success score" while the second state a "failure score". In Appendix B3, a sample description of the procedure for eliciting probabilities for the CPTs is illustrated.

To summarise, Phase 1 of the present study methodology was devoted to developing the risk model for MPS failure likelihood prediction. Phase 1 has also demonstrated how the six-sigma, BN, OOBN, SMEs elicitation, and hypothesis testing methods could be harmonised to develop a risk analysis tool for systems or accidents risk assessment use. The following section uses the proposed model to conduct a failure risk assessment for the MPS with the help of literature data.

3.2.4. Description of Phase 2 of the RBM methodology

With the risk analysis model developed in Phase 1, MPS failure risk assessment was conducted in the present section using the model. For an RBM study, failure risk assessment typically involves estimating the system's failure probability, consequence and risk impact scores, and posterior probability for structural variables [35, 36]. While the present section will only dwell on these estimations, it must be noted that the developed model's capability goes beyond these and can perform sensitivity and vulnerability analyses too. The data used for the risk assessment analyses are defined next, followed by the MPS failure assessment.

3.2.4.1.Data to facilitate MPS failure risk assessment

Benchmarked data on ship machinery failure probabilities were sourced from Aziz et al. [16] as prior probabilities for the model's basic variables. Table 3.2 is a sample of the failure probabilities for gearbox components; those for other subsystems are in Appendix B4. When a component's failure probability was not found in Aziz et al. [16], the offshore reliability data handbook [62] was consulted. For the present study purposes, MPS subsystems are limited to only high-level RF (i.e., all mid-level RF are not subsystems).

Table 3.2. Prior probabilities for components of the gearbox.

Number	Component	State name	Prior probability
1	Thrust bearing	Failed	7.50E-02
2	Hub	Failed	2.59E-01
3	Oil seal	Failed	4.87E-01
4	O ring	Failed	2.59E-01
5	Forward pinion	Failed	4.09E-02
6	Clutch plate	Failed	2.59E-01
7	Pressure plate	Failed	1.03E-01
8	Reverse clutch spider	Failed	2.53E-01
9	Forward clutch spider	Failed	1.26E-01
10	Idler gear	Failed	4.09E-01
11	Output gear wheel	Failed	1.89E-01
12	Reverse driven gear	Failed	4.09E-01
13	Gear selector lever	Failed	3.93E-01
14	Gearcase	Failed	1.00E-02
15	Forward driven gear	Failed	4.09E-02
16	Idler shaft	Failed	1.15E-02
17	Input shaft	Failed	4.60E-02
18	Output shaft	Failed	8.05E-02
19	Clutch shaft	Failed	2.30E-02

Krishnasamy et al. [36] and Khan and Haddara [37], by their studies, showed that machinery failure outcomes, in the end, present cost consequences due to production loss, maintenance requirement, human health loss, and environmental degradation and reversing. MPS failure aboard a ship would be no exception. Hence, the four cost elements were used to compute the consequence impact costs for MPS and its subsystems. The studies of Jeong et al. [20], Jones et al. [67], and Jones et al. [68], provided data for estimating the costs assuming failure occurrence. Below is the extracted data, with cost items in Great Britain Pounds (GBP). It is more common to see shipping related costs in the United States Dollars (US$), hence, the rate, 1 GBP to 1.37 US$ was employed.

- Loss per hour incurred when not fishing = GBP 1500
- Cost per hour of the inspection personnel, $Cost_{ip}$ = GBP 67.00
- Cost of maintenance personnel per hour, M_{staff} = GBP 28.00
- Generator alternator specialist hire = GBP 710.00
- Propeller corrosion treatment specialist hire = GBP 2500.00
- Gearbox specialist hire = GBP 300.00
- Cost of the consequences a failure could have on human health = $Cost_H$

  $GBP\ 5000.00 < Cost_H < GBP\ 83800.00$
- Cost of the consequences a failure could have on plant items and structure = $Cost_C$

  $GBP\ 133000.00 < Cost_C < GBP\ 375000.00$
- Cost of the consequences a failure could have on the environment = $Cost_D$

  $GBP\ 200000.00 < Cost_D < GBP\ 445000.00$
- Factor relating to clean-up time = F_r = 0.2

Using the cost ranges above, approximate estimates were made for health, collateral, maintenance, and damage costs (see Section 3.2.4.4 too). Also, estimates of failure inspection duration, repair duration, and costs for equipment downtime, parts replacement, and spares (see Table 3.3) were made with recourse to Jones et al. [67] and Jones et al. [68].

Table 3.3. Data for MPS subsystem's failure consequence cost estimation.

Number	Subsystem	Inspection Downtime (T_{insp}, days)	Repair Downtime (T_{repair}, days)	Equipment Downtime cost (GBP/hr)	Replacement parts and spares cost (GBP)	$Cost_D$ (GBP)
1	Main engine	0.46	7.00	63.00	1143.00	244103.00
2	Shaft line	0.95	1.00	74.00	2083.00	299258.00
3	Propeller	0.61	2.00	97.00	2299.00	379484.00
4	Thrust block	0.31	4.00	97.00	2795.00	200355.00
5	Gearbox	0.32	6.00	111.00	913.00	394672.00
6	Generator	0.60	3.00	93.00	923.00	276394.00

3.2.4.2.Forward analysis

Forward analysis was done to estimate the failure probabilities of MPS and its subsystems. First, the prior probabilities in Appendix B4 were inserted at root node sections of the model. The update button in GeNIe was then run [65], and the model estimated the failure probabilities for MPS and its subsystems, using the joint probability distribution in Equation (3.1). The results are presented in Section 3.3.1.

$$P(MPS\ failure\ likelihood) = \prod_i^n P(S_i|pa(S_i)) \quad (3.1)$$

where, $pa(S_i)$ is the parent set of the high-level RF (or MPS subsystems), S_i is the high-level RF, and "n" is the number of high-level RF present in the model (see Figure 3.4).

3.2.4.3.Probability updating

The model was used to facilitate probability updating of MPS failure risk factors. As observed in Khakzad et al. [63] and Khakzad et al. [64], probability updating is the evidential reasoning and learning about risk factors when a failure or accident occurs. As a result, prior probabilities are updated to posterior probabilities to reflect what the probabilities would have been if the failure or accident had occurred. Therefore, the uncertainty about the future state of risk factors given the failure or accident occurrence is handled through probability updating. By setting the "Failed" state of the leaf node in the model to 100% and running GeNIe, the root nodes' probabilities were updated based on the Bayes' theorem (see Equation (3.2)). The results are presented and discussed in Section 3.3.2.

$$P(d_i|MPS) = \frac{P(d_i, MPS)}{P(MPS)} \quad (3.2)$$

where, the left-hand side is the hypothesis (i.e., probability updating); the right-hand-side numerator is the joint probability, the right-hand-side denominator is the total probability, MPS is "MPS failure likelihood", d_i is the "*ith"* root node, and "i" is a marker ranging from one to the total number of root nodes in the model (i.e., 143 in the present study).

3.2.4.4.MPS failure risk estimation

MPS failure probability was estimated during the "forward analysis" (see Section 3.2.4.2). Therefore, combining the failure probability and the consequence impact by Equation (3.3) would provide a risk estimate for MPS failure.

$$\text{Risk impact} = \text{failure probability} \times \text{consequence impact} \quad (3.3)$$

System failure consequences can be detrimental to operations performance, the environment, and humans in the vicinity. As a result, consequence estimation [5, 36, 37, 67] has been focused broadly on production or performance loss, environmental loss, maintenance cost, and human health loss. Jones et al. [67] and Jones et al. [68] provided mathematical relations (see Equations (3.4) to (3.13)) to estimate these consequences. Unlike Khan and Haddara [37] and Leoni et al. [35], the present study adopted the cost approach by Krishnasamy et al. [36] to estimate the consequence and risk impacts for MPS subsystems.

It is assumed that the fishing vessel understudy is like the one in Jeong et al. [20], which had a maintenance budgeted amount of US$ 882,290.00. Thus, the risk acceptance criteria (RAC) for the present study is US$ 882,290.00, and the general characteristic of the vessel is given in Table 3.4.

Table 3.4. Fishing vessel's general characteristics.

Characteristic	Dimension
Tonnage	135.00 tonnes
Length	43.50 m
Breadth	12.20 m
Draught	1.73 m
Speed	9 knots
Installed power	2 × 450 kW main engine and 1 × 50 kW generator
Operating zone	> 30 nautical miles from Ghana's shore

Time at sea	1 day to 1.5 weeks
Catch capacity	1000 kg and above
Number of fishers	5 to 20 people
Fish hold types	Ordinary, insulated, and refrigerated holds
Vessel type	Fishing trawler

The cost elements and their formulations are explained next:

- ***Maintenance cost:*** MPS failure will be due to a subsystem or component failure. To bring back the MPS onstream, the failed subsystem or component must be maintained, which will come at a cost classified as maintenance cost. It is usually in two parts, inspection and breakdown repair costs. These costs can be estimated using Equations (3.4) and (3.5). Inspection cost caters for the diagnosis of the problem that resulted in the failure. In contrast, breakdown repair cost addresses the monetary requirement to perform the actual maintenance on the subsystem or component. Equation (3.6) then combines these costs to arrive at the maintenance cost.

$$Cost_I = \left(Cost_{ip} + Cost_d\right)T_{insp} \tag{3.4}$$

where, $Cost_I$ is the inspection cost (US$); $Cost_{ip}$ is the cost per hour charged by the inspection personnel (US$/hr.); $Cost_d$ is the cost of equipment downtime per hour (US$/hr.); and T_{insp} is the amount of time, on average, the inspection would take.

$$Cost_B = \left(M_{staff} + Cost_d\right)\left(T_{insp} + T_{repair}\right) + S_p + S_e \tag{3.5}$$

where, $Cost_B$ is breakdown repair cost (US$), M_{staff} is the cost per hour charged by the maintenance personnel (US$/hr.), T_{repair} is the time taken to repair the faulty equipment (hr.), S_p is the spares and replacement parts cost (US$), S_e is the cost for any specialised equipment or personnel hired for the repair work (US$).

$$Cost_M = Cost_I + Cost_B \tag{3.6}$$

where, $Cost_M$ is the maintenance cost.

- ***Performance loss:*** MPS failure leads to loss of ship propulsion, which either delays or aborts the ship's mission (e.g., to reach a designated spot to fish). These losses, among others, account for the performance loss. The performance loss can include the profits accrued if the mission was successful and other costs incurred because the intended mission was not achieved. In the present study, performance loss has been limited to the inability of the fishing vessel to harvest fish due to MPS failure and was estimated using Equation (3.7).

$$Cost_P = Cost_{lfh}\left(T_{insp} + T_{repair}\right) \quad (3.7)$$

where, $Cost_P$ is the cost incurred due to the loss of fishing (US$) and $Cost_{lfh}$ is the hourly cost rate for not fishing (US$/hr.).

- ***Environmental impact cost:*** MPS failure can lead to environmental damages, which must be restored. MPS failure while a fishing vessel is at sea may cause the vessel to run into nearby offshore pipelines, resulting in environmental pollution damage. The study of Liu et al. [69] is evidence that such hazards do occur. Also, MPS failures due to crankcase explosions, as mentioned in Cicek and Celik [70], occur aboard marine vessels, with consequential damage to ship structure and injury to engine-room personnel. Thus, the environmental damage from MPS failure must consider the human health, collateral loss, and damage reversal impacts. The environmental cost implications are therefore, from these areas and were modelled by Equations (3.8) to (3.12).

$$Cost_H = (Cost_{h1} \times life_{h1})P_1 + (Cost_{h2} \times life_{h2})P_2 + (Cost_{h3} \times life_{h3})P_3 + (Cost_{h4} \times life_{h4})P_4 + (Cost_{h5} \times life_{h5})P_5 \quad (3.8)$$

where, $Cost_H$ is the cost incurred due to health loss (US$); $Cost_{h1}$ is the cost of being unwell (US$); $life_{h1}$ is the number of people unwell; P_1 is the probability of the event "being unwell" happening; $Cost_{h2}$ is the cost of ill health (US$); $life_{h2}$ is the number of people ill; P_2 is the probability of the event, "ill health", happening; $Cost_{h3}$ is the cost of hospitalization (US$); $life_{h3}$ is the number of people hospitalized; P_3 is the probability of the event, "being hospitalized", happening; $Cost_{h4}$ is the cost of disability (US$); $life_{h4}$ is the number of people with disabilities; P_4 is the probability of having someone disabled; $Cost_{h5}$ is the cost of life (US$); $life_{h5}$ is the number of people lost; P_5 is the probability of losing a human life.

$$Cost_C = \left(Cost_{plant} \times P_{plant}\right) + \left(Cost_{Res} \times P_{Res}\right) \quad (3.9)$$

where, $Cost_C$ is the cost of the possible damages a failure can do to plant items and residential buildings (US$); $Cost_{plant}$ is the cost of plant items damaged (US$); P_{plant} is the probability of plant items being damaged; $Cost_{Res}$ is the cost of residential buildings damaged (US$); P_{Res} is the probability of damaging a residential building.

$$Cost_D = Cost_{clean} \times P_{clean} \quad (3.10)$$

where, $Cost_D$ is the cost of the damage to the environment caused by the failure (US$); $Cost_{clean}$ is the cost to clean up the damage (US$); P_{clean} is the probability of spillage (or lack of containment of the failure).

$$Cost_R = \frac{cost_D}{(1-F_r)} \quad (3.11)$$

where, $Cost_R$ is the cost of restoring the environment to its original undamaged state (US$) and F_r is a factor relating to the cleanup time (see Table 3.5).

Table 3.5. The F_r value for various times to cleanup a failure [67, 68].

Cleanup time	F_r	Rank
0-4 weeks	0.10	Low
1-3 months	0.20	
3-12 months	0.30	
1-3 years	0.40	Medium
3-7 years	0.50	
7-10 years	0.60	
10-25 years	0.70	High
25-50 years	0.80	

50-100 years	0.90	Very high
100+ years	1.00	

The above costs were summed up to give the environmental impact cost ($Cost_E$) because of MPS failure (see Equation (3.12)).

$$Cost_E = Cost_H + Cost_C + Cost_R \quad (3.12)$$

- ***Consequence impact:*** the sum of performance loss, maintenance, and environmental impact costs is the consequence impact (Con) (see Equation (3.13)). The cost realised is substituted into Equation (3.3) to arrive at the risk estimate for MPS failure.

$$Con = \ Cost_M + Cost_P + Cost_E \quad (3.13)$$

The data provided in Section 3.2.4.1 for consequence estimation were inserted into the above equations, and as a result, the risk impacts for the MPS subsystems were computed. The results are presented and discussed in Section 3.3.3.

3.2.5. Description of Phase 3 of the RBM methodology

Phase 3 is the stage in the RBM methodology where the maintenance plan was developed for addressing MPS maintenance needs. From Figure 3.1, to arrive at the maintenance plan, three main activities were carried out: (1) identifying MPS subsystems that do not meet the RAC, (2) computing the maintenance interval time (MIT) for those subsystems, and (3) estimating the profit made from implementing the RBM methodology. These activities are described in detail subsequently.

3.2.5.1.Identifying MPS subsystems that failed the set criteria

The following steps were followed to identify the MPS subsystems that did not meet the set criteria for risk acceptance.

- ***Set the risk acceptance criteria (RAC):*** as explained in Section 3.2.4.4, the RAC was set as a risk estimate not exceeding US$ 882,290.00.

- ***Evaluate the MPS subsystems risks:*** the MPS subsystems' risk amounts were compared with the set RAC. A risk index of the risk amount to the RAC was computed. For a subsystem whose risk index was greater than one, the risk exceeded the RAC, and therefore, a maintenance plan will be required to reduce the failure risk. Subsystems whose risk index are one or less were deemed acceptable risks and did not require a maintenance plan. For example, consider a subsystem "A" whose failure probability is 0.75 and the consequence impact (after going through Equation (3.13)) is US$ 1,331,620.16. The following calculations will be done:

  Risk impact for subsystem "A" $= 0.75 \times US\$\ 1331620.16 = \ US\$\ 998{,}715.12$

  Risk index $= \frac{Risk\ impact}{RAC} = \frac{US\$998{,}715.12}{US\$882{,}290.00} = 1.13$; thus, subsystem "A" risk index is greater than one, so its components must undergo maintenance planning.

- ***Compute new probabilities for basic variables:*** for the subsystems identified in the previous step needing a maintenance plan, new failure probabilities were estimated for their components. The procedure is like probability updating (see Section 3.2.4.3). However, the "Working" state of the subsystem in question was identified in the model and instantiated to 100%. Subsequently, the emerged failure probabilities define the likelihood of the components failing when the subsystem is working. These are the new failure probabilities required for maintenance interval estimation.

  After probability updating, a zero-failure probability is recorded for the subsystem, which translates into zero risk index and impact cost. Hence, the subsystem failure is avoided to enhance the MPS operability. Using the hypothetical subsystem "A" example, the updated risk index and impact cost can be computed from Equation (3.3) and Step 2 above as follows:

New risk impact for subsystem “A” $= 0 \times US\$1{,}331{,}620.16 = 0$

New risk index for subsystem “A” $= \frac{New\ risk\ impact}{RAC} = \frac{0}{US\$882{,}290.00} = 0$

The new failure probability and its risk are zero, but the consequence impact remains US$ 1,331,620.16 because the suspected happenings (see Section 3.2.4.4) should subsystem “A” fail, are active. From the above results, subsystem “A” is no longer a threat to MPS operability.

- ***Estimate the maintenance interval time (MIT):*** the MIT is the duration within which maintenance works must be carried out on the affected subsystems' components. The formulations used by Leoni et al. [35] and Abbassi et al. [42] for MIT estimation agreed with the fourth assumption of the present study, so they were adopted. After combining the formulations, Equation (3.14) emerged and was used to compute the MIT for each affected subsystems' components. Equation (3.14) was derived based on exponential distribution, and the sum of failure probability and the reliability equals one (see Equation (3.15)).

$$MIT = \frac{\ln(1-P_U)}{\ln(1-P_R)} \times t \tag{3.14}$$

where, *MIT* is the maintenance time interval (in time unit), “t” is the time interval data being used (e.g., one year period), P_R is the prior failure probability, and P_U is the updated failure probability based on Step 3.

$$P(t) = 1 - e^{-\lambda t} \tag{3.15}$$

where, $P(t)$ is the annual probability of failure when t is set to a year, and λ is the failure rate expressed in failure per year.

Let us assume for the hypothetical subsystem “A” example (see Steps 2 and 3 above), a component within has $P_R = 0.65$ and $P_U = 0.35$. If the yearly fishing period for a given vessel is 317 days, then $t = 317$ days, and $MIT = \frac{\ln(1-0.35)}{\ln(1-0.65)} \times 317 days = 130.08\ days$.

The component must undergo maintenance each time subsystem "A" is operated for 130 days, approximately every four months.

With the MIT result, the maintenance plan was drawn as a table of subsystems components and the timelines for maintenance work to be carried out. The table is shown in Section 3.3.4.

3.2.5.2.RBM profitability analysis

For the hypothetical fishing vessel understudy, the amount profited from applying the RBM technique is discussed later in Section 3.3.3. The vessel is assumed to be operating in the capital city (i.e., Accra) of Ghana, where fishing is not allowed on Tuesdays. Hence, in a year of 365 days, "t" in Equation (3.14) is 317 days. The following steps were then taken to compute the savings made in the US$ 882,290.00 budgeted for the vessel maintenance annually due to the RBM initiative:

- ***Identify the highest risk index among the subsystems needing maintenance:*** rank the MPS subsystems by the risk index (see Section 3.2.5.1, second bulletin). Select the highest risk index among the subsystems requiring maintenance.
- ***Compute MPS failure risk cost:*** the cost is the highest risk impact cost among the MPS subsystems needing maintenance. Look out for the risk impact cost associated with the selected risk index in step one.
- ***Compute RBM profitability:*** subtract the US$ 882,290.00 from the amount in step two.
- ***Compute the percentage gain:*** divide the amount realised in step three by US$ 882,290.00 to arrive at the percentage gain made due to RBM programming. It describes how profitable RBM planning was to the fishing vessel's company or owner.

With the profitability analysis completed, the RBM methodology for maintaining fishing vessels' MPS is fully developed. The results for the computations in Phases 2 and 3 and the emerging simple maintenance plan are presented and discussed in the next section.

3.3.Results and Discussion

The results of all computations in Section 3.2.4 are presented and discussed here. Also, limitations to the proposed RBM methodology for MPS failure risk mitigation are enumerated at the end. The discussion is done to answer the following questions:

(1) What is the probability of an MPS failure occurring during operation?

(2) What root factors are most likely to trigger MPS failure at the above rate?

(3) How much savings did the organisation in charge of the fishing vessel make by implementing an RBM plan?

(4) From the maintenance plan, what components are the riskiest and which are not?

3.3.1. Discussion of the forward analysis result

Figure 3.5 and Table 3.6 show the forward analysis results. The first research question can be answered; there is a 76% (i.e., 0.757 probability) chance of MPS failure occurring aboard the fishing vessel during operation. The 76% score is relatively high and insinuates frequent MPS failure occurrences during fishing. However, using Equation (3.15), the probability gives a failure rate of 1.43 per year, which suggests that not more than two MPS failures would occur in a given fishing year. Also, going by the Ghana case presented in Section 3.2.5.2, the failure rate translates into 4.51×10^{-3} failures per fishing day (i.e., 317 days per year). The result shows that the vessel would rarely have its MPS failing to function on a given fishing day. Thus, though the failure probability is high, it does not necessarily mean there will be frequent failures.

The probability score must be interpreted relative to the failure rate to give more meaningful information. The causal factors responsible for the 76% MPS failure probability can be learned from the model (see Figure 3.5): 76%, 68%, 68%, 66%, 22%, and 47%. These are failure contributions from thrust transfer to the hull, electrical power generation, engine speed reduction, mechanical power generation, mechanical power transmission to the propulsor, and the propulsor functioning, respectively.

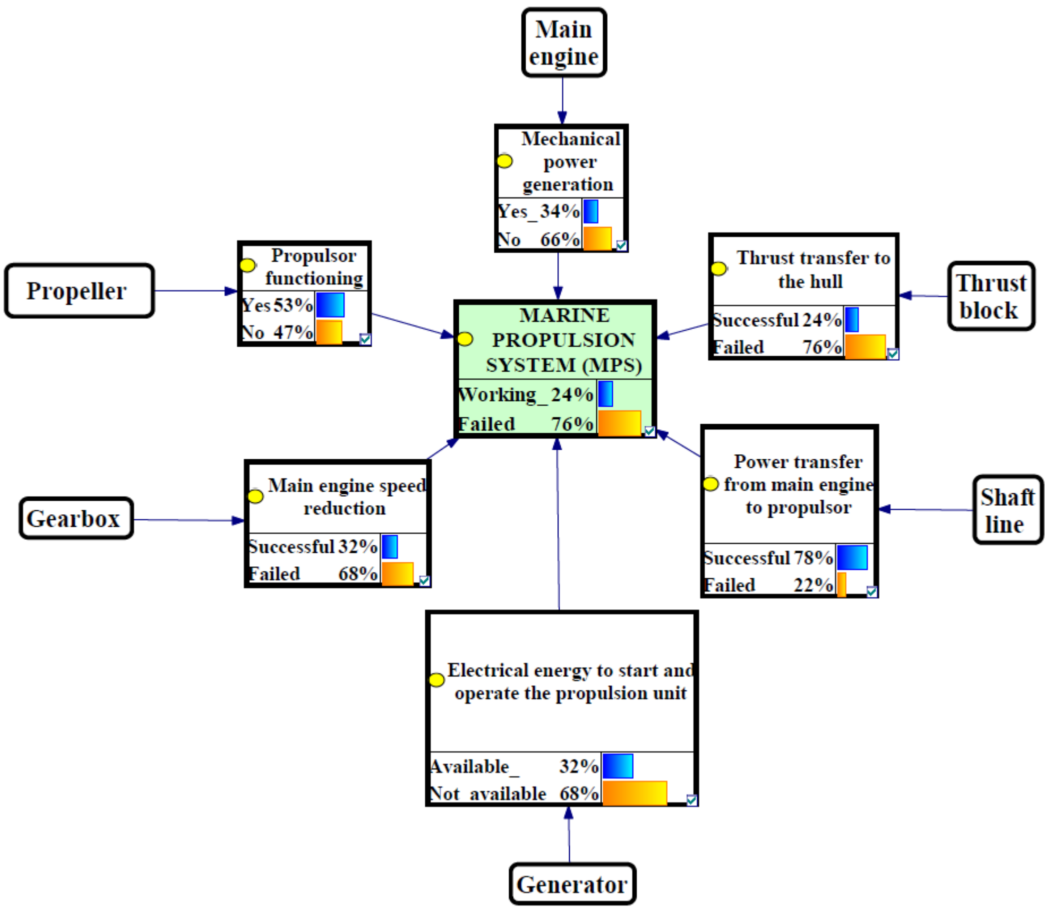

Figure 3.5. Forward analysis result computed by the developed model.

Zhao et al. [71] attest to thrust inefficiencies negatively impacting MPS performance. While such inefficiencies could be traced to the propulsor, from the results (see Table 3.6), the gearbox and main engine are more liable since their failure probabilities (i.e., 68% and 66%, respectively) are higher than the propeller’s 47% failure probability. The main engine may contribute to low thrust efficiency when incomplete combustion occurs. With the "Fuel oil supply system" at 99.9% failure probability, the air and fuel mixture's expected balance could be inadequate, leading to incomplete combustion and reduced performance from the main engine. The system's components might be faulty hence their inability to ensure the proper air to fuel ratio. Gearbox malfunctions were identified by Li et al. [9] as a significant causality for MPS breakdowns. As explained in the first paragraph, the last two columns of Table 3.6 show that the MPS subsystems do not fail so often in service due to their low failure rates.

Table 3.6. MPS subsystems failure probabilities.

Number	Sub-system	Prior probability	Failures per year	Failures per day
1	Gearbox	6.80E-01	1.14	3.60E-03
2	Generator	6.80E-01	1.14	3.60E-03
3	Main engine	6.60E-01	1.08	3.41E-03
4	Automation and control system	6.70E-01	1.11	3.50E-03
5	Freshwater cooling system	6.60E-01	1.08	3.41E-03
6	Fuel oil supply system	9.99E-01	6.91	2.18E-02
7	Lubricating oil system	9.80E-01	3.91	1.23E-02
8	Scavenge air system	5.50E-01	0.80	2.52E-03
9	Seawater cooling system	3.00E-01	0.36	1.14E-03
10	Starting air system	3.40E-01	0.42	1.32E-03
11	Propeller	4.70E-01	0.64	2.02E-03
12	**Shaft line**	**2.20E-01**	**0.25**	**7.89E-04**
13	Thrust block	7.60E-01	1.43	4.51E-03
14	Four-stroke cycle operation	5.60E-01	0.82	2.59E-03

With a 22% failure probability, the shaft line among the high-level RF has the lowest failure rate (see number twelve in Table 3.6), and so it is the most efficient. As mentioned in Section 3.2.4.1, the data used in estimating the 76% MPS failure likelihood (yielding 1.43 failures per year) came from Aziz et al. [16]. Unlike the present study, Aziz et al. [16] used fault tree analysis (FTA) to estimate 6.96 failures per year for the MPS. The two failure rates are way apart, and the difference in estimates could be the choice of modelling technique used. While the network structures differ between the two studies, the conditional probabilities employed are another source of the lack of convergence in results. FTA has a limitation regarding conditional probabilities; only hard evidence (i.e., zero or one score) is accepted in the CPTs. On the other hand, as illustrated in

Section 3.2.3.2, Step 2, in addition to the hard evidence, BN or OOBN employs soft evidence (i.e., scores between zero and one) too in CPTs.

3.3.2. Discussion of probability updating result

After updating the prior probability as described in Section 3.2.4.3, the posterior probabilities realised are shown in Appendix B4. Table 3.7 summarizes the ten components that gave the most significant changes between prior and posterior probabilities. These components deserve attention since they are the prime risk factors that would trigger MPS failure. The fuel filter answers the second research question and explains why the "fuel oil supply system" recorded such a high failure probability per the discussion in Section 3.3.1, the second paragraph. Also, at the bottom of Table 3.7, the components of the MPS that had no significant change between prior and posterior probabilities are shown. Such components are not the top priority in risk control mitigation.

Table 3.7. The difference in prior and posterior probabilities for MPS components.

d_i	Component	Subsystem	Difference in probability
1	Fuel filter	Fuel oil supply system	2.04E-01
2	Lube oil cooler	Lubricating oil system	1.89E-01
3	Valves	Freshwater cooling system	1.38E-01
4	Shaft bearings	Shaft line	7.40E-02
5	Piping	Freshwater cooling system	5.63E-02
6	Switchboard selector	Emergency generator	3.34E-02
7	Control valve	Parts specific to controllable-pitch propeller	2.59E-02
8	Crankpin	Parts specific to controllable-pitch propeller	2.36E-02
9	Starting system	Emergency generator	2.34E-02
10	Intermediate shaft	Shaft line	2.01E-02
.	.	.	.
.	.	.	.
.	.	.	.
141	Fuel injectors	Fuel oil supply system	0.00E+00
142	Governor	Fuel oil supply system	0.00E+00
143	Centrifuge	Fuel oil supply system	0.00E+00

3.3.3. Discussion of risk impact results

Based on the data presented in Section 3.2.4.1 and its processing by the procedures and formulations outlined in Section 3.2.4.4, Table 3.8 emerged as the consequence and risk impact results for the MPS subsystems: main engine, shaft line, propeller, thrust block, gearbox, and generator. From column three, when MPS fails in service due to main engine failure, the loss to fish harvesting is greater than in the case of the other subsystems. Main engine failure must, hence, be curtailed. By summing the costs from column three to column eight, the cost of the consequence impact was computed in column nine. On the other hand, the sum of the costs from column six to column eight yielded the costs due to environmental damage caused by the failure of MPS subsystems. From column nine, the gearbox presents the highest consequence costs and must be guarded against failure.

The risk impact costs in column ten show that the propeller is the most vulnerable subsystem, followed by the gearbox. That explains the importance of risk estimation; it is not sufficient to concentrate only on the failure probability or consequence impact only. As would be expected, the last column results show that the propeller and gearbox need maintenance planning; their risk indices exceeded one. The remaining subsystems (see column two) and their components do not require maintenance programming due to the less than one risk indices.

Table 3.8. Consequence estimates for MPS subsystems failures.

Number	Subsystem	$Cost_P$ (US$)	$Cost_I$ (US$)	$Cost_B$ (US$)	$Cost_H$ (US$)	$Cost_C$ (US$)	$Cost_R$ (US$)	Consequence impact (US$)	Risk impact (US$)	Risk index
1	Main engine	122642.40	81.93	2073.04	87404.00	418983.00	418026.39	1049210.76	692479.10	0.78
2	Shaft line	32058.00	183.51	2355.49	10778.00	470940.00	512479.33	1028794.33	226334.75	0.26
3	Propeller	42908.40	137.05	5245.96	81068.00	445432.00	649866.35	1224657.76	**1077698.83**	**1.22**
4	Thrust block	70856.40	69.65	3533.09	10234.00	227831.00	343107.94	655632.08	498280.38	0.56
5	Gearbox	103900.80	78.04	2416.52	95099.00	454250.00	675875.80	1331620.16	905501.71	**1.03**
6	Generator	59184.00	131.52	2229.77	19650.00	234671.00	473324.73	789191.02	536649.89	0.61

As explained in Section 3.2.5.2, US$ 1,077,698.83 emerged as the highest risk impact cost before RBM planning (see Table 3.8, column ten) and translates into the highest risk index score. When RBM was implemented, the risk costs for the propeller and gearbox became zero (as explained in Section 3.2.5.1, step 3). Therefore, following the computational procedures outlined in Section 3.2.5.2, the fishing vessel's company saved US$ 195,408.83, which is 22.15 % of the budgeted amount for maintenance. The company, thus, avoided spending US$ 195,408.83 extra if the MPS failed due to propeller failure, when the RBM plan was not in place. Similar calculations could be done for the gearbox, and a US$ 23,211.71 being 2.63% of the amount budgeted for maintenance, realised as the gain for implementing the RBM planning. As answer to research question three, the company saved a total sum of US$ 218,620.54, which translates into 24.78% savings of the budgeted amount for maintenance due to RBM planning. The RBM plan for the propeller and gearbox is presented next.

3.3.4. The RBM programme for high-risk MPS subsystems

In the earlier section, the propeller and gearbox emerged as the subsystems with highest risk indices (see Table 3.8, column eleven). The components of these subsystems underwent RBM programming as described in Section 3.2.5.1, and Table 3.9 emerged as the maintenance plan. Columns three and six show the new failure probabilities of the components. The corresponding MIT to the probabilities is also shown in columns four and seven. Once maintenance works are carried out on these components within the stated period, the propeller and gearbox will not fail in service, and the MPS will remain functional while delivering the 24.78% savings on maintenance costs.

The piston blade seal has the shortest maintenance period. It will be the most critical component on the schedule due to its frequent maintenance needs. The valve rod and blade will be the next critical components on the maintenance plan, with 65- and 88-days intervals for maintenance. Meanwhile, the clutch plate has 974 days interval for maintenance checks. It will be the least critical component on the maintenance plan due to its low demand for maintenance. The final research question is thus, addressed.

Table 3.9. The maintenance plan for the gearbox and propeller.

Number	Gearbox components	Updated failure probability	MIT (Days)	Propeller components	Updated failure probability	MIT (Days)
1	Thrust bearing	5.80E-02	209	Piston rod	5.50E-02	511
2	Hub	3.19E-01	406	Control valve	9.50E-02	137
3	Oil seal	6.21E-01	461	Crankpin	2.74E-01	536
4	O ring	1.15E-01	129	Piston blade seal	7.00E-03	31
5	Forward pinion	4.50E-02	350	Blade bolts	5.40E-02	161
6	Clutch plate	6.02E-01	974	Crank ring	1.38E-01	317
7	Pressure plate	4.40E-02	131	Blade	2.40E-02	88
8	Reverse clutch spider	2.69E-01	341	Servo motor cylinder	7.00E-03	358
9	Forward clutch spider	1.01E-01	250	Pilgrim nut	2.00E-02	276
10	Idler gear	4.09E-01	317	Valve rod	4.33E-04	65
11	Output gear wheel	2.59E-01	454	Bose	3.00E-02	339
12	Reverse driven gear	3.65E-01	274			
13	Gear selector lever	3.50E-01	274			
14	Gearcase	8.00E-03	253			
15	Forward driven gear	4.50E-02	350			
16	Idler shaft	8.00E-03	220			
17	Input shaft	3.20E-02	219			
18	Output shaft	5.50E-02	214			
19	Clutch shaft	1.60E-02	220			

3.3.5. Summary of the study outcomes and limitations of the proposed RBM methodology

Although the present study aims to alleviate the MPS failure problem aboard commercial fishing vessels, the RBM methodology proposed is also applicable to any other marine vessel, provided its main engine is a four-stroke diesel engine. The developed "MPS OOBN model" can also be used for MPS failure risk assessment on any marine vessel if steps are taken to compare subsystems and components to incorporate missing risk factors into the model. The risk assessment would ensure vulnerable subsystems and components to the vessels' propulsion system are identified prior to maintenance planning.

Through the proposed methodology, (1) fishing vessels can now have a simple maintenance planning approach for the main propulsion system, (2) chief engineers and ship superintendents for fishing vessels (and other marine vessels with a four-stroke diesel engine as the main engine) now have a tool to learn the components whose failure can impact the vessel's propulsion mission adversely, and (3) the commercial fishing industry can minimise its operational expenditure on MPS maintenance by 24.78%. Nevertheless, the methodology can be revised:

- A fuzzy probability elicitation approach can be used to replace the six-sigma one proposed.

- Although filling CPTs by hypothesis testing is objective, it can be overwhelming. A completely subjective approach can be considered to minimize the computational workload.
- The Goal-DRIT introduced by the present study is particularly useful when the system under study is extremely complex. Conventional hazard identification methods (e.g., what-if analysis and hazard identification) may be more suited for fishing vessels with very few subsystems in the MPS.
- The consequence impact of MPS failure can also be done in nonmonetary value as in Leoni et al. [35] and Khan and Haddara [37].
- The maintenance time interval was sought based on the exponential distribution function; the Weibull distribution function could be used instead.
- Leoni et al. [35] and Abbassi et al. [42] instantiated the safe state of the leaf node in their risk model to update the probabilities of root nodes for maintenance planning. Their approach can be tried since the present study adopted the approach by Krishnasamy et al. [36] and Khan and Haddara [37], which focuses on subsystems instead for MIT estimation.

3.4.Conclusion

Propulsion machinery failure has been identified as a common ship-related accident in the commercial fishing industry. Poor maintenance planning for the propulsion machinery aboard fishing vessels was cited as the leading cause of marine propulsion system (MPS) failure during fishing operations. Therefore, the present study proposes a simple maintenance plan to resolve the MPS failure problem aboard fishing vessels. The maintenance plan is developed from risk-based maintenance (RBM) scheduling. Before maintenance planning, a risk assessment model, the "MPS

OOBN model", was developed and used to estimate the failure probabilities of MPS and its subsystems given the subsystems components prior failure data. The model was applied to the case study of a fishing vessel operating in Ghana, and 1.43 MPS yearly failure rate was estimated. However, the failure rate is rather high, which prompted maintenance planning to identify the critical subsystems and their components for maintenance scheduling purposes. The propeller and gearbox were identified as the critical subsystems, and as such, an RBM plan was developed for the components of the subsystems.

The RBM methodology proposed brings three main achievements to the fishing industry: (1) chief engineers and superintendents for fishing vessels would use the "MPS OOBN model" to identify the riskiest subsystems and components for MPS failure, (2) while ensuring the operational health integrity of MPS subsystems and components, the industry can additionally reduce its budgeted maintenance amounts, and (3) the abrupt interruptions in fish harvesting operations and the exposure to MPS failure consequences can be significantly minimised, which would enhance fishing safety and continuity.

The present study made new contributions to the scholarly community. First, the hybridisation of the six-sigma method, Bayesian network (BN), object-oriented Bayesian network (OOBN), subject matter experts (SME) use, and hypothesis testing to develop a risk analysis tool (i.e., the MPS OOBN model). The model captures the subsystems and components within the MPS in fragmented structures and address the uncertainties regarding information insufficiency that arise in data-driven decision-making. Second, the development of an RBM programme for marine vessels' main propulsion system. Third, the "Goal-directed risk identification technique (Goal-DRIT)" developed purposely for risk factors identification in extremely complex systems or complicated scenarios. The inspiration for developing the Goal-DRIT was drawn firstly from consideration of the several factors in ship propulsion and the decision-making about what to include or exclude during risk factors identification for the MPS, and secondly, the effectiveness of the "Goal-directed task analysis" which is popular in situation awareness studies.

The RBM methodology proposed could be applied to offshore supply vessels and cargo vessels. Some offshore supply vessels also use four-stroke diesel engines as main engines like fishing vessels. For those that use electric propulsion, it will be interesting to know the riskiest factors and then develop a suitable RBM plan. Reliability-centered maintenance programme for cargo vessels MPS is common in the literature; however, that of RBM is scarce. The key message for the present study is that probabilistic risk assessment and maintenance programming can be merged to develop a unique RBM methodology for achieving the maintenance scheduling needs of a fishing vessel's propulsion system. The study is recommended to fishing vessel owners or companies and agencies overseeing commercial fishing vessels' affairs.

References

[1] J. Zhou, Y. Yang, Z. Zhao, and S. X. Ding, "A fault detection scheme for ship propulsion systems using randomized algorithm techniques," *Control Eng. Pract.*, vol. 81, no. June, pp. 65–72, 2018.

[2] S. C. Abou, "Fuzzy-logic-based network for complex systems risk assessment: Application to ship performance analysis," *Accid. Anal. Prev.*, vol. 45, pp. 305–316, 2012.

[3] H. M. Gaspar, A. M. Ross, D. H. Rhodes, and S. O. Erikstad, "Handling Complexity Aspects in Conceptual Ship Design," *Int. Mar. Des. Conf.*, no. June, pp. 1–14, 2012.

[4] F. Baldi, F. Ahlgren, F. Melino, C. Gabrielii, and K. Andersson, "Optimal load allocation of complex ship power plants," *Energy Convers. Manag.*, vol. 124, pp. 344–356, 2016.

[5] G. Vizentin, G. Vukelić, and M. Srok, "Common failures of ship propulsion shafts," *Multidiscip. Sci. J. Marit. Res.*, vol. 31, no. 2, pp. 85–90, 2017.

[6] G. Vizentin, G. Vukelic, L. Murawski, N. Recho, and J. Orovic, "Marine propulsion system failures—a review," *J. Mar. Sci. Eng.*, vol. 8, no. 9, pp. 1–14, 2020.

[7] I. Lazakis, Y. Raptodimos, and T. Varelas, "Predicting ship machinery system condition through analytical reliability tools and artificial neural networks," *Ocean Eng.*, vol. 152, pp. 404–415, Mar. 2018.

[8] Z. Li and Z. Peng, "A new nonlinear blind source separation method with chaos indicators for decoupling diagnosis of hybrid failures: A marine propulsion gearbox case with a large speed variation," *Chaos, Solitons & Fractals*, vol. 89, pp. 27–39, Aug. 2016.

[9] Z. Li, X. Yan, C. Yuan, J. Zhao, and Z. Peng, "Fault detection and diagnosis of a gearbox in marine propulsion systems using bispectrum analysis and artificial neural networks," *J. Mar. Sci. Appl.*, vol. 10, no. 1, pp. 17–24, 2011.

[10] Q. Meng, T. Wang, and S. Wang, "Short-term liner ship fleet planning with container transshipment and uncertain container shipment demand," *Eur. J. Oper. Res.*, vol. 223, no. 1, pp. 96–105, Nov. 2012.

[11] T. A. Santos and C. Guedes Soares, "Methodology for ro-ro ship and fleet sizing with application to short sea shipping," *Marit. Policy Manag.*, vol. 44, no. 7, pp. 859–881, 2017.

[12] J. Wang, A. Pillay, Y. S. Kwon, A. D. Wall, and C. G. Loughran, "An analysis of fishing vessel accidents," *Accid. Anal. Prev.*, vol. 37, no. 6, pp. 1019–1024, Nov. 2005.

[13] D.-J. Kim, "Classification of the Most Influential Maritime Accident Types using Grey Theory," *Asia-pacific J. Converg. Res. Interchang.*, vol. 6, no. 6, pp. 73–82, 2020.

[14] P. Kujala *et al.*, "Review of risk-based design for ice-class ships," *Mar. Struct.*, vol. 63, no. July 2018, pp. 181–195, 2019.

[15] J. Dai, S. W. Nam, M. Pande, and G. Esmaeili, "Medium-voltage current-source converter drives for marine propulsion system using a dual-winding synchronous machine," *IEEE Trans. Ind. Appl.*, vol. 50, no. 6, pp. 3971–3976, 2014.

[16] A. Aziz, S. Ahmed, F. Khan, C. Stack, and A. Lind, "Operational risk assessment model for marine vessels," *Reliab. Eng. Syst. Saf.*, vol. 185, no. January, pp. 348–361, 2019.

[17] L. He, W. Xu, W. Bu, and L. Shi, "Dynamic analysis and design of air spring mounting system for marine propulsion system," *J. Sound Vib.*, vol. 333, no. 20, pp. 4912–4929, Sep. 2014.

[18] Y. G. Kim and U. K. Kim, "Design and analysis of the propulsion shafting system in a ship with single stern tube bearing," *J. Mar. Sci. Technol.*, vol. 25, no. 2, pp. 536–548, 2020.

[19] J. Ahn, Y. Noh, S. H. Park, B. Il Choi, and D. Chang, "Fuzzy-based failure mode and effect analysis (FMEA) of a hybrid molten carbonate fuel cell (MCFC) and gas turbine system for marine propulsion," *J. Power Sources*, vol. 364, pp. 226–233, 2017.

[20] B. Jeong, E. Oguz, H. Wang, and P. Zhou, "Multi-criteria decision-making for marine propulsion: Hybrid, diesel electric and diesel mechanical systems from cost-environment-risk perspectives," *Appl. Energy*, vol. 230, no. April, pp. 1065–1081, 2018.

[21] M. Tadros, M. Ventura, and C. Guedes Soares, "A nonlinear optimization tool to simulate a marine propulsion system for ship conceptual design," *Ocean Eng.*, vol. 210, no. April, p. 107417, 2020.

[22] M. Altosole, M. Figari, and M. Martelli, "Time-domain simulation for marine propulsion applications," *Proc. 2012 - Summer Comput. Simul. Conf. SCSC 2012, Part SummerSim 2012 Multiconference*, vol. 44, no. 10, pp. 36–43, 2012.

[23] R. Lu, O. Turan, and E. Boulougouris, "Voyage optimization, prediction of ship specific fuel consumption for energy efficient shipping," *Low Carbon Shipp. Conf.*, vol. 44, no. 0, pp. 1–11, 2013.

[24] M. Tadros, M. Ventura, and C. Guedes Soares, "Optimization procedure to minimize fuel consumption of a four-stroke marine turbocharged diesel engine," *Energy*, vol. 168, pp. 897–908, 2019.

[25] M. Anantharaman, F. Khan, V. Garaniya, and B. Lewarn, "Reliability Assessment of Main Engine Subsystems Considering Turbocharger Failure as a Case Study," *TransNav, Int. J. Mar. Navig. Saf. Sea Transp.*, vol. 12, no. 2, pp. 271–276, 2018.

[26] I. Lorencin, N. Anđelić, V. Mrzljak, and Z. Car, "Multilayer perceptron approach to condition-based maintenance of marine CODLAG propulsion system components," *Pomorstvo*, vol. 33, no. 2, pp. 181–190, 2019.

[27] J. Weng and D. Yang, "Investigation of shipping accident injury severity and mortality," *Accid. Anal. Prev.*, vol. 76, pp. 92–101, Mar. 2015.

[28] F. Lasserre, "Case studies of shipping along Arctic routes. Analysis and profitability perspectives for the container sector," *Transp. Res. Part A Policy Pract.*, vol. 66, no. 1, pp. 144–161, 2014.

[29] N. S. Arunraj and J. Maiti, "Risk-based maintenance-Techniques and applications," *J. Hazard. Mater.*, vol. 142, no. 3, pp. 653–661, 2007.

[30] G. Kumar and J. Maiti, "Modeling risk based maintenance using fuzzy analytic network process," *Expert Syst. Appl.*, vol. 39, no. 11, pp. 9946–9954, 2012.

[31] IMO, *Treaties and international agreements filed and recorded: International Convention for the Safety of Life at Sea, 1974*, vol. 1184, no. 18961. 1981, pp. 278–453.

[32] MCA, *Fishing vessel surveys and inspections*. Government of United Kingdom.

[33] M. Anantharaman, "Using Reliability Block Diagrams and Fault Tree circuits, to develop a Condition Based Maintenance Model for a Vessel's Main Propulsion System and Related Subsystems," *TransNav, Int. J. Mar. Navig. Saf. Sea Transp.*, vol. 7, no. 3, pp. 409–413, 2013.

[34] M. Anantharaman, F. Khan, V. Garaniya, and B. Lewarn, "A holistic approach to Reliability and Safety on the operation of a main propulsion engine subjected to a harsh working environment .," in *3rd Workshop and Symposium on Safety and Integrity Management of Operations in Harsh Environments (C-RISE3)*, 2014, pp. 18–20.

[35] L. Leoni, A. BahooToroody, F. De Carlo, and N. Paltrinieri, "Developing a risk-based maintenance model for a Natural Gas Regulating and Metering Station using Bayesian Network," *J. Loss Prev. Process Ind.*, vol. 57, no. November 2018, pp. 17–24, 2019.

[36] L. Krishnasamy, F. Khan, and M. Haddara, "Development of a risk-based maintenance (RBM) strategy for a power-generating plant," *J. Loss Prev. Process Ind.*, vol. 18, no. 2, pp. 69–81, 2005.

[37] F. I. Khan and M. M. Haddara, "Risk-based maintenance (RBM): A quantitative approach for maintenance/inspection scheduling and planning," *J. Loss Prev. Process Ind.*, vol. 16, no. 6, pp. 561–573, 2003.

[38] X. Zhao, J. Sun, Q. Qiu, and K. Chen, "Optimal inspection and mission abort policies for

systems subject to degradation," *Eur. J. Oper. Res.*, vol. 292, no. 2, pp. 610–621, 2021.

[39] X. Zhao, Y. Fan, Q. Qiu, and K. Chen, "Multi-criteria mission abort policy for systems subject to two-stage degradation process," *Eur. J. Oper. Res.*, vol. 295, no. 1, pp. 233–245, 2021.

[40] J. Shen, L. Cui, and Y. Ma, "Availability and optimal maintenance policy for systems degrading in dynamic environments," *Eur. J. Oper. Res.*, vol. 276, no. 1, pp. 133–143, 2019.

[41] J. Cullum, J. Binns, M. Lonsdale, R. Abbassi, and V. Garaniya, "Risk-Based Maintenance Scheduling with application to naval vessels and ships," *Ocean Eng.*, vol. 148, no. August 2017, pp. 476–485, 2018.

[42] R. Abbassi, J. Bhandari, F. Khan, V. Garaniya, and S. Chai, "Developing a quantitative risk-based methodology for maintenance scheduling using Bayesian network," *Chem. Eng. Trans.*, vol. 48, pp. 235–240, 2016.

[43] J. Khorsandi and T. Aven, "Incorporating assumption deviation risk in quantitative risk assessments: A semi-quantitative approach," *Reliab. Eng. Syst. Saf.*, vol. 163, no. January, pp. 22–32, 2017.

[44] F. Goerlandt and G. Reniers, "On the assessment of uncertainty in risk diagrams," *Saf. Sci.*, vol. 84, pp. 67–77, 2016.

[45] T. Aven, "Improving risk characterisations in practical situations by highlighting knowledge aspects, with applications to risk matrices," *Reliab. Eng. Syst. Saf.*, vol. 167, no. October 2016, pp. 42–48, 2017.

[46] B. Khan, F. Khan, B. Veitch, and M. Yang, "An operational risk analysis tool to analyze marine transportation in Arctic waters," *Reliab. Eng. Syst. Saf.*, vol. 169, no. July 2017, pp. 485–502, 2018.

[47] V. Domeh, F. Obeng, F. Khan, N. Bose, and E. Sanli, "Risk analysis of man overboard scenario in a small fishing vessel," *Ocean Eng.*, vol. 229, p. 108979, Jun. 2021.

[48] M. Stamatelatos and H. Dezfuli, "Probabilistic risk assessment overview," in *Probabilistic risk assessment procedures guide for NASA managers and practitioners*, 2011, pp. 3–1 to 3–27.

[49] F. L. Cooke, "Plant maintenance strategy: Evidence from four British manufacturing firms," *J. Qual. Maint. Eng.*, vol. 9, no. 3, pp. 239–249, 2003.

[50] E. Bianchi Janetti, M. Riva, and A. Guadagnini, "Natural springs protection and probabilistic risk assessment under uncertain conditions," *Sci. Total Environ.*, vol. 751, p. 141430, 2021.

[51] T. Sakurahara, Z. Mohaghegh, S. Reihani, E. Kee, M. Brandyberry, and S. Rodgers, "An integrated methodology for spatio-temporal incorporation of underlying failure mechanisms into fire probabilistic risk assessment of nuclear power plants," *Reliab. Eng. Syst. Saf.*, vol. 169, no. August 2017, pp. 242–257, 2018.

[52] P. Mazidi, Y. Tohidi, A. Ramos, and M. A. Sanz-Bobi, "Profit-maximization generation maintenance scheduling through bi-level programming," *Eur. J. Oper. Res.*, vol. 264, no. 3, pp. 1045–1057, 2018.

[53] E. C. Özcan, S. Ünlüsoy, and T. Eren, "A combined goal programming – AHP approach supported with TOPSIS for maintenance strategy selection in hydroelectric power plants," *Renew. Sustain. Energy Rev.*, vol. 78, no. May 2016, pp. 1410–1423, 2017.

[54] S. M. Pour, J. H. Drake, L. S. Ejlertsen, K. M. Rasmussen, and E. K. Burke, "A hybrid Constraint Programming/Mixed Integer Programming framework for the preventive signaling maintenance crew scheduling problem," *Eur. J. Oper. Res.*, vol. 269, no. 1, pp. 341–352, 2018.

[55] F. Khan, M. Haddara, and M. Khalifa, "Risk-based inspection and maintenance (RBIM) of power plants," *Springer Ser. Reliab. Eng.*, vol. 50, no. November, pp. 249–279, 2012.

[56] A. Wilkinson, R. Kupers, and D. Mangalagiu, "How plausibility-based scenario practices are grappling with complexity to appreciate and address 21st century challenges," *Technol. Forecast. Soc. Change*, vol. 80, no. 4, pp. 699–710, 2013.

[57] A. Sharma, S. Nazir, and J. Ernstsen, "Situation awareness information requirements for maritime navigation: A goal directed task analysis," *Saf. Sci.*, vol. 120, no. October 2018, pp. 745–752, 2019.

[58] A. F. Molland, "Chapter 6: Marine engines and auxiliary machinery," in *The maritime engineering reference book*, 2008, pp. 344–480.

[59] D. A. Taylor, *Introduction to marine engineering*. 2003.

[60] N. T. Limited, "PRM120 Marine Gearbox Workshop Manual."

[61] J. S. Carlton, "Propeller repair," in *Marine Propellers and Propulsion*, 2012, pp. 503–505.

[62] OREDA, *Offshore Reliability Data Handbook*. 2002.

[63] N. Khakzad, F. Khan, and P. Amyotte, "Dynamic safety analysis of process systems by mapping bow-tie into Bayesian network," *Process Saf. Environ. Prot.*, vol. 91, no. 1–2, pp. 46–53, 2013.

[64] N. Khakzad, F. Khan, and P. Amyotte, "Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches," *Reliab. Eng. Syst. Saf.*, vol. 96, no. 8, pp.

925–932, 2011.

[65] Genie, "GeNIe Modeler," *Genie*, 2016.

[66] M. O. Sanni-Anibire, A. S. Mahmoud, M. A. Hassanain, and B. A. Salami, "A risk assessment approach for enhancing construction safety performance," *Saf. Sci.*, vol. 121, pp. 15–29, Jan. 2020.

[67] B. Jones, I. Jenkinson, and J. Wang, "The use of fuzzy set modelling for maintenance planning in a manufacturing industry," *Proc. Inst. Mech. Eng. Part E J. Process Mech. Eng.*, vol. 224, no. 1, pp. 35–48, 2010.

[68] B. Jones, I. Jenkinson, and J. Wang, "Methodology of using delay-time analysis for a manufacturing industry," *Reliab. Eng. Syst. Saf.*, vol. 94, no. 1, pp. 111–124, 2009.

[69] Y. Liu, H. Hu, and D. Zhang, "Probability analysis of damage to offshore pipeline by ship factors," *Transp. Res. Rec.*, no. 2326, pp. 24–31, 2013.

[70] K. Cicek and M. Celik, "Application of failure modes and effects analysis to main engine crankcase explosion failure on-board ship," *Saf. Sci.*, vol. 51, no. 1, pp. 6–10, 2013.

[71] F. Zhao, W. Yang, W. W. Tan, W. Yu, J. Yang, and S. K. Chou, "Power management of vessel propulsion system for thrust efficiency and emissions mitigation," *Appl. Energy*, vol. 161, no. 2016, pp. 124–132, 2016.

CHAPTER 4

4.0. An operational risk awareness tool for small fishing vessels operating in harsh environment

Preface

*A version of this chapter has been published in **Reliability Engineering and System Safety 234 (2023) 109139**. I am the primary author alongside co-authors Francis Obeng, Faisal Khan, Neil Bose, and Elizabeth Sanli. I developed the conceptual framework for the operational risk awareness conducted for small fishing vessels. I carried out the literature review, developed the operational risk awareness (RAw) tool, performed the engineering analysis, and prepared the first draft of the manuscript. Subsequent revisions of the manuscript based on co-authors' and peer review feedback were also done by me. Co-author Francis Obeng read the first draft of the manuscript and drew my attention to obvious areas of concern. Co-author Faisal Khan helped in the concept development and testing of the logic behind the RAw tool, reviewing and revising the manuscript. Co-author Neil Bose provided fundamental assistance in validating, reviewing, and correcting the model and results. Co-author Elizabeth Sanli assisted in validating, examining the technical writing constructs and correcting the model results. The co-authors also contributed to the review and revision of the manuscript after receiving peer-review feedback from the journal.*

Abstract

Probabilistic safety assessment using the Bayesian network (BN) has emerged as a popular method for developing risk analysis tools. The method allows for risk-influencing factors from several areas to be captured probabilistically, enabling an easy-to-use safety assessment tool to be developed. Meanwhile, because the resulting tool is a BN model, the use of subject-matter experts in eliciting probabilities for the conditional probability tables (CPT) makes the method subjective. The subjectivity makes the tool's output result less reliable since different experts rarely produce the same probabilities for CPTs. Therefore, the present study proposed a probability-scoring scale that uses pre-determined scores to assign probabilities to CPTs. Using the scale ensures that different experts working on a common CPT produce identical probabilities. That way, the variability among experts' results is minimised while the reliability of a BN's output result increases. The scale was applied to a BN-based risk-awareness (RAw) tool developed for monitoring safety aboard small fishing vessels (SFV). Advanced safety monitoring equipment is lacking aboard many SFVs, especially those in developing countries. Hence, the RAw tool developed in the present study demonstrates how the probabilistic safety assessment method could be leveraged to equip SFVs with safety monitoring tools. The study will benefit SFV owners and operators, the commercial fishing industry, and maritime administrations in charge of ensuring safety aboard SFVs.

Keywords: Situational or situation awareness (SA), probabilistic safety assessment, Bayesian network (BN), small fishing vessels (SFV), risk analysis, reliability, fishing accidents.

4.1.Introduction

The availability of situational (or situation) awareness (SA) information is a significant step in mitigating accident occurrences in risky industries. Around 71% of human error occurrences in the maritime sector could be blamed on the lack of SA information. From Sharma et al. [1], SA is an individual's continuous awareness of the ongoing events within an incident. Thus, with adequate SA information, humans in charge of systems and operations are better equipped to take decisions. Like other transport systems, marine vessels rely heavily on equipment to gather the SA information required for navigation and safety monitoring.

While marine vessels employed in shipping and industrial fishing have sufficient safety equipment, the same cannot be said for most small fishing vessels (SFV) within the commercial fishing fleet [2—4]. As a result, some SFVs lack adequate SA information to properly monitor accident scenarios at sea. Several SFV accidents have been recorded [5, 6] because of the lack of adequate SA information, leading to several cases of fisher injury, death, and loss of vessels at sea. In fishing safety publications [4—8], the SFV sector has been identified for minimising the high fatality rate in the global fishing industry.

The definition of SFV varies a lot in the publications. Generally, the SFV is known as a fishing boat with an overall length not exceeding 12—15 m [9]. In other parts of the world too, the gross tonnage is the basis for differentiating SFVs from the industrial-fishing vessels [10]. The gross tonnages are small with a typical example being the 30 tons fishing boat used in Budiyanto et al. [10] to study the cooling performance of fish holds aboard SFVs. Most SFVs use traditional methods to harvest fish and propel the boat. Some, however, have been modernized by using outboard engines for propulsion. Still, very little change can be observed in the fish harvesting methods handed down to the fishers by their forefathers.

For those SFVs with outboard engines, some have lengths exceeding 15 m. Although SFVs are the most populous in commercial fishing, their operation is not thoroughly regulated like industrial-fishing vessels or shipping vessels. As a result, the use of safety equipment aboard SFVs is sometimes left at the will of boat owners and operators. This class of marine vessels need safety equipment adapted to their operations to help curb the frequent accidents they experience at sea.

The present study developed a risk awareness (RAw) tool in the Bayesian network (BN) to contribute to the inadequate equipment for safety monitoring aboard SFVs. The RAw tool, when engaged, connects risk factors to fishing accidents through SA-information. That way, the SA information—not readily available—could be traced back to the risk factors. Consequently, appropriate control measures can be implemented to forestall the SA realised and avoid a possible fishing accident. In the study, risk factors are the active failures and categorised broadly into technical factors (i.e., operational activities related to fishing and the vessel and machinery running), environmental factors (i.e., the marine and onboard environmental conditions and elements within), and human-related factors (i.e., human commissions and omissions).

Often, fishers are previewed to these factors but may not know how they combine as SA to cause a fishing accident. Hence, SA-information describes SA with the potential to cause a fishing accident. Once the tool identifies the prime SA-information, fishers can trace back to the conducive condition(s) onboard, favouring their existence. The fishing accident, which is either vessel-related (e.g., capsize, grounding, fire and explosion, etc.) or person-related (e.g., injury, person overboard, death, etc.), can now be mitigated by eliminating the conducive condition.

By developing the RAw tool and demonstrating its implementation, the present study aims to provide SFV skippers, owners, and maritime administrations in charge of fishing safety with a digital tool to create awareness about the conducive conditions existing aboard for fishing-accident occurrence while on a voyage. The tool shows how the probabilistic safety assessment method could be leveraged to build digital tools for safety monitoring aboard marine vessels, particularly SFVs. Subjectivity is a current challenge in probabilistic safety assessment using BN. The challenge arises due to subject-matter experts' engagement to elicit probabilities for the conditional probability tables (CPT). As seen in Sonal and Ghosh [11] and Elidolu et al. [12], multiple experts providing probabilities for a CPT produce different dataset per expert. The variability in resulting datasets raises questions about consistency in the conditional probability elicitation approach and the reliability of the output result from BN.

In addition to the statistical methods available for addressing the variability challenge, the present study proposes using a probability scoring scale. The scale with predefined probability scores and objective guidelines on choosing a score purpose to eliminate subjectivity on the experts' side, minimise (if not avoid) variability in conditional probabilities elicited, and boost the reliability of BN result. That way, more trust would be repose in the outcome of a BN modelling for probabilistic safety assessment. Just as machinery reliability [13] continues to receive considerable attention in research, so, by proposing this scoring scale, the present study also aims to further the discussion on the reliability of probabilities elicited for CPTs in BN.

The specific objectives the study tackled are as follows: (1) To demonstrate how the fishers' experience at sea and the existing literature on how fishing accidents occur can be consolidated to develop the RAw tool for SFV operational safety monitoring purposes, (2) To use the RAw tool to facilitate decision-making about the time-to-time dangerous situations that fishers at sea must be aware of in advance, and (3) To leverage on the RAw tool's capabilities, to design a safety monitoring programme for SFVs. These objectives provided answers to the questions—what fishing accidents are the most probable at a given time—what situations are the drivers of the identified fishing accidents?

Thorvaldsen [14] and other researchers [15, 16] mentioned that fishers in the SFV sector have rich knowledge about the risk factors and fishing accidents they encounter during voyages. The fishers have gained this knowledge through years of experience in fishing. Meanwhile, Abdullah-Bin-Farid et al. [17], Braga and Schiavetti [18], and Wekke and Cahaya [19] identified that these fishers have low educational levels, usually not beyond the high school level. Therefore, to make the RAw tool user-friendly, the present study adopted the cause-effect modelling approach for developing the tool. The risk factors were identified as causes, while fishing-accidents became the effects. The literature review uncovered the SA information that presents the scenarios under which risk factors translate into fishing accidents. In defining accident scenarios, Animah and Shafiee [20] discussed how helpful literature on the subject matter could be, especially at the initial stages of a research study. In that vein, the present study's use of literature for cause-effect modelling could be considered satisfactory. Hence, the RAw tool is primarily a cause-effect model. Fishers only have to input the risk factors (i.e., technical, environmental, and human-related factors)—the tool then identifies the fishing accidents and associated conducive conditions (i.e., the SA information).

The RAw tool development is the practical contribution made by the present study to SFV's operational safety. Theoretically, the study contributed to the existing knowledge on probabilistic safety assessment applications by demonstrating the tool's functionality in safety monitoring aboard an SFV. Publications in that area are quite scarce. The probability scoring scale introduced for conditional probability elicitation to achieve higher reliability in BN modelling [5, 21] is another theoretical contribution made by the study.

When the CPTs are filled using the proposed scale, each time fishers activate the prevailing risk-factor states in the tool, fishing accidents and SA-information are assigned percentages ranging from zero to 100%. When the estimated percentage for a fishing accident is 100% or closer, the interpretation is that a conducive condition exists onboard, which could cause the accident. Furthermore, an SA-information with an estimated percentage of exactly 100% or closer is considered critical and more likely to trigger an accident. Such SA information must be controlled first to lower the chances of a fishing accident occurring.

The remainder of the paper is organized as follows; Section 4.2 is next and discusses the literature on fishing accidents, their causation factors, and the BN modelling approach. The RAw tool development is explained in Section 4.3, together with its case study application. Then, Section 4.4 discusses the case study results and the study limitations. Finally, Section 4.5, the concluding section, presents the main findings, the key message, and future research directions.

4.2.Literature Review

The current section discusses the literature on fishing accidents and their contributing factors and explains BN modelling before it is used in the next section. The review aimed at providing enough background for the particular probabilistic safety assessment approach used in the cause-effect modelling that resulted in the BN model named RAw tool. The probability scoring scale introduced is also explained in detail here.

4.2.1. Fishing accidents and the causation factors

Commercial fishing is counted among the world's occupations with the high number of employee deaths and injuries [5, 6, 8]. In Case et al. [22], commercial fishing in the United States of America (USA) recorded 86 deaths per 100,000 employees in 2016. This fatality rate was significant because it was 23 times more than the fatality rate for all USA employees in the period. Similarly, Byard [23] study in 2012 says commercial fisher deaths were 52.4 times more than fatality rates for other British sector employees in the United Kingdom. In 2003, South Africa also published a fatality rate of 162 yearly—meaning at least one fisher dies every two days [24]. The rates in other countries, like Australia, Canada, New Zealand, Norway, Poland, and Sweden, are no different

[24, 25]. Fishing accidents are, thus, a global challenge and are fast diminishing the human workforce in the commercial fishing industry.

Table 4.1 presents some fishing accidents in the last three decades. Besides the deaths and injuries, vessel losses are also a major consequence of fishing accidents. Hence, solutions to curb fishing-accident occurrences must consider both the human and vessel perspectives. Broadly, fishing-accident resulting in damage to the vessel is called a vessel accident, while if causing injury to fishers or leads to fisher deaths, the fishing accident is referred to as a personal accident [5, 6, 26, 27].

Meanwhile, the studies of Uğurlu et al. [5], Roberts [6] and Domeh et al. [26] show that, often, the bulk of the fishing accidents (see Table 4.1) are traced to the SFVs. In Byard [23], it is said that about 59% of fisher deaths realised at one time in the Danish fisheries were linked to the SFV group. With Table 4.1 showing evidence of similar accidents in various parts of the world, alongside their happening even in the last four years, tools to envisage accident causation factors before they result in the accident are undoubtedly needed.

Table 4.1. Summary record of sampled fishing accidents in publications.

Researcher	Publication source	Investigation period	Fishing accident	Accident consequence	Region of occurrence
Bye and Lamvik [28]	Reliability Engineering and System Safety Journal	1990 - 1999	Man overboard Capsize Collision Grounding Drowning	34 fisher deaths 3 fisher deaths 5 fisher deaths 9 fisher deaths 16 fisher deaths	Norway
Wang et al. [27]	Accident Analysis & Prevention Journal	1994 – 1999	Machinery damage Foundering and flooding Collision and contact Fire and explosion Capsize and list Heavy weather damage	128 fisher deaths 179 vessels lost	United Kingdom
McGuinness et al. [25]	Safety Science Journal	1990 – 2011	Capsize Foundering Collision Grounding Crush/impact Drowning Man overboard	281 fisher deaths	Norway
Kum and Sahin [29]	Safety Science Journal	1993 – 2011	Occupational accident Collision Grounding Machinery failure Flooding/foundering Fire and explosions Capsizing	In all: 30 accidents, 27 injuries, 1fisher death	Canada, Greenland, Russia Federation, USA, Denmark, Iceland
Arctic Council [30] Smith et al. [31]	Arctic Marine Shipping Assessment 2009 Report Proceedings of the ASME 2015 34th International Conference on Ocean, Offshore and Arctic Engineering Fire and explosion Grounding	1995 - 2010	Collision Grounding Machinery failure Sinking	108 accidents in total	Circumpolar north region in Canada, Faroe

	Machinery failure				Islands, USA,
Rezaee et al. [32]	Ocean & Coastal Management Journal				Iceland,
Khan et al. [33]	Reliability Engineering and System Safety Journal				Norway
Roberts [6]	Accident Analysis & Prevention Journal	1996 - 2000	Man overboard Capsize Collision Grounding Fire and explosion Struck by gear Struck by waves Entangled in gear Asphyxiated by fumes	32 fisher deaths 59 fisher deaths 5 fisher deaths 14 fisher deaths 3 fisher deaths 10 fisher deaths, injury 6 fisher deaths, injury 11 fisher deaths 4 fisher deaths	United Kingdom
Uğurlu et al. [5]	Ocean Engineering Journal	2008 - 2018	Man overboard Collision Sinking Grounding Fire and explosion Occupational injury	20 fisher deaths 29 fisher deaths, 17 vessels lost; 37 fisher deaths, 44 vessels lost; 12 fisher deaths, 14 vessels lost; 1 fisher death, 10 vessels lost; 21 fisher deaths, 1 vessel lost	Europe, Australia, Canada
Paolo et al. [34]	Transportation Research Procedia	2009 – 2019	Capsize Collision Damage to vessel Fire Flooding Grounding Machinery failure Occupational/work accident	23 % Vessel lost 32 % fisher deaths	Worldwide

The literature on fishing accidents abounds. They can be sourced from as far back as the 1960s [35—37] to as recent as the 2020s [5, 38, 39]. Studying these publications to unveil the accident causation factors is cost-effective and saves time. Additionally, because the authors of these publications are diverse in location, educational background, and objective of their studies, the literature survey helps to analyse fishing-accident causes from several perspectives. A field study typically would localise accidents causes and not give complete information about the various ways the accidents could happen.

Comprehensive information on fishing-accident causalities is an excellent way to match the causes to typical accident types. When the accident causes are traced to root causes, the technical (which involves operational matters), environmental, and human-related factors at the forefront of fishing-accidents occurrences are identified. Building a cause-effect relationship is then possible and could become a valuable tool for fishers to connect the daily happenings at sea to potential fishing accidents. That way, SFV fishers can proactively correct onboard situations to avoid a fishing-accident occurrence.

Figure 4.1 is an example model of a cause-effect relationship for a fishing accident, "Grounding". Information to develop the model was sourced from Byard [23]: *"Grounding on rocks or at harbour entrances has been documented in conditions of poor visibility or at night when watchmen were either fatigued or had fallen asleep. Fatigue is contributed to by long working hours at sea with short rest periods, cramped sleeping spaces, interruption of sleep by engine noise and vibration and the effects of heavy seas."* The arcs in the figure extend from a cause factor to the effect, resulting in a cause-effect diagram for SFV-grounding based on factors abstracted from the italicised information.

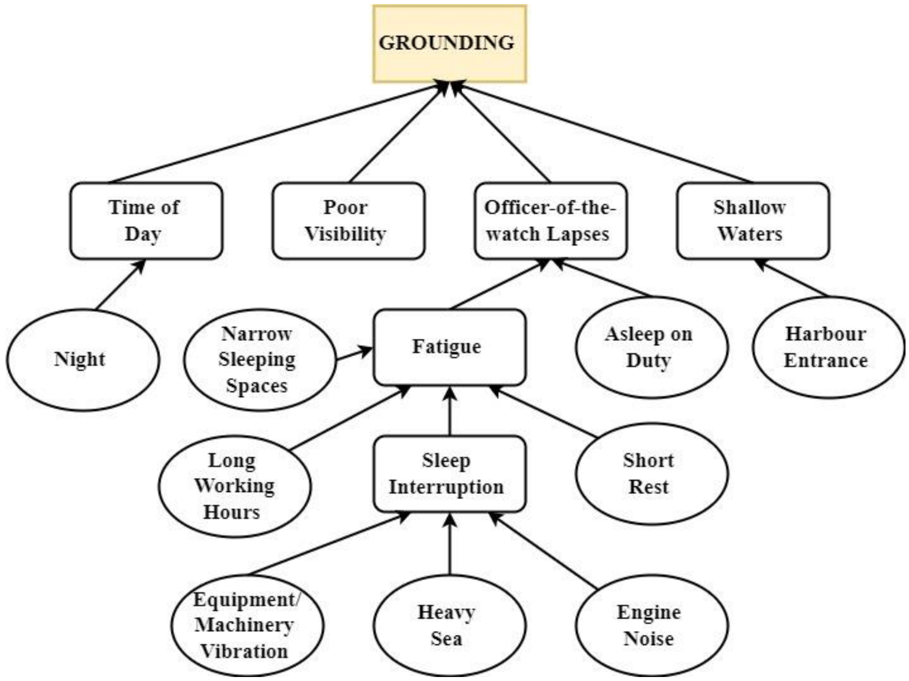

Figure 4.1. A cause-effect diagram for SFV Grounding (in yellow) showing direct failures in rounded rectangles and indirect failures in ellipses.

From the diagram in Figure 4.1, "Poor visibility" and "Shallow waters" are environmental factors, while "Officer-of-the-watch lapses", "Fatigue", and "Sleep interruption", have direct human involvement, so they qualify as human factors. Although, the "Time of day" has an environmental connotation, the factor also provides a physically immersive work experience, and so it could be viewed as a technical factor. Meanwhile, all these factors are brought about by operational conditions (i.e., the factors of space, time, and force concerning a given objective), as evident in the factors within the ellipses.

As an example, if not for operational conditions of working long hours and machinery running to cause vibration, the "SA information", "Fatigue" and "Sleep interruption" would not emerge, triggering "Officer-of-the-watch lapses" and, eventually, "Grounding". Thus, operational conditions often are the underlying causes for the technical, human, and environmental factors resulting in fishing accidents aboard SFVs. For easy identification, however, the present study in

Section 4.3 broadly grouped SFV accident causality into technical, human, and environmental factors; then, within each group, the typical operational conditions were defined.

Furthering the discussion on Figure 4.1, the factors in ellipses, for example, “Short rest”, “Engine noise”, or “Harbour entrance”, are explicitly defined. Fishers can identify with them more quickly than those in the rounded rectangles, like, “Poor visibility” or “Officer-of-the-watch lapses”. Hence, such explicitly defined factors are the root causes of SFV “Grounding”, and the present study refers to them as risk factors. Poor visibility, like other factors in the rounded rectangles, needs further breakdown to uncover their risk factors. These factors are still at the information stage, and the present study referred to them as SA information.

The SA information is challenging to conceive from a glance, mainly because, in reality, they occur with the simultaneous actions of several risk factors at the same time. For SFV fishers, who typically employ low monitoring technology and have a low educational background, the mental exercise of perceiving the individually occurring risk factors to culminate into an SA-information and, subsequently, an accident is the challenge to resolve when fishing. If fishers could easily connect vibration from equipment (or machinery) to “Officer-of-the-watch lapses”, fishers can conclude that a conducive condition exists aboard for “Grounding” to occur. Fishers would then take appropriate steps to find the onboard situation responsible for the vibration and address it. In that regard, the cause-effect model has been worthwhile.

In the methodology section, the above procedure was followed to define risk factors and SA information for the various fishing accidents encountered by SFVs. The resulting cause-effect model was later transformed into a BN to become the RAw tool by putting together all the risk factors and SA information.

4.2.2. Bayesian network modelling

The BN is a directed acyclic graphical model excellent at representing causal relationships in which probabilistic safety assessment is the objective. In recent times, probabilistic safety assessment [40, 41] has emerged as a useful method in identifying the risk influencing factors responsible for an incident. Apart from identifying risk factors, their occurrence rate updating and the most probable accident scenarios analyses [42, 43, 44] are also studied in probabilistic safety assessment. The BN has a data-driven modelling capability that makes possible all these tasks, and as such, it is highly favoured by researchers undertaking probabilistic safety assessment.

Fan et al. [43] used BN to develop a human factors analysis tool for marine vessels. The tool facilitated the human error rate prediction for different ship types and accident scenarios. Yu et al. [45] used BN to bring together factors from multiple sources, resulting in a data-driven model that estimated the overall risk of ships in coastal waters. Animah and Shafiee [20] also commended the flexibility BN offers in merging information elements of diverse backgrounds. Moreso, the modelling of ships colliding with offshore installations was also done by Yu et al. [46] using BN. The application areas of BN are numerous. BN presents a straightforward way for data-driven tools development for probabilistic safety assessment. Later in the methodology section of the present study, BN was used to develop the RAw tool proposed for safety monitoring aboard SFVs.

In BN, information describing the cause-effect relationship is represented by nodes bearing their respective names. Each node is also given states (which vary from two onwards) to tell the occurrence or non-occurrence of the information. Arcs are then extended from one node to another to realise the network structure for the relationship under study. Two kinds of nodes are in a BN model: child and parent nodes. An arc can only be extended from a parent node to the respective child node; the opposite is not allowed due to the acyclic nature of BN. Hence, information only flows from parent nodes to child nodes. In Figure 4.2, an example BN model is shown for the "Sleep interruption" information in Figure 4.1. The "Engine noise", "Heavy sea", and "Equipment/machinery vibration" factors being the information describing "Sleep interruption" are the parent nodes while the later, is the child node.

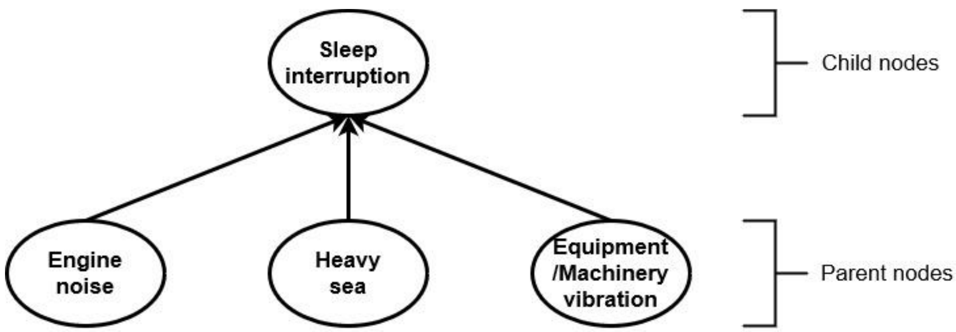

Figure 4.2. A BN model for "Sleep interruption" scenario aboard an SFV.

Data-driven decision-making is made possible in BN models through the estimation of percentage scores that can be used to infer the chances of a situation happening. To do the estimation, child nodes have CPTs that establish the mathematical relationship between parent and child nodes. These CPTs must be filled with probability values, which, as mentioned in the introduction section, is usually done by subject-matter experts [5, 21]. In the present study, however, the scoring scale in Figure 4.3 is proposed to complement the expert elicitation approach. Using the scale would help minimise (if not remove) the variability in different expert scores when assigned the same CPT. Thus, the scale presents an objective approach to eliciting probabilities for CPTs in BN.

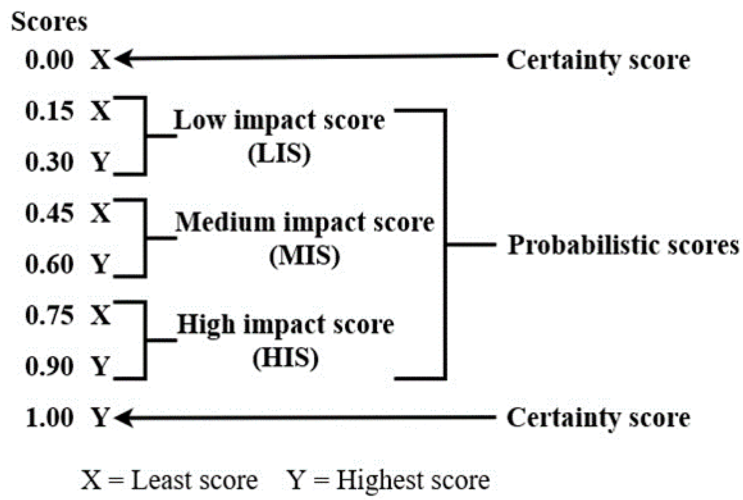

Figure 4.3. The proposed scale for eliciting probabilities required in a CPT.

From Figure 4.3, the scale has mainly two score types, certainty and probabilistic. Certainty scores, one or zero, are issued if all parent nodes indicate only occurrence or non-occurrence states, respectively. The probabilistic scores are used instead when the states for parent nodes are a mix of occurrence and non-occurrence. Depending on the number of non-occurrence states in the mix, the choice score may be low-impact, medium-impact, or high-impact. High-impact scores must be selected for the least number of non-occurrence states in the mix. Medium-impact score will be the best choice as the number of non-occurrence states increases in the mix. However, if the non-occurrence state number is greater than the occurrence state number in a mix, the score would come from low impact.

As also shown in Figure 4.3, within each probabilistic score class, two scores exist from which the analyst (or expert) would decide whether to give a low (X) or a high (Y) score. For the situation where the occurrence states outnumber the non-occurrence states, the "Y" score must be assigned. The "X" will be the chosen score in the opposite situation. Where there is a tie in the state types number, the analyst may decide between "X" and "Y" in the medium-impact class through consideration for the severity of the child node impact on the incident (e.g., a fishing accident) under study. Otherwise, the mean score of 0.53 can be used instead. Also, the number of parent nodes connected to the child node can be controlled by object-oriented programming to avoid the tie situation. The scoring approach described is based on the proposed scale and encourages objectivity when eliciting probabilities for CPTs. Ultimately, the scale aims at eliminating variability in expert scores for CPTs. Reliability is then enhanced, and more trust is reposed in the model outcome result.

Let us demonstrate the proposed probability scoring approach using the example BN in Figure 4.2. Each node has two states: Engine noise, “High/Low”; Heavy sea, “Yes/No”; Equipment vibration, “High/Low”; and Sleep interruption, “Possible/Not-possible”. The goal is to develop the CPT for “Sleep interruption”, the child node, and then fill the CPT with probability scores. From Equation (4.1), eight probability values are expected at the “Possible” state of the “Sleep interruption” node. By subtracting the “Possible” state probability score from one, the corresponding probability for the “Not-possible” state is realised. That is to say, the sum of probabilities for a node’s occurrence and non-occurrence states is equal to one.

$$N_{CPT} = 2^{n_p} \tag{4.1}$$

where, N_{CPT} is the number of probability scores expected in the child node states if each parent node has exactly two states, and n_p is the number of parent nodes connected to the child node.

Using the proposed scale and following the procedure described earlier, the analyst (or expert) would score the probabilities in the last two columns of Table 4.2. Therefore, Table 4.2 is the CPT with the elicited probabilities for the “Sleep interruption” node. With the CPT filled, once prior probabilities are entered for each parent node, the total probability, Equation (4.2), is used to estimate the percentage score that defines the likelihood of “Sleep interruption” occurring (i.e., the “Possible” state score).

Table 4.2. CPT for the "Sleep interruption" node.

Number	Engine noise	Heavy sea	Equipment vibration	Score type appropriate	Sleep interruption	
					Possible state	Not-possible state
1	High	Yes	High	Y Certainty	1.00	0.00
2	High	Yes	Low	Y High-impact	0.90	0.10
3	High	No	High	Y High-impact	0.90	0.10
4	High	No	Low	X Low-impact	0.15	0.85
5	Low	Yes	High	Y High-impact	0.90	0.10
6	Low	Yes	Low	X Low-impact	0.15	0.85
7	Low	No	High	X Low-impact	0.15	0.85
8	Low	No	Low	X Certainty	0.00	1.00

$$P(A) = P(A) \times P(A|B = occurred) + P(A) \times P(A|B = not - occurred) \quad (4.2)$$

where, A and B are two conditional events; $P(A)$ is the total probability of event A; and $P(A|B)$ is the conditional probability of A given the occurrence or nonoccurrence of B.

BN modelling has seen several applications in fishing safety studies. Domeh et al. [26] and Obeng et al. [38] used BN to model man overboard and capsize scenarios for SFVs, respectively. Also, Uğurlu et al. [5] used BN to model fishing vessel sinking and collision. Sotiralis et al. [47] developed a BN model that incorporates human factor issues into vessel collision incident. In all these researches, a completely subjective expert elicitation procedure is used in eliciting probabilities for the CPTs involved.

The BN developed for the RAw tool in the present study differs from those of previous researchers. That is because of the semi-objective approach adopted to elicit probabilities for CPTs, using the proposed scoring scale. By using the scale as described, variability in experts' scores for CPTs could be minimised, reliability in experts' scores enhanced, and more trust reposed in risk results from BN modelling. The following section discusses detailed information on the RAw tool development and the proposed scoring scale application.

4.3. The Methodology to Develop the RAw Tool and the Proposed Monitoring Programme

The method applied in developing the RAw tool is BN modelling, which uses probabilistic safety assessment [40, 41] to estimate percentage scores for leaf and intermediate nodes in the network. Probabilistic safety assessment tools to aid accident monitoring aboard SFVs are scarce in the literature, so the development of the RAw tool is a significant contribution in that regard. As mentioned in section one, the percentage scores only give quantitative measurements for the likelihood of a fishing accident and the presence of conducive conditions aboard the SFV, favouring the accident.

The BN modelling done here is also different from those of Uğurlu et al. [5], Domeh et al. [26], and Obeng et al. [38] due to the application of the proposed probability scoring scale, which adds to the scholarly contribution made by the present study to the existing BN modelling methodologies [21, 47]. By applying the proposed scoring scale in Figure 4.3, the study presents a more objective viewpoint for experts' judgement when eliciting probabilities for CPTs. Compared with other expert elicitation approaches [43, 45, 46], the present one aims for consistency and reliability in experts' judgement.

In Section 4.2.2, BN modelling was discussed in detail. The current section describes the step-by-step procedures employed to develop the RAw tool as a BN model. The methodology framework is described first.

4.3.1. Framework to develop the RAw tool

The concept framework to develop, operate, and maintain the RAw tool, is shown in Figure 4.4. In all, five steps are involved: information elements identification (Step 1), cause-effect database design (Step 2), the RAw tool development (Step 3), voyage situation assessment (Step 4), and maintaining the RAw tool (Step 5). Before starting the database design, verifying if sufficient information elements have been identified is essential. That was achieved through inspection to ensure no obvious fishing-accident type, SA-information, or risk factor was left out of the identified elements from Step 1. After the tool has been developed and used, it is crucial to constantly inquire if new accident types have emerged or information elements have changed. That way, Step 4 would be relevant and help keep the tool up-to-date with future changes in fishing safety aboard an SFV.

If no new knowledge is discovered about fishing safety aboard SFVs, then Step 5 will be skipped to end the accident monitoring. At the higher-level, Figure 4.4 is sectioned into three: Steps 1 to 3, the aim is to develop the RAw tool; Step 4, demonstrates the RAw tool in application; and Step 5 is aimed at updating the RAw tool so that it remains relevant to current and future fishing safety needs. In the proceeding sections, each step is described in more detail.

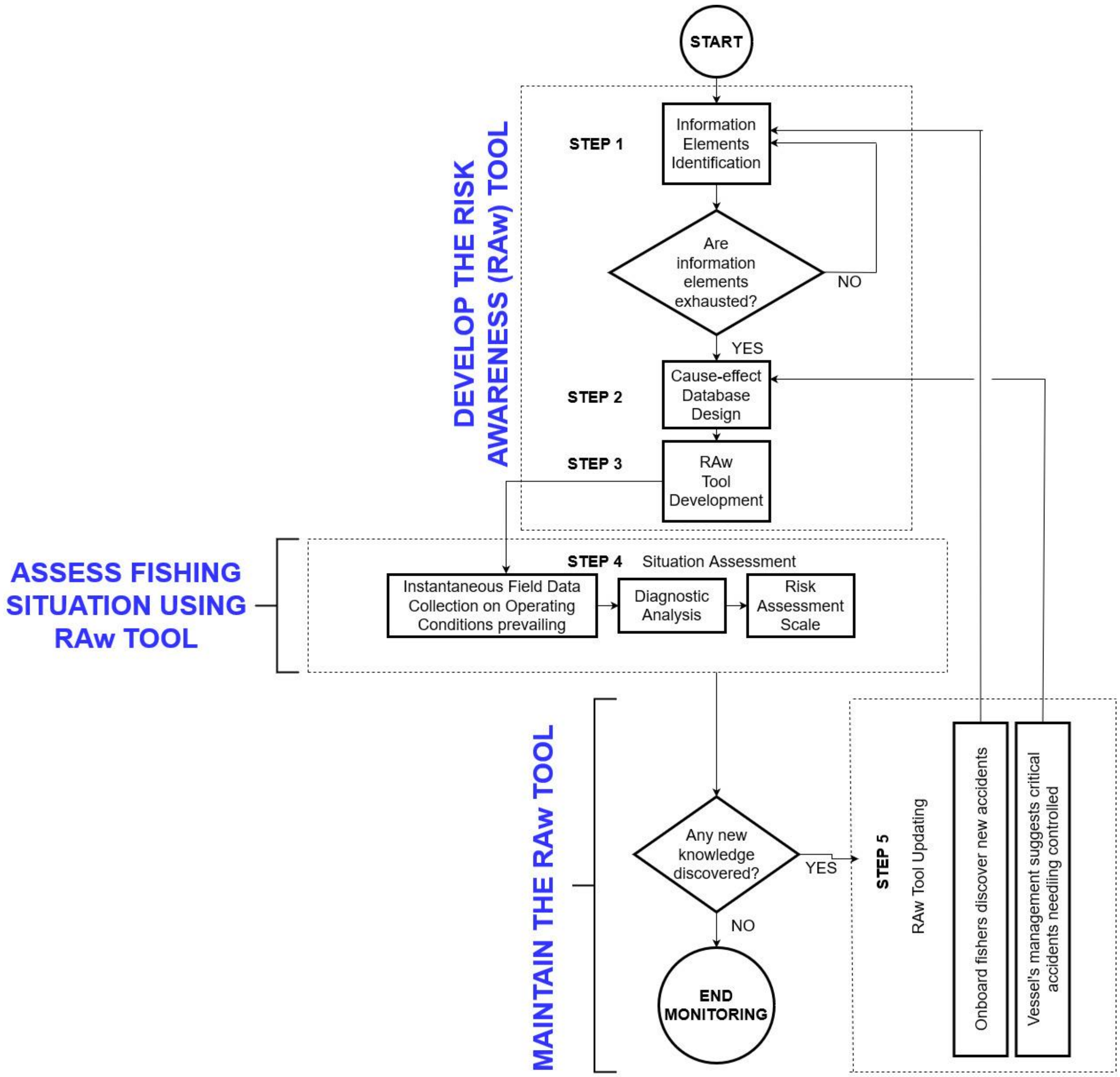

Figure 4.4. The framework for developing and operationalising the RAw tool.

4.3.2. Step 1: Information elements identification

The goal of this section was to define fishing-accidents and their information elements. The goal was achieved by surveying literature in Scopus, Google Scholar, and the databases of Fish, Fisheries and Aquatic biodiversity Worldwide. These databases hold several journals from various publishers studying commercial fishing. Also, to ensure that credible information elements are sourced, only journal articles and conference papers from top-tier publishers and in English were used. The query statement used was “(Commercial OR Small) AND Fishing (Vessel OR Boat) AND Accident”. More than 105 thousand paper results were realised when the query statement was executed. By prioritizing journal articles and conference papers, leading scientific journal types, studies primarily focused on fishing safety, leaving out review papers, and not going beyond twenty years back from 2023, the results were filtered to 28, which was used for the survey.

For the selected papers, the text inside each paper was searched, and portions of relevance were copied, as demonstrated earlier in section 4.2.1, paragraph four. Each copied text was mined by developing cause-effect diagrams similar to Figure 4.1. Finally, the information elements realised from the diagrams were organised into Table 4.3; the complete information elements are in Appendix C1. In the table, active and latent failures have been captured under information elements whilst the personal and vessel-related accidents became fishing accidents. As a result, further review was done in Step 2 to realise the database used in developing the RAw tool.

Table 4.3. Fishing accidents and associated information elements.

Number	Information element	Fishing-accident	Citation
1	UKC*, squat effect, storm, navigation error, alcohol use, fatigue, drifting ice, human error, poor visibility, adverse weather, and tall waves.	Grounding	[5, 6, 48—52]
2	Operational status of GPS*, ECDIS*, Radar AIS*, radio system (VHF/MF)*, steering system, communication channels (portable radios, PA systems*), signal lights, main engine controls on bridge, propulsion system, human error, paper nautical chart detection, and bridge system software malfunction.	Navigation failure	[1, 47, 48, 53—55]
3	Poor visibility, ambient temperature, seawater temperature, wind speed, ocean current, sea swell, wave height, and sea surface appearance.	Adverse weather	[1, 53, 56]
4	Adverse weather, loss of buoyancy (overloading, loss of watertightness, damaged pipelines, ice accretion on ship), and loss of intact stability (unstable loading, fishing gear operating, and ice accretion on ship).	Sinking	[5]
.	.	.	.
.	.	.	.
.	.	.	.
20	Fuel shortage and engine breakdown.	Loss of power	[27, 37]
21	Adverse weather and loss of power.	Lost/stranded at sea	[27, 37]
22	Lightning, engine room fire, fire fighting equipment failure, electric spark, cooking gas leakage, smoking, and lack of ventilation.	Fire and explosion	[27, 37]
23	Human factor, burns, loss of finger or whole limb, injury from sharp tools, knife use, negligence, fatigue, holding fish without gloves on, and beheading a life fish manually.	Occupational injury	[5, 29, 34, 57, 58]

*UKC: under keel clearance; GPS: global positioning system; ECDIS: electronic chart display and information system; AIS: automatic identification system; VHF: very high frequency; MF: medium frequency; and PA: public address.

4.3.3. Step 2: Cause-effect database design

With Step 1 completed, three objectives were targetted in Step 2 to ensure a suitable database is realised for RAw tool development in Step 3. The first objective was to put the information elements collected in Table 4.1 and Appendix C1 into SA-information and risk factors. That was achieved by inspecting the elements in the second column of Table 4.1 and Appendix C1 and putting those elements that are latent failures (e.g., human factor, poor visibility, and adverse weather) under SA-information. The remainder of the elements are active failures and, therefore, were noted under risk factors. Active failures are the everyday happenings at sea that fishers know because they are so evident and fundamental. However, the latent failures are implicit and would be triggered by the risk factors, so they are not evident to fishers.

The second objective was to identify SA-information without risk factors. A further literature search was conducted to define appropriate risk factors for such elements. Lastly, all risk factors were inspected, and those found to be advanced were replaced with replica ones. The reason for doing this is that the present study aimed at adapting the RAw tool to the safety monitoring needs of SFVs not using advanced safety equipment and systems. Hence, technological systems like the global positioning system, automatic identification system, and high-frequency and medium frequency radios were considered too advanced and must be replaced.

In Størkersen and Thorvaldsen [16] and Menakhem [37], it was discovered that SFV fishers had adopted practices that enabled fishers to perform the functions that the named advanced systems do. The systems broadly serve communication and identification purposes. Menakhem [37] also realised SFV fishers do the following to ultimately achieve the same purposes: "Able to use water colour to tell vessel location (Yes/No)", "Shouts to nearby vessels understood (Yes/No)", "Hearing whistle sound from nearby vessels (Yes/No)", "Seeing flags of other vessels (Yes/No)", "Seeing a fishing float or bobber (Yes/No)", "Paper nautical chart (Useable/Not-used)", "Flashing torchlight acknowledged by nearby vessels (Yes/No)", "Shouts from nearby vessels understood (Yes/No)", and "Able to use wind speed intensity and direction to tell vessel location (Yes/No)". The present study saw these operations instead as befitting fishers running SFVs in remote communities. Accordingly, they replaced the advanced equipment for the global positioning system, automatic identification system, and very high-frequency and medium-frequency radios.

To conclude Step 2, a database was designed to collate all the information elements realised from the activities of Step 2. The database had columns named risk factors, SA-information, and fishing accident. Each column held information elements of that type as its data. A summary of the resulting database is Table 4.4; the complete database is shown in Appendix C2. Information elements in the database were given state names, too, describing their occurrence and non-occurrence.

Table 4.4. Fishing accidents, SA information, and risk factors

Number	Risk factor	SA information	Fishing accident
1	Steering gear (Failed/**Working**) Helm (Failed/**Working**)	Difficult manoeuvring	
2	Wind speed (Calm/Light-air/Light-breeze/ Gentle -breeze/**Moderate- breeze**/Fresh-breeze/Strong-breeze/Near-gale/Gale /Gale Strong-gale/Storm-gale/Storm Violent-storm/Hurricane) Seasons (**December-to-March**/April-to-May/ June -to-September/October-to- November) Ocean current (Horizontal-current/**Vertical-current**)	Ice drifting	
3	Ocean type (Arctic-ocean/North-Atlantic-ocean/ Southern-ocean/**Others**) Seawater temperature (Cold/**Warm**) Seasons (**December-to-March**/April-to-May/ June -to-September/October-to- November)	Iceberg present	
4		[a]**Iceberg present** [a]**Ice Drifting** [a]**Difficult manoeuvring**	**Ship besetting**
5	Behaviour in emergency (**Unsafe**/Safe) Fishing know-how (Unsafe/**Safe**) Cultural practice (**Unsafe**/Safe) Understanding of modern fishing practices (**Low**/High)	**Unheeded risk taking**	
6	Manual beheading of fish (Yes/No) Fish filleted manually (Yes/No) Fish gutted manually (Yes/No) Fish skinned manually (Yes/No)	Injury from knife	
7	Fishing gear shooting (Ongoing/Not-performed) Working close to fishing gear (Yes/No) Fishing gear hauling (Ongoing/Not-performed) Guardrail (Low/High) Working area (Close-to-guardrail/Not-close-to-guardrail) Strolling (Close-to-guardrail/Not-close-guardrail) Drug use (Yes/No) Alcohol (Consumed/Not-consumed)		Man overboard (MOB)

[a]Risk factors to the SA-information have been defined earlier.

4.3.4. Step 3: RAw tool development

This section was devoted to using the information in the database (see Appendix C2) to develop the RAw tool in the GeNIe software environment. GeNIe is a BN modelling software belonging to the BayeFusion Lab [63]. The lab has made available a free academic version of GeNIe for educational purposes. It is widely used in research publications; it was used by Yu et al. [45] in the BN model developed to assess the overall risk of ships in coastal waters. Being a BN model, the RAw tool was developed using chance nodes for all information elements except for risk factors.

Decision nodes instead were used to define risk factors. The decision node type was used because, in operationalising the tool, the fisher is not expected to input numerical data. Instead, a fisher would choose among a node's states based on the evidence gathered about the risk factor. Both chance and decision nodes had their names in the database inscribed on the nodes and were given state names too. Each node had at least two state names to tell its occurrence or non-occurrence. The number of states (or state names) depends on the physical states of the information element in real-life applications.

Following the explanation in Section 4.2.2 about BN modelling and guided by the database information, the nodes were joined successfully. A fishing-accident node is a child node to its SA-information, and the SA-information is also a child to its risk factors. Ultimately, risk factors are the parent nodes. Because the nodes were so many due to the equally many information elements, object-oriented programming (OOP) was done to prevent the resulting network from becoming cumbersome and complicated. For a step-by-step approach to doing OOP in BN, the reader is encouraged to consult the studies of Domeh et al. [26] and Khan et al. [33].

For the present study, OOP was done by grouping risk factors into technical, environmental, and human risk factors. The submodel feature in GeNIe [63] was then used to capture these groupings into separate sub-networks. The resulting three sub-networks were further captured into a new sub-network called "Dynamic operational conditions at sea (Dynamic OCS)", as shown in Figure 4.5. In Appendices C2 and C3, the risk factors in each of the three subnetworks are shown.

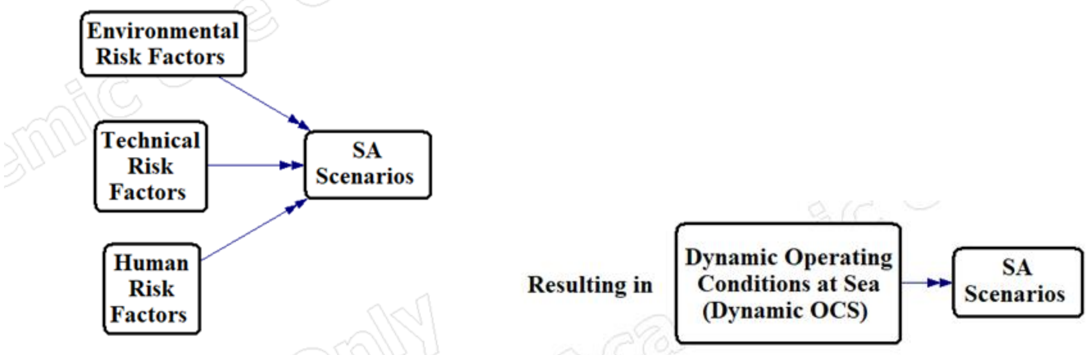

Figure 4.5 Illustrates how the "Dynamic OCS" sub-network was formed.

The submodel feature was again engaged to put SA-information into three sub-networks: human-related SA, vessel-and-equipment SA, and prevailing-conditions SA. As the names imply, human activities, vessel and shipboard equipment operations, and the onboard and marine environmental conditions, which are SA-information in Appendix C2, were captured as fragments in the sub-networks. All the fishing accidents were also captured as a separate sub-network, as shown in Figure 4.6. Through further abstraction, the sub-networks for the three groups of SA-information, and the fishing accidents, were absorbed into a new sub-network called SA-scenarios sub-network. In all, sixteen fishing accidents and sixty-two SA-information were considered for SFV safety monitoring using 145 risk factors. The sixteen accident types considered are succinctly defined in Table 4.5 in the context of SFV operation.

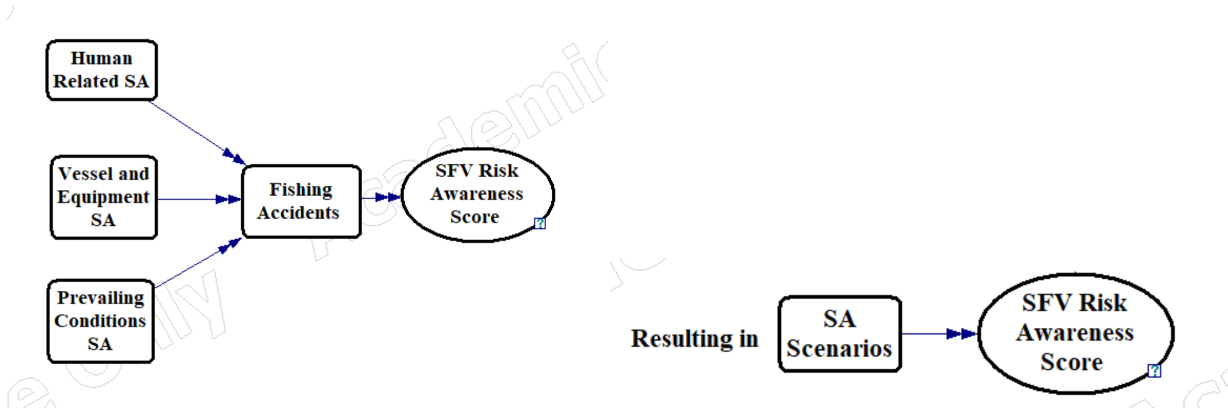

Figure 4.6. Illustrates how the fishing accident and SA-scenario sub-networks were formed.

Table 4.5. Definitions for fishing accident types considered in the modelling.

Number	Fishing accident	Definition
1	Capsize	The accident of the SFV turning over at sea and emptying its content into the water
2	Collision	The accident of impact between an SFV and another SFV or different ship type
3	Contact	The accident of impact between an SFV and an offshore structure or marine mammal
4	Fire and explosion	An accident leading to fire occurrence onboard and possibly, the burning of items and humans
5	Flooding/Foundering	The accumulation of water inside the ship due to hull damage and bursting of internal pipelines carrying liquids
6	Gear entanglement	The accident of a fisher caught in a fishing gear or restrained from movement by a gear
7	Grounding	The accident of an SFV's underwater hull touching the sea floor due to being in shallow waters
8	Hull integrity failure	The accident of the underwater hull section of a ship being opened for ingress of sea water due to damage to the hull
9	Hypothermia	The accident of a fisher experiencing abnormally low body temperature due to exposure to extremely cold temperatures
10	Lost/Stranded at sea	The accident of the fishing crew unable to return home from sea often due to the SFV's propulsion system failure or bad weather that makes navigation on chosen course extremely difficult
11	Man overboard	The accident of a fisher unintentionally falling off the SFV into the sea water and requiring rescue thereof
12	Musculoskeletal disorder	The accident of a fisher experiencing pain in the muscles and joints due to strenuous work performances
13	Occupational injury	A physical injury, disease, or death sustained by a fisher due to fishing tasks undertaken
14	Piracy and armed robbery	The attack of an SFV at gun point by robbers in territorial and international waters
15	Ship besetting	The accident of an SFV being surrounded closely by ice, making manoeuvring difficult, and the vessel liable to hull integrity failure
16	Sinking	The submerging of an SFV entirely below the water surface

*SFV: Small fishing vessel

Finally, the RAw tool was realised by connecting the SA-scenarios sub-network to the "SFV risk awareness score" node, as shown in Figure 4.7. In BN, the node, "SFV risk awareness score", is called the leaf node. The tool uses the joint probability distribution in Equation (4.3) to estimate

“High-risk” and “Low-risk” percentage scores at the leaf node. As mentioned in earlier sections, the percentage scores estimated by the RAw tool only indicate that conducive conditions exist aboard the SFV and could result in a fishing accident. The scores are not estimates of the probability of the accident happening. The closer the leaf nodes, “High-risk” score is to 100%, the more substantial the evidence that conducive conditions exist aboard the SFV. The evidence is weak if the “Low-risk” score exceeds the “High-risk” score.

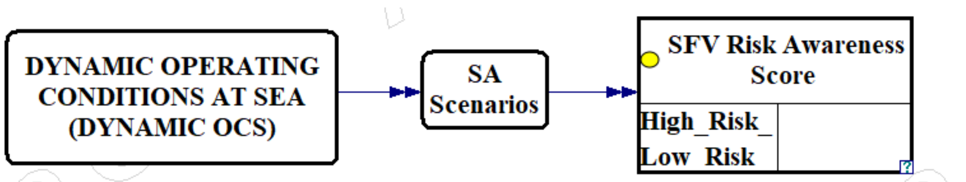

Figure 4.7. The RAw tool for safety monitoring aboard an SFV.

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i|Parents(X_i)) \tag{4.3}$$

where, X_i are the factors (i.e., fishing accidents, SA-information, and risk factors), n is the number of factors present, $Parents(X_i)$ is the parents of X_i, $P(X_1, X_2, \ldots, X_n)$ is the joint probability, and $P(X_i|Parents(X_i))$ is the conditional probability.

4.3.5. Step 4: Situation assessment aboard an SFV using the RAw tool

Now that the RAw tool has been developed, it is time to demonstrate how it will be used in practice. Three operations must be performed to illustrate how the tool works. First, field data must be collected on the fishing situation observed during the assessment. Second, using the data collected, the appropriate state names for risk factors in the tool must be activated and the tool run. Lastly, the results outputted by the tool must be analysed diagnostically to identify critical fishing accidents and their SA-information. The SA-information is what the onboard fishers would work towards de-escalating to avoid any potential accident. The following sections describe the hypothetical case study that shows how all three operations are performed.

4.3.5.1.The example case study

Let us consider the case of a hypothetical SFV, single-decked, operating in Ghana's territorial waters. Assume the SFV has no advanced safety monitoring equipment, and it is agreed to use the RAw tool at various time instants so that decision can be made regarding the presence of conditions favouring fishing-accident occurrence.

Ghana is a West African country boarded by Togo (on the east), Cote d'Ivoire (on the west), Burkina Faso (in the north), and the Gulf of Guinea (on the south). The country has a 228,000 km^2 exclusive economic zone, a 550 km coastal line, and twenty-six coastal districts [64, 65] where marine commercial fishing thrives. In 2013, Ghana's Ministry of Fisheries and Aquaculture Development survey [64] revealed a total of 139,155 fishers operating 12,728 artisanal fishing vessels (i.e., canoes) and 403 semi-industrial fishing vessels [65].

Both vessel types are locally made, but unlike the canoes, the semi-industrial ones are single-decked and not open to the atmosphere. These two groups of vessels constitute the SFV industry in Ghana and contribute immensely to the total annual fish catch. These vessels mostly do not use advanced systems and lack the appropriate safety monitoring equipment. Often, fishers aboard these vessels rely on years of experience gained in the fishing profession to decide on their safety when on a voyage. The case study SFV is assumed to be one of these vessels operating in Ghana's territorial waters for demonstration purposes.

4.3.5.2.Data collection to define risk factors states

The goal here is to choose, for each risk factor, the state that describes the observed happening at sea at the time of data collection. The vessel crew must observe the onboard environment, marine environment, and fishers' behaviours to decide on the most appropriate state name for each technical, environmental, and human risk factor. Assume the following sea conditions have been prevailing in Ghana's territory of the Gulf of Guinea at the time of data collection: sea state, light winds; wind speed, 16 knots; wind direction, south-southwest; wave height, 6 ft; wave period, 14 seconds; temperature, 28.1°C; tides, 2 ft above sea level; latitude/longitude, 2°40.14'N/0°10.56'E; and water depth, 1569.2 m. Then, by benchmarking the observed conditions against the Beaufort scale in Table 4.6, the crew selected the state names in Table 4.7 for the risk factors: "Sea swell", "Wave height", and "Wind speed".

Table 4.6. Beaufort scale for wave, wind, and water surface appearance at sea.

Beaufort number	Beaufort description	Wind Speed (knot)	Wave height (m)	Wave height code	Sea surface appearance	Sea swell
0	Calm	< 1	0	Code0	Calm glassy	None
1	Light air	1-3	0.0-0.2	Code1	Calm rippled	Low short
2	Light breeze	4-6	0.2-0.5	Code2	Smooth wavelets	Low long
3	Gentle breeze	7-10	0.5-1.0	Code3	Slight	Moderate short
4	Moderate breeze	11-16	1.0-2.0	Code4	Moderate	Moderate average
5	Fresh breeze	17-21	2.0-3.0	Code5	Rough	Moderate long
6	Strong breeze	22-27	3.0-4.0	Code6	Very rough	High short
7	Near gale	28-33	4.0-5.5	Code7	High	High average
8	Gale	34-40	5.5-7.0	Code8	Very high	High long
9	Strong gale	41-47	7.0-10.0	Code9	Phenomenal	Confused
10	Storm	48-55	10.0-12.5	Code9	Phenomenal	Confused
11	Violent storm	56-63	12.5-14.0	Code9	Phenomenal	Confused
12	Hurricane	> 64	> 14	Code9	Phenomenal	Confused

For the remaining environmental risk factors, some state names were assumed (i.e., simulated conditions) for purposes of acquiring data to demonstrate the workability of the RAw tool. Some risk-factor states, too, have been selected based on objective reasons, as shown in the "Reference" column of Table 4.7. Because Ghana is in the tropical region and it does not snow, the state "No", defined for the risk factors "Blowing snow" and "Freezing rain/ice pellets", is objectively defined. Similar objective reasons have been given for non-simulated state names.

Table 4.7. The defined state names for environmental risk factors.

Number	Risk factor	State	Reference
1	Ambient/workplace temperature	Warm	Ghana is in the tropics
2	**Blowing snow**	**No**	**It does not snow in Ghana**
3	Daytime	No	Ghanaian fishers, fish at dawn
4	Fog	No	Simulated condition
5	**Freezing rain/ice pellets**	**No**	**Absent in Ghana's climate**
6	Huge aquatic animal in vessel's way	Yes	Simulated condition
7	Lightning occurrence	No	Lightning is not common at dawn
8	Nighttime	Yes	Ghanaian fishers, fish at dawn
9	Ocean current	Vertical current	Present
10	Ocean type	Others	Gulf of Guinea (i.e., Atlantic ocean)
11	Polar day	No	Absent in the Gulf of Guinea
12	Polar night	No	Absent in the Gulf of Guinea
13	Polar region	Southern hemisphere	Gulf of Guinea is more southern
14	**Sea swell**	**Moderate long**	**Beaufort scale-point 5 (see Table 4.4)**
15	Seasons	December to March	Simulated condition
16	Seawater temperature	Warm	Gulf of Guinea in the tropics
17	Submerged offshore structure in vessel's way	No	Simulated condition
18	Typical area	Others	Gulf of Guinea was put in this category
19	Vessel geographical location at sea	Gulf of Guinea	Place of fishing
20	Water depth	Shallow	Simulated condition
21	**Wave height**	**Code5**	**Simulated condition: 6 ft; see Table 4.4**
22	**Wind speed**	**Moderate breeze**	**Simulated condition: 16 knots; see Table 4.4**

To define state names for the technical-risk factors, the crew in charge would have to observe the ongoing fishing operations, machinery systems running, and the shipboard environment for clues on making the right decision. Again, let us assume that the states defined in Table 4.8 apply to the hypothetical case study. Because technical factors in the RAw tool are many, Table 4.8 is only a portion; the complete list is in Appendix C3. Like Table 4.7, some state names have been simulated too in Table 4.8, while others are based on objective reasons. The purpose is to gather data to facilitate the demonstration of how to operationalise the RAw tool.

When defining state names for the human-risk factors, the SFV crew would have to observe the fishers performing their duties and then choose a state name that best describes the human behaviour for each risk factor. Like was done for technical and environmental risk factors, let Table 4.9 represent the states defined for the human-risk factors. Appendix C3 has the complete list of human-risk factors as well.

Table 4.8. The defined state names for technical risk factors.

Number	Risk factor	State name chosen	Reference
1	Block coefficient	Slender	Fishing vessel hulls are mostly not bulky
2	Bridge management system	Not working	Simulated condition
3	Pipe burst	Yes	Simulated condition
4	Collision avoidance alarm	Not working	Simulated condition
5	Deck spray-washed	Water spill	Simulated condition
6	Cooking gas leaking	Yes	Simulated condition
7	Cooking stove on	No	Simulated condition
8	Crossing surf	Yes	Simulated condition
9	Deck fittings	Tight	Simulated condition
10	Defence measures aboard	None	Only lookout personnel are available aboard
11	Electric spark	Yes	Simulated condition
12	Human machine interface problems	Exist	Simulated condition
13	Equipment/machinery age	Old	The vessels and equipment are usually old
14	Unsafe loading	Yes	Simulate condition
15	Equipment/machinery automation	Insufficient	Equipment operation is mainly manual
16	Fish stock caught	Large	Simulated condition
17	Fishing gear hauling	Ongoing	Simulated condition
18	Fishes caught kicking tails	Yes	Simulated condition
19	Fishing gear shooting	Not performed	Simulated condition
20	Fishing gear snags	Yes	Simulated condition

Table 4.9. Human risk factors and the defined state names.

Number	Risk factor	State	Reference
1	Alcohol	Not consumed	Simulated condition
2	Back pain	Yes	Simulated condition
3	Behaviour in emergency	Unsafe	Simulated condition
4	Bending over guardrail/gunwale	Defecating at gunwale edge	Simulated condition
5	Caught up in fishing gear	No	Simulated condition
6	Prestige consideration	Low	Simulated condition
7	Confusing/conflicting directives	Yes	Simulated condition
8	Crew number aboard	Adequate	Simulated condition
9	Cultural practice	Unsafe	Simulated condition
10	Inadequate rest/sleep	No	Simulated condition
11	Distractions	No	Simulated condition
12	Diving	Yes	Simulated condition
13	Drug use	Yes	Simulated condition
14	Economic and financial pressures	High	Simulated condition
15	Elbow pain	No	Simulated condition
16	Emotional condition/mental health	Not suitable for work	Simulated condition
17	Fatigue	No	Simulated condition
18	Fish filleted manually	Yes	Simulated condition
19	Fish gutted manually	Yes	Simulated condition
20	Fish skinned manually	Yes	Simulated condition

Once Tables 4.7 to 4.9 have been realised, the data collection exercise to determine risk-factors states has been completed. The risk analyst activates the defined states in the RAw tool and runs the tool to perform diagnostic analysis.

4.3.5.3.Diagnostic analysis

The diagnostic analysis uses a bottom-up approach to enable the RAw tool to compute scores for each SA-information node; after, the fish-accident node scores are computed. The analyst must first activate in the tool the state names in Tables 4.7 to 4.9. After which, the tool is run, and the result is analysed. The result is the percentage score at each fishing accident and SA-information node, as well as the "SFV risk awareness score" node. The RAw tool calculates the percentage scores using the total probability theory in Equation (4.2).

Results for the "SFV risk awareness score" node are analysed first, after which the results of the fishing-accident nodes follow, and lastly, the SA-information nodes' results. At the "SFV risk awareness score" node, if the high-risk-state score exceeds the low-risk-state score, it means conducive conditions favouring fishing-accident occurrence most likely exist. The vice-versa situation is interpreted as weak evidence for claims of conducive conditions existence. Similarly, suppose the possible-state score is higher than the not-possible-state score at a fishing-accident node, then, the interpretation is that, most likely, conducive conditions exist aboard in favour of that fishing accident. The opposite scenario would mean that fishing-accident is not expected to occur.

For SA-information nodes, when a possible-state score is greater than the not-possible-state score, the SA-information in question is a conducive condition and could trigger a fishing accident. It is such SA information that an SFV crew would note and remedy to promote safety aboard the SFV as they fish. That way, the RAw tool has aided in monitoring incidents during fishing to avoid a possible fishing accident. Section 4.4 discusses the diagnostic analysis results for the hypothetical case study.

4.3.5.4.Risk assessment scale

For decision-making on whether a score is severe or not and if a control measure must be administered, the five-points scale in Figure 4.8 was developed. A score identified as point five or point four is severe. The fishing crew are encouraged to apply necessary control measures. A point of five or four on the scale is severe because the occurrence-state score is greater than the non-occurrence-state score. Thus, the evidence favouring the SA information or fishing accident linked to the score is strong.

When a score earns a point of two or one on the scale, there is weak evidence against the occurrence of the SA information or fishing accident linked to the score. The crew may not prioritise the information element for remedy purposes. At point three, an SA-information or fishing accident would require attention only when its occurrence-state score exceeds 50%. If the occurrence-state score is exactly 50%, the crew may choose to or not to focus on that SA information or fishing accident linked to the score. Resource availability may be considered when making a final decision in cases like that.

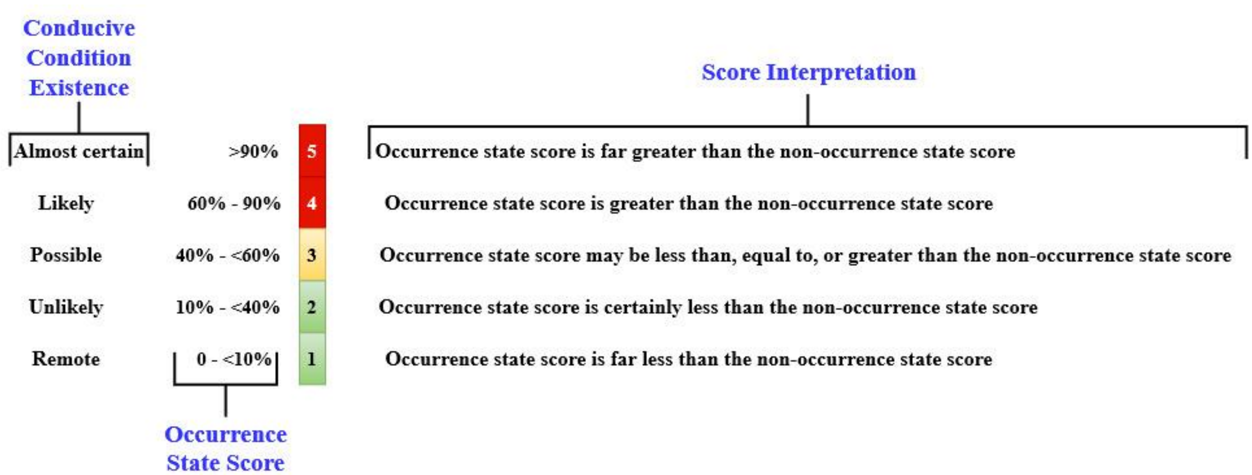

Figure 4.8. A five-point scale to assess scores estimated by the RAw tool.

4.3.6. Step 5: RAw tool updating

To ensure the RAw tool can tackle present and future safety monitoring issues aboard SFVs when Section 4.3.5 is ongoing, information elements missing from the tool or new situations encountered by fishers must be noted. The SFV's management may also wish to give some fishing accidents or SA information priority attention and would like the risk analyst to make some changes in the RAw tool to serve the purpose. All these information would be collected and used to update the tool accordingly.

4.3.7. The proposed monitoring programme for SFVs

For effective safety monitoring of SA aboard SFVs, the RAw tool and the various monitoring assessments discussed must be programmed into an instantaneous monitoring system. A schematic layout to develop such a system is shown in Figure 4.9. With such a monitoring system in place, the fishing crew can follow the procedures described in sections 4.3.5.2 to 4.3.5.4 to monitor and address fishing incidents.

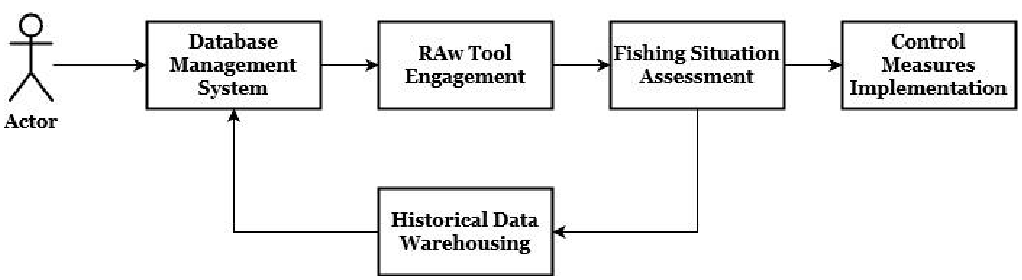

Figure 4.9. The proposed system for safety monitoring aboard SFVs.

The actor represents the fishing crew or a designated individual among the crew responsible for initiating the monitoring process. At a given instant, the command is issued for data collection on risk factors in the "Dynamic OCS" sub-network. The raw data collected is stored in a database, where the data is processed into decision-state names specific to each risk factor. Therefore, the database management system (DMS) functions to facilitate data storage, processing, and retrieval. The DMS chosen for the monitoring programme could be as simple as a notebook with ruled columns specifying data types collected, including the time and date for the data collection. The DMS could be advanced, too, like the cloud-based ones (e.g., MySQL). However, the ability of the SFV crew to operate the chosen DMS must be the defining factor. After completing the DMS activities, the decision-state names realised are activated in the RAw tool to perform diagnostic analysis. The five-point scale identifies the fishing accidents and SA information with high occurrence-state scores at the assessment stage. Risk control measures are subsequently implemented to avoid a fishing accident. Meanwhile, the computed scores must be warehoused as historical data in the DMS for future data analysis tasks.

4.4. Results and Discussions

The case study results are discussed first, after which discussions on the present study's contributions and limitations follow to highlight future works.

4.4.1. Risk awareness score for the case study SFV

The RAw tool estimated 39% at the high-risk state of the leaf node, as shown in Figure 4.10. From the five-point scale, a 39% occurrence-state score is in the green zone. Hence the tool infers there is no problem as far as the risk-factor states defined in Section 4.3.5.2 are concerned. The conditions existing aboard the case study vessel are not conducive enough to trigger a fishing accident. However, it is important to study also, the fishing accident scores to know which ones have scores in the red zone.

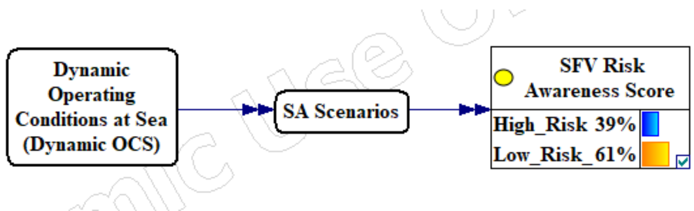

Figure 4.10. The RAw tool with the leaf node results.

4.4.2. The most probable fishing accidents identified

The occurrence state diagnostic analysis results for fishing-accident nodes are shown in Figures. 4.11 and 4.12. For the case studied, these figures show that a person-related accident is more likely to occur than a vessel-related one. Ship besetting is the least likely to occur (see Figure 4.12); which is expected since ice does not form in the Gulf of Guinea. Meanwhile, only "Occupational injury", demands immediate attention since its 71% (see Figure 4.11) occurrence state puts it in the red zone according to the five-point risk assessment scale in Figure 4.8, also evident in Figure 4.13. The SFV crew need to seek for the SA-information responsible for the 71% rate. When doing so, some fishing accidents in the yellow zone may also need redress since Figure 4.13 reveals that zone as presenting the second highest risk. As the pie-chart shows 94% of the fishing accidents out of the red zone, it could be concluded that the SFV in the defined states is safe.

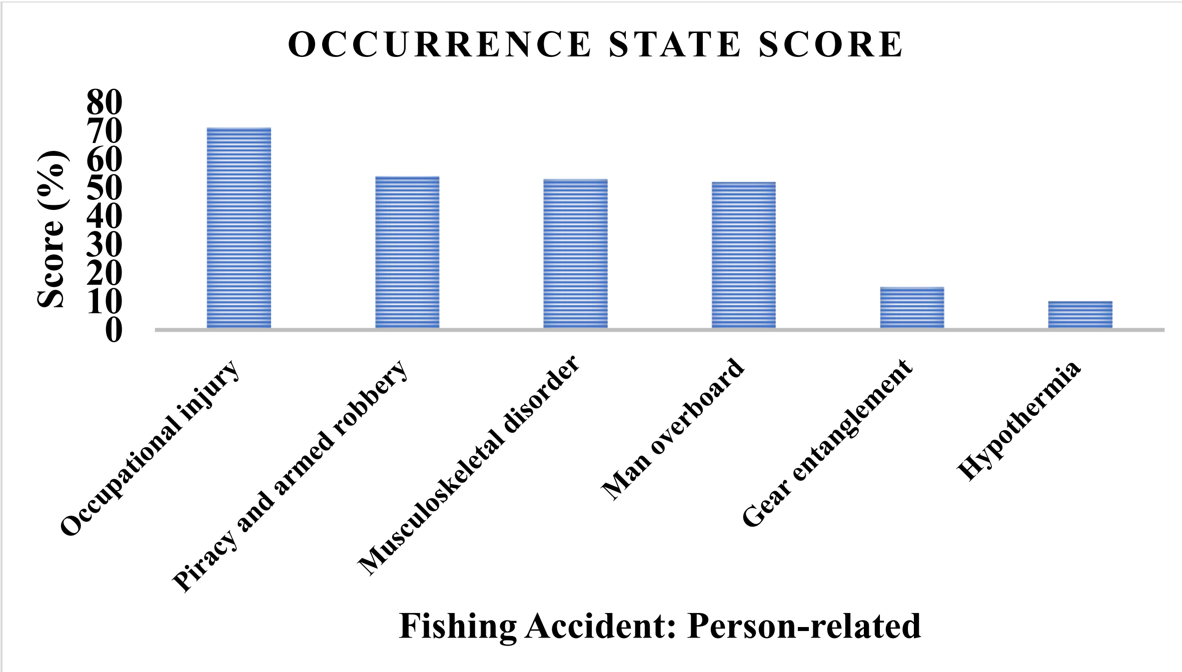

Figure 4.11. Result of the tool's estimates for person-related fishing accidents.

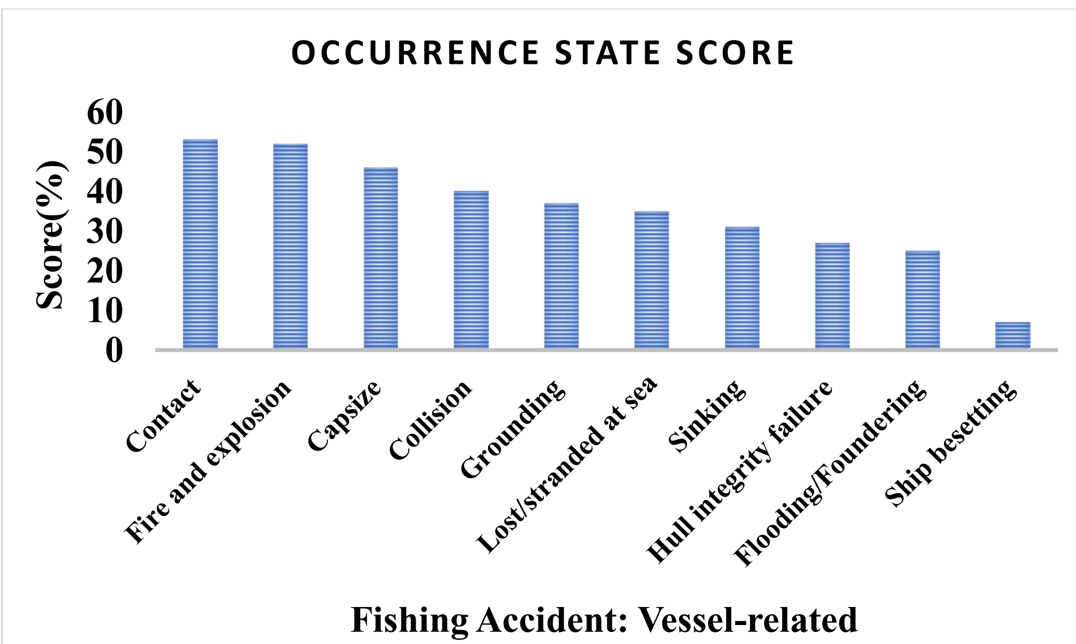

Figure 4.12. Result of the tool's estimates for vessel-related fishing accidents.

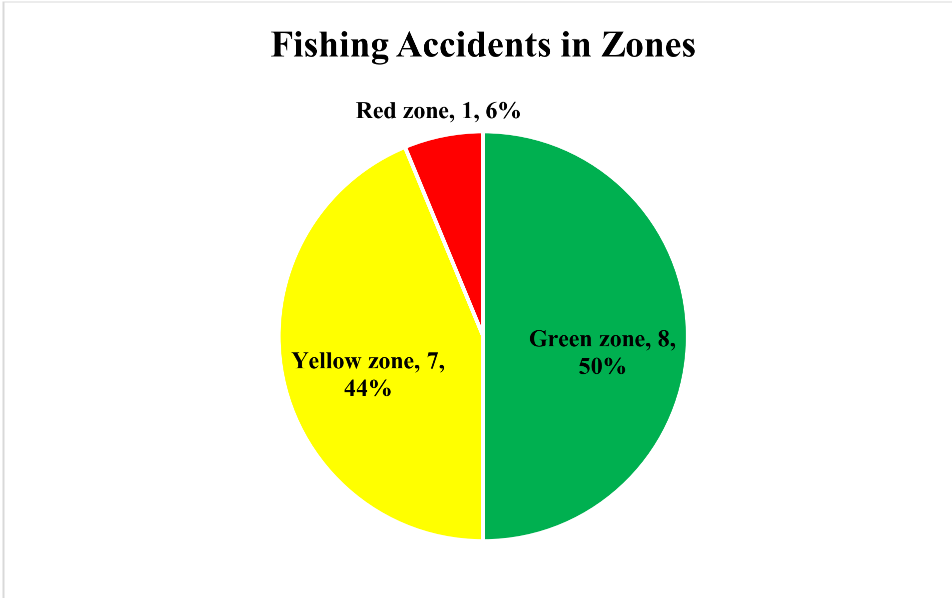

Figure 4.13. The fishing accidents zoned into red (1 accident), yellow (7 accidents), and green (8 accidents) using the five-point-risk-assessment scale.

4.4.3. Situation awarenesses contributing to the most probable fishing accidents

The occurrence state diagnostic analysis results for SA-information nodes are shown in Table 4.10 (human-related), Table 4.11 (vessel-and-equipment), and Table 4.12 (prevailing conditions). Any SA information in bold fonts is in the red zone when the result is subjected to the five-point risk assessment scale in Figure 4.8. These ones need immediate control measures since their occurrence-state scores suggest strong evidence favouring the presence of conducive conditions aboard the SFV to cause a fishing accident.

As Figure 4.14 deduced from the tables show, the conducive conditions are more likely to be caused by humans, vessel features, and onboard equipment than the marine or onboard environmental conditions. Only “Slippery deck” (i.e., an onboard environmental condition) and “Vessel in pirate zone” (i.e., a marine geographical condition) are the prevailing conditions needing urgent control measures. Meanwhile, the mean score for the “Human-related SA” (53.67%) is greater than that for the “Vessel and equipment SA” (45.88%). Showing that, even though these categories of SA information have equal numbers in the red zone on the five-point scale, human-related conducive-conditions are more probable. This outcome is not surprising since the fishing accident identified as falling in the red zone in Section 4.4.2, the "Occupational injury", is a human type.

Table 4.10. Diagnostic analysis results for human-related SA with scores greater than 59% emboldened.

Number	SA Information	Occurrence state score (%)
1	Swept overboard	21
2	**Unheeded risk taking**	**90**
3	Fall overs due to slip	53
4	**High risk-taking behaviour**	**73**
5	Struck by waves	49
6	Cigarette burn	53
7	Smooking in cooking compartment	0
8	Injury to finger and whole limb	15
9	**Wounds from fishing gear**	**90**
10	Mistrust among fishers/Information mistrust	53
11	**Human error**	**67**
12	Burns	52
13	Contusions	30
14	Watchkeeping failure	35
15	Competing with other boats	53
16	Bites and stings	53
17	**Fire due to cooking**	**72**
18	**Officer-of-the-watch failure**	**67**
19	**Fall overs due to bending over guardrail/gunwale**	**100**
20	**Injury from knife**	**100**
21	**Loss of finger**	**60**
22	Injury by storm	34
23	Onboard defence personnel unready	53
24	Communication channels failure	15

Table 4.11. Diagnostic analysis results for vessel-and-equipment SA with scores greater than 59% emboldened.

Number	SA Information	Occurrence state score (%)
1	**Vessel unnoticed by nearby ships**	**90**
2	Fire in accommodation	28
3	Navigation failure	54
4	**Reduction in transverse metacentric height**	**90**
5	Difficult manoeuvring	0
6	**Machinery damage**	**77**
7	Squat effect	15
8	Electrical fire	53
9	Cooking compartment heated	50
10	Submarine trawling fishing gear	0
11	**Inter-ship communication failure**	**60**
12	**Rotational motion**	**90**
13	**Nearby ships detection failure**	**100**
14	Unseaworthy	22
15	Propulsion system failure	15
16	**Loss of power**	**60**
17	**Under keel clearance**	**100**
18	Translational motion	15
19	Fishing gear setting	0
20	Overloading	15
21	Firefighting equipment failure	15
22	Freezing of firefighting equipment	15
23	Ship motion	55
24	**Fire in engine-room**	**75**
25	Fire due to lightning	53

Table 4.12. Diagnostic analysis results for prevailing conditions SA with scores greater than 59% emboldened.

Number	SA Information	Occurrence state score (%)
1	**Slippery deck**	**100**
2	Iceberg present	0
3	Severe temperature	0
4	Polar darkness	0
5	Darkness	28
6	Ice/snow accretion on superstructure and main deck	0
7	Adverse weather	7
8	Unsafe external loading	55
9	Atmosphere during voyage	53
10	Seastate rough	45
11	Poor visibility	0
12	Ice drifting	45
13	**Vessel in pirate zone**	**100**

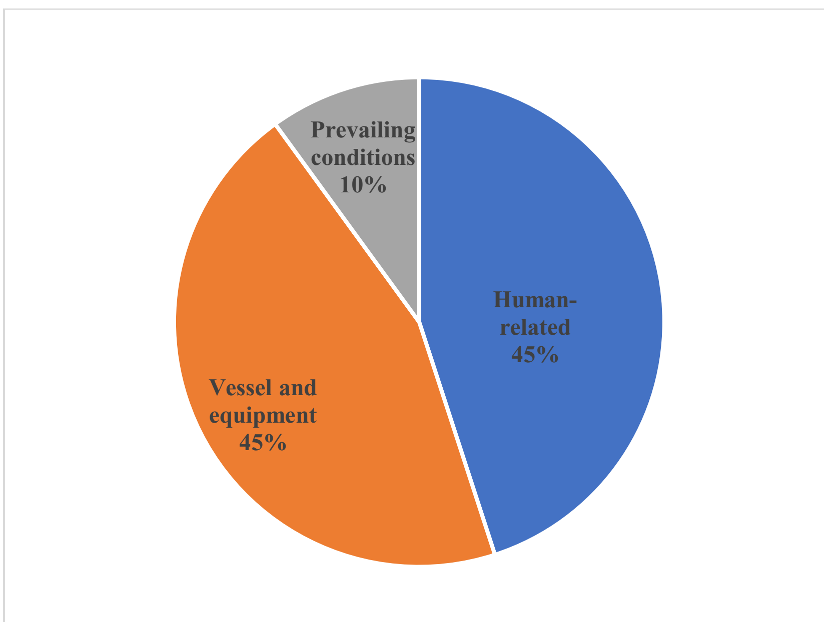

Figure 4.14. Percentage results for SA information in the red zone.

It is important to note that the scores show that the situations represented by the SA information in these tables were present aboard the SFV but unnoticed. Also, fishers often see the risk factors responsible for this SA information during their daily fishing routines. However, fisherfolk may find it challenging to draw a direct connection between the SA information and risk factors to help control any possible fishing accident. Therefore, using the RAw tool, the SA information hidden from fishers is made known, and appropriate controls can be applied to avoid a fishing accident. Let us use the SA information, "Injury from knife", as an example illustration. From Table 4.10, its occurrence-state score is 100%. This score means the conducive condition, favouring an injury from knife use, was present while fishers were doing their work. Fishers could be too busy for their cognition to comprehend a possible knife injury. Therefore, by using the RAw tool, the root causes would be traced to "Manual beheading of fish", "Fish filleted manually", "Fish gutted manually", and "Fish skinned manually" (see Table 4.4). Appropriate control measures include reminding fishers performing the duty to be careful with the knife or, better still, asking them to put on thick gloves while undertaking the tasks. That way, the conducive conditions for a possible knife injury are brought under control, and any accident it might lead to, such as "Occupational injury", is avoided too.

4.4.4. RAw tool and results validation

The question of whether the RAw tool predicts right is vital to show how well the tool can replicate real scenarios. Another equally important question is whether the tool's estimated scores are reasonable. Both questions centre on the validity of the tool and its predictions. This section of the study investigated the validity issue by studying snippets of the tool and results.

Compare the scores for "Unheeded risk-taking" and "Ship besetting" in Table 4.10 and Figure 4.12, respectively. Their risk factors are in Table 4.4, items one to five. The tool used the selected states shown to compute the less than 10% and 90% occurrence-state rates for "Ship besetting" and "Unheeded risk-taking", respectively. The moderate breeze selected for wind speed is on the low side compared to a hurricane state (see Tables 4.4 and 4.7). On the contrary, the December-to-March state is the top occurrence state for seasons (see Tables 4.4 and 4.7). Meanwhile, the Gulf of Guinea, where the case study SFV fished, is in Ghana. Due to that, the high score for seasons will be neutralized by the states, others (i.e., Gulf of Guinea) and warm, belonging to ocean type and seawater temperature, respectively (see Tables 4.4 and 4.7). As a result, the tool computes an occurrence rate of around 10% for “Ship besetting”.

In reality, a fishing vessel operating in Ghana’s territorial waters would not encounter an iceberg since the region is in the tropics, so no ship besetting must be expected. On the other hand, the selected occurrence states for risk factors of “Unheeded risk taking” are the culpable states for the SA information to happen. Consequently, the tool appropriately scores “Unheeded risk taking” 90%. It would have been 100% if the risk factor, “Fishing know-how”, had an “Unsafe” state instead (see Table 4.4). Thus, one can say the tool is practical in its predictions by face validity. The scores inferred are also meaningful and reasonable.

4.4.5. The study contributions, limitations, and future work

The present study made four significant contributions. First, a tailormade monitoring tool, the RAw tool, was developed to monitor safety aboard an SFV. The tool is unique from the ones by Uğurlu et al. [5], Obeng et al. [38], Özaydın et al. [39], and Yu et al. [45] because its root factors are decision nodes and not chance nodes. As a result, the SFV crew only have to input non-numerical facts and not probabilities, which comes with the challenges of uncertainty in data.

As the second contribution, the tool was situated in a monitoring system resulting in a proposed safety monitoring programme layout for SFVs. The programme would promote instantaneous inquiry into fishing safety aboard a vessel. Thirdly, a risk assessment scale, the five-point scale, was developed to tell which results outputted by the RAw tool must be considered for mitigation purposes. The scale is unique from others [26, 45] because it compares risk-item-states results to decide whether strong or weak evidence exists for the risk item to happen. The fourth and final contribution is the proposed scale for eliciting probabilities for CPTs. Using the proposed scale minimizes the variations in probability values produced by multiple subject-matter experts for the same CPT.

As future work, the proceeding limitations are being considered. Firstly, the RAw tool only serves instantaneous safety monitoring needs aboard SFVs. If real-time data collection and RAw tool operation can be done, a time-driven-dynamic tool would emerge for SFV risk monitoring. Next, it would be more convenient to have the RAw tool as a handheld device like the calculator. Fishers can then operate it with ease. Also, knowing that SFV fishers might not have high levels of education, it is likely interpreting the tool's results by themselves, as described in the study, could be a difficult task for the fishers. Future studies will explore the possibilities of integrating the five-point scale into the RAw tool. That way, only red, yellow, and green colours would be used to show the severity of a risk item.

Also, probability updating was not performed for the chance nodes. That is because the present study's objective was diagnosing probable fishing accidents and the conducive conditions for their occurrence; uncertainty measurement was not prioritised. Nevertheless, future studies would consider uncertainty in the RAw tool scores to determine how much variability exists between prior and posterior probabilities. Meanwhile, the study is limited by the publications sourced to define risk factors, SA information, and fishing accidents. Different publications may give additional information elements that would enrich the RAw tool. It also could mean context defining is essential when developing the RAw tool. If one is sure that the necessary information elements in the defined context have been captured, then it is most likely that a suitable RAw tool would emerge to serve the intended purpose.

4.5. Conclusion

Most artisanal and semi-industrial fishing vessels, constituting the small fishing vessel (SFV) sector, do not have adequate safety monitoring systems to decide on possible accidents ahead of time. Meanwhile, SFV fishers know the risk factors they encounter daily. Also, literature on fishing accidents abounds and contains information on how the accidents occur. The present study consolidated the information on fishing accidents from literature and fishers' risk factors awareness to develop a risk analysis tool.

First, a cause-effect diagram was developed from the information gathered. Through the method of probabilistic safety assessment using Bayesian network (BN) modelling, the collected information was used to develop a risk monitoring model called the risk awareness (RAw) tool. Broadly, the RAw tool has three kinds of information elements: risk factors as root causes, situation awareness (SA) information as latent failures, and fishing accidents as incidents targeted for monitoring. Because decision nodes were used for risk factors and fishers already know about the root causes of safety at sea, the tool can be operated relatively easily.

An SFV crew only needs to activate the state evidence for each risk factor by observing the marine and shipboard environment for the technical, environmental, and human-related operational factors occurring during fishing. The RAw tool then uses a bottom-up approach to estimate percentage scores for SA information nodes and, after, fishing-accident nodes. The scores are assessed on a five-point scale developed as a risk assessment tool. Because each SA-information node and fishing accident node has two states defining its occurrence and non-occurrence, the five-point scale compares the states' scores at each node to prioritise an SA information and a fishing accident for control purposes.

Results indicating that the occurrence-state score is greater than the non-occurrence-state score is strong evidence that the SA information, or the fishing accident in question, must be prioritised. The vice-versa would mean weak evidence, so SA information or fishing-accident may not receive immediate attention. Once the prioritised fishing accidents are defined, they can also be traced to the high-score SA information. Then, the noted conducive conditions aboard favouring the SA information and fishing accidents would be identified and controlled to avoid an actual accident.

Apart from the RAw tool and the five-point scale, the present study introduced an objective approach to eliciting probabilities for conditional probability tables (CPT) in BN. The approach provides a probability-scoring scale that guides a subject-matter expert (SME). Using the approach could help the probabilities estimated by multiple SMEs to converge. This would help minimise SME results variations when using the subjective approach. In the long run, the proposed elicitation approach aims to improve the reliability of BN results since CPT is an integral part of BN modelling. The less variability is expected when SMEs estimate probabilities a CPT, resulting in reliable BN results.

The study is recommended to small fishing boat owners, skippers, and fishing administrations overseeing SFV operations. The study demonstrates how the probabilistic safety assessment method facilitates sourcing information on fishers knowledge about risks encountered at sea and from the existing secondary data on how fishing accidents occur, and brings the gathered information together to develop a risk analysis tool that would serve the safety monitoring needs of small fishing boats. In the future, researchers will work at making the RAw tool dynamic through real-time data collection and time-driven operation of the RAw tool. Also, the tool in its current form is digital and would be more convenient to use if made into a handheld device such as a calculator.

References

[1] A. Sharma, S. Nazir, and J. Ernstsen, "Situation awareness information requirements for maritime navigation: A goal directed task analysis," *Saf. Sci.*, vol. 120, no. October 2018, pp. 745–752, 2019.

[2] D. Dalaklis, "Chapter 9: Safety and security in shipping operations," in *Shipping operations management*, 2017, pp. 197–213.

[3] K. An, "E-navigation Services for Non-SOLAS Ships," *Int. J. e-Navigation Marit. Econ.*, vol. 4, pp. 13–22, 2016.

[4] D. Jin, H. Kite-Powell, and W. Talley, "The safety of commercial fishing: Determinants of vessel total losses and injuries," *J. Safety Res.*, vol. 32, no. 2, pp. 209–228, 2001.

[5] F. Uğurlu, S. Yıldız, M. Boran, Ö. Uğurlu, and J. Wang, "Analysis of fishing vessel accidents with Bayesian network and Chi-square methods," *Ocean Eng.*, vol. 198, no. December 2019, 2020.

[6] S. E. Roberts, "Britain's most hazardous occupation: Commercial fishing," *Accid. Anal. Prev.*, vol. 42, no. 1, pp. 44–49, 2010.

[7] C. G. Loughran, A. Pillay, J. Wang, A. Wall, and T. Ruxton, "A preliminary study of fishing vessel safety," *J. Risk Res.*, vol. 5, no. 1, pp. 3–21, 2002.

[8] H. Ugurlu and I. Cicek, "Analysis and assessment of ship collision accidents using Fault Tree and Multiple Correspondence Analysis," *Ocean Eng.*, vol. 245, no. September 2021, p. 110514, 2022.

[9] F. Obeng, V. Domeh, F. Khan, N. Bose, and E. Sanli, "Analyzing operational risk for small fishing vessels considering crew effectiveness," *Ocean Engineering*, vol. 249, Apr. 2022, doi: 10.1016/j.oceaneng.2021.110512.

[10] M. A. Budiyanto, F. Azharrisman, and A. F. Utama, "Cooling performance of modular fish hold for 30 gross-tonnage fishing vessel," Journal of Marine Engineering and Technology, 2022, doi: 10.1080/20464177.2022.2094655.

[11] Sonal and D. Ghosh, "Impact of situational awareness attributes for resilience assessment of active distribution networks using hybrid dynamic Bayesian multi criteria decision-making approach," *Reliab Eng Syst Saf*, vol. 228, Dec. 2022, doi: 10.1016/j.ress.2022.108772.

[12] G. Elidolu, S. I. Sezer, E. Akyuz, O. Arslan, and Y. Arslanoglu, "Operational risk assessment of ballasting and de-ballasting on-board tanker ship under FMECA extended Evidential Reasoning (ER) and Rule-based Bayesian Network (RBN) approach," *Reliab Eng Syst Saf*, vol. 231, Mar. 2023, doi: 10.1016/j.ress.2022.108975.

[13] D. Kimera and F. N. Nangolo, “Reliability maintenance aspects of deck machinery for ageing/aged fishing vessels,” *Journal of Marine Engineering and Technology*, vol. 21, no. 2, pp. 100–110, 2022, doi: 10.1080/20464177.2019.1663595.

[14] T. Thorvaldsen, “The importance of common sense: How Norwegian coastal fishermen deal with occupational risk,” *Mar. Policy*, vol. 42, pp. 85–90, 2013.

[15] B. Paterson, “Tracks, trawls and lines-Knowledge practices of skippers in the Namibian hake fisheries,” *Mar. Policy*, vol. 60, pp. 309–317, 2015.

[16] K. V. Størkersen and T. Thorvaldsen, “Traps and tricks of safety management at sea,” *Saf. Sci.*, vol. 134, no. November 2018, 2021.

[17] B. S. Abdullah-Bin-Farid, S. Mondal, K. A. Satu, R. K. Adhikary, and D. Saha, “Management and socio-economic conditions of fishermen of the Baluhar Baor, Jhenaidah, Bangladesh,” *J. Fish.*, vol. 1, no. 1, p. 30, 2013, doi: 10.17017/jfish.v1i1.2013.7.

[18] H. de O. Braga and A. Schiavetti, “Attitudes and local ecological knowledge of experts fishermen in relation to conservation and bycatch of sea turtles (reptilia: Testudines), Southern Bahia, Brazil,” *J. Ethnobiol. Ethnomed.*, vol. 9, no. 1, pp. 1–13, 2013, doi: 10.1186/1746-4269-9-15.

[19] I. S. Wekke and A. Cahaya, “Fishermen Poverty and Survival Strategy: Research on Poor Households in Bone Indonesia,” *Procedia Econ. Financ.*, vol. 26, no. 15, pp. 7–11, 2015, doi: 10.1016/s2212-5671(15)00962-4.

[20] I. Animah and M. Shafiee, “Application of risk analysis in the liquefied natural gas (LNG) sector: An overview,” *J. Loss Prev. Process Ind.*, vol. 63, no. August 2019, p. 103980, 2020, doi: 10.1016/j.jlp.2019.103980.

[21] S. H. Chen and C. A. Pollino, “Good practice in Bayesian network modelling,” *Environ. Model. Softw.*, vol. 37, pp. 134–145, 2012, doi: 10.1016/j.envsoft.2012.03.012.

[22] S. L. Case, J. M. Lincoln, and D. L. Lucas, “Fatal Falls Overboard in Commercial Fishing — United States , 2000 – 2016,” 2018.

[23] R. W. Byard, “Commercial fishing industry deaths-Forensic issues,” *J. Forensic Leg. Med.*, vol. 20, no. 3, pp. 129–132, 2013, doi: 10.1016/j.jflm.2012.05.010.

[24] M. J. S. Windle, B. Neis, S. Bornstein, M. Binkley, and P. Navarro, “Fishing occupational health and safety: A comparison of regulatory regimes and safety outcomes in six countries,” *Mar. Policy*, vol. 32, no. 4, pp. 701–710, 2008, doi: 10.1016/j.marpol.2007.12.003.

[25] E. Mcguinness, H. L. Aasjord, I. B. Utne, and I. Marie, “Fatalities in the Norwegian fishing fleet 1990 – 2011,” *Saf. Sci.*, vol. 57, pp. 335–351, 2013.

[26] V. Domeh, F. Obeng, F. Khan, N. Bose, and E. Sanli, “Risk analysis of man overboard scenario in a small fishing vessel,” *Ocean Eng.*, vol. 229, p. 108979, Jun. 2021.

[27] J. Wang, A. Pillay, Y. S. Kwon, A. D. Wall, and C. G. Loughran, “An analysis of fishing vessel accidents,” *Accid. Anal. Prev.*, vol. 37, no. 6, pp. 1019–1024, 2005.

[28] R. Bye and G. M. Lamvik, “Professional culture and risk perception: Coping with danger on board small fishing boats and offshore service vessels,” Reliab Eng Syst Saf, vol. 92, no. 12, pp. 1756–1763, Dec. 2007, doi: 10.1016/j.ress.2007.03.024.

[29] S. Kum and B. Sahin, “A root cause analysis for Arctic Marine accidents from 1993 to 2011,” *Saf. Sci.*, vol. 74, pp. 206–220, 2015.

[30] A. Council, “Arctic marine shipping assessment 2009 report,” 2010.

[31] D. Smith, B. Veitch, F. Khan, and R. Taylor, “An accident model for Arctic shipping,” in *Proceedings of the ASME 2015 34th International Conference on Ocean, Offshore and Arctice Engineering (OMAE2015)*, 2015, pp. 4–9.

[32] S. Rezaee, R. Pelot, and A. Ghasemi, “The effect of extreme weather conditions on commercial fishing activities and vessel incidents in Atlantic Canada,” *Ocean Coast Manag*, vol. 130, pp. 115–127, Oct. 2016, doi: 10.1016/j.ocecoaman.2016.05.011.

[33] B. Khan, F. Khan, B. Veitch, and M. Yang, “An operational risk analysis tool to analyze marine transportation in Arctic waters,” *Reliab. Eng. Syst. Saf.*, vol. 169, no. July 2017, pp. 485–502, 2018.

[34] F. Paolo *et al.*, “Investigating the Role of the Human Element in Maritime Accidents using Semi-Supervised Hierarchical Methods,” *Transp. Res. Procedia*, vol. 52, pp. 252–259, 2021.

[35] A. Chochinov, “Alcohol ‘on board,’ man overboard - Boating fatalities in Canada,” *Can. Med. Assoc. J.*, vol. 159, no. 3, pp. 259–260, 1998.

[36] O. C. C. Jensen, G. Petursdottir, I. M. ari. Holmen, A. Abrahamsen, and J. Lincoln, “A review of fatal accident incidence rate trends in fishing,” *Int. Marit. Health*, vol. 65, no. 2, pp. 47–52, 2014, doi: 10.5603/IMH.2014.0011.

[37] B.-Y. Menakhem, “Risks and dangers in small-scale fisheries : an overview,” 2000. [Online]. Available: https://ideas.repec.org/p/ilo/ilowps/993427803402676.html.

[38] F. Obeng, V. Domeh, F. Khan, N. Bose, and E. Sanli, “Capsizing accident scenario model for small fishing trawler,” *Saf. Sci.*, vol. 145, no. October 2020, p. 105500, 2022.

[39] E. Özaydın, R. Fışkın, Ö. Uğurlu, and J. Wang, "A hybrid model for marine accident analysis based on Bayesian Network (BN) and Association Rule Mining (ARM)," *Ocean Eng.*, vol. 247, no. October 2020, 2022, doi: 10.1016/j.oceaneng.2022.110705.

[40] S. Kwag, E. Choi, S. Eem, J. G. Ha, and D. Hahm, "Toward improvement of sampling-based seismic probabilistic safety assessment method for nuclear facilities using composite distribution and adaptive discretization," *Reliab Eng Syst Saf*, vol. 215, Nov. 2021, doi: 10.1016/j.ress.2021.107809.

[41] J. W. Park and S. J. Lee, "Simulation optimization framework for dynamic probabilistic safety assessment," *Reliab Eng Syst Saf*, vol. 220, Apr. 2022, doi: 10.1016/j.ress.2021.108316.

[42] H. Li, X. Ren, and Z. Yang, "Data-driven Bayesian network for risk analysis of global maritime accidents," *Reliab Eng Syst Saf*, vol. 230, p. 108938, Feb. 2023, doi: 10.1016/j.ress.2022.108938.

[43] S. Fan, E. Blanco-Davis, Z. Yang, J. Zhang, and X. Yan, "Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network," *Reliab Eng Syst Saf*, vol. 203, Nov. 2020, doi: 10.1016/j.ress.2020.107070.

[44] S. Pristrom, Z. Yang, J. Wang, and X. Yan, "A novel flexible model for piracy and robbery assessment of merchant ship operations," *Reliab Eng Syst Saf*, vol. 155, pp. 196–211, Nov. 2016, doi: 10.1016/j.ress.2016.07.001.

[45] Q. Yu, Â. P. Teixeira, K. Liu, H. Rong, and C. Guedes Soares, "An integrated dynamic ship risk model based on Bayesian Networks and Evidential Reasoning," *Reliab Eng Syst Saf*, vol. 216, Dec. 2021, doi: 10.1016/j.ress.2021.107993.

[46] Q. Yu, K. Liu, Z. Yang, H. Wang, and Z. Yang, "Geometrical risk evaluation of the collisions between ships and offshore installations using rule-based Bayesian reasoning," Reliab Eng Syst Saf, vol. 210, Jun. 2021, doi: 10.1016/j.ress.2021.107474.

[47] P. Sotiralis, N. P. Ventikos, R. Hamann, P. Golyshev, and A. P. Teixeira, "Incorporation of human factors into ship collision risk models focusing on human centred design aspects," *Reliab. Eng. Syst. Saf.*, vol. 156, pp. 210–227, 2016.

[48] A. Galieriková, "The human factor and maritime safety," *Transp. Res. Procedia*, vol. 40, no. Transcom, pp. 1319–1326, 2019.

[49] Z. Lusic, M. Marcic, M. Bakota, and D. Pusic, "Detecting a man in the sea," in *8th International Maritime Science Conference*, 2019, pp. 560–570.

[50] O. A. Valdez Banda, F. Goerlandt, J. Montewka, and P. Kujala, "A risk analysis of winter

navigation in Finnish sea areas," *Accid. Anal. Prev.*, vol. 79, pp. 100–116, 2015.

[51] G. Zhang and V. V. Thai, "Expert elicitation and Bayesian Network modeling for shipping accidents: A literature review," *Saf. Sci.*, vol. 87, pp. 53–62, 2016.

[52] Ö. Uğurlu, E. Köse, U. Yıldırım, and E. Yüksekyıldız, "Marine accident analysis for collision and grounding in oil tanker using FTA method," *Marit. Policy Manag.*, vol. 42, no. 2, pp. 163–185, 2015.

[53] M. S. Rahman, F. Khan, A. Shaikh, S. Ahmed, and S. Imtiaz, "Development of risk model for marine logistics support to offshore oil and gas operations in remote and harsh environments," *Ocean Eng.*, vol. 174, no. January 2018, pp. 125–134, 2019.

[54] M. Hänninen and P. Kujala, "Influences of variables on ship collision probability in a Bayesian belief network model," *Reliab. Eng. Syst. Saf.*, vol. 102, pp. 27–40, 2012.

[55] M. Afenyo, F. Khan, B. Veitch, and M. Yang, "Arctic shipping accident scenario analysis using Bayesian Network approach," *Ocean Eng.*, vol. 133, no. August 2016, pp. 224–230, 2017.

[56] B. Khan, F. Khan, and B. Veitch, "A Dynamic Bayesian Network model for ship-ice collision risk in the Arctic waters," *Saf. Sci.*, vol. 130, no. June, pp. 1–9, 2020.

[57] P. Abraham, "International comparison of occupational injuries among commercial fishers of selected northern countries and regions.," in *Proceedings of the International Fishing Industry Safety and Health Conference.*, 2002, pp. 455–465.

[58] J. M. Lincoln and D. L. Lucas, "Occupational fatalities in the United States commercial fishing industry, 2000-2009," *J. Agromedicine*, vol. 15, no. 4, pp. 343–350, 2010.

[59] B. Davis, B. Colbourne, and D. Molyneux, "Analysis of fishing vessel capsizing causes and links to operator stability training," *Saf. Sci.*, vol. 118, pp. 355–363, Oct. 2019.

[60] S. Fulmer, B. Buchholz, M. Scribani, and P. Jenkins, "Musculoskeletal Disorders in Northeast Lobstermen," *Saf. Health Work*, vol. 8, no. 3, pp. 282–289, 2017.

[61] P. Kujala, M. Hänninen, T. Arola, and J. Ylitalo, "Analysis of the marine traffic safety in the Gulf of Finland," *Reliab. Eng. Syst. Saf.*, vol. 94, no. 8, pp. 1349–1357, 2009.

[62] R. Islam, F. Khan, R. Abbassi, and V. Garaniya, "Human error assessment during maintenance operations of marine systems – What are the effective environmental factors?," *Saf. Sci.*, vol. 107, no. April, pp. 85–98, 2018.

[63] L. BayesFusion, "GeNIe Modeler: User manual," 2016.

[64] S. Akyeampong, K. Amador, and B. Nkrumah, "Report on the 2013 Ghana Marine Canoe

Frame Survey," 2013.

[65] MoFAD, "Fisheries management plan of Ghana: A National Policy for the Management of the Marine Fisheries Sector," pp. 1–48, 2019.

CHAPTER 5

5.0. Loss of stability risk analysis in small fishing vessels

Preface

A version of this chapter has been submitted to ***Ocean Engineering Journal*** *and currently undergoing review. I am the primary author alongside co-authors Francis Obeng, Faisal Khan, Neil Bose, and Elizabeth Sanli. I developed the conceptual framework to study the loss of stability risk in small fishing vessels. I carried out the literature review, developed the Bayesian network model for loss of stability risk estimation, performed the engineering analysis, and prepared the first draft of the manuscript. Subsequent revisions of the manuscript based on co-authors' and peer review feedback were also done by me. Co-author Francis Obeng read the first draft of the manuscript and drew my attention to obvious areas of concern. Co-author Faisal Khan helped in the concept development and testing of the logic behind the loss of stability model, reviewing and revising the manuscript. Co-author Neil Bose provided fundamental assistance in validating, reviewing, and correcting the model and results. Co-author Elizabeth Sanli assisted in validating, examining the technical writing constructs and correcting the model results. The co-authors also contributed to the review and revision of the manuscript after receiving peer-review feedback from the journal.*

Abstract

A quantitative risk analysis tool to study loss of stability (LoS) aboard small fishing vessels (SFV) was developed in the present study. The LoS is one of the everyday occurrences that happen as a ship is underway. Often, LoS is the precursor to vessel capsize accidents. SFV accident reports identify LoS as the hidden causality for fishing boat capsizes and the related fisher deaths in the commercial fishing industry. While shipping vessels and most large fishing vessels have adequate systems and equipment to proactively estimate LoS and take necessary actions to avoid it leading to a possible accident, SFVs lack such equipment. Therefore, in the present study, through Bayesian network (BN) modelling, the LoS risk analysis tool was developed for the SFV sector. By adopting a systems engineering approach, the tool captures, at a high-level, the risk influencing factors responsible for LoS occurrence. Given the current situation at sea, the tool estimates a percentage score to tell LoS likelihood. The scenarios favouring the estimated score, too, can be learned from the tool. Compared with similar risk analysis tools, this one is different because the BN modelling employs De Morgan gates. Using the tool is one simple way of proactively ensuring intact stability aboard SFVs. The study is recommended to SFV owners, the commercial fishing industry, and anyone interested in developing BN models relying on the independence of causal influence for qualitative or quantitative risk analysis.

Keywords: Bayesian network (BN), De Morgan gates, Independence of causal influence (ICI), Loss of stability, Probabilistic risk assessment, Qualitative risk analysis, Quantitative risk analysis, Small fishing vessels.

5.1. Introduction

The Loss of Stability (LoS) is among the most everyday occurrences while a marine vessel is voyaging. It is also a precursor for the capsize accident [1, 2], known in the maritime industry as one of the leading ship accidents with high fatality rates [3, 4]. That means LoS is the immediate causality for vessel capsize occurrence. The expectation is that, for such a critical causality, ship accident risk models [1, 4—6] would treat it as a top event and not a basic one. In this way, the risk-influencing factors (RIF) associated with LoS will be uncovered and analysed to properly understand how these factors lead to LoS and, ultimately, capsize accidents. A detailed understanding of LoS occurrence is essential to marine vessel safety since virtually any change in sea state, and the vessel displacement could lead to the LoS.

A vessel's stability is its ability to return to the upright position whenever heeled port or starboard. When the heeled vessel is unable or struggling to return to the upright position, it is said to have LoS [7,8]. Ship stability is quantified as the measure of metacentric height [7—9]. Hence, a reduction in metacentric height is an estimate of LoS. As LoS increases, the righting moment to upright the heeled vessel reduces, resulting in the vessel remaining inclined. At this point, should the heeling force increase in momentum, the vessel is heading for capsize. Fundamentally, a reduction in metacentric height occurs due to loading, discharge, or shifting of mass onboard [9—11].

While a vessel is underway, the changes caused by these load operations can increase the distance between the loaded centre of gravity and the keel, leading to metacentric height reduction and, eventually, LoS [7—9]. Thus, the LoS is primarily influenced by changes in mass aboard. However, there are several ways in which mass changes occur [10, 1]. As examples, the shipboard crew movement on deck, tank ballasting, the consumption of fuel by shipboard machinery, and the wave load impact, which causes sloshing in fuel tanks, are typical ways the masses making up the ship displacement change when on a voyage. Therefore, LoS is characterised by many RIFs and the uncertainty in their occurrence likelihood. All of which makes the LoS suitable for quantitative risk analysis.

The LoS has been and continues to be a topical area in ship research. Quiet often, it is also called pure loss of stability to signify the total loss of intact stability in waves due to the simultaneous reductions in the righting moment's arm and the set minimum limit for initial metacentric height that happens [12, 13]. Thus, without the "pure", LoS examination is done for calm waters using the 1968 Intact Stability Criterion discussed in detail in Francescutto [14].

Meanwhile, since the introduction of the Second Generation of Intact Stability Criterion (SGISc) in 2020 by the International Maritime Organisation [15], the ship stability research community has focused more on pure LoS [16—19]. This is because the pure LoS is among the four failure scenarios the SGISc targeted for a ship to pass before it is adjudged seaworthy. As a result, the assessment methods proposed in these studies [116—19] are carried out before voyage commencement. Therefore, the methods are presumptive and may not estimate the true measure of a ship's stability due to their inability to accurately capture the time-to-time dynamics at sea.

With or without "pure", the goal remains unchanged: the LoS investigation ensures a ship at sea maintains adequate intact stability and avoids a possible vessel capsize. The present study then uses LoS to represent both views of the investigation. The LoS in quartering and following seas were studied by Liu et al. [16], Lu et al. [17], and Lu et al. [18]. Their studies show vessels are more vulnerable to LoS and capsize accident in such seas. Andrei et al. [20] also studied LoS in relation to longitudinal waves. Longitudinal waves, often of the ship's length, can reduce stability significantly during severe weather conditions. Depending on how long the ship remains on the wave crest and the loaded displacement, parametric rolling may be severe, resulting in LoS.

Water on deck, asymmetry of the superstructure, wind direction, resonance, and centrifugal force, were also mentioned in Szozda and Krata [21] as contributing factors to LoS. Most studies on LoS focus on shipping vessels [16—18, 22] rather than fishing vessels. Even when the LoS research is about fishing vessels, like in Chorab [12], Míguez González and Bulian [23], Uğurlu et al. [24], and Míguez González et al. [25], only the vessels with at least 24 metres length overall are considered. Meanwhile, González et al. [26] discovered that fishing vessels of less than 24-metre length overall suffer LoS often, resulting in their capsize and fisher deaths. The study also mentioned that most vessels in this group, the small and medium fishing vessels, lack the appropriate equipment to notice LoS ahead of time. Therefore, the crew find it challenging to prevent avoidable vessel capsizes caused by LoS.

Aimed at contributing towards overcoming the equipment inadequacies in the analysis of LoS on small and medium fishing vessels, the present study developed a quantitative risk analysis (QRA) tool. As He et al. [27] discussed, the QRA is an established method that enables data-driven tools to be developed for risk analysis studies. The resulting tool emerged from the QRA conducted. The RIFs for LoS occurrence were identified and linked together probabilistically to estimate a percentage rate as the LoS risk. If the rate exceeds its epistemic uncertainty, the vessel crew must take steps to reduce the vessel's centre of gravity height. This action will increase the metacentric height and minimise or eliminate LoS.

If the LoS rate is estimated to be less than its uncertainty variant, the evidence of possible intact stability loss and vulnerability to capsize accident is weak. The crew are not required to take any remedial action. This approach to managing LoS while a vessel is underway is more practical since the prevailing conditions at the time of evaluation are factored in when estimating the LoS. Hence, the risk analysis tool developed is operationally driven and will assist in proactively managing LoS aboard small and medium fishing vessels. The tool also aids in scenario analysis to better understand the conditions for which a vessel is more susceptible to LoS.

The present study would interest small and medium fishing vessel owners and operators, maritime administrations in charge of fishing safety, and researchers addressing safety challenges aboard fishing vessels. The QRA approach used in developing the LoS tool integrates De Morgan gates [28—30] into the Bayesian network (BN) [31, 32]. As a result, qualitative reasoning can be done alongside the probabilistic risk analysis, setting the tool apart from its contemporaries [6, 24, 31, 32] in the field of QRA. From Chowdhury and Misra [33], integrating De Morgan gates into BN provides a means to reduce the number of causal influences and conditional probabilities required at the child node in a BN model.

A child node with two states in a typical BN model needs "2^n" causal influences for the "*n*" parent nodes connected to the child. If De Morgan gates are integrated into the BN model, the "2^n" causal influences reduces to "*n*" only. When building a vast network, this reduction means significant savings in labour-hours and computational time, making De Morgan gates very useful and vital in BN model development for decision-making. The present study's contributions are the QRA tool development for LoS risk analysis and the integration of De Morgan gates into BN.

In reporting the study, it is sectioned into four. The current section is the first, followed by Section 5.2, which describes the methodology used to develop the QRA tool for LoS as it pertains to small and medium fishing vessels. In Section 5.3, a demonstration of how to apply the tool in practice is given through a case study. The results of the case study are also presented in the same section. Finally, Section 5.4 concludes the report by summarising the main points into the key message, main findings, and future research proposals.

5.2. Methodology to Develop the QRA Tool for LoS

The QRA tool developed for LoS risk analysis was based on the systems engineering approach (SEA) and probabilistic risk assessment. As McGuinness and Utne [34] showed, systems engineering encourages systems thinking to discover high-level factors describing an incident of interest. That way, the focus is on the wholes that makeup the incident and not the basic or structural variables.

The SEA [35] is particularly useful when analysing complex systems for modelling purposes. Because complex systems usually have several subsystems and many components, focusing on high-level factors to uncover the elements to include in a model is essential, if a simple but realistic model must be realised; the SEA provides a means to do so. Also, in QRA, the unavailability of data at the basic level of some incidents may call for modelling an incident at the high-level, making the SEA very useful in that regard.

The LoS is very difficult to represent explicitly. When the literature [12, 13, 17, 20] on LoS is studied critically, one hardly finds individual publications exhausting the complete list of factors influencing LoS. The situation could be attributed to the many areas from which these factors can be sourced, making enlisting LoS risk factors complex and challenging to do exhaustively. Therefore, in modelling LoS in the present study, the focus was on the marine environment surrounding a small or medium fishing vessel, the human role in countering LoS, and the shipboard operations that happen while on a voyage.

By applying SEA to these three broad areas, high-level RIFs were sourced for the LoS. Bayesian network modelling, a method for developing probabilistic risk assessment tools, was then used to capture the RIFs resulting in the developed QRA tool for LoS risk analysis [36, 37]. Through probability theory, probabilistic risk assessment can estimate percentages that can be used to measure the likelihood of an incident. Previous studies have applied the method successfully in various areas of interest to small and medium fishing vessels, including boat capsize [6], sinkage [24], and human failure analysis [31, 38]. Using the SEA and probabilistic risk assessment methods then, facilitated the tool development for LoS risk analysis. The concept framework for the development process is described after enumerating the assumptions the study adopted.

5.2.1. The modelling assumptions

Contextualising risk model development is necessary if the variability in the methodical approach adopted must be minimised. As Goerlandt and Reneiers [39] and Khorsandi and Aven [40] showed, assumptions and conditions framing is one way to do contextualisation. The following assumptions and conditions guided the proposed methodology and the development of the QRA tool for LoS risk analysis:

- The LoS is a complex problem deserving a SEA—this allowed for high-level RIFs to be used in modelling LoS through abstraction;
- The abstraction is broadly focused on environmental factors and human and shipboard activities in small and medium fishing vessels—making the emerged risk analysis tool operationally driven;
- Only latent failures causing LoS are considered for RIFs during abstraction—this ensured that all parent and child nodes in the tool were high-level factors;
- The risk analyst understands very well how LoS occurs aboard the fishing vessel and has defined a standard way of estimating initial probabilities for RIFs as done in Obeng et al. [6], Uğurlu et al. [24], Özaydın et al. [31], Obeng et al. [38], or Chapter 5 of the current thesis—this ensures that the tool is tailor-made for a specific small or medium fishing vessel;

- Independence of causal influence in-between the defined RIFs—this made it possible to integrate De Morgan gates into BN, resulting in the tool; hence,
    - every node has only two states—True (T) and False (F) for the occurrence and nonoccurrence of the RIF, respectively;
    - each parent node must independently impact the child node; and
    - an impact on a child node must be one of these kinds: (a) CAUSE—the parent node has a positive influence on the child node and would increase the child's occurrence score, (b) BARRIER—the parent node has a negative influence on the child node and would decrease the child's occurrence score, (c) REQUIREMENT—the parent node is required for the child node to happen, or (d) INHIBITOR—the parent node prevents the child node from happening. The more (c) present or (d) absent in the tool, the higher the likelihood score for LoS occurrence. On the contrary, the likelihood score will be less if more of (c) is absent or more of (d) is present in the tool. The CAUSE, BARRIER, REQUIREMENT, and INHIBITOR [30] are the De Morgan gates, as shown in Figure 5.1.

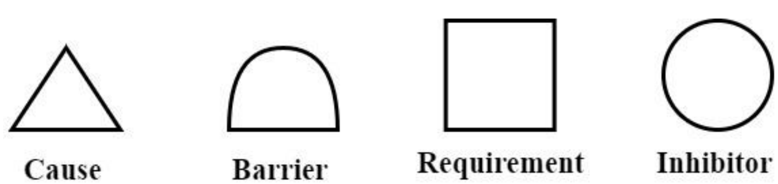

Figure 5.1. De Morgan gates for causal influence representation.

5.2.2. The methodology framework

The conceptual framework followed to develop and apply the QRA tool for LoS risk analysis is shown in Figure 5.2. The framework, broadly, consists of three phases following the linear SEA model discussed in Kossiakoff and Sweet [41]. The linear SEA is among the earliest approaches

[35, 41] developed for systems engineering and offers a logical, straightforward step-by-step way of actualising systems engineering projects. Concept development is the first phase in the linear approach, where information is gathered on the problem or incident defined for systems engineering. This helps in knowing the wholes constituting the incident and the factors involved in each whole. For the present study, the incident under investigation is LoS. Tasks in Phase 1 were executed so that high-level LoS factors could be sourced. Subsequently, the RIFs to the high-level factors were also determined.

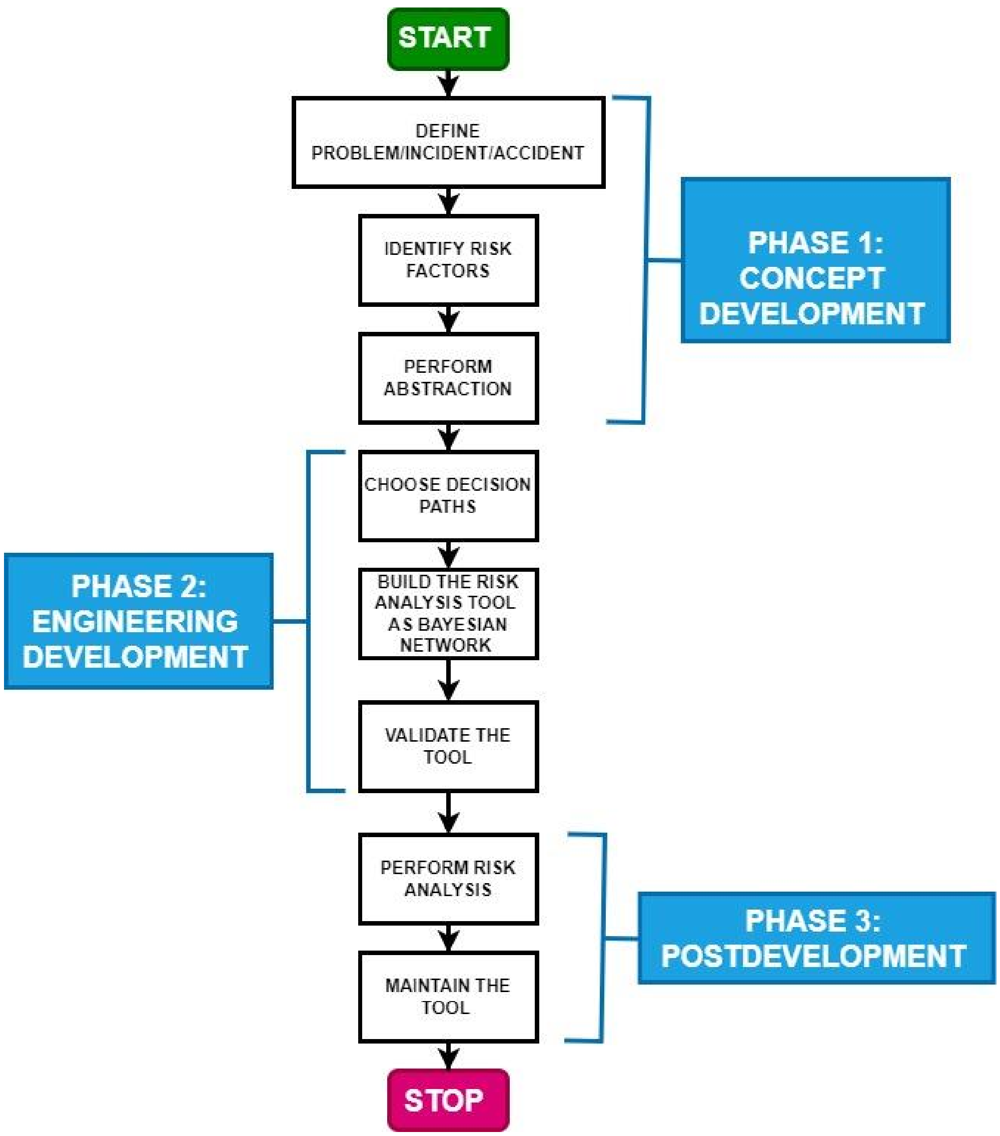

Figure 5.2. The conceptual framework to develop the tool for loss of stability risk analysis.

After gathering the information, they are used to develop the tool to facilitate LoS risk analysis. The development process involved bringing together the RIFs identified in Phase 1 through probabilistic analysis, and that is Phase 2, engineering development. Once a model of the incident is ready, scenarios can be analysed to understand the LoS properly and answer questions relating to LoS risk. Meanwhile, the tool needs maintenance so that it continues to serve its purpose. The risk analysis and maintenance of the model makeup the postdevelopment phase. The proceeding sections discuss individual tasks in the SEA phases in detail, focusing on the procedures and techniques used.

5.2.3. Task 1—Define the incident

The incident, accident, or problem of interest can be known through various methods. A field study by observation and interviewing is a typical method to define an incident deserving attention. Also, survey study through questionnaire administering is another method. However, because these methods demand on-site presence or personnel interviewing, and the present study did not aim at that, a literature survey was used instead. The survey of literature for studying accidents and incidents is one method encouraged by researchers, especially at the initial stages of research projects. The method has been applied in several studies, including Uğurlu et al. [24], Özaydın et al. [31], and Animah and Shafiee [42].

The literature survey involved retrieving and reviewing fishing accident reports and journal and conference papers from credible sources. The keywords “small fishing vessel”, “small fishing boat”, “medium fishing vessel”, “medium fishing boat”, “accident”, and “hazard” were used to write a query statement. After, the query statement was used to search within academic and maritime accident databases for relevant literature. The academic databases searched included Scopus, Emerald, IEEE Xplore Digital Library, ProQuest, SpringerLink, Taylor and Francis

Online, EBSCOhost, Engineering Village, Google Scholar, and the Fisheries and Oceans Canada Library. For the maritime accident databases, the Global Integrated Shipping Information System, Marine Accident Investigation Branch, European Maritime Safety Agency, Australian Transport Safety Bureau, and Transportation Safety Board of Canada were searched.

At this point in the study, the aim was to review the literature to identify the pressing issues confronting small and medium fishing vessels. During the review, LoS [24] was seen to underpin most vessel-related and person-related accidents happening aboard these vessels. Current risk assessment studies also focused less on studying LoS as a top event. Bayesian network modelling of LoS risk was also scarce in the published literature. Considering all these knowledge gaps and the ease with which the LoS transitions into a vessel capsize accident amidst the impending danger of fisher deaths, undertaking a LoS risk analysis was deemed necessary, hence the present study.

5.2.4. Task 2—Identify risk factors

The present study again used literature survey to identify the RIFs for LoS. Other methods, such as hazard and operability study, hazard identification, checklist, fault tree analysis, or event tree analysis, are equally capable [43, 44]. To focus attention on LoS and the small and medium fishing vessels, a query statement was formed to search the earlier databases for qualified papers: "(small OR medium) AND (vessel OR boat) AND ("loss of stability" OR "stability loss") AND fishing". Papers deemed qualified met the following conditions: published in peer-reviewed scientific journals, journal or conference papers in English, and published within the last two decades. These papers were downloaded as PDF documents into a folder.

Next, the editor tab for each PDF document was clicked to activate the "Find" tool within PDF documents. Then, by keying "loss of stability", "stability loss", or "stability" into the "Find" tool, it was possible to narrow down to sections in the PDF with information about LoS. Finally, those sections were read, and the RIFs identified and written down. The results were compiled to produce Table 5.1. Although many documents were retrieved, only ten papers qualified for the review due to the emphasis on fishing vessels with less than 24-metre length overall. However, because the RIFs in Table 5.1 covered the broad areas of LoS envisaged by the present study, the few papers realised were not a challenge to the modelling process.

Table 5.1. Risk-influencing factors for loss of stability occurrence.

Reference	Year published	Risk-influencing factor identified
[2]	2019	Operators" understanding of stability, shipped water, flooding
[45]	2005	Wave, down flooding, shipped water, severe seas
[46]	2009	Longitudinal/quartering waves
[26]	2012	Small-size vessel, close hatch doors, scuppers open, gear moved from deck into hold, catch moved from deck into cargo hold, freeboard amidship at least 20 cm, avoid excessive aft trim, minimum freeboard at stern 20 cm, avoid following sea, avoid large heeling moment when hauling gear, change of trim and heel when freeing snagged gear, avoid areas with danger of icing, remove snow and ice from vessel, loose fish on deck
[10]	2022	Restoring moment, parametric roll, head wave, following wave
[11]	2011	Intact stability--righting arm, beam waves, wind, fishing gear
[1]	2014	Large heeling
[6]	2022	Loss of hull integrity, human factor, unsafe loading, free surface effect, stern anchoring, excessive trim, boat moving at high speed
[47]	2003	Following seas, zero degree heading angle, transverse stability reduction, wave crest amidship, vessel"s own radiated wave, low encounter frequency, wave crest amidship, low initial stability
[48]	2017	Wind speed, ice coverage, Laplacian of pressure, vessel modification, vessel weight, Watertight integrity of the hull and superstructure, vessel overloading, wave height

5.2.5. Task 3—Perform abstraction

Following the SEA [35, 41], this section aims to put the RIFs into main scenarios (i.e., systems) and sub-scenarios (i.e., subsystems). The main scenarios realised through abstraction and encapsulation were "Rough marine environment", "Dangerous vessel loading", "Adequate human intervention", "Intact stability requirement satisfied", and "Improper fishing operations". These groupings ensured that RIFs were captured as operational, environmental, and human causes for LoS occurrence, as the second condition in Section 5.2.1 demanded. Next, the RIFs in Table 5.1 were examined (and abstracted where necessary) and appropriately placed under the main scenarios defined earlier.

Table 5.2 is the outcome of the abstractions carried out. During the abstraction, some generalisations were needed so that the systems perspective of LoS could be described fully. Hence, in the second column of Table 5.2, all items with 1a, 1b, 1c, and 1d superscripts were generalised as wave load, wave direction, wind speed, and ice load, respectively. A severe sea is characterised by massive wave loads moving at great wind speeds. Due to that, wave load and wind speed were captured under "Severe sea", resulting in Figure 5.3 for "Rough marine environment".

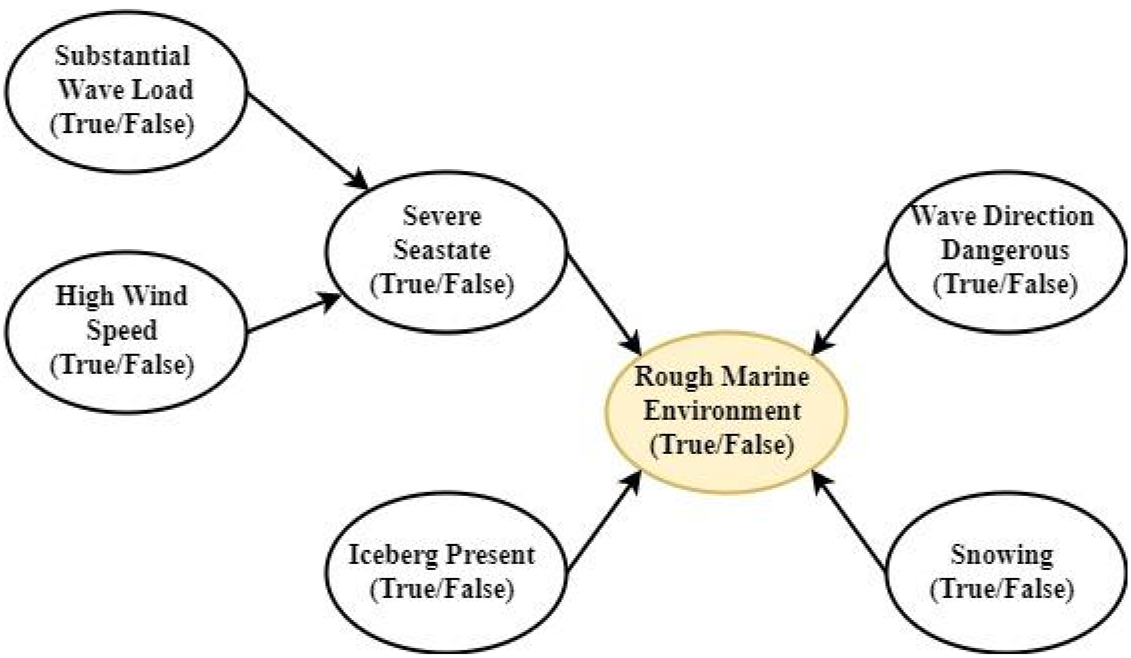

Figure 5.3. Sub-scenarios to cause the rough marine environment and lead to LoS.

Table 5.2. Risk-influencing factors are categorised under the abstracted main scenarios.

Reference	Rough marine environment	Dangerous vessel loading	Adequate human intervention	Intact stability requirement satisfied	Improper fishing operation
[2]		Shipped water [2a]Flooding	Operators" understanding of stability		
[45]	[1a]Wave Severe seas	[2a]Down flooding Shipped water			
[46]	[1a]Longitudinal or quartering waves				
[26]	[1b]Avoid following sea [1d]Avoid areas with danger of ice	Remove snow and ice from vessel Loose fish on deck		Small-size vessel Close hatches doors Scuppers open Gear moved from deck into hold Catch moved from deck into cargo hold Freeboard amidship at least 20 cm [3a]Avoid excessive aft trim Minimum freeboard at stern 20 cm	Avoid large heeling moment when hauling gear Change of trim and heel when freeing snagged gear
[10]	[1b]Head wave [1b]Following wave			Restoring moment Parametric roll	
[11]	[1b]Beam waves [1c] Wind			Righting arm	Fishing gear load
[1]				Large heeling	
[6]		[2b]Loss of hull integrity Unsafe loading Stern anchoring	Human factor	Free surface effect [3a]Excessive trim Boat moving at high speed	
[47]	[1b]Following sea [1b]Zero-degree heading angle			Transverse stability reduction [3b]Wave crest amidship [3b]Vessel"s own radiated wave [3b]Low encounter frequency Low initial stability	
[48]	[1c]Wind speed [1d]Ice coverage [1a]Wave height	Vessel modification Vessel weight [2b]Watertight integrity of the hull and superstructure Vessel overloading		Laplacian of pressure	

[1, 2, 3]: Items in the columns that have been grouped and given a generalised name; [a, b, c, d]: Groups of items generalised.

By looking at Table 5.2, similar networks were formed as Figures 5.4—5.7 for the remaining main scenarios. The abstraction and encapsulation tell the story of a harsh marine environment coupled with subjecting the vessel to improper loading and fishing operations amidst a lack of human intervention when needed and intact stability failures, are the immediate precursors to LoS. While RIFs in Figures 5.3, 5.4, 5.6 and 5.7 are combinations of the marine weather and operational factors, the RIFs in Figure 5.5 are human factors. The human errors in Figure 5.5 are human factors from crew actions and inactions that would lead to LoS. In each figure, the arc head points to the child node, and the arc tail is connected to the parent node yielding parent-to-child or cause-effect relationship diagrams. Each node has two states, "True" and "False", defining an occurrence and nonoccurrence, respectively.

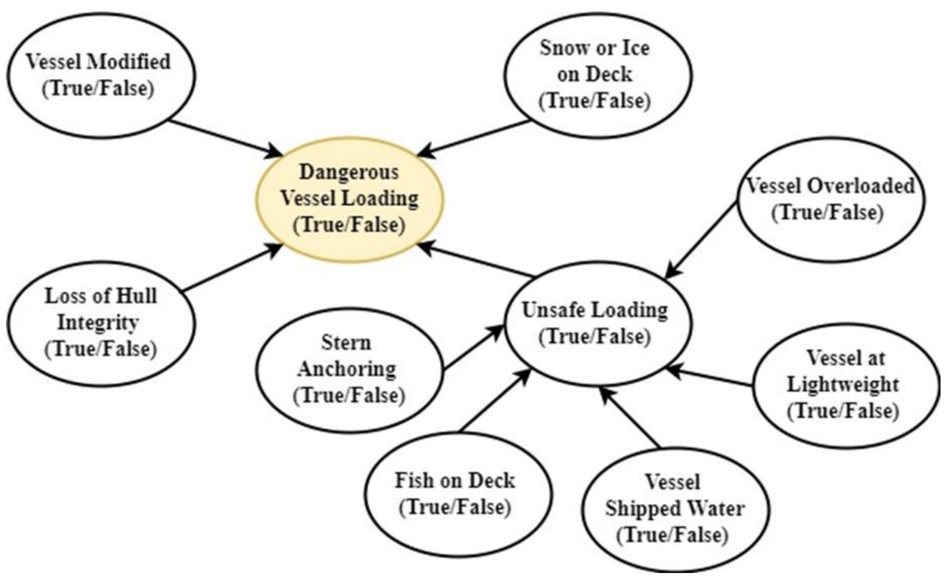

Figure 5.4. Sub-scenarios to cause dangerous vessel loading and lead to LoS.

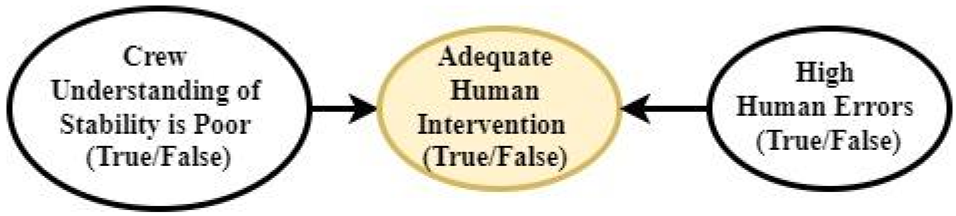

Figure 5.5. Sub-scenarios to cause human intervention challenges and lead to LoS.

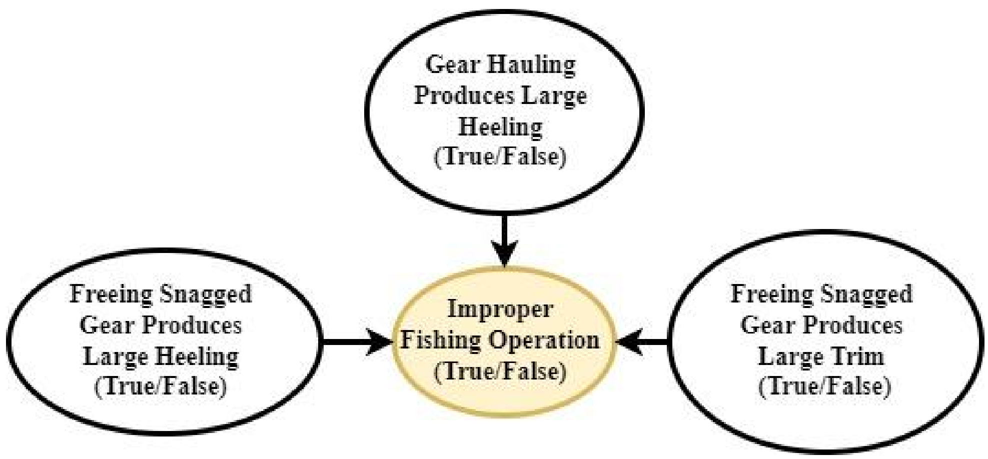

Figure 5.6. Sub-scenarios to cause improper fishing operation and lead to LoS.

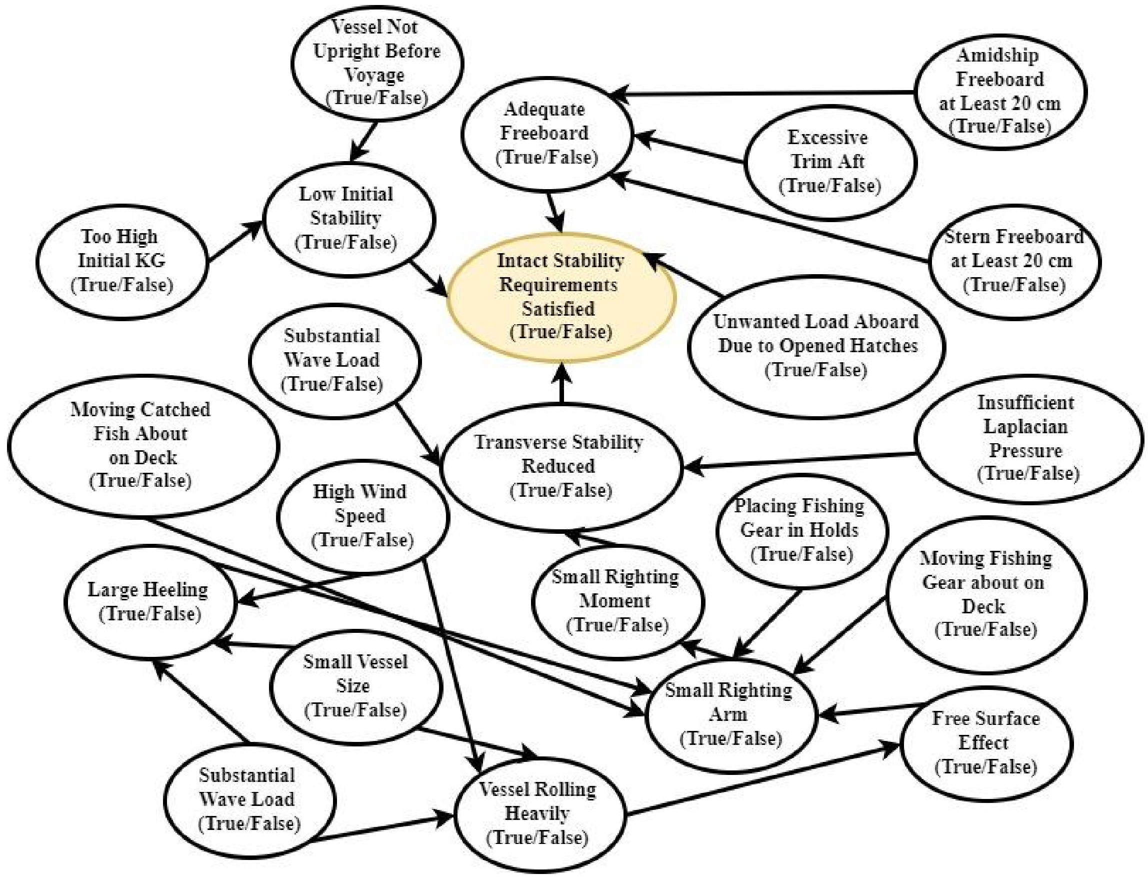

Figure 5.7. Sub-scenarios to cause intact stability problems and lead to LoS.

5.2.6. Task 4—Choose decision paths

Choosing decision paths means defining the dependency relationship between a parent node and its child node. The De Morgan gates defined in Section 5.2.1 were employed to do so. Figures 5.3—5.7 were studied carefully, and the appropriate gate type was assigned to each child node. Table 5.3 shows the gates realised for the nodes in Figure 5.3. Reasons have also been given for the gate choice for each dependency type. Those for Figures 5.4—5.7 are in Appendix D1.

While in Table 5.3, published literature was employed to facilitate decision-making on the gate choices made for dependency type, this is not absolute. Other means, such as operating manuals, statutory regulations, and experience with an item's functioning, can also guide the decision-making process. Table 5.3 and Appendix D1 are the materials that aided the development of the LoS risk analysis tool. The procedures involved are described in the next section.

Table 5.3. The dependency relationship between parent and child nodes.

Number	Parent node	Child node	Dependency type	Reason for choice	Reference
1	Severe seastate	Rough marine environment	Cause	A severe sea is chaotic and would make the marine environment rough.	[49, 50]
2	Wave direction dangerous	Rough marine environment	Requirement	The wave direction creates the type of sea; following, beam, and head seas are known to have an adverse effect on stability; they are hence required for LoS.	[49, 50]
3	Iceberg present	Rough marine environment	Cause	Iceberg creates a hostile environment for the SFV; collision could occur, leading to hull failure, flooding, and finally, LoS.	[6, 51, 52]
4	Snowing	Rough marine Environment	Cause	Snow creates top load on an SFV resulting in LoS; thus, snow causes a harsh environment for the ship.	[6, 51, 52]
5	Substantial wave load	Severe seastate	Requirement	Heeling is critical to LoS; substantial wave load is needed to cause heeling.	[26, 53]
6	High wind speed	Severe seastate	Requirement	Wind is another element required in the marine environment for heeling.	[26, 6, 53]

5.2.7. *Task 5—Build the LoS risk analysis tool*

The academic version 4.0 of QGeNle was the software used to develop Figures 5.3—5.7 into the QRA tool for LoS risk analysis. The QGeNle is a product of the BayesFusion [29, 30], suitable for developing BN models using the independence of causal influence. As mentioned in Díez and Druzdzel [29], these BNs are canonical models of which the NoisyOR and NoisyAND are typical examples. A NoisyOR model is formed when the BN is modelled using the CAUSE and BARRIER gates. On the other hand, a NoisyAND model emerges when the BN is modelled with REQUIREMENT and INHIBITOR gates. Earlier in Section 5.2.1, the meanings of the gates were given.

When all four gate types are used to develop a BN model, a De Morgan type of canonical model is said to evolve. Such a BN model is superior to the NoisyOR or NoisyAND ones since it combines the two to do more complex decision-making analysis tasks. However, as independent-causal-influence models, all three have the advantage of reducing the number of conditional probabilities required at the child node to the number of parents connected to it. This number would have been exponential in a typical BN model, resulting in more computational workload and increased labour hours. These canonical models are preferred to the typical BN [6] if each RIF can independently affect the incident, which is the case of the LoS under study.

The NoisyOR and NoisyAND models are the canonical (i.e., independence of causal influence) forms of the Boolean OR and AND gates models, respectively, and in BN modelling, employs Equations (5.1) and (5.2) to estimate occurrence probability for an incident.

For $Y = NoisyOR(X_1, v_1, X_2, v_2, \dots, X_n, v_n, l)$

$$\Longrightarrow P(Y = true|X_1, \dots, X_n) = 1 - (1 - l) \times \prod_{X_i \, is \, true}(1 - v_i) \tag{5.1}$$

For $Y = NoisyAND(X_1, v_1, X_2, v_2, \dots, X_n, v_n, l)$

$$\Rightarrow P(Y = false|X_1, \dots, X_n) = 1 - (1 - l) \times \prod_{X_i \; is \; false}(1 - v_i) \tag{5.2}$$

where, "Y" is the child node to be evaluated; $X_1, \dots, X_n$, are "n" parent nodes; each $i = 1, \dots, n,$ has a number between zero and one called, v_i, the weight associated with "X_i"; "l" is the leak factor and has a value between zero and one; and $P(Y)$ is the conditional probability of "Y" occurrence depending on the states, true or false.

BayesFusion [30] has made the academic version of QGeNIe freely available for educational research. In QGeNIe, RIFs are represented as nodes. Each node has only two states—True and False—defining occurrence and nonoccurrence, respectively. QGeNIe is a versatile software, allowing for qualitative and quantitative analyses through De Morgan gates implementation. The software is grounded in probability theory and so, capable of probabilistic risk assessment. Aside from the probability scores, QGeNIe uses colour and colour intensity to make qualitative inferences about the question a resulting BN model is to answer. By default, red and green colours show undesirable and desirable states. Also, deep or light colouring represents colour intensity.

Deep colouring means there is more certainty in the undesirability or desirability state. Light colouring offers an opposing interpretation, revealing less certainty in the state assertion. When making inferences in QGeNIe, the objective is not only on interpreting the probability scores (as it is for non-canonical BNs in Obeng et al. [6] and BayesFusion [54]) but also the colouring intensity and the thickness of the arcs connecting the nodes. A thicker arc symbolises the prime information flow channel in the model. Further qualitative reasoning can be done based on the definitions for the De Morgan gates.

With De Morgan gates in QGeNIe, the emerging model computes probability, e, for a child node using Equation (5.3). For "e" to happen, all REQUIREMENT factors must be present, and all INHIBITOR factors must be absent. CAUSES and BARRIERS are not mandated to be present simultaneously before "e" can be computed due to the union ($\cup$) conjunction. To indicate a factor is present in the model, its node's occurrence state (True) must be activated. The factor is absent when the nonoccurrence state (False) is activated instead. The intersection conjunction shows that the more REQUIREMENT factors present, the greater the estimate for "e". The complement of the INHIBITORS ($\bar{\iota}_1 or\ \bar{\iota}_2$) connected by the intersection ($\cap$) conjunction shows that as more INHIBITOR factors are absent, the probability of "e" increases. When integrating De Morgan gates into BN in QGeNIe, it is essential to assign the gates correctly, based on their definitions provided in Section 5.2.1, to ensure a representative model of the incident at hand is realised.

$$e = \left(c_1 \cup c_2 \cup \bar{b}_1 \cup \bar{b}_2\right) \cap r_1 \cap r_2 \cap \bar{\iota}_1 \cap \bar{\iota}_2 \tag{5.3}$$

where, "e" is the estimated probability for a child node, "c_1" and "c_2" are CAUSE gate variables, "b_1" and "b_2" are BARRIER gate variables, "r_1" and "r_2" are REQUIREMENT gate variables, and "i_1" and "i_2" are INHIBITOR gate variables.

Using the De Morgan gates, the QRA tool for LoS risk analysis was developed as a canonical BN model in QGeNIe. The tasks in Figure 5.8 were performed to arrive at the tool. Tasks are shown in the rectangle, and inside the ovals are the tools and materials to complete the tasks. First, a node each was defined for LoS and its RIFs in Figures 5.3—5.7. Next, arcs were extended from parent nodes to child nodes. Finally, the appropriate De Morgan gates (or causal influences) were assigned, according to Table 5.3 and Appendix D1. Because the nodes were many, the tool was simplified into sub-networks using the "submodel" feature in QGeNIe. The resulting tool is shown in Figure 5.9.

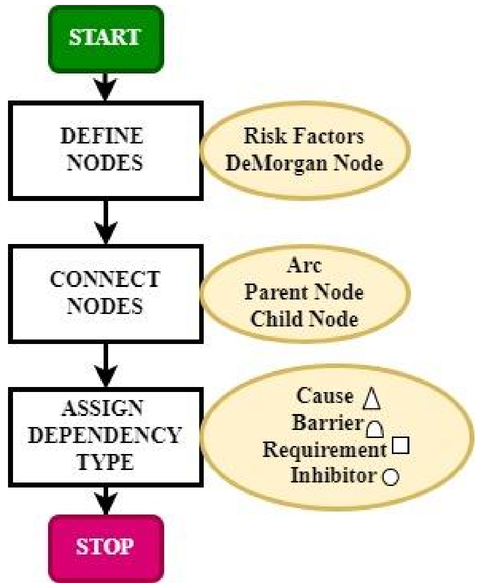

Figure 5.8. Flow chart to develop a risk analysis tool for LoS in QGeNle software.

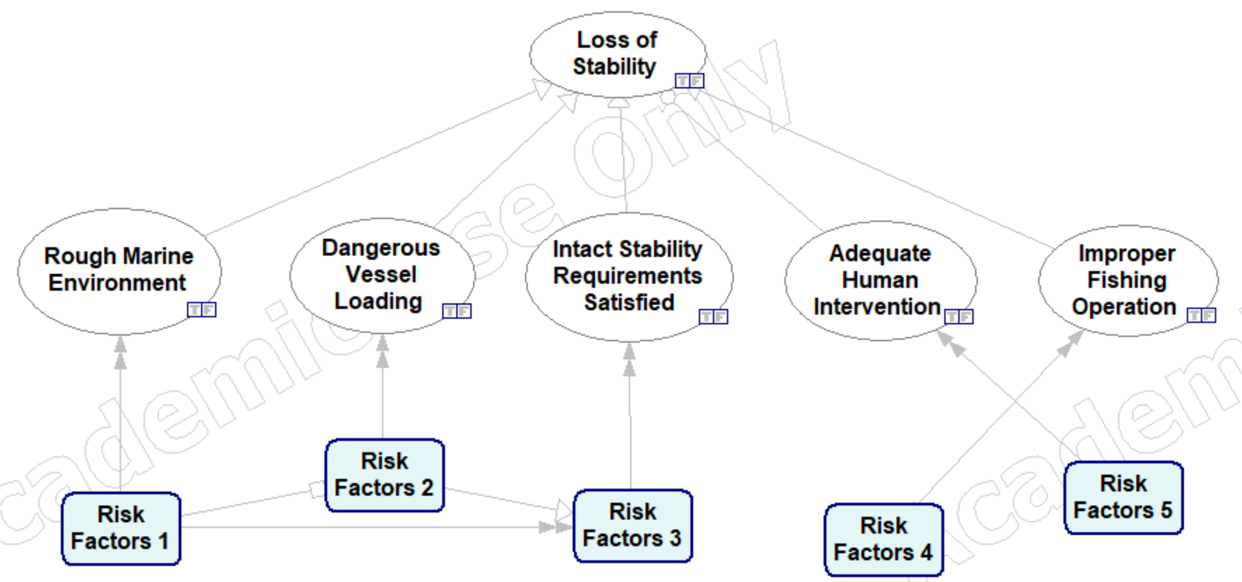

Figure 5.9. The QRA tool for loss of stability risk analysis.

Figure 5.9 shows five precursor factors for LoS. These are the direct or main scenarios responsible for LoS occurrence aboard a small or medium fishing vessel. The risk factors as defined in Figures 5.3—5.7 are held within the sub-networks, Risk Factors 1—5. From the model, apart from "Intact stability requirements satisfied" and "Adequate human intervention nodes", which use BARRIER and INHIBITOR gates, the remaining main scenarios, have CAUSE gates. The occurrence of RIFs with CAUSE gate would mean an LoS occurrence too. As a BARRIER, when a vessel's intact stability requirements are satisfied throughout the voyage, LoS is not likely to occur. The INHIBITOR models the responsibility shipboard crew have to ensure that necessary measures are put in place to ensure adequate intact stability. Their timely intervention, therefore, will de-escalate any potential threat in favour of LoS occurrence aboard the vessel. The LoS risk analysis tool is ready to be used to answer questions about LoS occurrence when the vessel is on fishing expeditions.

5.2.8. Task 6—The model validation and maintenance

Before using the developed tool to answer questions on LoS, validation exercises were performed to ensure the model's predictability was reasonable. The face, content, construct, and predictive validities were conducted to achieve the validation objective, as described by Turocy [55] and Yu et al. [56]. Content validity inquires if the model has captured the concept of LoS. The construct validity focused on knowing if the modelling followed acceptable guidelines. Then face validity found out if the outcome results of the model would make sense. On the other hand, predictive validity inquired if the model results could be associated with different existing results from similar operations.

5.2.8.1.Examining for content validity

Standard naval architecture textbooks on ship stability were consulted to verify content validity. The RIFs and their associations with LoS were checked from the textbooks: Introduction to Naval Architecture [7], Naval Architecture for Marine Engineers [8], Maritime Engineering Reference Book [9], Basic Ship Theory [57], and Ship Hydrostatics and Stability [58]. These factors were present in the textbooks and had a relationship with LoS. Hence, it can be said that the contents of the developed QRA tool are relevant to the LoS incident, so content validity has been achieved.

5.2.8.2.Examining the construct validity

For construct validity to be adjudged adequate, the model was first examined by the assumptions and conditions (see Section 5.2.1) governing the modelling process. A major modelling consideration was presenting a systems perspective of the LoS incident. From Figures 5.3—5.7, it is evident that root causes can be assigned to each RIF present, indicating that the abstraction performed enabled the model to capture high-level factors or main scenarios about LoS incidents.

Also, in Table 5.3, reasons to justify the choices made for dependency types used in the model were given. With De Morgan gates involved, the developed QRA tool is a canonical model and valid for modelling LoS because, from standard naval architecture textbooks [7—9, 57, 58] and ship stability regulations, each RIF can independently influence the LoS occurrence. Therefore, to a large extent, the tool has been developed based on the principles of independence of causal influences, De Morgen's conditions, and SEA perspectives. Hence, it could be said that construct validity has been attained.

Another aspect of the construct investigated is the colour coding for nodes. It was inquired whether the colour corresponding to the state and risk defined will show when a "True" or "False" state is activated. The expectation is that, if the construct is correct, an undesirable factor with a "True" state activated must show the colour red at the node. On the other hand, if the "False" state is activated, the colour must be green. For a desirable risk node, green must show when the state "True" is activated, but red when "False" is the activated state. See Figures 5.10 and 5.11, as example demonstrations. The nodes are in the Risk Factor 3 sub-network of the LoS risk analysis tool (see Figure 5.9). The RIF, "Putting fishing gear into holds", tends to mitigate LoS. Hence, that is a desirable RIF, and so, the node's colour is green when the "True" state is activated, as shown in Figure 5.10. Meanwhile, the RIF—"Too high initial KG"—will lead to LoS, making the factor undesirable. Accordingly, that node shows red when "True" is activated, again in Figure 5.10. With the "False" state activated in Figure 5.11, the colours have changed accordingly. The red and green colours indicate accident causation and no causation, respectively. All the nodes in the tool were examined for these observations, and the colour coding was correct throughout. These also add to the evidence of construct validity attainment in the developed tool.

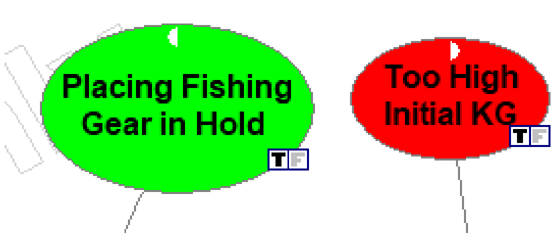

Figure 5.10. Nodes colours when "True (T)".

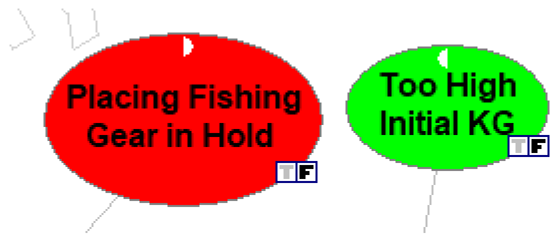

Figure 5.11. Nodes colours when "False (F)".

5.2.8.3.Examining for face and predictive validities

Finally, face and predictive validities tests focused on Equation (5.3). Some important information can be retrieved from the equation: (1) all RIFs with REQUIREMENT gate (r_1 and r_2) must be present for the full estimate of "e" to be made; the absence of any such RIF would decrease the "e" score; and (2) all RIF with INHIBITOR gate (i_1 and i_2) must be absent to register the total estimate for "e"; the presence of any such RIF would decrease the score. These observations are due to the intersection conjunction in the equation, which implores the factors to be present if a full estimate of "e" is to be made. However, the RIFs with CAUSE and BARRIER gates may be present or absent since the union conjunction does not compel these to be present always. Let us check in the next paragraph if the "e" for a child node in the tool complies with the above observations.

The child nodes, “Adequate human intervention” and “Unsafe loading” are connected to parent nodes for which the gates are INHIBITORS and REQUIREMENTS, respectively, as shown in Figures 5.12 and 5.13. The procedure for preparing the sub-networks for inference is described later in the case study section. Here, only the presence or absence analysis for causal influences (i.e., the gates) was done to confirm face and predictive validities. Before the analysis, the “True” state scores evident from the figures are 18% and 49% for “Adequate human intervention” and “Unsafe loading” nodes, respectively.

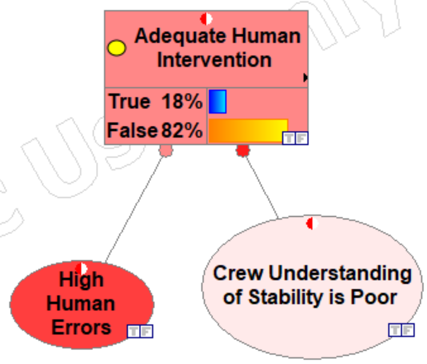

Figure 5.12. A sub-network with INHIBITOR gates.

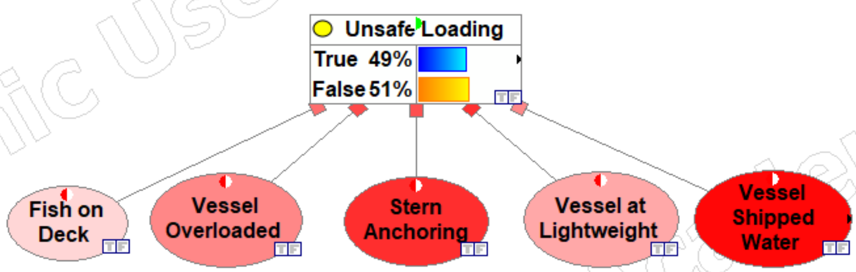

Figure 5.13. A sub-network with REQUIREMENT gates.

The analysis was carried out first for Figure 5.12 and after, Figure 5.13. State “F” of parent nodes in Figure 5.12 was activated to mean INHIBITOR gate complement,$\bar{\iota}$ (i.e., the gate is absent). Similarly, the state “T” for parent nodes in Figure 5.13 was activated to indicate the complement of the REQUIREMENT gate, $\bar{r}$ (i.e., the gate is absent). Figures 5.14 and 5.15, respectively, are the results of this first analysis.

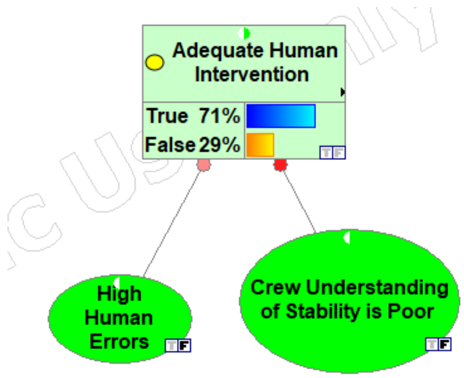

Figure 5.14. Result when all INHIBITOR gates are absent due to state "F" activation.

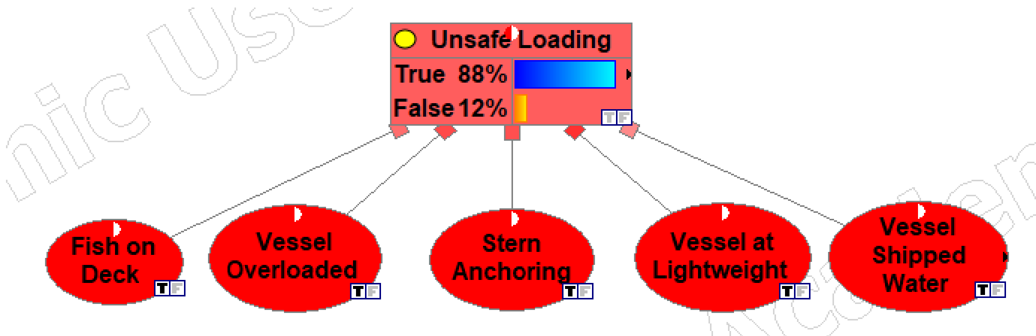

Figure 5.15. Result when all REQUIREMENT gates are present because state "T" is activated.

The previous steps were repeated in the second analysis set, but one "F" state was changed to a "T" for "Adequate human intervention", and while, one "T" to an "F" for "Unsafe loading". Accordingly, the results are Figures 5.16 and 5.17, respectively. The new state activated represents an INHIBITOR gate presence in Figure 5.16 and a REQUIREMENT gate absent in Figure 5.17.

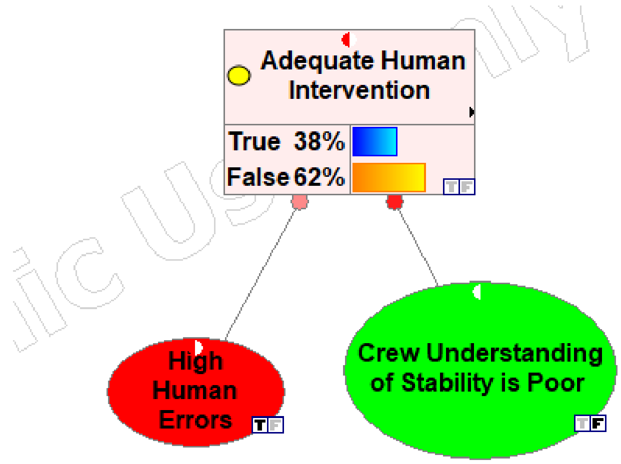

Figure 5.16. Result for one INHIBITOR gate present.

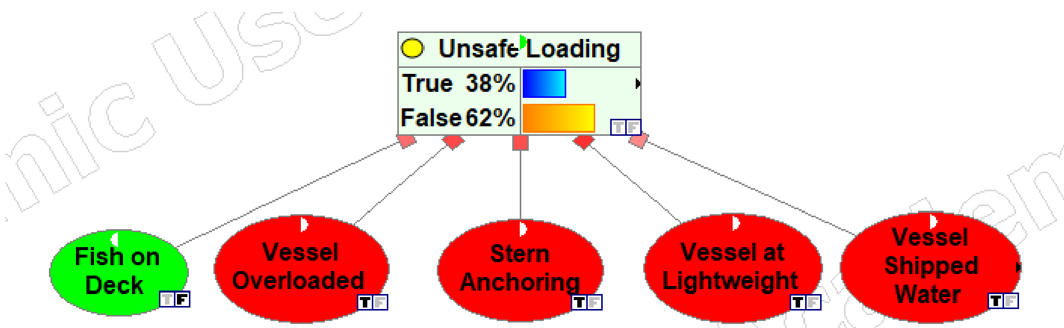

Figure 5.17. Result for one REQUIREMENT gate absent.

Again, the analysis process was repeated with one more increase in a "T" state for Figure 5.16 and an "F" addition in Figure 5.17. Figures 5.18 and 5.19 are the latest results.

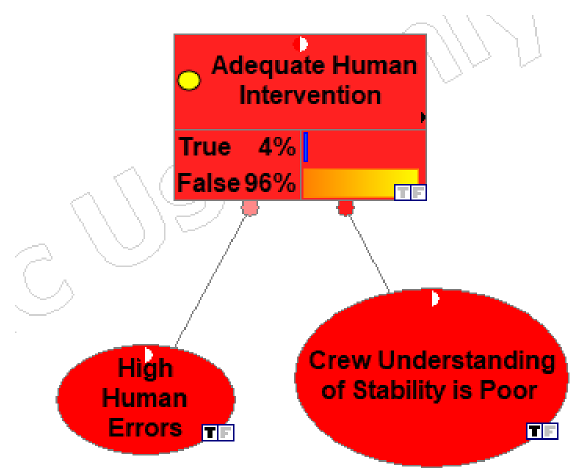

Figure 5.18. Result for two INHIBITOR gates present.

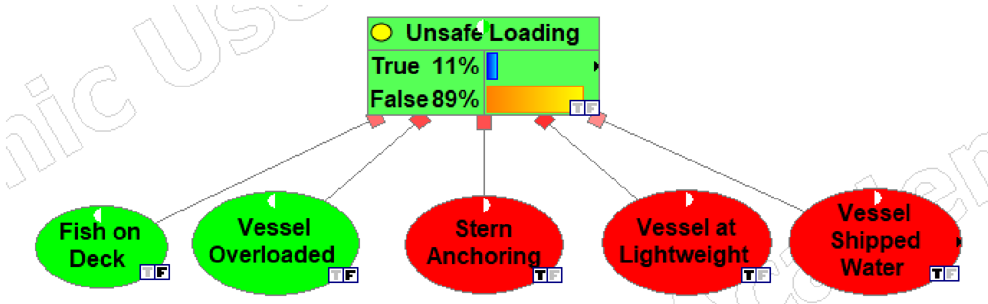

Figure 5.19. Result for two REQUIREMENT gates present.

The results from Figures 5.12—5.19 were compared to inquire whether the LoS risk analysis tool would predict correctly based on the two observations deduced earlier from Equation (5.3). The "T" state results for the "Adequate human intervention" node are 18%, 71%, 38%, and 4%. On the other hand, the "Unsafe loading" node results are 49%, 88%, 38%, and 11%. The 18% and 49% beginning the result sets serve as boundary conditions. When all the INHIBITOR gates were inactive, the score (e) increased to 71%. Similarly, when all the REQUIREMENT gates were active, the score increased to 88%.

These high scores thereafter decreased and kept decreasing due to the simultaneous presence of the active and inactive states of the causal influences. Therefore, the tool has followed the deductions from Equation (5.3), named in the first paragraph. Because face validity and predictive validity are about the model giving results consistent with underlining principles, the demonstration outcomes prove that these validity types have also been attained. Therefore, the tool is expected to yield good results when analysing LoS scenarios in small and medium fishing vessels.

5.3. The case study for LoS risk analysis and the discussion of its results

This section demonstrated using the LoS risk analysis tool to study scenarios. The scenario studied was a question about LoS, to which an answer was sought. In this section too, both the analysis and results are discussed.

5.3.1. The question and its background

The question answered was the likelihood of LoS when the following nodes are in their accident causation states: "Vessel shipped water", "Gear hauling produces large heeling", "Too high initial KG", "Amidship freeboard at least 20 cm", "Stern freeboard at least 20 cm", "Small vessel size", and "Free surface effect". The question is essential because Krata [49], like other researchers [1, 6, 24, 53], identified vessel capsize as a typical accident leading to several fisher deaths, particularly aboard small fishing vessels (SFV). Fishing safety literature [2, 7—9, 57, 58] shows that, the LoS is the latent failure leading to such SFV capsizes.

The accident reports on these vessels capsizes showed that factors such as towing of fishing gear, vessel size, freeboard lowering, the rising height of the centre of gravity, water trapped on the vessel deck, low stern, and free surface effect contribute towards the LoS occurrence. Because these factors are like the RIFs identified for investigation, the case study question is relevant. Therefore, the LoS risk analysis tool was engaged to estimate a numeric value for LoS occurrence likelihood and perform further inferences.

5.3.2. Acquiring initial probabilities for nodes and information paths

The first step in answering the question is to provide the initial probability for each node and information path (i.e., the arcs). As the initial probability dataset, the vessel crew would use their judgement to estimate values between zero and one based on their belief of the occurrence likelihood for nodes and arcs. Values close to one means that the belief of occurrence likelihood is high. However, very little belief is attributed to an occurrence likelihood for values close to zero. The initial probabilities serve as the foundational data for learning from the tool, making it possible to do a probabilistic risk assessment alongside qualitative risk analysis through colour coding and arc thickness investigation. From the study assumption four in Section 5.2.1, Tables 5.4 and 5.5 are presumed as the initial probabilities sourced by a vessel crew to answer the question posed. The nodes in bold fonts were the factors activated for the analysis per the question.

Table 5.4. The initial probabilities selected for parent nodes.

Parent node	Prior probability	Parent node	Prior probability
Substantial wave load	0.84	High wind speed	0.92
Iceberg present	0.74	Wave direction dangerous	0.95
Snowing	0.76	Vessel modified	0.77
Loss of hull integrity	0.87	Stern anchoring	0.94
Fish on deck	0.68	**Vessel shipped water**	0.99
Vessel at lightweight	0.77	Vessel overloaded	0.82
Crew understanding of stability is poor	0.63	High human errors	0.92
Freeing snagged gear produces large heeling	0.88	**Gear hauling produces large heeling**	0.87
Freeing snagged gear produces large trim	0.71	Vessel not upright before voyage	0.36
Too high initial KG	0.29	**Amidship freeboard at least 20 cm**	0.83
Excessive trim aft	0.59	**Stern freeboard at least 20 cm**	0.44
Insufficient Laplacian pressure	0.99	Placing fishing gear in holds	0.75
Moving fishing gear about on deck	0.81	**Small vessel size**	0.99
Moving catched fish about on deck	0.89		

Table 5.5. The initial probabilities selected for child nodes.

Child node	Leak probability	Child node	Leak probability
Severe seastate	0.63	Rough marine environment	0.64
Unsafe loading	0.88	Dangerous vessel loading	0.54
Snow or ice on deck	0.91	Human intervention inadequate	0.71
Improper fishing operation	0.31	Low initial stability	0.51
Adequate freeboard	0.42	Intact stability requirements satisfied	0.69
Unwanted load aboard due to opened hatches	0.79	Transverse stability reduced	0.72
Small righting moment	0.82	Small righting arm	0.89
Free surface effect	0.75	Vessel rolling heavily	0.69
Large heeling	0.59	Loss of stability	0.78

In QGeNIe, initial probabilities for parent nodes, child nodes, and information paths are called prior probabilities, leak probabilities, and interaction probabilities, respectively. Prior probability measures the likelihood of the risk factor occurring during an SFV's voyage. Leak probability also measures the likelihood of the child node occurring when its parents are inactive. The inactive state is called the distinguished state [29, 30] and depends on the De Morgan gate type connecting a child node to its parent node. For the gates, CAUSE, BARRIER, REQUIREMENT, and INHIBITOR, the distinguished states are "False", "True", "True", and "False", respectively. The interaction probability, however, is a weighting (i.e., v_i in Equations (5.1) and (5.2)) that project the strength with which the parent influences the child. In the following sections, interacting probabilities are shown along the arcs in the tool.

5.3.3. Entering the initial dataset into the tool

The datasets in Tables 5.4 and 5.5 were entered into the LoS risk analysis tool. Figure 5.20 is the outcome after all the probabilities were entered into the model. The light red colour shows that LoS is likely to occur, and it is because the marine environment is not calm, and the loading situation aboard is problematic. Meanwhile, "Intact stability requirements satisfied", "Human intervention inadequate”, and “Improper fishing operation”, are not responsible for LoS occurrence due to their green colour. While LoS occurrence could be due to “Rough marine environment” or “Dangerous vessel loading”, the latter is more liable since its red colour is much more intense. Similar interpretations can be made at the sub-network levels for Risk Factors 1—5 (see Appendix D2).

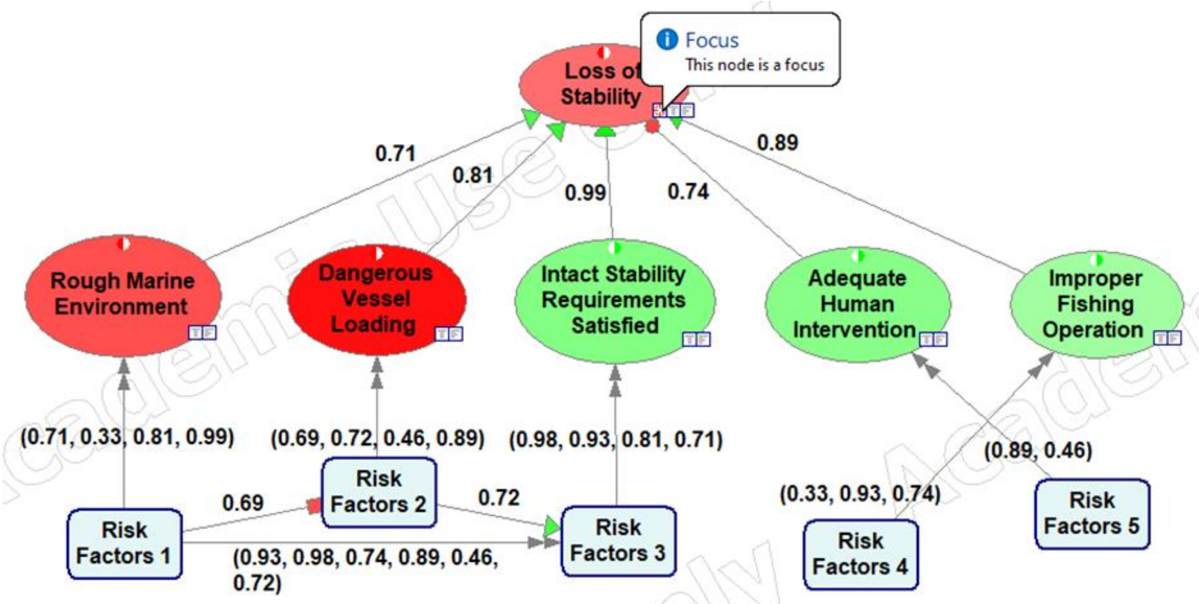

Figure 5.20. The tool with the prior, leak, and interaction probabilities entered.

5.3.4. Performing analysis to answer the given question

The question wants to know the state of LoS, given that the factors mentioned in Section 5.3.1 have been activated. As a result, the focus was set on the “Loss of stability” node in the tool and the state, “True”, was activated for the nodes, “Vessel shipped water”, “Gear hauling produces large heeling”, “Too high initial KG”, “Small vessel size”, and “Free surface effect”. For the nodes, “Amidship freeboard at least 20 cm” and “Stern freeboard at least 20 cm”, the state “False” was activated instead. Figures 5.20 and 5.21 show the focus setting on the “Loss of stability” node and the activation of the appropriate node states. In Figure 5.21, the “T” in bold font at the right-down corner of the nodes—“Free surface effect”, “Too high initial KG”, and “Small vessel size”—means “True”, signaling the nodes activation. If the state was “False”, the “F” would have been boldened as in nodes “Amidship freeboard at least 20 cm” and “Stern freeboard at least 20 cm”. Meanwhile, all remaining nodes do not have either “T” or “F” activated. That shows those nodes are excluded from the analysis.

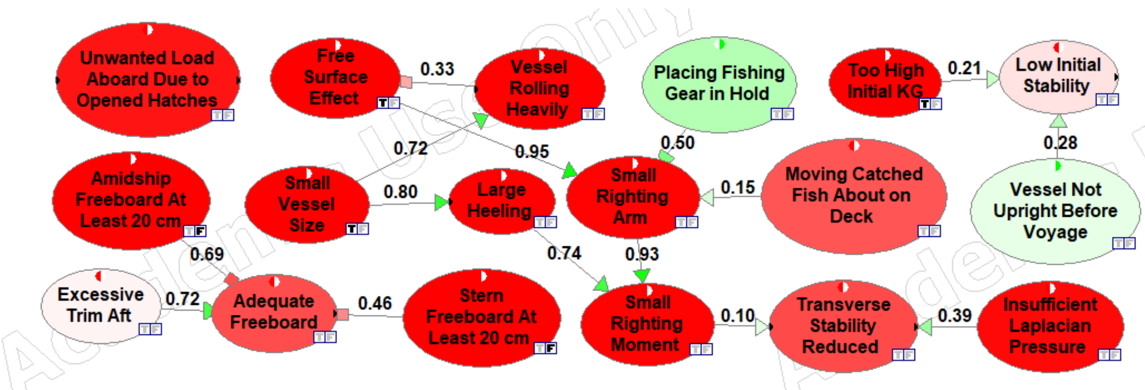

Figure 5.21. The activated factors with their “True (T)” and “False (F)” states.

The analysis result is shown as bar graphs and colour coding in Figure 5.22. When the result is compared with Table 5.5, the difference in data indicates that the activation of the states in Figure 5.21 is responsible for the results in Figure 5.22. Thus, one can answer the question by saying that the tool infers that a 0.86 probability exists for LoS to occur, given the RIFs activated. Krata [49] and Obeng et al. [6] also reached a similar conclusion regarding the RIFs involved.

The estimated probability for LoS occurrence is not because of failures linked to stability requirements or inappropriate fishing operations, since their associated nodes are green, and so do not present any danger. Instead, the sea environment being rough (90%), deficient human intervention (82%), and, more importantly, safety-threatening loading conditions aboard, which is almost certain (98%), are liable for the 0.86 probability of LoS occurring.

Also, in Figure 5.22, the arc widths (corresponding to the interaction probabilities specified in Figure 5.20) have thickened. It was achieved by engaging the "Enable variable arc widths" feature in QGeNle. Judging from the thickness of the arc widths, the information path for the Risk Factors 1 sub-network is the least critical.

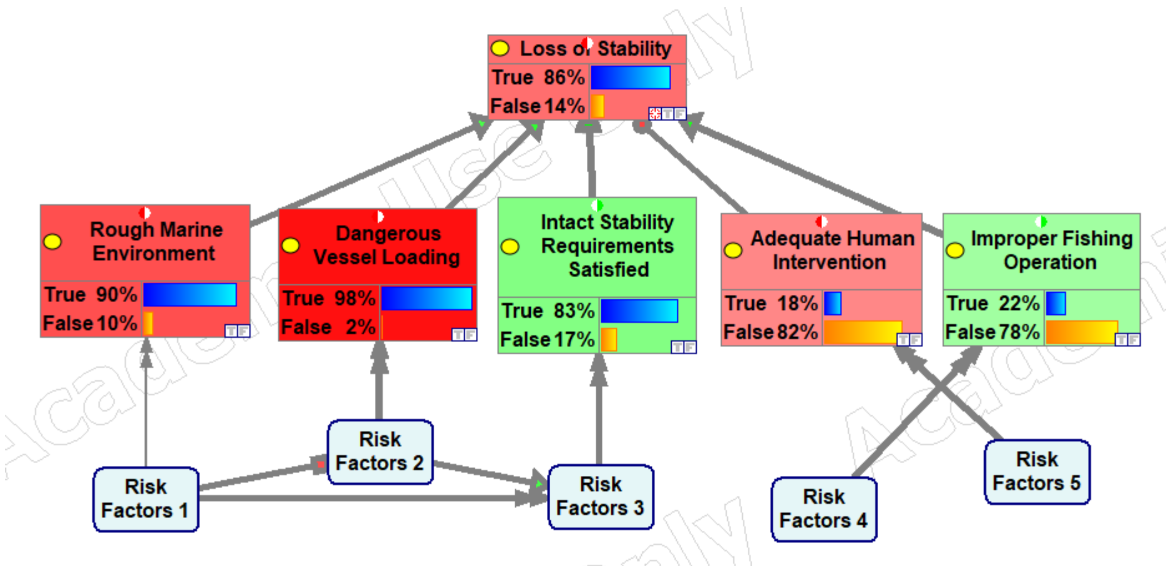

Figure 5.22. The analysis results based on the risk influencing factors activated.

From the above discussion, if Figure 5.22 is shown without the scores, as in Figure 5.23, the colour coding and arc widths can be used to reach the same conclusions drawn so far. Thus, as qualitative measures, the colouring and visual display of arc thickness facilitate qualitative risk analysis. The qualitative measures can help reach the same conclusions as the PRA.

Also, the De Morgan gates are additional qualitative measures. By activating the node, the impact of the gate type it is connected to in the LoS risk analysis tool can be studied, and inferences made about the status of risk perceived. Therefore, developing a BN model using De Morgan gates gives not only the advantage of reducing the size of conditional probability tables at child nodes but also enables qualitative and quantitative risk analyses to be undertaken simultaneously.

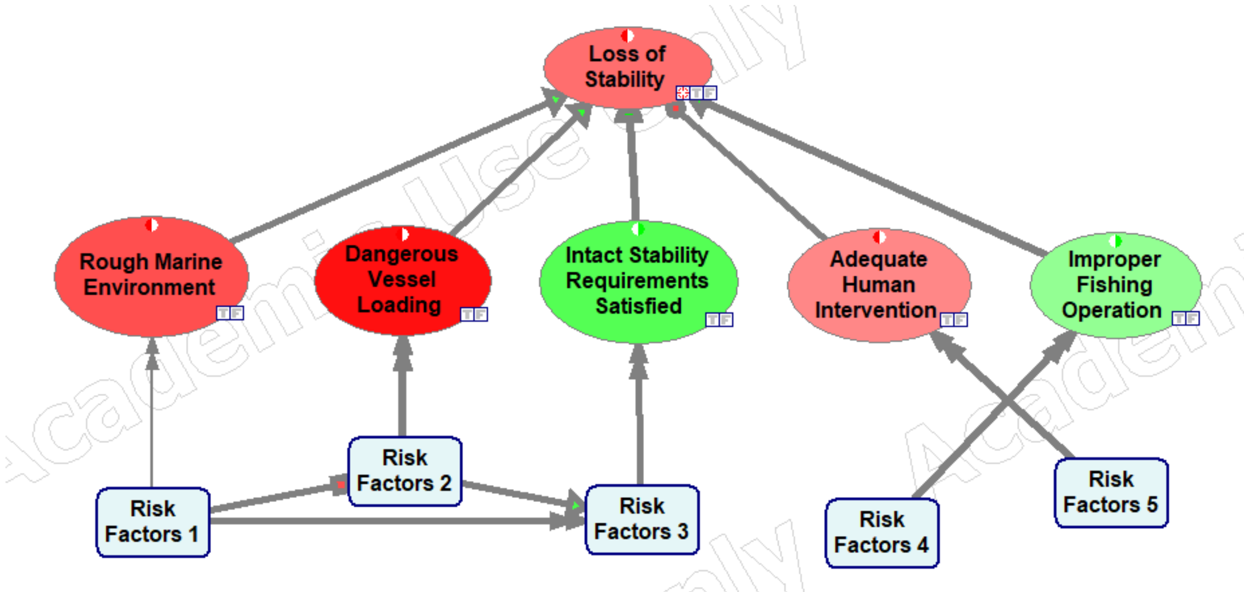

Figure 5.23. The analysis results in qualitative form only.

5.3.5. Predicting a remedy to lower the LoS probability

It is essential to know the RIFs to address to avoid the possibility of LoS. These are risk factors contributing significantly to the 86% LoS occurrence rate. QGeNIe allows you to learn these factors through the software's "Most effective actions window" feature. It identified (see Figure 5.24) "Adequate human intervention" and "Crew understanding of stability is poor" as the top factors needing redress to reduce the probability of LoS occurrence. However, the high score of 63% informs that control measures targeted at "Adequate human intervention" is the most effective action to minimise the 86% LoS occurrence rate.

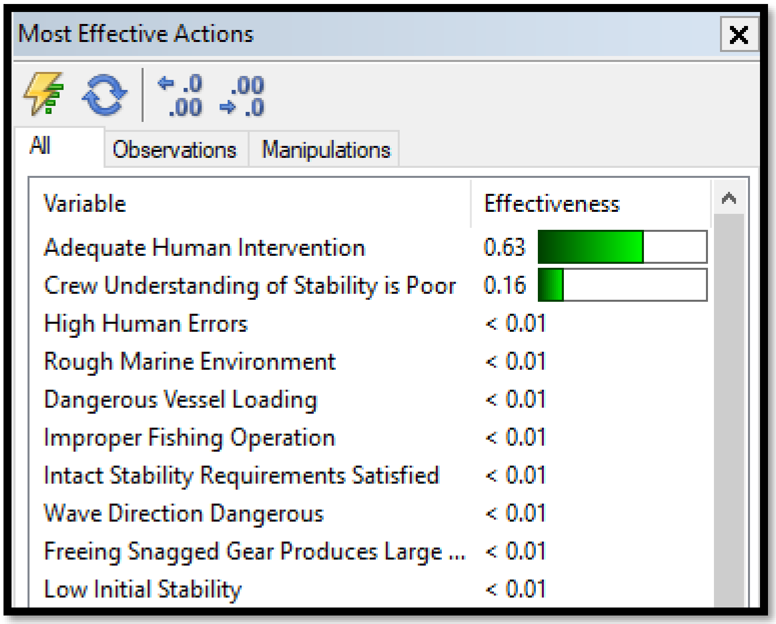

Figure 5.24. Effectiveness scores for nodes in the QBN model.

To confirm the effectiveness of the predicted corrective measure, the "True" state (i.e., True = 100%) of the "Adequate human intervention" node was activated. The LoS risk analysis tool updates the results, as shown in Figure 5.25. The "Loss of Stability" node is now green, illustrating that it is unlikely (74%) that LoS would occur. Therefore, the corrective measure predicted is indeed effective. Practically, the corrective measure could be implemented by checking all the human-related operations for sufficient risk control measures and ensuring fishers do their work correctly.

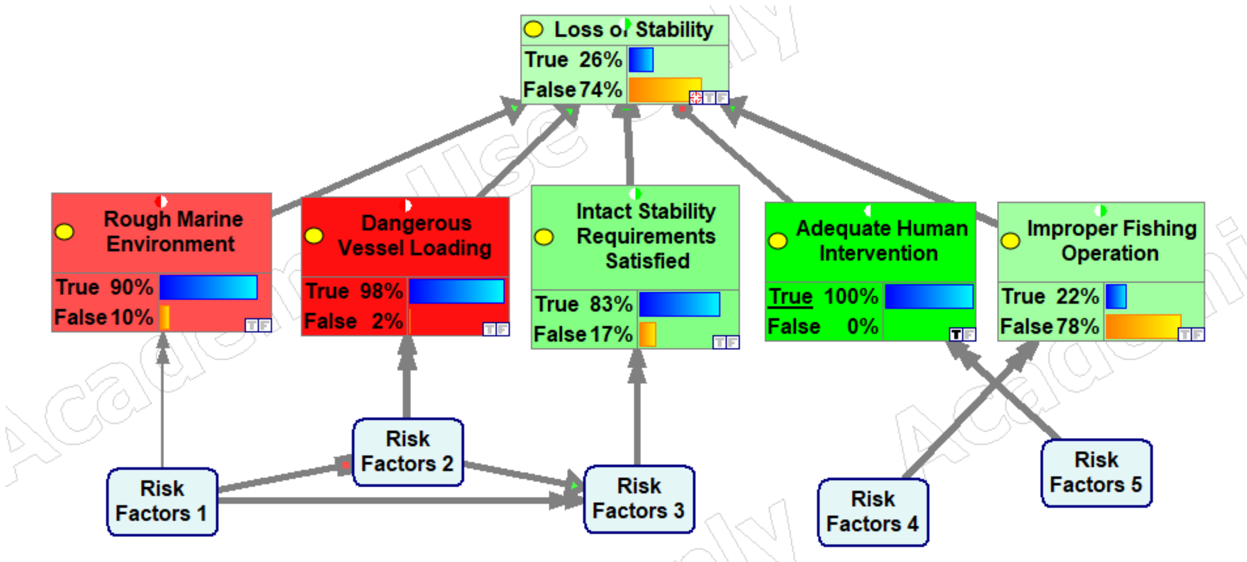

Figure 5.25. New score for the loss of stability after effecting correction.

5.3.6. Summary of findings and the study limitations

The study undertaken for LoS risk analysis resulted in four main findings. First, factors influencing LoS aboard small fishing vessels can be captured at the systems level by SEA and conveniently modelled in BN for the purpose of analysing ship stability proactively through LoS risk estimation. Because the RIFs independently impact LoS and the impact varies beside a cause, the ability to use De Morgan gates for LoS risk modelling is considered important. Secondly, using De Morgan gates produces less cumbersome conditional probability tables in a BN model, making the LoS risk analysis tool simple to develop. Thirdly, the case study shows that the shipboard crew only need to observe the state of a RIF and use the tool to evaluate the likelihood of an LoS. Lastly, apart from the probability scores outputted by the tool, which enables LoS likelihood to be determined numerically, the colouring of nodes in the tool and the width of the arcs joining the nodes could also be used to arrive at the same likelihood decision. This means the LoS risk analysis tool can facilitate quantitative or qualitatively probabilistic risk assessment.

Meanwhile, using De Morgan gates gives rise to subjective limitations. Apart from differences that could arise in the network structure due to how RIFs were captured by SEA, among a group of analysts, different choices of gates could emerge. Thus, inconsistency in assigning gates correctively is a suspected challenge. Nevertheless, these limitations can be overcome with deep knowledge about the incident being modelled, detailed understanding of how it occurs, and engaging the services of an experienced risk analyst.

Unlike the BN model, where a risk factor with more than two states can be modelled, in the developed LoS risk analysis tool, only two states are allowed for a RIF. Hence, such tools must be developed only for incidents whose RIFs have only two states. The independence of causal influence adhered to in the tool (due to the use of De Morgan gates) calls for proper investigation prior to the BN modelling to ensure there are no child nodes that depend on the simultaneous occurrence of more than one parent node. Each parent node must independently influence the child node for the tool to be adjudged structurally accurate.

Finally, the tool is likely limited by the RIFs considered for LoS risk analysis. Such limitation would probably come from the innovation researchers sought to make, and the references consulted in enlisting RIFs. The limitation could be overcome by broadening the scope of references beyond small and medium fishing vessels to include LoS issues in other marine vessel types if the tool must be used outside the SFV sector.

5.4. Conclusion

In this study, a quantitative risk analysis tool was developed for loss of stability (LoS) investigation in small fishing vessels (SFV). Literature on SFV identifies LoS as a precursor for vessel capsize accidents. Meanwhile, vessel capsize is among the leading accidents in the commercial fishing industry, causing SFV fisher deaths in alarming numbers. Tackling LoS risk, then, is a significant step towards addressing vessel capsize accidents. The developed risk analysis tool can learn various scenarios under which LoS may occur for a given likelihood rate. In an example case study, a 0.86 probability for LoS occurrence was predicted. The corresponding scenarios the tool predicted for the 0.86 rate were rough sea (90%), poor loading aboard (98%), and lapses in human interventions (18%). With these results, the shipboard crew can now take adequate steps to address the scenarios and reduce the 86% chance of LoS. Any possible capsize accident would then be avoided.

Compared with other LoS studies, the current study differs in many ways. First, most existing LoS studies subscribe to the deterministic view, making their resulting tools deterministic. On the contrary, the current study adopted the probabilistic viewpoint since varied factors are involved when it comes to LoS on ships; additionally, when and how these factors would occur is covered with lots of uncertainty. Secondly, for previous studies with probabilistic LoS tools, the focal risk influencing factors (RIF) have usually been the shipboard loads and the marine environment dynamics. In addition to these RIFs, the current study's tool incorporates human factors since the shipboard crew's actions and inactions are vital to ship stability at sea. Lastly, the current study differs from other LoS studies because LoS is approached as a risk problem, and the tool developed for it is based on Bayesian network modelling with De Morgan gates involved.

De Morgan gates enable the LoS risk analysis tool developed to do both quantitative and qualitative risk analysis simultaneously. In previous studies, it is not common to find risk analysis tools that use De Morgan gates to do a probabilistic risk assessment. Therefore, through the developed LoS risk analysis tool, the current study contributes towards bridging this knowledge gap. The tool adds to similar easy-to-use tools available for SFVs safety management.

Owners of SFVs, the commercial fishing industry, fishing safety researchers, and shipping companies are the main beneficiaries of the present study. They could follow the methodology to develop tailor-made risk analysis tools for managing LoS aboard specific vessels. For future studies, developing similar tools for SFV incidents whose RIFs could be modelled as independence of causal influence is encouraged.

Reference

[1] F. Mata-Álvarez-Santullano and A. Souto-Iglesias, "Stability, safety and operability of small fishing vessels," Ocean Engineering, vol. 79, pp. 81–91, Mar. 2014, doi: 10.1016/j.oceaneng.2014.01.011.

[2] B. Davis, B. Colbourne, and D. Molyneux, "Analysis of fishing vessel capsizing causes and links to operator stability training," Saf Sci, vol. 118, pp. 355–363, Oct. 2019, doi: 10.1016/j.ssci.2019.05.017.

[3] J. Alvite-Castro, J. A. Orosa, D. Vergara, Á. M. Costa, and R. Bouzón, "A new design criterion to improve the intact stability of galician small fishing vessels," J Mar Sci Eng, vol. 8, no. 8, Jul. 2020, doi: 10.3390/JMSE8070499.

[4] F. Mata-Álvarez-Santullano and A. Souto-Iglesias, "Fishing effort control policies and ship stability: Analysis of a string of accidents in Spain in the period 2004-2007," Mar Policy, vol. 40, no. 1, pp. 10–17, Jul. 2013, doi: 10.1016/j.marpol.2012.12.027.

[5] M. M. González, P. C. Sobrino, R. T. Álvarez, V. D. Casás, A. M. López, and F. L. Peña, "Fishing vessel stability assessment system," Ocean Engineering, vol. 41, pp. 67–78, Feb. 2012, doi: 10.1016/j.oceaneng.2011.12.021.

[6] F. Obeng, V. Domeh, F. Khan, N. Bose, and E. Sanli, "Capsizing accident scenario model for small fishing trawler," Saf Sci, vol. 145, Jan. 2022, doi: 10.1016/j.ssci.2021.105500.

[7] E. C. Tupper, "Flotation and Initial Stability," in Introduction to Naval Architecture, 4th ed., Burlington: Elsevier Ltd., 2004, pp. 62–86.

[8] R. Pemberton and E. A. Stokoe, "Stability of Ships," in Naval Architecture for Marine Engineers, 5th ed., London: Bloomsbury Publishing Plc, 2018, pp. 63–92.

[9] A. Molland, "Flotation and stability," in The Maritime Engineering Reference Book - A Guide to Ship Design, Construction, and Operation, Burlington: Elsevier Ltd., 2008, pp. 75–114.

[10] M. Iqbal, M. Terziev, T. Tezdogan, and A. Incecik, "Operability analysis of traditional small fishing boats in Indonesia with different loading conditions," Ships and Offshore Structures, 2022, doi: 10.1080/17445302.2022.2107300.

[11] J. L. Mantari, S. Ribeiro E Silva, and C. Guedes Soares, "Intact stability of fishing vessels under combined action of fishing gear, beam waves and wind," Ocean Engineering, vol. 38, no. 17–18, pp. 1989–1999, Dec. 2011, doi: 10.1016/j.oceaneng.2011.09.018.

[12] P. Chorab, “Scientific Journals, Sample calculations using a draft method for assessment of the vulnerability to pure loss of stability of a fishing vessel,” Zeszyty Naukowe, vol. 40, no. 112, pp. 39–46, 2014.

[13] N. Umeda and Y. Yamakoshi, “Probability of ship capsizing due to pure loss of stability in quartering seas,” Naval Architecture and Ocean Engineering , vol. 30, pp. 73–85, 1998.

[14] A. Francescutto, “Intact stability criteria of ships - Past, present and future,” Ocean Eng., vol. 120, pp. 312–317, 2016.

[15] N. Petacco and P. Gualeni, “IMO second generation intact stability criteria: General overview and focus on operational measures,” J. Mar. Sci. Eng., vol. 8, no. 8, 2020.

[16] L. Liu, C. Yao, D. Feng, X. Wang, J. Yu, and M. Chen, “Numerical study of the interaction between the pure loss of stability, surf-riding, and broaching on ship capsizing,” Ocean Engineering, vol. 266, Dec. 2022, doi: 10.1016/j.oceaneng.2022.112868.

[17] J. Lu, M. Gu, and E. Boulougouris, “Model experiments and direct stability assessments on pure loss of stability in stern quartering waves,” Ocean Engineering, vol. 216, Nov. 2020, doi: 10.1016/j.oceaneng.2020.108035.

[18] J. Lu, M. Gu, and E. Boulougouris, “Model experiments and direct stability assessments on pure loss of stability of the ONR tumblehome in following seas,” Ocean Engineering, vol. 194, Dec. 2019, doi: 10.1016/j.oceaneng.2019.106640.

[19] A. Maki et al., “On the loss of stability of periodic oscillations and its relevance to ship capsize,” Journal of Marine Science and Technology (Japan), vol. 24, no. 3, pp. 846–854, Sep. 2019, doi: 10.1007/s00773-018-0591-x.

[20] C. Andrei, M. Danut Lamba, and R. H. Pazara, “A PROPOSED CRITERION FOR ASSESSMENT THE PURE LOSS OF STABILITY OF SHIPS IN LONGITUDINAL WAVES,” U.P.B. Sci. Bull., Series D, vol. 77, no. 2, 2015.

[21] Z. Szozda and P. Krata, “Towards evaluation of the second generation intact stability criteria - Examination of a fishing vessel vulnerability to surf-riding, based on historical capsizing,” Ocean Engineering, vol. 248, Mar. 2022, doi: 10.1016/j.oceaneng.2022.110796.

[22] K. Wróbel, J. Montewka, and P. Kujala, “Towards the assessment of potential impact of unmanned vessels on maritime transportation safety,” Reliab Eng Syst Saf, vol. 165, pp. 155–169, Sep. 2017, doi: 10.1016/j.ress.2017.03.029.

[23] M. Míguez González and G. Bulian, “Influence of ship dynamics modelling on the prediction of fishing vessels roll response in beam and longitudinal waves,” Ocean Engineering, vol. 148, pp. 312–330, Jan. 2018, doi: 10.1016/j.oceaneng.2017.11.032.

[24] F. Uğurlu, S. Yıldız, M. Boran, Ö. Uğurlu, and J. Wang, “Analysis of fishing vessel accidents with Bayesian network and Chi-square methods,” Ocean Engineering, vol. 198, Feb. 2020, doi: 10.1016/j.oceaneng.2020.106956.

[25] M. Míguez González, V. D. Casás, L. P. Rojas, F. J. Ocampo, and D. P. Agras, “Application of Second Generation IMO Intact Stability Criteria to Medium – Sized Fishing Vessels.”

[26] M. M. González, P. C. Sobrino, R. T. Álvarez, V. D. Casás, A. M. López, and F. L. Peña, “Fishing vessel stability assessment system,” Ocean Engineering, vol. 41, pp. 67–78, Feb. 2012, doi: 10.1016/j.oceaneng.2011.12.021.

[27] R. He, X. Li, G. Chen, Y. Wang, S. Jiang, and C. Zhi, “A quantitative risk analysis model considering uncertain information,” Process Safety and Environmental Protection, vol. 118, pp. 361–370, Aug. 2018, doi: 10.1016/j.psep.2018.06.029.

[28] S. Majid, “Quantum geometry of Boolean algebras and de Morgan duality,” Nov. 2019, [Online]. Available: http://arxiv.org/abs/1911.12127.

[29] F. J. Díez and M. J. Druzdzel, “Canonical Probabilistic Models for Knowledge Engineering,” 2006.

[30] L. BayesFusion, “QGeNle Modeler User Manual ,” Jun. 2022. Accessed: Dec. 19, 2022. [Online]. Available: https://support.bayesfusion.com/docs/.

[31] E. Özaydın, R. Fışkın, Ö. Uğurlu, and J. Wang, “A hybrid model for marine accident analysis based on Bayesian Network (BN) and Association Rule Mining (ARM),” Ocean Engineering, vol. 247, Mar. 2022, doi: 10.1016/j.oceaneng.2022.110705.

[32] A. A. Baksh, R. Abbassi, V. Garaniya, and F. Khan, “Marine transportation risk assessment using Bayesian Network: Application to Arctic waters,” Ocean Engineering, vol. 159, pp. 422–436, Jul. 2018, doi: 10.1016/j.oceaneng.2018.04.024.

[33] S. G. Chowdhury and K. B. Misra, “Use of De Morgan”s Theorem in System Reliability Studies ,” in Microelectronics and Reliability , G. W. A. Dummer and H. Reiche, Eds. 1990, pp. 465–468.

[34] E. McGuinness and I. B. Utne, “A systems engineering approach to implementation of safety management systems in the Norwegian fishing fleet,” Reliab Eng Syst Saf, vol. 121, pp. 221–239, 2014, doi: 10.1016/j.ress.2013.08.002.

[35] INCOSE, INCOSE Systems Engineering Handbook, Version 3. 2006.

[36] H. Li, X. Ren, and Z. Yang, “Data-driven Bayesian network for risk analysis of global maritime accidents,” Reliab Eng Syst Saf, vol. 230, p. 108938, Feb. 2023, doi: 10.1016/j.ress.2022.108938.

[37] Y. E. Senol and F. Yasli, “A risk analysis study for chemical cargo tank cleaning process using Fuzzy Bayesian Network,” Ocean Engineering, vol. 235, Sep. 2021, doi: 10.1016/j.oceaneng.2021.109360.

[38] F. Obeng, V. Domeh, F. Khan, N. Bose, and E. Sanli, “Analysing operational risk for small fishing vessels considering crew effectiveness,” Ocean Engineering, vol. 249, Apr. 2022, doi: 10.1016/j.oceaneng.2021.110512.

[39] F. Goerlandt and G. Reniers, “On the assessment of uncertainty in risk diagrams,” Safety Science, vol. 84. Elsevier, pp. 67–77, Apr. 01, 2016. doi: 10.1016/j.ssci.2015.12.001.

[40] J. Khorsandi and T. Aven, “Incorporating assumption deviation risk in quantitative risk assessments: A semi-quantitative approach,” Reliab Eng Syst Saf, vol. 163, pp. 22–32, Jul. 2017, doi: 10.1016/j.ress.2017.01.018.

[41] A. Kossiakoff, W. N. Sweet, S. J. Seymour, and S. M. Biemer, “Systems Engineering Approaches ,” in Systems Engineering Principles and Practice , 2nd ed., A. P. Sage, Ed. A John Wiley & Sons, Inc. , 2011, pp. 36–37.

[42] I. Animah and M. Shafiee, “Application of risk analysis in the liquefied natural gas (LNG) sector: An overview,” Journal of Loss Prevention in the Process Industries, vol. 63. Elsevier Ltd, Jan. 01, 2020. doi: 10.1016/j.jlp.2019.103980.

[43] Anand Pillay, “FORMAL SAFETY ASSESSMENT OF FISHING VESSELS,” 2001.

[44] M. Leimeister and A. Kolios, “A review of reliability-based methods for risk analysis and their application in the offshore wind industry,” Renewable and Sustainable Energy Reviews, vol. 91. Elsevier Ltd, pp. 1065–1076, Aug. 01, 2018. doi: 10.1016/j.rser.2018.04.004.

[45] B. Deakin, “DEVELOPMENT OF STABILITY AND LOADING INFORMATION FOR SMALL FISHING VESSELS.” [Online]. Available: www.mcga.gov.uk.

[46] A. Francescutto, G. Bulian, M. U. Larios, and M. Arroyo Ulloa, “Stability and dynamical effects of water on deck on the survivability of small fishing vessels,” 2009.

[47] P. Rojas, L. Abad, P. Arribas, and F. Arias, “SOME EXPERIMENTAL RESULTS ON THE STABILITY OF FISHING VESSELS.”

[48] S. Rezaee, M. R. Brooks, and R. Pelot, “Review of fishing safety policies in Canada with respect to extreme environmental conditions and climate change effects,” WMU Journal of Maritime Affairs, vol. 16, no. 1, pp. 1–17, Jan. 2017, doi: 10.1007/s13437-016-0110-z.

[49] P. Krata, “Total Losses of Fishing Vessels Due to the Insufficient Stability,” 2008.

[50] I. Senjanović, J. Parunov, and G. Ciprić, “Safety analysis of ship rolling in rough sea,” Chaos Solitons Fractals, vol. 8, no. 4, pp. 659–680, Apr. 1997, doi: 10.1016/S0960-0779(96)00114-2.

[51] Z. Yu, Y. Shen, J. Amdahl, and M. Greco, “Implementation of linear potential-flow theory in the 6DOF coupled simulation of ship collision and grounding accidents,” Journal of Ship Research, vol. 60, no. 3, pp. 119–144, Sep. 2016, doi: 10.5957/JOSR.60.3.160012.

[52] B. T. Hill, S. John, and C. Brian, “Ship Collision with Iceberg Database.” [Online]. Available: http://nparc.cisti-icist.nrc-cnrc.gc.ca/npsi/jsp/nparc_cp.jsp?lang=frL”accèsàcesiteWebetl”utilisationdesoncontenusontassujettisauxconditionsprésentéesdanslesitehttp://nparc.cisti-icist.nrc-cnrc.gc.ca/npsi/jsp/nparc_cp.jsp?lang=en.

[53] M. A. Santos Neves, N. Pérez, and O. Lorca, “Analysis of roll motion and stability of a fishing vessel in head seas,” Ocean Engineering, vol. 30, no. 7, pp. 921–935, 2003, doi: 10.1016/S0029-8018(02)00066-5.

[54] L. BayesFusion, “GeNle Modeler User Manual,” Oct. 2022. Accessed: Dec. 19, 2022. [Online]. Available: https://support.bayesfusion.com/docs/.

[55] P. S. Turocy, “Survey Research in Athletic Training: The Scientific Method of Development and Implementation,” Association, Inc, 2002. [Online]. Available: www.journalofathletictraining.org.

[56] Q. Yu, K. Liu, C. Chang, Z. Y.-R. E. & S. Safety, and undefined 2020, “Realising advanced risk assessment of vessel traffic flows near offshore wind farms,” Elsevier, Accessed: Dec. 20, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0951832020305871.

[57] K. J. Rawson and E. C. Tupper, “Stability,” in Basic Ship Theory, Woburn : Butterworth-Heinemann , 2001, pp. 91–137.

[58] A. B. Biran and R. Lopez-Pulido, Ship Hydrostatics and Stability, 2nd ed. Waltham: Elsevier Ltd., 2014.

CHAPTER 6

6.0. Summary, Conclusions, and Recommendations

6.1. Summary of the Thesis Study

The literature on commercial fishing accidents identifies the small fishing boat (or vessel) sector as one area to reduce the high accident rate in the fishing industry. Worldwide, the industry is known among the most dangerous occupations due to the frequent fisher deaths and injuries recorded [1, 2]. Most of these deaths and injuries are traceable to fishers in small fishing boats (SFB) [3, 4]. Hence, the expectation is that if safety can be enhanced aboard SFBs, the industry will be on its way to reducing the record-high-accident rate substantially.

These boats, which generally have a length overall not exceeding 24 m, are not regulated directly by the International Maritime Organisation (IMO). Instead, national maritime authorities regulate and oversee how fishers practice their profession. However, not all maritime administrations in the various countries where these boats operate may have detailed and very effective policies to curb accident occurrences aboard SFBs. As a result, SFBs and their sector industry are not adequately tooled to handle the safety threats confronting fishers at sea [4, 5].

To improve safety aboard SFBs, researchers have been developing assessment tools to identify fishing incidents and their risk-influencing factors before they result in an accident. Some fishing accidents have been studied, and appropriate probabilistic safety analysis (PSA) tools have been developed by the researchers for pre-accident analysis. For example, Obeng et al. [6] and Uğurlu et al. [7] developed PSA tools for vessel capsize, collision, and grounding. Meanwhile, similar tools for fishing incidents—man or person overboard (MOB), main propulsion system failure, loss of situation awareness, and the loss of stability—are absent in the literature. These incidents are among the leading accidents occurring aboard SFBs. Therefore, this thesis study focused on these accident types and developed methodologies and PSA tools for their pre-accident assessment needs.

In recent years, quantitative risk analysis using the Bayesian network (BN) has emerged as one approach for developing pre-accident analysis tools [1, 8]. In industries such as chemical, offshore, and maritime shipping, where the approach has been widely applied, suitable tailor-made PSA tools capable of pre-accident analysis have been developed to enhance safety [8—10]. The approach is also gradually gaining popularity in the fishing industry. As a result, quantitative risk analysis using BN was applied to the incidents: MOB, main propulsion system failure, loss of situational awareness, and loss of stability. In the end, risk analysis tools tailored to the safety needs of SFBs were developed for the incidents mentioned.

6.2. Conclusions from the Thesis Study

This thesis study published three peer-reviewed journal articles on MOB scenario analysis, risk-based maintenance (RBM) programming for ships' main propulsion system, and loss of situational awareness. A fourth paper on loss of stability risk analysis is undergoing peer review in Ocean Engineering. These publications are contributions made by the thesis to the literature on SFB safety and the development of pre-accident analysis tools for accident or incident management. Apart from the PSA tools in the publications, the RBM schedule for SFBs, the MOB intervention model, and the fusion of BN and De Morgan gates to model the loss of stability incident are other novel theoretical contributions the thesis study made. Below are the main findings realised from the study:

- Easy-to-use PSA tools can be developed in BN to compensate for the inadequate equipment aboard SFBs for safety assessment. The risk analysis models developed for a person overboard, main propulsion system failure, loss of situation awareness, and loss of stability are typical examples of the PSA tools emerging from BN modelling;
- By integrating fishers' knowledge about their experiences at sea and the science of cause-effect modelling, simple-to-use monitoring programmes can emerge to create awareness of potentially dangerous situations ahead of time. This was achieved by the risk awareness tool and its subsequent instantaneous monitoring programme developed for SFB use in chapter four of the thesis study;
- Risk-based maintenance (RBM) scheduling is known for decreasing maintenance costs and extending the availability of machinery. The US$ 218,620.54 reduction in maintenance cost plus the most critical maintenance interval time of 65 days, both from the case-study RBM done in the thesis chapter three, are a confirmation that the cost savings and extended availability time assertions for the RBM are true;
- When De Morgan gates—CAUSE, INHIBITOR, REQUIREMENT, and BARRIER—are integrated into the BN model, qualitative analysis and probabilistic risk analysis can be performed simultaneously. The BN model developed in the thesis chapter five and its subsequent application to the incident, loss of stability aboard SFBs serves as evidence for this finding;
- In evaluating risk estimates from BN models, comparing the occurrence and nonoccurrence state scores for a node is another way of assessing a risk influencing factor for its likelihood to occur. The five-points-risk-assessment scale developed in the fourth chapter of the thesis study is typical evidence of this risk evaluation approach;

- The variability in subject-matter experts scoring when eliciting probabilities for the conditional probability tables (CPT) in BN could be minimised through pre-defined probability scoring scale use. This was done in chapter four, and the outcome showed that the reliability of estimates from BN models could be enhanced when such scales are used;
- A knowledge mobilization plan is required to promote the PSA tools use in the SFB sector, particularly in remote fishing communities. It will create awareness of the usefulness of the tools in solving the safety challenges confronting these fishing communities. Typical elements in the plan may include creating and distributing flyers, organising stage plays, and engaging the local fishing associations in discussions on PSA tools use;
- Because PSA tools application is still new in the SFB sector and has subjective components, policy formulation is required by national governments wanting to use the tools. Among other things, the policy must consider the scope for defining risk-influencing factors for an incident or accident and the probability scores to assign to CPTs.

6.3. Recommendations for Practice and Future Research

The thesis study is recommended to fishing vessel owners and skippers, the SFB sector in particular, fishing safety researchers, and maritime administrations in charge of commercial fishing safety. The PSA tools developed in the thesis aim to aid in understanding and managing safety challenges in SFBs. Policy analysts may find the tools helpful in analysing the variety of ways accidents can happen aboard SFBs, thereby helping them develop the appropriate policies to implement control measures.

When using the tools, it must be noted that, because the risk factors employed in developing the tools were sourced from literature, the tools are limited in that context. Additionally, the tools are fundamentally BN models, and so, are also limited by the probabilities inputted into CPTs. Hence, before using the tools developed, the risk factors and probabilities for CPTs must be examined to know if they fit the application context well. The concept for modelling scenarios and incidents leading to the tools development is subjective too, partly based on the literature reviewed and partly on the innovation the thesis author sought to reveal. It is, therefore, advisable to examine the tool's programming logic for compatibility with the case to be applied.

Suggested research to further the discussion on understanding and managing safety aboard small fishing boats are as follows:

- Engineering the PSA tools into portable devices—most small fishing boat fishers have education levels below high school. As such, operationalising the PSA tools as described in the thesis study may prove difficult for some onboard fishers. Engineering the tools into portable devices, like the handheld calculator, could make them operationally friendly to the fishers;
- Risk communication in small fishing boats—communicating risk is very vital in risk management. In well-equipped marine vessels, sensors, warning symbols, signposts, and even shipboard drills are ways risk is communicated. It may be useful to study risk communication aboard SFBs since they do not have sophisticated equipment and organised programmes for that purpose;
- A dynamic risk management programme for SFB safety—the ability to collect real-time data automatically for time-driven operationalisation of the PSA tools developed, must be considered if a robust risk management system is envisaged for these boats;
- The study objectives could be implemented in a specific SFB to uncover field-based risk influencing factors and to develop tailor-made PSA tools for that SFB.

References

[1] F. Uğurlu, S. Yıldız, M. Boran, Ö. Uğurlu, and J. Wang, "Analysis of fishing vessel accidents with Bayesian network and Chi-square methods," Ocean Engineering, vol. 198, Feb. 2020, doi: 10.1016/j.oceaneng.2020.106956.

[2] S. E. Roberts, "Britain's most hazardous occupation: Commercial fishing," Accid Anal Prev, vol. 42, no. 1, pp. 44–49, Jan. 2010, doi: 10.1016/j.aap.2009.06.031.

[3] E. McGuinness, H. L. Aasjord, I. B. Utne, and I. M. Holmen, "Fatalities in the Norwegian fishing fleet 1990-2011," Saf Sci, vol. 57, pp. 335–351, Aug. 2013, doi: 10.1016/j.ssci.2013.03.009.

[4] J. Wang, A. Pillay, Y. S. Kwon, A. D. Wall, and C. G. Loughran, "An analysis of fishing vessel accidents," Accid Anal Prev, vol. 37, no. 6, pp. 1019–1024, 2005, doi: 10.1016/j.aap.2005.05.005.

[5] B. Davis, B. Colbourne, and D. Molyneux, "Analysis of fishing vessel capsizing causes and links to operator stability training," Saf Sci, vol. 118, pp. 355–363, Oct. 2019, doi: 10.1016/j.ssci.2019.05.017.

[6] F. Obeng, V. Domeh, F. Khan, N. Bose, and E. Sanli, "Capsizing accident scenario model for small fishing trawler," Saf Sci, vol. 145, Jan. 2022, doi: 10.1016/j.ssci.2021.105500.

[7] Ö. Uğurlu, E. Köse, U. Yıldırım, and E. Yüksekyıldız, "Marine accident analysis for collision and grounding in oil tanker using FTA method," Maritime Policy and Management, vol. 42, no. 2, pp. 163–185, Feb. 2015, doi: 10.1080/03088839.2013.856524.

[8] H. Liwång, J. W. Ringsberg, and M. Norsell, "Quantitative risk analysis - Ship security analysis for effective risk control options," Saf Sci, vol. 58, pp. 98–112, Oct. 2013, doi: 10.1016/j.ssci.2013.04.003.

[9] S. Nguyen, P. S. L. Chen, Y. Du, and W. Shi, "A quantitative risk analysis model with integrated deliberative Delphi platform for container shipping operational risks," Transp Res E Logist Transp Rev, vol. 129, pp. 203–227, Sep. 2019, doi: 10.1016/j.tre.2019.08.002.

[10] M. Yazdi, A. Nedjati, E. Zarei, and R. Abbassi, "A novel extension of DEMATEL approach for probabilistic safety analysis in process systems," Saf Sci, vol. 121, pp. 119–136, Jan. 2020, doi: 10.1016/j.ssci.2019.09.006.