Risk Assessment and Dynamic Decision Making in Maritime Transportation

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By

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DECLARATION

I, **Sunay Pundalik Pai**, hereby declare that this thesis represents work which has been carried out by me and that it has not been submitted, either in part or full, to any other University or Institution for the award of any research degree.

Place: Taleigao Plateau.

Date: 16-12-2021 **Sunay Pundalik Pai**

CERTIFICATE

I hereby certify that the above Declaration of the candidate, **Sunay Pundalik Pai,** is true and the work was carried out under my supervision.

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ABSTRACT

Health and safety are indispensable. Risk assessment is a principal management tool in ensuring not only the health and safety of people around but also identifying and eliminating hazards that may create harm to the environment. Decision making in risk assessment is mostly based on ambiguous data. The problem of risk assessment and decision making in static and dynamic conditions in maritime transportation is attempted here. The problem is dealt with using fuzzy, neutrosophic and plithogenic set theories.

After the initial introduction and literature survey, the risk assessment problem related to maritime transportation is stated. The research problem is threefold: (i) checking the effectiveness of the tools like Bayesian belief network, evidential reasoning and fuzzy multi criteria decision making methods suitable for efficient reasoning under uncertainty (ii) creating a framework for estimating the risk in maritime transportation and (iii) introducing a framework for dynamic decision making in integrated approach/method

Major solution methodologies used in this thesis are Interpretive structural modeling, fuzzy analytical network process, D-S theory of evidence, DSmT theory of evidence, fuzzy set theory, neutrosophic set theory, plithogenic set theory, methods for combining experts' judgement and distance measures.

In the first part, a new hybrid risk assessment method is devised suitable for applications in complex systems with many interconnected factors. The data are incomplete and fuzzy. Interpretive Structural Modelling is used to get the interrelations between factors. A fuzzy analytical network process is used to get the weight of the factors. The evidential reasoning approach is used to get the risk level of the system. A new alternative is added in the D-S theory of evidence to overcome its limitations when the series of evidence to be combined are in a high degree of conflict. The proposed alternative incorporated the possibility of error from experts while making judgements.

In the second part, risk assessment and safety analysis of the marine systems is carried out. Three cases are formulated using the concept of neutrosophic logic IF-THEN rules, neutrosophic set theory and plithogenic set theory, respectively.

In the real world, decisions are required to be taken in dynamic conditions. Here, factors influencing the decisions change periodically. Decision making in dynamic conditions requires the fusion of data gathered at different periods and different operating conditions. Such problem of decision making in dynamic conditions is dealt with in the last part of the thesis. This includes creating three operators: basic belief assignment operator, dynamic basic belief operator and dynamic weight vector operator.

Keywords: Risk Assessment, Interpretive Structural Modelling, Fuzzy Analytical Network Process, D-S Theory of Evidence, DSmT Theory of Evidence, Fuzzy Set Theory, Neutrosophic Set Theory, Plithogenic Set Theory, Basic Belief Assignment Operator, Dynamic Basic Belief Assignment Operator, Dynamic Weight Vector Operator

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List of Abbreviations, Notations and Nomenclature

Abbreviations

IMO	: International Maritime Organisation
UN	: United Nations
SOLAS	: Safety of Life at Sea
STCW	: Standards of Training, Certification and Watchkeeping for Seafarers
AHP	: Analytical Hierarchy Process
FMEA	: Failure Mode Effects Analysis
DST	: Dempster-Shafer Theory of Evidence
ETA	: Event Tree Analysis
FTA	: Fault Tree Analysis
BBA	: Basic Belief Assignment
FST	: Fuzzy Set Theory
SVNS	: Single Valued Neutrosophic Set
NST	: Neutrosophic Set Theory
PST	: Plithogenic Set Theory
BBN	: Bayesian Belief Network
ISM	: Interpretive Structural Modelling
FANP	: Fuzzy Analytical Network Process
ER	: Evidential Reasoning
FSA	: Formal Safety Assessment
RL	: Risk Level
FL	: Failure Likelihood
CS	: Consequence Severity
RCO	: Risk Control Options
SSIM	: Structural Self Interaction Matrix
IRM	: Initial Reachability Matrix
FRM	: Final Reachability Matrix
ANP	: Analytical Network Process
SVNN	: Single Valued Neutrosophic Number

WAM	: Weighted Average Method
EIJ	: Error in Judgement
IVIFS	: Interval Valued Intuitionistic Fuzzy Set
SVTNN	: Single Valued Trapezoidal Neutrosophic Number
INN	: Interval Neutrosophic Number
DIVNS	: Dynamic Interval Valued Neutrosophic Set
DIVNN	: Dynamic Interval Valued Neutrosophic Number
DBBAO	: Dynamic Basic Belief Assignment Operator
DBBA	: Dynamic Basic Belief Assignment
DWV	: Dynamic Weight Vector
DWVO	: Dynamic Weight Vector Operator
WDBBA	: Weighted Dynamic Basic Belief Assignment

Notations

$\cup$	: Union operator
$\cap$	: Intersection Operator
$\bar{A}$	: Compliment of A
$\vee$	: Max or maximum
$\wedge$	: Min or minimum
$\oplus$	: Addition
$\sum$	: Summation
$\otimes, \pi$	: Product

Nomenclature

μ_A	: Membership function of fuzzy set A
Ω, U	: Universe of discourse
$T_A(X)$	: Truth membership function of neutrosophic/plithogenic set A
$I_A(X)$	: Indeterminacy membership function of neutrosophic/plithogenic set A
$F_A(X)$	: Falsity membership function of neutrosophic/plithogenic set A
$m(A)$	: Belief mass assigned to set A
K	: Normalisation constant
D^{Θ}	: Hyper power set
$m^f(\Theta)$	: Free DSm model

$\tilde{A}_{TN}$	: Triangular neutrosophic number
$\tilde{B}_{TZ}$	: Trapezoidal neutrosophic number
d_{ij}	: Similarity distance between m_i and m_j
$cor(m_i, m_j)$	: Degree of correlation coefficient between m_i and m_j
$r(m_i, m_j)$	: Correlation coefficient between m_i and m_j
α	: Alpha cut
w_s	: Eigen vector
λ_{max}	: Principal eigen value
$f(FL,\ CS)$	: Function of FL and CS
β	: Number of focal elements
ψ	: Mean of the masses
σ	: Standard deviation of the masses
δ	: Standard error of the masses
m'	: Revised masses
γ_n	: Membership degree of crisp input
R_i	: Risk model of i^{th} category
cd_i	: Contradiction degree for i^{th} attribute
$\bar{S}(E_t)$	: Crisp value of plithogenic number
W_E^T	: Weight vector
m_D	: Dynamic basic belief assignment
m_{wD}	: Weighted dynamic basic belief assignment
$\overline{w}_D$	: Dynamic weight vector

Chapter 1

Introduction

1.1 General

Nowadays, in industries, there is a growing awareness of safety. Safeguarding their employees, assets and protecting the environment is the top priority of every organisation. The regulatory bodies formulate and enforce laws in industries for safe operations to lower the chances of accidents. By properly managing and adhering to safe working practices, the occurrence of accidents can be reduced and safety at work can be improved. But accidents are unplanned and unexpected events. Therefore, there is a pressing need for proper risk assessment. Accidents are not caused by only one factor but these are events influenced by complex causation between varieties of factors. Hence identifying hazards and associated risks are fundamental and form the basis of such approaches.

The problems of risk assessment and decision making in static, as well as in dynamic conditions in maritime transportation, are addressed in this research work. Fuzzy, neutrosophic and plithogenic set-based methods and models are proposed for decision making. A new alternative is proposed to Dempster-Shafer's theory of evidential reasoning to overcome its limitations of giving illogical and counterintuitive results especially when the series of evidence provided by various experts are in a high degree of conflict.

1.2 Risk Assessment

Risk assessment involves the process of identifying hazards and potential causes that tend to cause harm or damage to personnel, machinery, and the environment. It helps to determine appropriate ways to remove the hazards or reduce the risk level if hazards cannot be eliminated. Hazards identification requires imagining and visualising the worst case scenarios. While risk assessment is the overall process, risk analysis is an analytical process and one of the steps in risk assessment that estimates the probabilities and expected consequences for the determined risks. It helps to prioritise and define high risks. Risk evaluation helps in understanding the significance of risks in relation to other risks by comparing against given risk criteria. It involves decision making about its consequences and how to manage the risks. The objectives of risk assessment can be summarised as:

1. Identifying hazards (potential causes, near misses, and untoward incidents)

2. Evaluating and arriving at the risk level (risk assessment)
3. Eliminating hazards
4. Taking proper Risk Control Options (RCO)
5. Reducing the risk level to As Low As Reasonably Practicable (ALARP)

These objectives are to be achieved at a minimum cost.

1.2.1 Historical Overview

The history of risk analysis dates back to 3200 B.C. In the Tigris-Euphrates valley, where a group called the Asipu was practicing consultancy for risky, uncertain or difficult decisions. The Asipu would identify important dimensions of the problem, and assign a plus sign if the alternative is favourable for maximising benefit or minimising cost. Finally, after summing up would recommend the best alternative [1]. The similarity between the present and Babylonian predecessors indicates that risk analysis was in practice for a long in a sophisticated and quantitative way. More than 2400 years back, Athenians also intended their interest to assess risk before making decisions [2]. However, the growth of risk analysis as a scientific field is very young and only 30-40 years old [3, 4].

1.2.2 Risk Assessment Approaches

There are two types of approaches in risk assessment.

1. Reactive approach

It is a reaction based approach to risk. It means actions are taken only after the occurrence of events. Improper safety culture, inaccurate risk assessment, and poor decision-making capabilities result in such type of response.

2. Proactive approach

It focuses on anticipating, and eliminating the events and problems before they lead to catastrophic accidents. The proactive approach involves strict compliance with rules and regulations, clearly identifying potential hazards, analysing them well in advance and practicing proper safety culture. Though accidents are unpredictable, their frequency can be reduced by the proactive approach by analysing the past reports on accidents.

State of the art approach in ensuring safety should be [5];

a. Proactive – anticipating dangers in advance
b. Systematic – devising a formal, well-structured and organised process for formulating new rules

c. Transparent – understandable about the level of safety and reliability each rule contributes to it.
d. Cost-effective – giving a trade-off between the safety and cost incurred to achieve it.

1.3 Maritime Industry

Maritime transport is one of the oldest modes of transport in the world to carry passengers, cargo, oil and goods across the globe. As per the International Chamber of Shipping, around 11 billion tons of goods are transported globally each year by sea route. The maritime industry has excellent supply chains for delivering goods from producers to consumers just in time. It is economical and has a major contribution to the world economy. It provides billions of dollars per annum and helps in employing lakhs of people globally. With technological change, the shipping industry is becoming highly efficient, economical and known for its swift mode of transport. Compared to earlier days, with the advancements of technology, and automation mechanisms installed in ships, the frequency of accidents is greatly reduced. Marine transport has become safer. But the possibility of any untoward incident on board the ship cannot be ruled out. In contrast to road, rail or aircraft accidents, marine accidents can cause damage to human beings, marine creatures, the environment and the ecosystem. It is a strenuous exercise to assess the risk when the system under consideration is complex with a low probability of accidents but having very high prospective impacts such as in the case of maritime transportation.

1.3.1 Types of Maritime accidents

The maritime domain faces several types of accidents. These accidents are not the result of one instantaneous cause, but the result of a series of factors networked and intermingled through complex relations. Some of the categories of accidents are given below:

1. **Collision**

   The ship may collide with the other ship on the course or anchored one. Collision may be with an iceberg, port or even with an offshore drilling platform. It may cause an oil spill, damage to ship structure, human losses, negative impact on the marine environment, permanent damage to the ship and may even block the ship's traffic. In case of collision, chances of loss of life are high. When a ship in a collision carries harmful products like oil, chemicals or any other harmful material, the impact may endanger human life, marine life and affect the environment.

2. **Capsizing**

Large sailing ships may capsize even if it heels a small angle and not able to right themselves to regain their proper position. A ship may turn on its side or even become upside down in the water. The hitting of large waves on the side can heel the ship leading to capsizing. Ships are designed to withstand the battering of the toughest sea swells. If the ship does not have sufficient buoyancy, it may eventually sink on capsizing.

3. **Foundering**

It is the sinking of the ship. Ship sinks due to leaking of water on board ship, heavy weather or breaking of a ship into two. Sinking of a ship due to collision is not categorised into foundering. Ship instability due to shifting of mass above the metacentre can result in tipping of ship and subsequently foundering. A ship can still founder despite building them by adhering to stringent rules and regulations from classification societies. The ship also founders when major mishaps occur on the ship.

4. **Fire/Explosion**

The ship may carry inflammable compounds like oil, chemical, cargo etc. The chemicals or other material on board the ship may ignite and eventually lead to an explosion. Fire may also originate from the engine room and spread to other areas. Other dangerous fires on a ship may be because of crankcase explosion, over-speeding of generators, boiler explosion, compressor airline explosion, high-pressure fuel line bursting, turbocharger explosion etc.

5. **Grounding**

In this, the ship may hit the seabed leading to the damage of the hull’s submerged part and ingress of water resulting in destabilising the ship’s structural integrity and stability. Most of the oil spill occurs after grounding. Ship grounding generates a tremendous load on ship structures damaging the hull and leading to hull breach, total ship loss and human casualties. The cargo may leak into the sea causing marine pollution if grounding develops a crack in the cargo hold of the ship (e.g. tanker).

1.3.2 Causes of Maritime Accidents

The causes of accidents may be direct or indirect. Direct causes have a straight influence on accidents. Indirect causes may lead to direct causes or create situations leading to direct causes. It is crucial to track the root cause and its relation with other factors to realise and avoid accidents [6]. Identifying causal factors for the root cause can help to prevent the triggering of events. This highlights the importance of ascertaining root causes and causal factors to prevent accidents. Damages are also caused to ships by natural hazards such as tsunami-genic earthquakes, super cyclones, hurricanes, and coastal floods which are considered non-traditional risks [7]. Failure of any critical system on a ship may also lead to an accident. The performance of a system on a ship greatly depends on the ship's age, equipment design and stability of the ship. Each of the factors requires broad, in-depth and substantial analysis to ascertain their contribution towards an accident. Some of the factors directly or indirectly posing risks are given below.

1. **Human errors**

About 80 % of marine accidents are attributed to human errors [8, 9]. Human errors point to those actions or decisions initiated by humans affecting the entire system. Human errors are primarily due to the crew's negligence towards responsibility [10]. Human factors responsible for accidents can be many such as overconfidence, lack of training, failure to comply with rules and regulations, fatigue, no proper coordination and cooperation among team members, communication gap and negligence towards safety rules [11]. There is a pressing demand for proper training and awareness to follow the international conventions, anticipate dangers, take prompt actions and measures to mitigate the risks. Some of the above key factors can reduce human errors.

2. **Equipment failure**

Equipment on a ship are very well designed and built to withstand the load and stresses that all marine vessels face while transporting through the oceans. But the systems are complex and contain numerous components. Equipment failure generally occurs because of corrosion of material, use of damaged seals or filter, wear of cylinder liner, fatigue failure of components etc. Improper operation of equipment by untrained operators, failure to schedule and perform preventive maintenance, failure in condition monitoring of the equipment, failure to follow standard operating procedures and overloading the equipment are some of the likely causes for equipment failure.

3. **Bad weather**

Bad weather can cause serious damage to ships and ships may even sink. Bad weather scenarios such as hurricanes, tornados and tropical storms can occur in any part of the world. They all result in a strong wind, heavy rainfall and swelling waves. Hurricanes can produce winds with a speed as high as 150 kilometres per hour. Though modern ships are designed to withstand such scenarios, they are still vulnerable to storms.

4. **Improper design**

Broad knowledge and understanding of the working culture onboard are necessary to design equipment that meets the requirement of seafarers. From the point of efficiency and safety, equipment design plays a major role. It should meet the required standards and have easy access for operation/maintenance. Once the accident happens, it is often claimed to be a human error but sometimes bad equipment design is the hidden cause.

1.3.3 Regulatory Bodies

United Nations (UN) specialised agency, the International Maritime Organisation (IMO) was established in 1948, with the focus on safety, the security of the maritime industry and to hamper the chances of marine and atmospheric pollutions by ships by promoting international regulations. IMO has responsibility for developing and establishing a broad regulatory framework for the shipping industry for safe and secure maritime transport. Three important IMO treaties are,

1. **The International Convention for the Safety of Life at Sea (SOLAS)**
   It first came into existence as an immediate reaction to an infamous accident of the sinking of TITANIC posing a question mark on the safety regulations. The subsequent upgraded versions of SOLAS came in 1929, 1948, 1960 and 1974 with new requirements. SOLAS convention provides the minimum standards towards architecture, construction and operation of ships well suited with their safety. The compliance with these regulations is validated through the certificates issued by respective flagships. SOLAS convention has documented various regulations among 14 chapters.
2. **The International Convention on Standards of Training, Certification, and Watchkeeping for Seafarers (STCW)**
   This convention came into force in 1984 and intends to prescribe minimum standards about training, certification and watchkeeping for seafarers on an international level. STCW conventions are summarised in eight different chapters. The basic requirements are given in STCW conventions which are further enlarged and explained in the STCW code. The STCW code is divided into two parts. Part A is mandatory and gives minimum standards of competence necessary for seagoing personnel, while part B contains recommended guidance to help interested parties to implement the STCW convention.
3. **The International Convention for the Prevention of Pollution from Ships (MARPOL)**
   The primary aim of this convention is to prevent and reduce pollution from ships. The Terry Caryon oil spill off the French and Cornish coast in 1967 prompted the creation of this convention with the significant development and updates in MARPOL. The present convention includes six technical Annexures devoted to regulations for the prevention of

pollution by oil, noxious liquid substances in bulk, harmful substances carried in packaged form, sewage from ships, garbage from ships and air pollution from ships respectively.
For safe maritime operations, IMO time and again upgrades the international conventions like SOLAS and International Management Code for the safe operations of ships and pollution prevention (ISM code). These regulations helped to gradually improve the safety of maritime operations [12]. However, the proactive approach for the marine industry towards safety is still in doubt [13].

1.4 Modelling Theories/Approaches

The maritime industry falls into the most dangerous and complex industry globally [14]. We find an enormous number of accidents in maritime transportation despite the best efforts to reduce it. But compared to the density of traffic in the sea, the percentage of such accidents is negligible. Among the many models proposed, there is no single model that can be satisfactorily applied to all the problems, systems and conditions in the marine industry. This makes risk modelling of great significance for researchers. In the last few decades, various methods (qualitative and quantitative) have been developed and used for risk assessment, such as the analytical hierarchy process (AHP) method [15-17], TOPSIS method [18], Failure Mode and Effects Analysis (FMEA) [19] and comprehensive evaluation method [20]. These traditional methods for decision making have shown popularity because of their simplicity and easiness in conducting the quantitative risk analysis. However, their inability to accurately assessing the real time practical problems is a major drawback. Their applications in precise evaluation of the risky situations are further constrained by the uncertainty in the risk data [21]. Many models aspire to find the relations between marine accident risk and associated safety factors like human error, external factors like weather conditions and the size of the vessel [22-25]. Researchers develop the risk models with a focus on risk figures neglecting the background knowledge [26]. The models developed with no firm evidence and solely based on one's intuition do not provide the real picture and are unsuitable for risk management purposes [27]. Risk models carry uncertainty due to insufficient knowledge about the primary causes. These uncertainties are classified into two types.

1. ***Aleatory uncertainty*****:** It is related to natural and physical phenomenon. The variability in this type of uncertainty is random. It is inbuilt (intrinsic). Such type of uncertainty is irreducible and cannot be parted with. It is embedded within the model. Addressing *aleatory* uncertainty is desirable for probabilistic risk analysis.

2. ***Epistemic uncertainty*: **It is related to knowledge and information about the subject. However, such type of uncertainty can be reduced to negligible quantity by improving the reliability of information collecting measures. *Epistemic* uncertainty is required to draw meaningful decision making. It is further differentiated into data uncertainty, statistical uncertainty and model uncertainty [28, 29].
   a. *Data uncertainty* may be related to faulty instruments.
   b. *Statistical uncertainty* may be due to less number of observations or improper techniques used for parameter estimation of distribution. Simulation or maximum likelihood can be used to reduce this type of uncertainty.
   c. *Model uncertainty* may be the result of assumptions and imperfections made in the physical model while formulating.

The uncertainty is dealt with by probability theory and possibility theory. Probability theory is applicable when uncertainty arises because of randomness [30]. Probabilities are obtained either by noting down the frequency of occurrence of an event or by assigning directly probabilities to various events by the experience of experts. These are categorised as subjective probabilities. Flage et al. [31] provided a standpoint on worries, threats and directions about how to represent and express uncertainty in risk assessments. The understanding and description of risk from researchers' perspectives have a great influence on the way risk is analysed and may create serious implications for risk management [3]. Possibility theory is applicable when uncertainty in the data arises because of vagueness in the semantic expressions assigned to describe the attributes of a feature. While probabilities should sum to one, possibilities can sum to any positive value. The emergence of new models based on fuzzy logic, Dempster-Shafer theory (DST) and Monte Carlo Simulation somehow managed to overcome the limitations of these traditional methods.

1.4.1 Probabilistic Approach

Probability theory is the study of uncertain outcomes where the probability distribution of every outcome is defined beforehand. The probability of occurrence of any event is the summation of the probabilities of all the outcomes in that event. The probabilities associated with the events characterise the uncertainties. It is the most frequent and common method used to handle uncertainty.

Monte Carlo Simulation is the most widely used probabilistic simulation technique. It generates random variables that are modelled with different probability distributions like normal and lognormal. It is one of the statistical techniques suitable to solve problems by estimating uncertainty in a process and where other analytical techniques are not suitable. Monte Carlo simulation is best suited to model uncertainty in a complex environment because of its flexibility towards realistic performance [32]. Its main drawback is the time of computation and the reliability of the result.

The Bayesian approach is a statistical process used to upgrade the probability of the hypothesis with the accumulation of new evidence. It can handle the two types of uncertainties inherently. Such approaches are appropriate for analysing data and experts' judgements [33].

Event Tree Analysis [ETA] and *Fault Tree Analysis [FTA]* are familiar techniques for probabilistic risk analysis [34]. Both these techniques represent the problem in the form of trees and suitable for quantitative as well as qualitative analysis. Qualitative FTA is about identifying individual scenarios leading to the top event. On the other hand, quantitative FTA is about estimating the frequency of the top event. FTA consists of the top event, intermediary factors, basic factors and logic gates [35]. FTA technique is constructed to ascertain the feasible combinations of factors that may lead to the occurrence of top events. A network of fault tree consists of factors which are the direct results of the factors occupied at the level just below through logical gates. Factors may be failure modes, human factors, design faults or equipment failure.

1.4.2 Possibilistic Approach

Possibility evaluates the degree by which the furnished evidence of the occurrence of the event matches with the fact or hypothesis that the event happens. This approach ideally represents the fuzziness by assigning possibility value rather than probability value to it thereby assigning a belief. The degree of belief towards the occurrence of an event is assigned a value from the interval [0, 1]. It is easy to generate possibility distributions for the data which is fuzzy and subjective. The possibility theory is considered to be more accurate for handling imprecise data without any randomness.

1.4.3 Evidence Theory

The evidence theory was introduced by Dempster [36] and then Shafer [37] developed it further. This theory narrows down the hypothesis set with the gathering of more and more data. It necessitates that all the hypotheses are mutually exclusive and exhaustive called the frame of discernment. Basic Belief Assignment (BBA) is the measure in evidence theory. BBA is associated only with an event and not with any of its subsets. Evidence theory is elaborated in section 3.6.3.

1.5 Fuzzy Set Theory

Fuzzy set theory (FST) was created [38, 39] to account for the information processing in the human mind which is subjective, and ambiguous. The main concept of FST was that of graded membership, allowing subsets to have partial membership. Graded membership permits us to infinitely extend the concept of crisp set theory. The fuzzy concept can be explained with an example of the position of the valve that conducts fluid. The valve may be completely shut or fully open. It may also take infinite positions in between. The crisp set cannot be used to specify the in between positions of a valve. The theory of fuzzy sets helps a smooth transition from the domain of precise, quantitative and accurate circumstances to imprecise, qualitative and vague creations.

1.5.1 Constructing Fuzzy Sets

In fuzzy sets, each element is mapped to [0, 1] by membership function $\mu_A: X \rightarrow [0, 1]$ where $[0, 1]$ represents any real number between 0 and 1 (both inclusive) [38, 39].

Case (i):

When U is the finite universe of discourse, the fuzzy set A defined on U is a mapping from U to the interval $[0, 1]$ and denoted by,

$$A = \left\{ \frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \frac{\mu_A(x_3)}{x_3} + \cdots \right\}$$

$$= \left\{ \sum_{i=1}^{n} \frac{\mu_A(x_i)}{x_i} \right\} \tag{1.1}$$

Case (ii):

When U is the continuous universe of discourse and infinite,

$$A = \left\{ \int \frac{\mu_A(x)}{x} \right\} \tag{1.2}$$

The summation symbol represents the collection of each element.

1.5.2 Fuzzy Set Operations

For two fuzzy sets A and B of the universe of discourse U and an element x of the discourse, the following association conveys the union, intersection and complement operations of fuzzy sets [38, 39].

- Union (Fuzzy OR)

The union of the above two fuzzy sets is a fuzzy set C such that,

$$\mu_C(x) = \mu_{A\cup B}(x) = \mu_A(x) \vee \mu_B(x) \quad \forall x \in U \tag{1.3}$$

- Intersection (Fuzzy AND)

The intersection of the above two fuzzy sets is a fuzzy set C such that,

$$\mu_C(x) = \mu_{A\cap B}(x) = \mu_A(x) \wedge \mu_B(x) \quad \forall x \in U \tag{1.4}$$

- Complement (Fuzzy NOT)

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x) \quad \forall x \in U \tag{1.5}$$

1.6 Neutrosophic Set Theory (NST)

For a given universe of discourse U, Atanassov [40] proposed the Intuitionistic Fuzzy Set (IFS) with the addition of a degree of non-membership $v_A(x) \in [0, 1]$ besides the membership degree $\mu_A(x) \in [0, 1]$ for each element $x \in U$ of a set A such that,

$$\mu_A(x) + v_A(x) \leq 1 \quad \forall x \in U \tag{1.6}$$

IFS cannot handle the possibility of the statement being true is 0.7, the statement being false is 0.5 and the statement not being sure is 0.2. To overcome this limitation, Smarandache [41] proposed the concept of a neutrosophic set. A neutrosophic set A is defined by a truth membership function $T_A(x)$, an indeterminacy membership function $I_A(x)$, and a falsity membership function $F_A(x)$. $T_A(x)$, $I_A(x)$ and $F_A(x)$ are real standard or non-standard subsets of $]^{-}0, 1^{+}[$. That is $T_A(x): x \to\ ]^{-}0, 1^{+}[$, $I_A(x): x \to\ ]^{-}0, 1^{+}[$ and $F_A(x): x \to\ ]^{-}0, 1^{+}[$. The unitary standard interval $[0, 1]$ used in IFS has been extended to the unitary non-standard interval of $]^{-}0, 1^{+}[$. There is no restriction on the sum of $T_A(x)$, $I_A(x)$, and $F_A(x)$ so $0^{-} \leq supT_A(x) + supI_A(x) + supF_A(x) \leq 3^{+}$. In the neutrosophic notation, the above example can be characterised as $A = \{\langle 0.7, 0.2\ 0.5\rangle\}$.

To facilitate the use of neutrosophic sets in real scientific and engineering applications, Wang et al. [42] proposed the concept of Single Valued Neutrosophic Set (SVNS) and specified the set theoretic operators to solve the practical and real life problems. SVNS has the form,

$$A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle; x \in U\} \tag{1.7}$$

where $T_A(x): x \rightarrow [0,1]$, $I_A(x): x \rightarrow [0,1]$ and $F_A(x): x \rightarrow [0,1]$

with $0 \leq supT_A(x) + supI_A(x) + supF_A(x) \leq 3 \qquad \forall x \in U$

1.6.1 Constructing Neutrosophic Sets

Consider the universe of discourse U and an element x of the discourse [42].

When U is continuous, SVNS A is written as,

$$A = \int_U \langle T_A(x), I_A(x), F_A(x) \rangle \qquad \forall x \in U \tag{1.8}$$

When U is discrete, SVNS A is written as,

$$A = \sum_{i=1}^{n} \langle T_A(x_i), I_A(x_i), F_A(x_i) \rangle \qquad \forall x_i \in U \tag{1.9}$$

1.6.2 Neutrosophic Set Operations

For two SVNS A and B of the universe of discourse U and an element x of the discourse, the following association conveys the union, intersection and complement operation of SVNS [42].

- UNION (neutrosophic OR)

The union of above two SVNS, is a SVNS C such that,

$C = A \cup B = \{\langle x, T_C(x), I_C(x), F_C(x) \rangle; x \in U\}$

where,

$$T_C(x) = max\big(T_A(x), T_B(x)\big)$$

$$I_C(x) = max\big(I_A(x), I_B(x)\big)$$

$$F_C(x) = max\big(F_A(x), F_B(x)\big) \ \forall x \in U \tag{1.10}$$

- INTERSECTION (neutrosophic AND)

The intersection of above two SVNS, is a SVNS C such that,

$C = A \cap B = \{\langle x, T_C(x), I_C(x), F_C(x) \rangle; x \in U\}$

where,

$$T_C(x) = min\big(T_A(x), T_B(x)\big)$$

$$I_C(x) = min\big(I_A(x), I_B(x)\big)$$

$$F_C(x) = min\big(F_A(x), F_B(x)\big) \qquad \forall x \in U \tag{1.11}$$

- COMPLEMENT (neutrosophic NOT)

The complement of above SVNS, is a SVNS $c(A)$ such that,

$c(A) = \{\langle x, T_{C(A)}(x), I_{C(A)}(x), F_{C(A)}(x)\rangle; x \in U\}$

where,

$T_{C(A)}(x) = F_A(x)$

$I_{C(A)}(x) = 1 - I_A(x)$

$$F_{C(A)}(x) = T_A(x) \qquad \forall x \in U \tag{1.12}$$

1.7 Plithogenic Set Theory (PST)

Plithogenic set [43, 44] consists of elements that are distinguished by more than one attribute which in turn can have any number of values. Plithogenic set is a generalisation of the crisp set, fuzzy set, Intuitionistic fuzzy set and neutrosophic set. All the above four types of sets are characterised by a single attribute value. Crisp and fuzzy sets are specified by only one membership value, Intuitionistic fuzzy set is specified by two values namely membership and non-membership while in a neutrosophic set there are three values i.e. membership, non-membership and indeterminacy. The salient feature of the plithogenic set is the contradiction degrees defined between each attribute value and the dominant attribute value. The contradiction degree compares between the dominant attribute value and any given attribute value. This smoothens out any discrepancy and provides a better result. Sometimes, the dominant value may not exist and is taken as zero while in the case of multiple dominant values, either contradiction degree function is suppressed or alternative relation is designed between attributes values.

1.7.1 Constructing Plithogenic Sets

Consider a universe of discourse U. Let A be a set of uni-dimensional attributes, $A = \{a_1, a_2, \dots, a_m\}, m \geq 1$ and $a \in A$ has a spectrum of values given by set S where S can be a finite discrete set, $S = \{S_1, S_2, \dots, S_l\}, 1 \leq l < \infty$, infinitely countable, $S = \{S_1, S_2, \dots, S_\infty\}$ or infinitely uncountable, $S =]a, b[, a < b$ where]... [is any open, semi-open or closed interval from the set of real numbers or other general sets. If V is the non-empty subset of S consisting of all possible values of attributes, $V = \{v_1, v_2, \dots, v_n\}, n \geq 1$. Amongst all the attribute values, experts choose the most important attribute value to be the dominant value for the given application.

1.7.2 Plithogenic Set Operations

Consider two plithogenic sets A and B of the universe of discourse U and an element x of the discourse, the following association conveys the union, intersection and complement operation of plithogenic sets [43, 44].

- UNION (Plithogenic OR)

The union of the above two plithogenic sets is a plithogenic set C such that,

$C = A \cup B = \{\langle x, T_C(x), I_C(x), F_C(x)\rangle; x \in U\}$

where,

$$T_C(x) = T_A(x) \vee T_B(x)$$
$$I_C(x) = \frac{1}{2}\left[\left(I_A(x) \wedge I_B(x)\right) + \left(I_A(x) \vee I_B(x)\right)\right]$$
$$F_C(x) = F_A(x) \wedge F_B(x) \qquad \forall x \in U \tag{1.13}$$

- INTERSECTION (Plithogenic AND)

The intersection of the above two plithogenic sets is a plithogenic set C such that,

$C = A \cap B = \{\langle x, T_C(x), I_C(x), F_C(x)\rangle; x \in U\}$

where,

$$T_C(x) = T_A(x) \wedge T_B(x)$$
$$I_C(x) = \frac{1}{2}\left[\left(I_A(x) \wedge I_B(x)\right) + \left(I_A(x) \vee I_B(x)\right)\right]$$
$$F_C(x) = F_A(x) \vee F_B(x) \qquad \forall x \in U \tag{1.14}$$

1.8 Aims and Objectives

The aim is to propose models to carry out a risk assessment and decision making in maritime transportation in dynamic conditions. The maritime industry is considered to be one of the dangerous industries wherein the safety of the ship, crew and goods is of prime importance. Getting immediate and prompt help in ships in case of emergency is very difficult due to their remote positioning. Under such circumstances, a proactive approach towards safety and risk is very important. Since historical data are scarce, vague and qualitative, they are bound to contain uncertainty and imprecision. Models applying the concept of fuzzy, neutrosophy and plithogeny are proposed to demonstrate how such approaches can be satisfactorily used for the analysis of such ambiguous data. The new alternative in D-S theory is also proposed to overcome its limitations in giving illogical results when series of evidence conflicts. This alternative considers the possibility of any error crippling while making judgements.

1.9 Organisation of Report

This thesis has seven chapters. The first chapter presents some basics of risk assessment, the maritime industry, FST, NST, PST and some related terms and definitions. The second chapter gives a review of the literature survey. An extensive survey has been conducted to know how the risk assessment is carried out over the years in the maritime industry, the difficulties faced by researchers and the current trends/directions used to overcome the difficulties. Survey also covers Bayesian Belief Network (BBN), FST, ETA /FTA and other probabilistic and possibilistic applications in risk assessment. A summary of the literature survey is presented at the end of the chapter. The third chapter describes the thesis problem identified based on the critical review of the literature. The formulation of the problem and solution methodologies are proposed in this chapter. In the fourth chapter, an integrated method using Interpretive Structural Modelling (ISM), Fuzzy Analytical Network Process (FANP) and Evidential Reasoning (ER) is used to address the first part of the thesis problem. In this chapter, a new alternative approach to D-S theory is proposed to overcome its limitations of giving illogical results when series of evidence conflicts. The next chapter proposes new methods for risk assessment. Neutrosophic logic, neutrosophic sets and plithogenic sets are used to develop three different models. Chapter six deals with the safety assessment in dynamic conditions using neutrosophic sets. In this chapter, two methods are proposed, i) to rank the failure modes posing risk hazards and ii) the method to arrive at the safety level of the system. Chapter seven is the conclusion chapter that also highlights the limitations of this study and the future scope of research.

Chapter 2

Literature Review

2.1 General

The safety of maritime transportation has been a topic for discussion since the past century. Maritime safety is achieved when any of the acts during transportation do not endanger human life, property, environment and any economic loss from departure to destination. This can be achieved by adhering to the predefined set of measures. A lot of research work towards risk assessment and safety analysis of systems onboard ship and maritime transportation is done to save personnel, machinery, and the environment [45-52]. Traditionally, the approach in the maritime industry towards risk aversion was mainly reactive which is passive and being criticised. This lead to a shift in the focus of research in risk assessment whose prime aim is to suggest proactive options. Human error is the primary cause of collision and grounding of ships. The unmanned merchant vessels in the sea will be a dream come true in near future mainly to reduce the potential human errors by reducing their numbers onboard ships [53]. Many authors contributed to the risk assessment by elaborating on different mathematical models and incorporating various approaches. This chapter presents a detailed review of the literature survey.

2.2 Risk Assessment Models

Over the last 50-60 years, researchers and shipping industries aim to achieve zero accidents in marine transport and to provide safety and reliability while increasing productivity. Marine transportation safety is a critical issue because of numerous factors. The ships have to navigate through severe operating conditions and unpredictable climate changes. There is also a high degree of uncertainty in the performance of various operating systems onboard the ship. Moreover, the ship is operating in a remote area and is deprived of any immediate help in case of emergencies. To improve the safety of maritime transportation and develop the shipping industry, researchers around the world focus on developing robust risk assessment models. This opened the way for engineers and researchers to explore flexible and exceptional risk models in the design and operation processes.

2.2.1 Bayesian Network Models

Bayesian network (BN) models have been broadly used in maritime risk assessments. BN can help to present complex scenarios and deal with uncertain and unobserved variables that cannot be assessed directly. It can also permit different types of evidence in the model. A directed acyclic graph serves as the angle to analyse the strength of evidence. Nodes represent the random variables while the directed arcs show the influence of one variable on the other. BN has attracted the researcher's attention mainly because of its capability in representing complex and uncertain relationships between variables. BN can deal with missing data, experts' knowledge, provide causal relationships and graphically represent the network for easy reference.

Lu et al. [54] tried the BN model to check the effectiveness of oil spill recovery in ice conditions. The required information to build the model is gathered from literature and expert interviews. Eight sub-models are used to build the BN model including the output sub-model- *Recovery Effectiveness*. The rest seven sub-models influencing recovery effectiveness such as *Oil spill Response, Forcing Representative Scenarios, Weathering and Transport, Atmospheric Environment, Sea Ice Environment* and *Recovery* form the main body of the model. The model helped to estimate, generate, and understand the potential of mechanical means towards the recovery of oil. The model considered different test scenarios for comparison and provided insights on the impact due to different oil spill conditions such as oil types, spill sizes and spill locations. The model may be expanded further to consider different weather conditions, locations and even different types of oils.

Yang et al. [55] presented a model integrating evidential reasoning with BNs to overcome the limitation of BNs in handling incomplete data emerging from subjective judgements from a group of experts. The generated method using the BN inference, Fuzzy Rule Base (FRB) and ER helped to identify in advance the Human Error Probability (HEP) of dangerous situations to prevent maritime accidents. Evidential reasoning is used to synthesise the experts' judgement to build the BN. The use of a degree of belief concept helped to model the BN network with incomplete knowledge and ignorance. The demonstration of the proposed model is done by using the Cognitive Reliability Error Analysis Method (CREAM) to estimate HEP in maritime area. The proposed ER-BN model seems to be effective in facilitating the HEP analysis in decision making.

Goerlandt et al. [56] presented the model to quantify risk using BN and applied to oil spillage case from tanker collisions. Here, the two-stage model is proposed wherein the first stage uses expert-review for evidence to construct BN. Decision-makers give judgements using subjective probabilities from the first stage analysis and form the basis for the second stage. The author highlighted that the model can be applied for risk only as decision support and not to make any recommendations about any actions to be taken. The model could explicitly represent the uncertainty and has a slight improvement in previous other risk analysis models which highlighted the inability of treating uncertainty in need of proper tools.

Khan et al. [57] presented an Object Oriented Bayesian Network (OOBN) to dynamically assess the probabilistic risk of ship-ice collision in Arctic waters. Visual representation of BN becomes tedious when it contains many nodes with similar fragments. This difficulty is overcome in this model by decomposing the network into smaller component models. OOBN can simplify the complicated model of marine accidents by hierarchical component-wise analysis and help to identify root causes for analysis. OOBN can effectively represent the evolving complexity of the model. The proposed model is applied to predict tanker collision with sea ice considering a case study of oil tanker navigation on the Northern Sea Route. It is seen that the model is suitable to select the navigational route and vessel operating decisions.

Norrington et al. [58] presented a BN model with all the key features that put a hindrance on the success of search and rescue operations within UK coastguard coordination centres. In this study, the BBN is constructed by collecting the primary data through a structured elicitation process. The scale of probability is provided to convert experts' subjective judgements into numerical assessments.

Sotiralis et al. [59] combined the Event Tree notion with the BN approach and implemented the human factor into risk assessment. A model incorporated the performance of human factors in different operational conditions towards collision. The model identified the factors contributing to human performance and ship collision. BN is used to quantify the factors such as stress and fatigue which have an impact on human performance. It also focussed on mechanical failures which may also contribute equally to the collision. Here, the BN model is used efficiently for prior and posterior probabilities. For better modelling of working conditions on the bridge, a hierarchical task analysis for normal, abnormal and critical operating phases is carried out.

Trucco et al. [60] developed a BBN for modelling Human and Organisation Factors (HOF) for risk analysis. In this model, they considered a complex socio-technical system and quantified the organisational structure to get a better estimate of the likelihood of occurrence of a hazard. The proposed approach used BBN to develop better risk models when it is required to take into consideration the HOF. This model can be used in risk analysis to further identify opportunities for reducing risk levels. Applicability of the model is presented with a case study of high-speed craft (HSC). The case study exhibited that the BBN can be used to effectively model HOF to explore new opportunities to mitigate the risk at the organisational and regulatory level of the maritime transport system (MTS). The model is suitable to integrate HOF into risk analysis in other sectors as well.

Hanninen [61] discussed how BN can contribute towards the prevention of maritime accidents and the challenges faced in its application to achieve maritime safety. In the paper, the author highlighted the suitability of BN in the modelling of complex systems by incorporating some of the epistemic uncertainties in the form of probabilities, combining experts' knowledge to update the model parameters, decreasing the uncertainties, giving flexibility of utilising the same model in multiple ways, and describing uncertain dynamic systems. However, it also faced challenges while developing a model since the clarity on the reason for accidents could not be established as a rare occurrence and underreporting of accidents does not provide enough data. The credibility of data is also questioned leading to heavily rely on expert's knowledge. With the increase in complexity of the system, generating the probability of parameters required becomes difficult.

Montewka et al. [62] developed a model using BBN which is specially focussed on ship-ship collision. It is used to assess the risk in the maritime transportation system. A case study of the maritime traffic system in the Gulf of Finland (GOF) is considered in which in the open sea, RoPax is struck by another ship. It analysed some of the selected accidental scenarios which lead to the loss of struck RoPax ship. It used a proactive approach to provide the expertise and awareness of the analysed system. The model though is applied only to some restricted boundary conditions, can be further modified to make it applicable in other varying conditions.

Chen et al. [63] developed a hybrid model using BN and FTA to analyse the risk in maritime accidents. BN is used to build the consequences and FTA is used to calculate the probability of maritime accidents. Experts' knowledge is used to collect data using a questionnaire. The probability of an accident at a particular level of consequence is calculated using BN. A total of ten variables influencing the accidents are identified. Three different parameters such as weather, technical failure and human errors are considered. FTA on three major categories i.e. collision, contact damage and grounding contributing more than 70% of the total number of accidents is performed by analysing all ten variables and three parameters. However, validation of the model is not done and since the data is obtained from experts, the possibility of uncertainty and biasedness still exists in the model.

2.2.2 Fault Tree Analysis Models

These are logical models. FTA models are built on three assumptions (i) faults are considered to be binary events (ii) faults are statistically independent of each other and (iii) logic gates can be used to represent the relationships between faults [64]. The graphical representation is used to model risk analysis for both qualitative and quantitative data. An FTA is an analytical technique that is used to find an undesirable event from an undesirable state of the system. In FTA, all the states are depicted graphically with clear inter-relationships between them. Here, a graphical model is constructed using a combination of various faults in parallel and serial relations. ETA mostly uses events instead of faults in building logical models. Various models developed for risk analysis using FTA and ETA are discussed below.

Aung et al. [65] presented a model using Fuzzy Fault Tree Analysis (FFTA) to find the reliability of the jacket cooling water system of a marine diesel engine. To overcome the problem of uncertain failure rates of basic events as it is difficult to get the exact values because of uncontrollable working conditions, the authors used FST to get the failure rate of the system. With logic gates as nodes, basic events are calculated and similarly by synthesizing the information upwards, the target event at the top is calculated. Two new fuzzy importance measures are also proposed in this paper using a fuzzy probability ranking method and Graded Mean Integration Representation (GMIR) distance method.

Celik et al. [51] presented a model using FFTA. The model is used to combine the effects of organisational faults and the shipboard technical system failures. It is developed in six stages starting from the qualitative judgements of experts in the field. To show the application of the proposed model in Shipping Accident Investigation (SAI), an accident case study of machinery breakdown resulting in a fire on-board ship is taken. The sensitivity analysis is carried out to partially validate the model as there is a lack of quantitative data and also to reduce the concerns about the quality of experts' judgements. The integration of FFTA and SAI is made to serve as a database for future reference to mitigate the accidents.

John et al. [66] presented a model with FFTA to optimise the performance of effectiveness of the system by analysing the hazards during ship and port interface operations. The methodology is designed to incorporate diverse sets of data to analyse the system where exact sets of data are not available. The use of FST in the traditional model of FTA help to accommodate homogeneous as well as heterogeneous experts. The framework for safety analysis is given in nine steps. The model is illustrated with the test case of a ship's accident that generally occurs at ship and port interface while the ship is maneuevering in West African port. The result indicated that the poor visibility at the port is the prime reason for accidents. The model is suitable for flexible responses to the operational uncertainties in the seaport systems. The proposed method can serve as a handy tool for safety specialists for evaluating maritime hazards in seaport operations.

Toz et al. [67] carried out a root cause analysis of the grounding of ships in the Bay of Izmir using the FTA technique. A total of 24 grounding accidents between 2001 and 2016 are analysed. The results showed that the grounding accidents in the Bay of Izmir are mainly attributed to equipment failure and geographical factors. Among equipment, rudder failure is the most important contributor to accidents. Rudder failure may be attributed to inappropriate maintenance. Grounding avoidance maneouevering is not possible even in an emergency due to a limited maneouevering area. However, the accident data taken are incomplete and not sufficient for full proof analysis. The model can be used to carry out an extensive study with more detailed information.

Antao and Soares [35] presented a model to identify hazards associated with casualties of RoPax vessels. RoPax vessels are chosen for the study because accidents in such types of vessels have considerable consequences on economic and human life. FTA is used to model the relations between relevant events. The conclusions of the modelling are not used directly for decision making but used for later stages of formal safety assessment (FSA). Since reliable data for basic events are not available, the constant failure rate for human and mechanical elements is used. Moreover, the unavailability of data hampered the degree of uncertainty in the model. The safety performance of the RoPax vessel is performed with different emergency scenarios and associated minimum cut sets (MCS). The sensitive analysis is performed to assess the role of human factors and the sensitivity of FTA to the probabilities of basic events.

Raiyan et al. [68] used ETA for quantitative study in the probabilistic analysis of maritime accidents in Bangladesh. Here, the most probable factors for accidents are identified and verified with the factors of previous accidents. The model, when applied to marine accidents in Bangladesh, concluded that the number of accidents can still be reduced drastically if the visibility during the voyage is increased (irrespective of weather conditions). ETA gives better results with a bigger volume of data sampling. But in this study because of limited available data, the probabilistic analysis did not involve the realistic number of incidents and hence the authors claimed that the results obtained may not represent the realistic results.

Arslan et al. [69] presented a hybrid model using FTA and Monte Carlo Simulation (MCS) focussing specifically on human factors that lead to accidents during loading and unloading operations at tanker terminals between 2000 and 2014. FTA is used to create causes of accidents while MCS is used to test the results. Initially, nineteen accident reports were considered for the study. After examining the reports based on the results, location, occurrence of accidents and the required data during loading and unloading periods, only ten vessels are taken for the final analysis. The other nine reports are excluded due to insufficient and incomplete data. The study identified that the failure to comply with rules, incomprehension, lack of proper training and tiredness to be the main causes of human error.

2.2.3 Fuzzy Set Models

Conventional tools like Probability Risk Assessment (PRA) are well suited in scenarios when there is negligible or no uncertainty of any kind. But as the complexity of the system increases, the uncertainty associated with it also increases. In such circumstances, FST provides a tool to model reality better than the traditional methods. It provides a mathematical framework to study vague phenomena. FST can be effectively used to deal with the *epistemic* type of uncertainty inherent in human knowledge. Fuzzy logic employing IF-THEN rules does not require precise quantitative analysis and can be used to model such types of uncertainties.

Akyuz [48] presented a Fuzzy based Success Likelihood Index Method (FSLIM) to assess human error while abandoning the ship. The author proposed a model wherein SLIM is used to calculate the HEP while the fuzzy set is used to capture the subjectivity in the experts' judgements and to interpret the expressions in decision making. A seven-step procedure is described starting from analysing various tasks to be completed by the ship's crew to arriving at the HEP for each task. The model is illustrated by taking an example of the procedure to abandon the ship in maritime transportation as the evacuation of the ship is critical to safeguard human life during an emergency. The findings of the study show that the highest HEP is at the preparatory stage especially in two sub-tasks namely, sending distress messages and reporting the situation. The model is suitable to reduce the likelihood of human error for a given task and improve the overall safety level onboard a ship.

Xue et al. [70] presented a fuzzy approach to model ship maneuvering in autonomous ships the way it is maneuvered by a human. Ship safety is often decided by how accurately the maneuvering decisions are taken. Autonomous ships also face scenarios of bad weather, other ships in waterways and require human-like decision making. Here, fuzzy number functions are designed to capture experts' knowledge. It evaluated the factors which influence maritime traffic safety in autonomous ships. The algorithm used can compute the numerical data in complex fuzzy systems using computer programming. Various actual navigational scenarios are simulated using a simulator to make them real-world scenarios. The model can be used to prioritise the influencing factors to make the autonomous ship a reality.

Akyildiz and Mentes [71] designed a risk assessment model integrating FST, Fuzzy Analytical Hierarchy Process (FAHP) and Fuzzy Technique for Order Preference by Similarity to an Ideal Solution (FTOPSIS). Cargo ship accidents are analysed using the four influential aspects of uncertainty ie. level of understanding, quality of knowledge, the uncertainty of cargo ship accidents and sensitivity level of model parameters. The effects of uncertainty parameters on model parameters in cargo ship accidents are analysed. The qualitative uncertainty assessment of cargo ship collision is carried out to illustrate the proposed model. Out of the ten model parameters, collision speed is the most important parameter. Also, the key is the knowledge and understanding of the system. The outcome also suggested improvement in human reliability.

Sii et al. [72] presented a fuzzy logic model for qualitative risk analysis in marine systems. The model developed and represented linguistic variables to model risk levels. The fuzzy sets are used to quantify these variables. The risk levels, fuzzy rule basis and risk expressions are derived using fuzzy membership functions. Risk level (RL) is assessed using two attributes of hazard namely, Failure Likelihood (FL) and Consequence Severity (CS) of a hazard. Triangular and Trapezoidal membership functions are used to represent RL, FL and CS sets definition. Risk factors are compared pairwise using AHP to determine the relative importance of risk factors. Various knowledge acquisition methods are used to formulate the fuzzy rules and membership functions. The suitability of the model is illustrated by an example onboard a ship. An example of fire on account of the failure of the fuel oil system in the engine room of a vessel is taken to illustrate the model.

Mentes et al. [73] presented a model with FST in combination with an ordered weighted geometric averaging operator (OWGA) and decision making trial and evaluation laboratory technique (DEMATEL). The model is proposed specifically to develop a risk method for cleaner and safer maritime transportation, identify and evaluate driving factors causing fatality for cargo ships, use ambiguous information and rank the failure modes. The model could handle efficiently qualitative and quantitative data in addition to ambiguous information. The proposed method helps to evaluate failure modes critically for risk. The model is illustrated by taking an example of a cargo vessel accident on the coasts and the open seas of Turkey. Entering and leaving ports are also examined. According to DEMATEL, entering a port is the more critical of the two.

2.2.4 Evidential Reasoning Models

The evidential reasoning approach is based on an algorithm developed in the 1990s to solve multi-criteria problems with uncertainties. The introduction of utility functions, unassigned belief degrees and weights in belief distribution, improved and developed the approach further to make it more realistic and rational. ER approach is more useful to solve Multi-Criteria Decision Making (MCDM) problems having subjective judgements, uncertainties related to data, incomplete information, quantitative and qualitative data. Because of its advantage of handling both complete and incomplete information, researchers have used the ER approach often for aggregation of risk in risk assessment models.

Wang et al. [74] presented a safety analysis model using FST and ER approach for describing each failure event and synthesizing the information respectively. Failure event is analysed using the three basic parameters the likelihood of occurrence of a failure, consequence severity associated with such a failure and the probability of failure consequences. With the hierarchy of subsystems in a complex system, the proposed model is useful in evaluating the information available at the lowest level and arriving at the safety level of the whole system. The model is illustrated by taking an example of the hydraulic hoisting transmission system of a marine crane. The model is best suited in circumstances where it is difficult to obtain the distribution of variables required for risk analysis.

Yang et al. [55] presented a hybrid model to perform Human Reliability Analysis (HRA) using ER and BNs. ER algorithm in the model helps to synthesize experts' judgement for Bayesian subjective probabilities to improve Cognitive Reliability Error Analysis Method (CREAM) for HRA. The model with the concept of degree of belief is flexible and has the potential to handle incompleteness in data for decision making. When degrees of ignorance with best and worst evaluation degrees are combined, the two BNs generated can describe the best and worst scenarios of COntextual COntrol Model Controlling Modes (COCOM-CM) probabilities.

Zhang et al. [75] presented a Fuzzy Rule Based Evidential Reasoning (FRBER) model. To facilitate the use of the ER approach, the quantitative data is suitably converted to a qualitative one using the FRB technique. The model is designed to conduct the navigational risk assessment of the Inland Waterway Transportation System (IWTS). Here qualitative and quantitative criteria are considered while constructing a hierarchical structure for modelling IWTS hazards. The proposed method is used to compare the navigational safety levels of three different regions in the Yangtze river. The model provides insights to improve the safety of the shipping industry and can be expanded further to assess risks in other scenarios.

Nguyen [76] presented an ER based model to capture Container Shipping Operational Risk (CSOR) with aleatory and epistemic uncertainties. A hybrid model of FMEA, ER and fuzzy rules Bayesian network (FRBN) is used for risk mapping. The risk level assessment is expressed in terms of Degree of Belief (DoB) and knowledge base evaluation is expressed in terms of the Undefined Degree of Belief (UDoB). Further, a combination of DoB and UDoB is achieved by FRBN. The model represented CSORs with a comparatively higher risk level and highlighted in the risk map showing the significance of epistemic uncertainty.

Wu et al. [52] produced a model using ER in combination with TOPSIS for decision making in emergencies. The model is designed specifically keeping in mind the safe handling of ships without command. The method proposes to use crisp values for selecting the best alternative as opposed to previous models which rely on an average of the maximum and minimum utility values. This solves the problem of choosing the best alternative even if the alternatives have overlapping interval numbers. The method can be applied directly to multiple attribute group decision making or after modification by decision-makers as per the existing situation.

2.2.5 Formal Safety Assessment Models

IMO proposed a scientific approach, a formal safety assessment (FSA) for consideration of safety regulations. Here, the risk is considered as an indicator of safety. It involves finding all the hazards, assessing the risk associated with hazards and taking steps to reduce the risk to an acceptable level. It is aimed at enhancing maritime safety and evaluating cost benefit trade-offs for reducing these risks. FSA is used to keep a check on risks. It is a tool to make transparent decisions after understanding and comparing all the available options and suggest suitable measures to reduce risks.

Sebe et al. [77] used FSA to assess and suggest actions to mitigate the risk of ship collisions with whales. The paper identified major collision hazards classified into two broad categories of detection failure and avoidance failure. Rather than quantifying the risk, the focus is to obtain the level of risk that is acceptable to the regulations. The approach used the notion of Limit Reference Points (LRP) i.e. risk acceptance at the population level and not at the individual level. FSA recommends suggesting Risk Control Options (RCOs) that are cost-effective, but since biodiversity like protecting whales cannot be quantified in exact monetary value, it still requires further research.

Kaneko [47] examined the scientific method of FSA to develop a holistic methodology for risk evaluation to estimate the chances of ship collision, to develop a method to reduce the scenarios that may escalate fires in the ship and a mock trial of fire risk in the ship cabin.

Computer simulations are used to verify the effectiveness of the method and the results obtained are similar to those obtained by analytical methods. However, experiments and also an examination of actual instances for validation of simulation are inconclusive.

Lois et al. [78] used the FSA framework for cruise passenger vessels and conducted a case study for demonstrating its feasibility. Statistics from the cruise ship industry are taken for study. The case study showed that there is plenty of room for improving safety in cruise ships in areas such as human reliability, fire fighting and communications within the people. There is a need for a clear understanding of actions to be taken in case of emergencies and dealing with the crowd. The adoption of FSA in cruise ships can bring down the risk level to minimum levels.

Kontovas and Psaraftis [79] have done a critical review of FSA. The paper highlighted some of the drawbacks of the scientific method. The paper criticised the usage of historical data for hazard identification which is not a proactive approach and RCOs suggested may not apply to new designs. Using the incomplete and wrong cause information databases of casualty may lead to skewed conclusions and not appropriate to reduce risks. The paper also criticised the formulation of a risk matrix that does not give equal justice to various parameters such as probability and severity. The findings of the study suggested modifying the methodology of FSA to suit all the types of ships and subjects.

Hu et al. [46] discussed quantitative risk assessment and the accuracy of the generic model of FSA. In certain cases when the probability is very low or unstable, it is difficult to identify the risk distribution. To make the model more predictable, it is suggested to incorporate more factors such as obligated severity. Obligated severity represents the proportion of each case on the responsibility of faults in an accident. The Model is built on Relative Risk Assessment (MRRA) using fuzzy functions incorporating such obligated severity.

Gasparotti and Rusu [80] presented the steps of FSA methodology. The authors have given the sources and causes of the Black Sea pollution. They have also highlighted the main accidents responsible for massive oil spills and the consequences of it such as loss of lives, serious injuries, loss of property and damage to the environment. The paper suggested the measures to be adopted to control, prevent and reduce the risks in operating ships. The paper mentioned that the best options to reduce the risks are established taking the cost-benefit trade-off of each option and recommended for decision making.

2.2.6 Analytical Hierarchy Process Models

Saaty [81] introduced Analytical Hierarchy Process (AHP) to help in evaluating decision making problems involving multiple criteria. In AHP, elements at each level are treated as independent and the problem under consideration is broken down into a linear hierarchy from top to bottom. AHP helps decision makers to make the best decisions by pairwise comparisons when dealing with complex decision making. According to the decision makers' comparisons, AHP generates a weight for each evaluation criteria. AHP being a flexible and simple yet powerful tool, researchers have used it in risk assessment models.

Nguyen [82] used the AHP to estimate the risk associated with the failure of the propulsion system of a ship. The required data are collected from a group of forty seven engineers. The experts provided their preferences about particular subsystems' contributions towards the probable causes of propulsion system failures. These data are then compared using five point scale. The AHP method is used for pairwise comparisons between the various sub-systems that contribute towards the failure of the propulsion system. In this paper, the logarithmic least square method is used for approximating the estimation matrices thereby creating a proper correlation between different experts' judgements.

Arslan [83] used AHP to identify and prioritise the precautions to be taken while assessing the risk of cargo operations on chemical tankers. In this paper, using the AHP, various priorities of precautions are sorted out that are taken before, during and after the cargo operations. The AHP is used only to obtain the ranking order of precautions as per importance and criticality comparing the identified precautions. To use the model, thorough initial work is required in identifying the potential risks with the frequency and consequences for properly monitoring the risk.

Mabrouki [17] assessed the major risks in Ro-Ro using the AHP. The structure of the model is designed at three levels. At the top level, the type of major risks is considered. The second level represents the pertinent criteria to achieve the goal while the lower level listed all the risk factors. A brainstorming session is used in the study to identify risk factors. Risk is determined quantitatively using risk analysis while the AHP method is used to select the most probable risks.

Incident and accident reports are not sufficient to arrive at the actual navigational risks because of incomplete data and we have to rely on experts' judgements. Sahin and Kum [84] used an Improved Fuzzy Analytical Hierarchy Process (IF-AHP) to obtain the numeric values of the risk level. They used MATLAB software to run the algorithm. Their results indicate that the factors outside the vessel such as environmental conditions, colliding with floating obstacles, and drift of pack ice are posing higher risks. Also, structural design and arrangement of equipment locations such as corrosion, risk of stability, and unusable design for maintenance equally pose a higher risk level.

2.2.7 Neutrosophic Set Models

Neutrosophic sets because of the incorporation of the hesitancy component handles the hesitancy part of experts' judgement in a better manner compared to fuzzy sets. The use of neutrosophic sets in the risk assessment of the marine industry is in its infant stage but these sets are generously used by researchers in solving MCDM problems related to risk assessment and safety analysis in other engineering applications.

Semantic models are convenient for risk analysis instead of quantitative models. Gou and Wang [85] demonstrated the suitability of neutrosophic sets in semantic risk analysis. The model used generalised fuzzy numbers to express linguistic terms. These terms are transformed into single valued neutrosophic sets. TOPSIS approach is then used to rank the future risks. Results of an illustrative example showed the effectiveness of the proposed neutrosophic approach compared to other existing methods in risk analysis.

Bashan et al. [86] integrated the single valued neutrosophic sets with FMEA and under the TOPSIS approach for evaluation of maritime risks. The model considered the twenty three most frequently occurring and interrelated failure modes for evaluation. It used the judgement of five experts in neutrosophic linguistic terms. The study pointed out that the human factor is one of the main contributing factors towards maritime accidents.

Most of the electronic equipment require a power supply product. The operation of these equipment depends on the reliability of the power supply products. Liou et al. [87] proposed a hybrid FMEA model using a neutrosophic set. The model could explore the uncertainty of failure mode evaluation and the hesitancy of experts' judgement. The team of experts identified all the failure modes and their risk values. The risk priority number is calculated using the neutrosophic weight aggregated sum product assessment method. The results of the case study suggested the importance of product development and the manufacturing stage in improving the reliability of the component.

Risk is inherent in all fields. Junaid et al. [88] assessed the supply chain risk in the automotive industry in Pakistan. The proposed model is based on AHP and TOPSIS using the neutrosophic set. The seventeen risks associated with the supply chain are identified. The results showed that supply chain agility is the best while supply chain robustness is the worst. The model illustrated the usefulness of neutrosophic sets in mitigating the supply chain risks.

Fine-Kinney based approach is used hugely in risk assessment problems in the industry. Gul et al. [89] discussed the use of single valued neutrosophic sets with TOPSIS to improve the Fine-Kinney approach for risk assessment. The proposed approach is illustrated with the case study of a wind turbine. The model is validated by carrying out a sensitivity analysis wherein the risk parameters are varied to see how it affects the ranking of hazards.

Luo et al. [90] addressed the risk assessment and mine safety evaluation problem using linguistic numbers. The decision making methodology focussed on integrating power average operator and Muirhead mean operators with linguistic neutrosophic numbers. The proposed model is applied to assess the safety and rank the gold mines as per decreasing order of safety. The sensitivity analysis is carried out further to show the flexibility and robustness of the method in solving complex decision making problems.

Abdul_Basset et al. [91] proposed a framework for risk assessment using neutrosophic sets. The model is specifically aimed at analysing the risk and suggesting options to mitigate the risk of the supply chain. The proposed neutrosophic AHP-TOPSIS approach is applied in an enterprise engaged in selling non-perishable goods. Total nine risks are identified and ranked in order with the most critical being on top.

2.3 Summary of Literature Survey

From the literature survey addressed in this chapter and from papers by various authors from distinguished journals, the focus of risk assessment models is identified under various heads. The previous models on risk assessment mostly used either crisp or fuzzy data. Because of the lack of historical records, experts' judgements are used by most of the researchers while designing a model. It is seen that there is no such model that can be applied under all the given conditions. Also, the qualitative data collected from experts using even the highest order fuzzy sets fail to represent the hesitancy associated with experts' judgements. The previous models also did not consider the fact that the experts are bound to make errors while making judgements except for carrying out the sensitivity analysis to reduce the concerns about the quality of experts' judegements. Moreover, in the real world, decisions are required to be made in dynamic conditions where the factors influencing the risk change dynamically. A summary of risk assessment models is presented in Table 2.1.

Table 2.1: Classification of Risk Assessment Models Based on Literature Survey

Regulatory framework	**Risk policies**	**Risk focus**
IMO SOLAS STCW MARPOL	Identify hazards Reduce risk level Minimise damage Maximise safety	Collision Capsizing Foundering Fire/Explosion Grounding

Scope of risk	**Modelling tools**	**Important attributes**
High speed craft RoPax Container ship Cruise passenger vessels Chemical tankers Ro Ro	Bayesian belief network Fault/Event tree analysis Fuzzy set theory Evidential reasoning Formal safety analysis Analytical hierarchy process Neutrosophic set theory	Human error Design failure Visibility Bad weather Natural calamity

Dependence	**System information**
Organisational Environmental Personnel	Incomplete Imprecise Vague Linguistic

Chapter 3

Problem Description and Solution Methodologies

3.1 Introduction

Risk assessment in an industry aims to achieve a high level of safety for workers, machinery and the environment at minimum cost. Untoward incidents, near misses and accidents, are documented and stored as records to comply with statutory requirements and for future references. Use of this past data or use of experts' knowledge in the absence of such records can reveal the root causes or probable causes of triggering a sequence of events leading to accidents staking the life of personnel or machinery at risk. If properly recorded, the past data can be an excellent source to know the frequency of accidents. Risk assessment is a vast area of safety engineering/operations research and the on-going research in risk assessment is stupendous. The proactive approach to eliminate the hazards in advance can bring down the likely damage due to accidents. The problem of risk assessment chosen for the research and study is as follows.

1. The maritime transportation system is selected for the study.
2. The fuzzy/neutrosophic/plithogenic available information or information obtained from experts about various parameters/variables is incorporated.
3. The neutrosophic/plithogenic risk assessment models using evidential reasoning are carried out.
4. The accident reports are scarce, incomplete and imprecise. To identify probable causes and their interrelationships, a group of experts from the field is invited to provide their expertise and created a hybrid model for risk assessment using Interpretive Structural Modelling (ISM)/Fuzzy Analytical Network Process (FANP)/Evidential Reasoning (ER) approach.
5. The effectiveness of ER approach in solving multicriteria decision making problems is checked. A new alternative is introduced to the D-S theory of evidential reasoning to overcome its limitations of giving illogical results in the conflicting environment.
6. Most risk scenarios in the industry vary periodically with changes in the type of hazards and severity. Risk assessment in such cases is challenging and requires decision making

dynamically. A dynamic decision-making model for risk assessment is proposed in the neutrosophic environment.

3.2 Motivation for Research Work

The vital problem faced by researchers in risk assessment is regarding the data. A sizeable amount of data are required to carry out the risk assessment, analyse the system and make decisions dynamically to assure the system's safety. Moreover, it is extremely difficult to get the required reliable and valid data from records. The experts from the field play a crucial role under such circumstances. Experts' assessments of the situation and system based on their expertise and knowledge help to analyse the safety through the judgements which are subjective and hence qualitative.

The qualitative data contain uncertainty. The conventional methods based on probability theory cannot give satisfactory results because of their inability in handling such type of uncertainty. The *epistemic uncertainty,* related to knowledge and information about the subject mainly due to imprecise data are bound to be present in all the forms of problems. Newer approaches like fuzzy set theory, neutrosophic set theory and more recently proposed plithogenic set theory with contradiction degrees are being looked upon as alternatives to the probabilistic approaches. All these approaches are adopted in this study in different scenarios to handle the problems.

For safe maritime transportation, risks posed due to unpredictable systems performance onboard a ship and threats due to unsafe navigation should be addressed. Very little work is done in risk assessment of the marine field with incomplete and imprecise data using experts' judgement in subjective form. An attempt is made to solve some of these problems using a fuzzy/neutrosophic/plithogenic set theory. Evidence combination theories such as evidential reasoning based on DST and DSmT have been incorporated in the models proposed in this research work.

3.3 Problem Statement

The problem area of the present research work is presented in Figure 3.1. The problem is stated below.

1. Checking the effectiveness of tools like Bayesian Belief Network, Evidential reasoning and Fuzzy multi-criteria methods suitable for efficient reasoning under uncertainty.
2. Creating a framework for estimating the risk in maritime transportation.

3. Introducing a framework for dynamic decision making in integrated approach/method.

3.4 General Assumptions

The general assumptions applicable to almost all the models developed in this thesis are stated here.

1. Data regarding modelling parameters of risk assessment are either not available or incomplete or scarce and it is not possible to use probability or Bayesian approach.
2. Fuzzy, neutrosophic and plithogenic sets have been assumed for collecting data from experts in linguistic variables. This assumption is considered for parameters like failure likelihood and consequence severity.
3. Linguistic scales (ratings and weights) in the form of neutrosophic/plithogenic sets are predefined by the knowledge engineer elicited from the domain experts (operation and maintenance engineers) and the methods best known to him/her. Further, opinions expressed in terms of semantic terms are converted into fuzzy/neutrosophic/plithogenic sets based on these pre-defined scales.
4. It is assumed that the chosen experts are authentic, knowledgeable, conversant and experienced in their discipline and their judgements/beliefs expressed in the form of fuzzy, triangular/trapezoidal neutrosophic and plithogenic numbers are perfect.
5. No expert will deliberately give incorrect judgement.
6. Experts have some idea of fuzzy/neutrosophic/plithogenic set theory and the consequences of their incorrect belief.

All the critical risk assessment decision criteria which have a considerable impact on the risk assessment and decision making have been considered and unnecessary criteria are neglected.

3.5 Scope of the Problem

As risk assessment is a vast area, understanding the scope and span of the problem is very crucial. The scope is also highlighted in Figure 3.1. The scope of the research problem tackled in the report is described in the section.

1. The fuzzy/neutrosophic/plithogenic risk assessment model development is restricted to maritime transportation which is described in chapter 1.
2. As mentioned earlier fuzzy/neutrosophic/plithogenic sets approach suits better for handling the uncertainty. Neutrosophic/plithogenic set theory has been used for dynamic risk assessment.

3. Fuzzy/neutrosophic/plithogenic set theories are used since most of the time data are partially available or are vague. The knowledge of the experts i.e. their opinions have been incorporated in the development of the models.

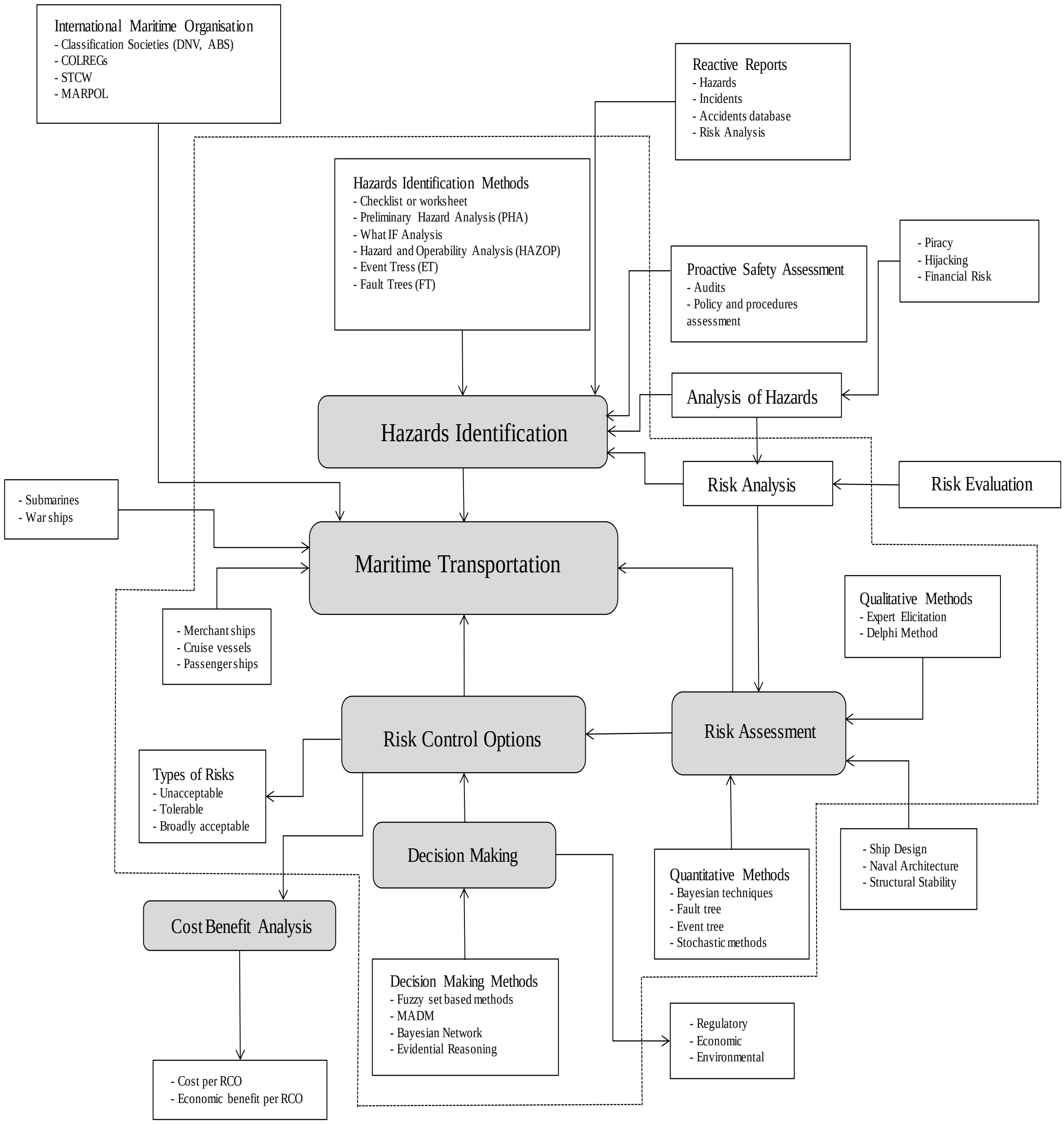

Figure 3.1: Problem Area Identification Diagram

3.6 Solution Methodologies

The appropriate methods are used to solve the problem presented in section 3.5. Some of the selected methods/approaches are presented in the following sections.

3.6.1 Interpretive Structural Modelling

Interpretive Structural Modelling (ISM) [92, 93] is a handy tool to understand complex scenarios. ISM is an interactive learning process. In this, the group's judgement is used to conclude how factors are related to each other by developing a Structural Self Interaction Matrix (SSIM) of factors by representing the pairwise relationship between various factors of the system as given by experts. Initial Reachability Matrix (IRM) is obtained from SSIM by using one's and zero's which is further converted into Final Reachability Matrix (FRM) after checking transitivity and changing the matrix if required. Reachability Matrix is partitioned into different levels using the Reachability set, Antecedent set and intersection set.

Transitivity assumption: If factor P is related to factor Q and factor Q is related to factor R, then factor P has to be related to factor R.

A directed graph is then drawn using the relationships from the reachability matrix after removing transitive links. It is modified into the ISM diagram where factor nodes are replaced with linguistic statements.

3.6.2 Fuzzy Analytical Network Process

Analytical Network Process (ANP) [94-96] is developed to evaluate decision-making problems containing factors that are interdependent and networked together [97–100]. It does not make any assumptions about the independence between factors at different levels and also within the factors at a particular level. ANP is popular to get the weight vectors when the factors are not in a hierarchy but a network. After evaluating the importance of all the factors by pairwise comparison, a supermatrix is created wherein each of the local priority vectors forms the column of a matrix. A weighted supermatrix is created next to maintain the column stochastic property. This weighted supermatrix is raised to large powers until it converges to get a limit supermatrix. This is done to produce the cumulative influence of each factor on every other factor. Priority weights of the factors are obtained from this limit supermatrix.

Limit supermatrix: A matrix having the same values across all columns.

In our study, FANP is used to get the priority weights of the factors. The process used is described in section 4.3.

3.6.3 Evidential Reasoning Approach

In MCDM, decision knowledge is often in qualitative and/or quantitative form with uncertainty. Such MCDM problems are solved using the ER approach. When the data available for decision making is uncertain, it cannot be assessed accurately using a crisp number and one has to use the fuzzy concept.

ER approach provides a strong alternative to aggregate conflicting information and provides a rigorous reasoning process [101, 102]. ER approach uses belief structure to represent the outcome as a distributed assessment and not as a single number. For example, the distributed assessment for the safety of the system could be {(Excellent, 28%), (Good, 35%), (Average, 18%), (Poor, 12%), (Worst, 7%)} which means the safety of the system is assessed to be Excellent with 28% of belief degree, Good with 35% of belief degree, Average with 18% of belief degree, Poor with 12% of belief degree and Worst with 7% of belief degree. Using such belief structures, the ER approach deals with MCDM problems with uncertainties. ER approach is enhanced based on the DST.

3.6.3.1 Dempster-Shafer Theory of Evidence (DST)

Dempster [36] and Shafer [37] established DST. It differs from probability theory in that, it allows beliefs not only to particular elements but also to sets of elements. Its base is the frame of discernment (Ω) – an exhaustive set of mutually exclusive hypotheses. A mass function $m(A)$ represents one's belief on subsets of Ω subject to,

$$m(\emptyset) = 0 \tag{3.1}$$

and

$$\sum_{A \subseteq \Omega} m(A) = 1 \tag{3.2}$$

Where $m(A)$ is the belief assigned to the subset A. If $m(A) > 0$, the element is called the focal element. If a mass is assigned to a whole set Ω, it implies that the piece of evidence has an uncertainty for a particular hypothesis in Ω is true.

If $m_1(B)$ and $m_2(C)$ represent two mass functions, they can be combined using D-S orthogonal sum rule of combination, denoted by,

$$m(A) = m_1(B) \oplus m_2(C) \tag{3.3}$$

The rule is defined as,

$$m(A) = \sum_{B \cap C} \frac{m_1(B) \cdot m_2(C)}{1 - K}$$

Where

$$K = \sum_{B \cap C = \emptyset} m_1(B) \cdot m_2(C) \tag{3.4}$$

K is a normalisation constant (conflict) and measures the degree of conflict between $m_1(B)$ and $m_2(C)$. If there is no conflict between $m_1(B)$ and $m_2(C)$, $K = 0$. On the other hand, if $m_1(B)$ and $m_2(C)$ are totally conflicting then $K = 1$. D-S theory is commutative and associative.

3.6.3.2 Dezert-Smarandache Theory of Evidence (DSmT)

Dezert-Smarandache in their paper [103] proposed a new theory of information which overcomes the major limitations of D-S theory such as, all hypothesis should be mutually exclusive and exhaustive, the third middle excluded principle and accepting Dempster's combination rule as the framework for combining independent sources of information. The free DSm model $\left(M^f(\Theta)\right)$ proposed by Dezert-Smarandache considers Θ as a frame of exhaustive elements, $\theta_i, i = 1, \dots, n$ which may overlap. This model is commutative and associative.

Let $\Theta = \{\theta_1, \dots, \theta_n\}$ be a finite set of n exhaustive elements. Hyper power set, D^Θ consists of all composite subsets built from elements of Θ with ∪ and ∩ operators such that,

a. $\emptyset, \theta_1, \theta_2, \dots, \theta_n \in D^\Theta$

b. If $A, B \in D^\Theta$, then $A \cap B \in D^\Theta$ and $A \cup B \in D^\Theta$

c. No elements belong to D^Θ, except those mentioned in above two rules.

The free DSm model $\left(M^f(\Theta)\right)$ with no constraints on elements of the frame of two independent sources of evidence is given by [103],

$$\forall C \neq \emptyset \in D^\Theta, m_{M^f(\theta)}(C) \equiv m(C) = m_1(A) \oplus m_2(B) = \sum_{\substack{A,B \in D^\Theta \\ (A \cap B) = C}} m_1(A) m_2(B) \qquad (3.5)$$

The rule is extended if $k \geq 2$,

$$\forall C \neq \emptyset \in D^\Theta, m_{M^f(\theta)}(C) \equiv m(C) = [m_1 \oplus m_2 \oplus \dots \oplus m_k](C) =$$

$$\sum_{\substack{x_1, x_2, \dots, x_k \in D^\Theta \\ (x_1 \cap x_2 \cap \dots \cap x_k) = A}} \prod_{i=1}^{k} m_i(X_i) \qquad (3.6)$$

and

$$m_{M^f(\theta)}(\emptyset) = 0 \qquad (3.7)$$

The free classical model of DSm theory is used in our study of dynamic decision making in chapter six.

3.6.4 Neutrosophic Number

Single Valued Neutrosophic Number (SVNN) $(\tilde{S})$ is defined as $\tilde{S} = \langle[(p_1, q_1, r_1, s_1);\ \alpha], [(p_2, q_2, r_2, s_2);\ \beta],\ \ [(p_3, q_3, r_3, s_3);\ \gamma]\rangle$ where $\alpha, \beta, \gamma\ \in [0, 1]$, the truth membership function, $(T_{\tilde{S}}): R \rightarrow [0, \alpha]$, the indeterminacy function, $(I_{\tilde{S}}): R \rightarrow [\beta, 1]$ and the falsity membership function, $(F_{\tilde{S}}): R \rightarrow [\gamma, 1]$ is given as [104],

$$T_{\tilde{S}}(x) = \begin{cases} T_{\tilde{S}_l}(x) & p_1 \leq x \leq q_1 \\ \alpha & q_1 \leq x \leq r_1 \\ T_{\tilde{S}_u}(x) & r_1 \leq x \leq s_1 \\ 0 & otherwise \end{cases} \tag{3.8}$$

$$I_{\tilde{S}}(x) = \begin{cases} I_{\tilde{S}_l}(x) & p_2 \leq x \leq q_2 \\ \beta & q_2 \leq x \leq r_2 \\ I_{\tilde{S}_u}(x) & r_2 \leq x \leq s_2 \\ 1 & otherwise \end{cases} \tag{3.9}$$

$$F_{\tilde{S}}(x) = \begin{cases} F_{\tilde{S}_l}(x) & p_3 \leq x \leq q_3 \\ \gamma & q_3 \leq x \leq r_3 \\ F_{\tilde{S}_u}(x) & r_3 \leq x \leq s_3 \\ 1 & otherwise \end{cases} \tag{3.10}$$

3.6.4.1 Triangular Single Valued Neutrosophic Number

Triangular neutrosophic number $(\tilde{A})$ is defined as, $\tilde{A}_{TN} = (a, b, c; d, e, f; g, h, i)$ whose truth, indeterminacy and falsity membership functions are defined as follows [104].

$$T_{\tilde{A}_{TN}} = \begin{cases} \frac{x-a}{b-a} & a \leq x < b \\ 1 & x = b \\ \frac{b-x}{c-b} & b < x \leq c \\ 0 & otherwise \end{cases} \tag{3.11}$$

$$I_{\tilde{A}_{TN}} = \begin{cases} \frac{x-d}{e-d} & d \leq x < e \\ 0 & x = e \\ \frac{f-x}{f-e} & e < x \leq f \\ 1 & otherwise \end{cases} \tag{3.12}$$

$$F_{\tilde{A}_{TN}} = \begin{cases} \frac{x-g}{h-g} & g \le x < h \\ 0 & x = h \\ \frac{i-x}{i-h} & h < x \le i \\ 1 & otherwise \end{cases} \tag{3.13}$$

where $0 \le T_{\tilde{A}_{TN}}(x) + I_{\tilde{A}_{TN}}(x) + F_{\tilde{A}_{TN}}(x) \le 3, \qquad x \in \tilde{A}$

3.6.4.2 Trapezoidal Single Valued Neutrosophic Number

Trapezoidal neutrosophic number $(\tilde{B})$ is defined as, $\tilde{B}_{TZ} = (a, b, c, d; e, f, g, h; i, j, k, l)$ whose truth, indeterminacy and falsity membership functions are defined as follows [105].

$$T_{\tilde{B}_{TZ}}(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \le x \le b \\ 1 & b \le x \le c \\ \frac{d-x}{d-c} & c \le x \le d \\ 0 & x > d \end{cases} \tag{3.14}$$

$$I_{\tilde{B}_{TZ}}(x) = \begin{cases} 1 & x < e \\ \frac{f-x}{f-e} & e \le x \le f \\ 0 & f \le x \le g \\ \frac{x-g}{h-g} & g \le x \le h \\ 1 & x > h \end{cases} \tag{3.15}$$

and

$$F_{\tilde{B}_{TZ}}(x) = \begin{cases} 1 & x < i \\ \frac{j-x}{j-i} & i \le x \le j \\ 0 & j \le x \le k \\ \frac{x-k}{l-k} & k \le x \le l \\ 1 & x > l \end{cases} \tag{3.16}$$

where $0 \le T_{\tilde{B}_{TZ}}(x) + I_{\tilde{B}_{TZ}}(x) + F_{\tilde{B}_{TZ}}(x) \le 3, \qquad x \in \tilde{B}$

3.6.5 Multi-Criteria Decision Making (MCDM)

Decision making involves selecting the best alternative subject to laid down criteria. This is difficult especially when the criteria are expressed in qualitative form. Under such a scenario, MCDM is one of the statistical methods that is recognised as an efficient tool to compare, rank and order various alternatives. MCDM has grown quickly and has been a focus of research for solving complex decision problems [106-110]. The majority of the time, the decision making in the complex environment involves data and criteria output which are not known precisely and contain uncertainty mainly because of their fuzziness. As mentioned in the literature review, many techniques and methods are devised in the past decades to deal with such problems [111–113]. A typical MCDM problem framework consists of evaluating alternatives subject to the number of criteria having values for each alternative. Let $A = \{A_1, A_2, \dots, A_n\}$ and $C = \{C_1, C_2, \dots, C_m\}$ be the sets of n alternatives to be evaluated w.r.t. to m criteria and obtain an optimum solution by maximising the benefit criteria and minimising the cost criteria.

3.6.6 Ranking Method

ER approach is used for aggregating the belief degrees. Qualitative attribute alternatives are assessed using grades. An example of grades is {Excellent, Average, Good, Poor, Worst}. ER approach does not restrict the number of grades for each attribute and this number may vary for every attribute. Also, every attribute may have a different number of grades. The result of an ER approach is a distributed assessment. For example, system safety can be {(Excellent, 28%), (Good, 35%), (Average, 18%), (Poor, 12%), (Worst, 7%)}. Utility function like similarity measures is also used to map all the distributed assessments to their ideal grades. The utility is a scale of priority of the decision making and usually is in the range of [0, 1], [0, 10] or [0, 100]. The highest number is allotted for the most favoured grade while the lowest number is for the least favoured grade.

3.6.7 Distance Measures for Evidence

A distance (dissimilarity) of evidence indicates the measure of dissimilarity between bodies of evidence. It is used to indicate if a given body of evidence is near or far from another body of evidence. Once the distance between bodies of evidence is quantified, one can check the similarity between bodies of evidence. Various types of distance or dissimilarity measures are developed in evidence theory. Some of the distance measures are discussed in the next paragraphs.

Consider m_i and m_j be two BBA's on the same frame of discernment Ω, containing N mutually exclusive and exhaustive hypotheses.

3.6.7.1 Jousselme Distance

Jousselme et al. [114] proposed a distance between m_i and m_j represented by,

$$d_{ij} = \sqrt{\frac{1}{2}\left(\vec{m}_i - \vec{m}_j\right)^T \cdot D \cdot \left(\vec{m}_i - \vec{m}_j\right)} \tag{3.17}$$

where D is a $2^N \times 2^N$ matrix. The element of D is defined as, $D(A,B) = \frac{|A \cap B|}{|A \cup B|}$, $A, B \in 2^{\Omega}$, $|\cdot|$ represents cardinality.

3.6.7.2 Song's Correlation Coefficient

Song et al. [115] proposed a correlation coefficient between two bodies of evidence as,

$$cor\left(m_i, m_j\right) = \frac{\langle m'_i, m'_j \rangle}{\|m'_i\| \cdot \|m'_j\|} \tag{3.18}$$

where $m'_i = m_i \cdot D$, $m'_j = m_j \cdot D$, $\langle m'_i, m'_j \rangle$ is the inner product of vectors and m'_i is the norm of a vector. Song et al.'s correlation coefficient estimates the degree of relevance between two bodies of evidence i.e. lower the value of $cor\left(m_i, m_j\right)$, the higher is the conflict. In this, Song et al. have used the Jaccard matrix D to modify BBA. But the limitation of this method is, the modified BBA does not satisfy the condition $\sum_{A \epsilon 2^{\Theta}} m(A) = 1$. Thus the correlation coefficient does not satisfy the property $cor\left(m_i, m_j\right) = 1 \leftrightarrow m_i = m_j$ and gives incorrect results.

3.6.7.3 Jiang's Correlation Coefficient

Jiang [116] proposed a new correlation coefficient between two bodies of evidence to quantify the conflict by the relevance between two bodies of evidence. If the value of relevance is higher, the degree of similarity is higher and the degree of conflict is lower and vice versa. Jiang's correlation coefficient is given by,

$$r_{BBA}\left(m_i, m_j\right) = \frac{c\left(m_i, m_j\right)}{\sqrt{c\left(m_i, m_j\right), c\left(m_j, m_j\right)}}$$

Where $c\left(m_i, m_j\right)$ is the degree of correlation defined as,

$$c\left(m_i, m_j\right) = \sum_{x=1}^{2^N} \sum_{y=1}^{2^N} m_i(A_x) \cdot m_j\left(A_y\right) \cdot \frac{A_x \cap A_y}{A_x \cup A_y} \tag{3.19}$$

where $x, y = 1, 2, \ldots, 2^N$; A_x, A_y are the focal elements of mass respectively and $|\cdot|$ is the cardinality of a subset. $r_{BBA} = 0$ implies no relevance between m_i and m_j while $r_{BBA} = 1$ implies m_i and m_j are identical.

Jiang has tried to measure the similarity between the bodies of evidence considering the relevance of the evidence. He has considered simultaneously the non-intersection and the difference among the focal elements. Jiang’s correlation coefficient is used in our study to get the measure of similarity between bodies of evidence.

3.6.8 Methods for Combining Experts’ Judgements

The experts express their opinions about the value of variables/parameters that may be used as inputs in decision making models. A peculiar characteristic is that each expert provides a subjective judgement about the variables. The purpose of combining experts’ judgements is to get a single resultant number when opinions of different experts are obtained in fuzzy/neutrosophic/plithogenic numbers. The study used three different methods for combining experts’ judgements. These are geometric average, evidential reasoning and averaged aggregation approach. These are explained later in section 4.3.2, section 5.5.5 and section 6.2.2.

3.7 Summary

In this chapter, the research problem is formulated. The motivation for the research problem and the general assumptions applicable to almost all the models are summarised. The solution methodologies used in the research work are given in detail along with the distance measures and methods for combining experts’ judgements used. The scope of the problem is broadly described in a detailed problem area identification diagram. The identified research problem is analysed in three parts. Analysis of these parts is given in chapter 4, chapter 5 and chapter 6 respectively.

Chapter 4

Risk Assessment Model for Efficient Reasoning under Uncertainty

4.1 Effectiveness of Bayesian Belief Network

Bayesian networks as a normative theory for reasoning have been quite successful in recent years. Bayesian conditioning requires that the relevant knowledge is available beforehand before fixing the probability distribution [117]. However, in real life, it is hard to believe that the initial knowledge is invariable. The recently gained knowledge may dominate the earlier knowledge. In such scenarios, the best option is to redefine the earlier probability distribution with the latest available information. The advantages of BNs are, they can represent the causal relationships, can include a variety of input data and make a provision to handle missing data along with the new evidence collected even after the network is built. Some of the advantages of using BN are it can easily translate human knowledge into probabilistic form and provides users more insights with causal representations making it easy for people with different background knowledge to understand the network. Thus, allowing users to make better predictions [118]. BN can furnish the latent variables of complex problems with graphical dimensions [54]. This makes it an appropriate tool for modeling complex scenarios. Additionally, BNs can incorporate different types of evidence in model building. The graphical network of BNs provides a good view to perceive and evaluate data and analyse the strength of evidence [54]. The BN network represents the background knowledge in graphical form. It allows combining types of evidence through probabilities and sets a base for carrying out sensitivity analysis. It permits to incorporate alternative hypotheses in the model [56]. It provides a method to convey the relationships between variables even in the condition when one is uncertain about their precise relationships. It can incorporate data from different sources and thus overcome the limitation of data scarcity. The challenges in constructing BN lie in efficiently handling incomplete data and the creation of simple and properly fitting probability distributions [118]. The BN also suffers from certain limitations regarding acyclic nature depriving of the feedback effects. Another limitation of Bayesian theory lies in that it cannot represent and process the uncertainty associated with an implicit knowledge and the prior probability distribution. This resulted in the emergence of many alternative approaches and extensions to Bayesian theory such as the D-S theory of evidential reasoning [117]. The ER approach can efficiently handle any kind of data such as incomplete, complete, imprecise, precise or even fuzzy. This makes ER approach a handy tool for combining the information and pieces of evidence for decision making while solving multicriteria problems.

4.2 Building an ISM Model

The typical engineering system consists of a complex network of many subsystems (factors) as shown in Figure 4.1. Risk assessment of such a system is difficult because of the interconnectivity and interrelationship between these factors. To overcome such a difficulty, a new hybrid risk assessment model has been proposed in this chapter. This chapter deals with the first part of the problem statement. Initially, ISM is used to find the interrelationship between various factors and ascertain the causable association between these factors. Weights of the factors using FANP are identified next. Fuzzy logic is used to deal with uncertainty in experts' opinions to get likelihood and consequence severity. The information obtained is synthesised using the ER approach to arrive at the risk level of the system. The proposed approach is illustrated with an example to assess the risk associated with fire on board the ship.

ISM is used to understand complex scenarios and establish the relationship between various factors using a binary matrix. This technique is chosen in our study as historical data are scarce, missing and also incomplete. Experts' judgements are used to identify the causable factors and their interrelationships.

4.2.1 Identifying the Risk and Associated Factors

The risk to be assessed is described by the committee of experts. The factors which are appropriate and associated with the given problem are identified. These factors directly or indirectly influence the risk. Identical factors are clubbed together in factor groups.

4.2.2 Determining Interdependence between Factors

SSIM is constructed using the contextual relationship among factors. Four characters V, A, X and O indicate the direction of relationships among the factors a and b (a < b).

V: factor a leads to factor b

A: factor b leads to factor a

X: factor a and b lead to each other

O: factor a and b are unrelated

IRM is constructed by replacing the characters by 0 and 1 as per the following rules.

1: If the cell (a, b) has entry V, fill cell (a, b) with 1 and cell (b, a) with 0.

2: If the cell (a, b) has entry A, fill cell (a, b) with 0 and cell (b, a) with 1.

3: If the cell (a, b) has entry X, fill cell (a, b) and (b, a) with 1.

4: If the cell (a, b) has entry O, fill cell (a, b) and (b, a) with 0.

FRM is constructed after ensuring transitivity and changing the matrix if required.

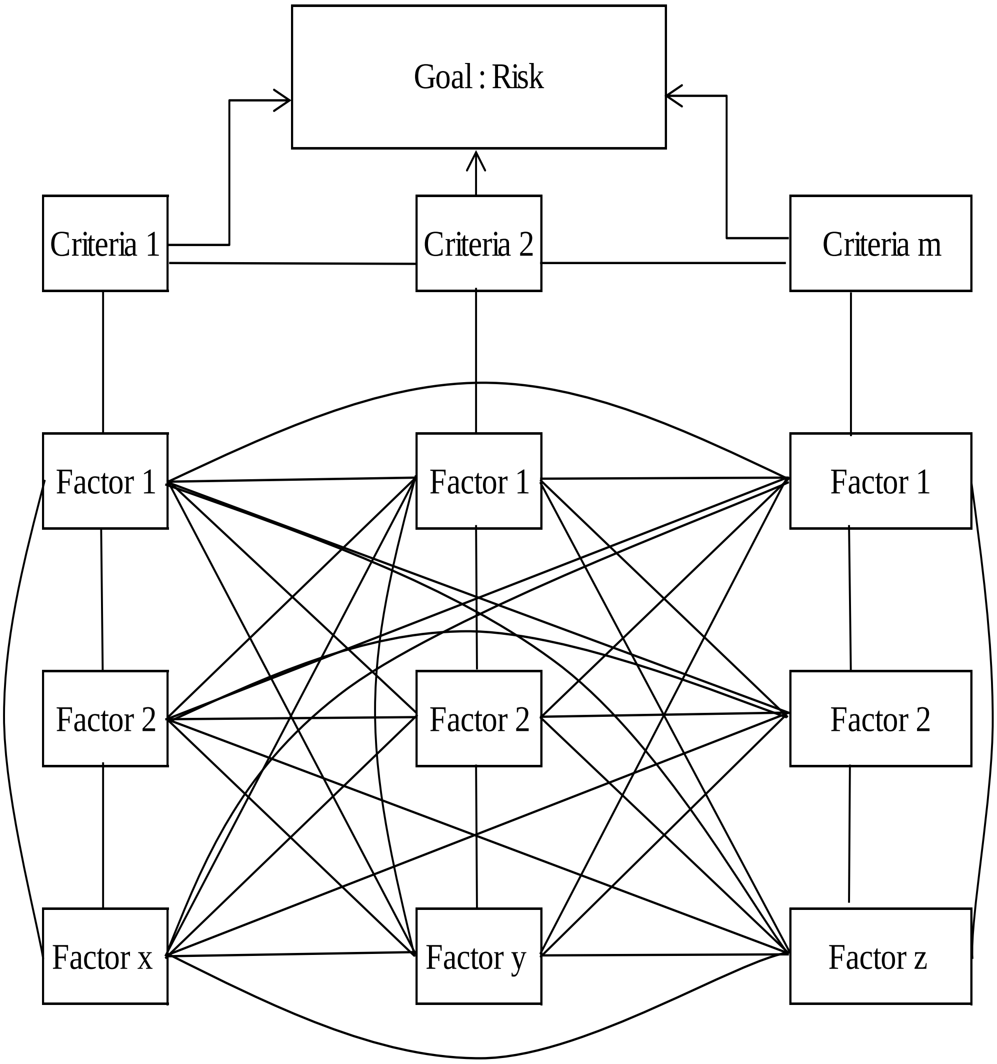

Figure 4.1: Typical Engineering System

4.2.3 Drawing an ISM Diagram

The Reachability matrix is partitioned into different levels using reachability set, antecedent set and intersection set. A directed graph (digraph) is drawn using the relationships from the reachability matrix after removing transitive links. Finally, an ISM diagram is drawn from the resulting digraph.

4.3 Obtaining Priority Weights of Factors

Factors and factor groups are compared pairwise using FANP to get the priority weights of factors. The global weights of all the factors are obtained by constructing the limit supermatrix. The procedure is explained in subsection 4.3.1 to subsection 4.3.4.

4.3.1 Collecting Experts' Judgements on Factors

All the factors and factor groups are compared pairwise by experts in linguistic terms. Triangular/Trapezoidal fuzzy numbers with membership functions as shown in Figure 4.2 convert the information in linguistic terms into trapezoidal fuzzy numbers.

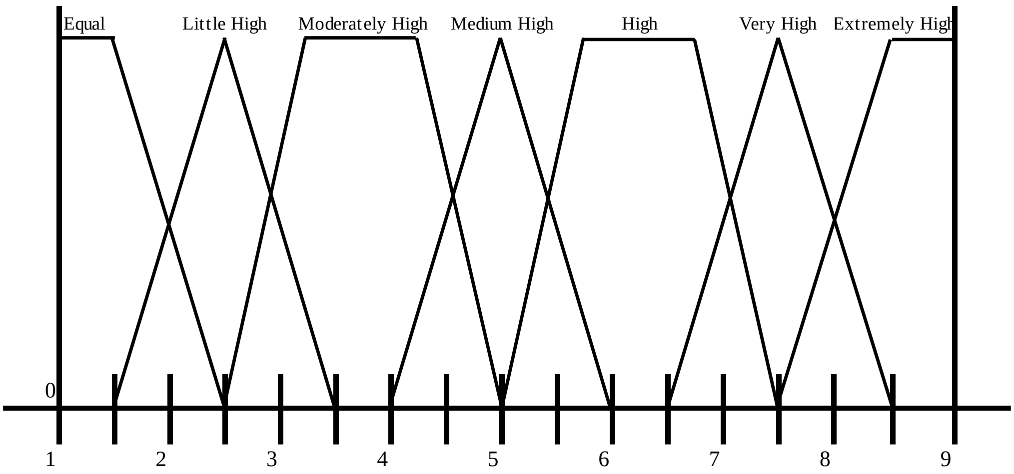

Figure 4.2: Membership Function of Fuzzy Numbers for Relative Importance/Performance

4.3.2 Aggregating Experts' Responses

Experts' responses are aggregated and trapezoid fuzzy numbers are resolved using the geometric average approach,

$$\tilde{r}_{ij} = \left(\tilde{a}_{ij1} \otimes \tilde{a}_{ij2} \otimes \dots \otimes \tilde{a}_{ijk}\right)^{1/k} \tag{4.1}$$

where $\tilde{a}_{ijk}$ represents pairwise comparison value between factor i and j given by k^{th} expert.

Next, the Yager ranking method [119] is used to defuzzify each fuzzy number into a crisp number.

$$r_{ij} = \int_0^1 \frac{1}{2}\left(\left(\tilde{r}_{ij}\right)_\alpha^l + \left(\tilde{r}_{ij}\right)_\alpha^u\right) d\alpha \tag{4.2}$$

Where $\left(\tilde{r}_{ij}\right)_\alpha^l$ and $\left(\tilde{r}_{ij}\right)_\alpha^u$ are the α-cuts of fuzzy numbers. α-cuts of fuzzy numbers are given in Table 4.1.

Table 4.1: α-cuts of Fuzzy Numbers

$\tilde{a}$	$(\tilde{a})_\alpha^L$	$(\tilde{a})_\alpha^U$
$\tilde{a}_{VH} = (7.5, 8.5, 9, 9)_{L-R}$	$(\tilde{a}_{VH})_\alpha^L = 7.5 + \alpha$	$(\tilde{a}_{VH})_\alpha^U = 9$
$\tilde{a}_H = (6.5, 7.5, 7.5, 8.5)_{L-R}$	$(\tilde{a}_H)_\alpha^L = 6.5 + \alpha$	$(\tilde{a}_H)_\alpha^U = 8.5 - \alpha$
$\tilde{a}_{MH} = (5, 5.75, 6.75, 7.5)_{L-R}$	$(\tilde{a}_{MH})_\alpha^L = 5 + 0.75\alpha$	$(\tilde{a}_{MH})_\alpha^U = 7.5 - 0.75\alpha$
$\tilde{a}_M = (4, 5, 5, 6)_{L-R}$	$(\tilde{a}_M)_\alpha^L = 4 + \alpha$	$(\tilde{a}_M)_\alpha^U = 6 - \alpha$
$\tilde{a}_{ML} = (2.5, 3.25, 4.25, 5)_{L-R}$	$(\tilde{a}_{ML})_\alpha^L = 2.5 + 0.75\alpha$	$(\tilde{a}_{ML})_\alpha^U = 5 - 0.75\alpha$
$\tilde{a}_L = (1.5, 2.5, 2.5, 3.5)_{L-R}$	$(\tilde{a}_L)_\alpha^L = 1.5 + \alpha$	$(\tilde{a}_L)_\alpha^U = 3.5 - \alpha$
$\tilde{a}_{VL} = (1, 1, 1.5, 2.5)_{L-R}$	$(\tilde{a}_{VL})_\alpha^L = 1$	$(\tilde{a}_{VL})_\alpha^U = 2.5 - \alpha$

An aggregated comparison matrix of crisp numbers is then developed.

$$W_s = \begin{bmatrix} 1 & r_{12} & \cdots & \cdots & \cdots & \cdots & r_{1j} \\ 1/r_{12} & 1 & \cdots & \cdots & \cdots & \cdots & r_{2j} \\ \vdots & \vdots & 1 & \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & 1 & r_{ij} & \cdots & \cdots \\ \vdots & \vdots & \vdots & 1/r_{ij} & 1 & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & 1 & \cdots \\ 1/r_{1j} & 1/r_{2j} & \cdots & \cdots & \cdots & \cdots & 1 \end{bmatrix} \tag{4.3}$$

Priority vector, W_s for the aggregated comparison matrix is obtained,

$$W_s \times w_s = \lambda_{max} \times w_s \tag{4.4}$$

Where w_s is the eigen vector and λ_{max} is the principal eigen value of W_s.

4.3.3 Examining the Consistency of Aggregated Comparison Matrix

Some inconsistencies may arise when experts carry out many pairwise comparisons. For example, when three factors are compared, experts may consider that the first factor is slightly more important than the second factor and the second factor is slightly more important than the third one. But by mistake expert may also consider that the third factor is slightly more important than the first one giving rise to an inconsistency. To check such inconsistencies, Saaty [81] proposed the Consistency Ratio $(C.R.)$ given by,

$C.R. = \frac{C.I.}{R.I.}$ (4.5)

where $C.I.$ is the Consistency Index, $C.I. = \frac{\lambda_{max} - n}{n-1}$ and n is the number of factors being compared. For small problems $(n \leq 10)$, $R.I.$ is given as,

n	1	2	3	4	5	6	7	8	9	10
R.I.	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

For a perfect and consistent decision, $C.I. = 0$ i.e. $R.I. = 0$ and a small inconsistency is accepted upto $C.R. \leq 10\%$. If $C.R. > 10\%$ the subjective judgements are revised again.
An aggregated comparison matrix of crisp numbers is then checked for consistency.

4.3.4 Constructing the Limit Supermatrix

An unweighted supermatrix is constructed using priority vectors ensuring that it is column stochastic. This matrix is raised to large power to obtain a limit supermatrix. This is done to produce the cumulative influence of each factor on every other factor. The global weights of all the factors are obtained from the limit supermatrix.

4.4 Synthesising the Information

The data on risk parameters of factors are collected from experts' judgements. These data are synthesised using the global weights as described in the following sections.

4.4.1 Collecting the data on Risk Parameters

Traditionally, the risk is considered to be a function of two parameters, FL and CS associated with the failure.

$Risk = f(FL, CS)$

$R = FL \times CS$ (4.6)

Most of the accidents in engineering are not reported due to a lot of stringent regulations and hence the data obtained from records are incomplete and imprecise. Less knowledge of information about any accident results in higher uncertainty and does not provide a correct picture of the risk involved. The effect of this is felt in the measures taken to reduce the risk level. To overcome this, the FL and CS of risk are identified by a group of experts from the straight line membership functions (triangular and trapezoidal). The likelihood is a fuzzy range of the frequency of occurrence of a particular incident and consequence is a fuzzy range of the outcome of that incident. Seven and four overlapping triangular and trapezoidal curves for likelihood and severity are constructed respectively. The fuzzy membership functions of the above curves are shown in Figure 4.3 and Figure 4.4.

Experts' responses are aggregated using the geometric average approach. Next, the fuzzy number is defuzzified to get a crisp number.

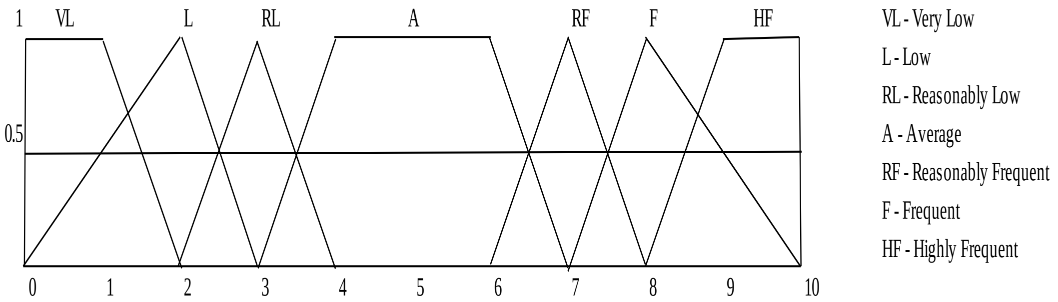

Figure 4.3: Fuzzy Likelihood Sets Definition

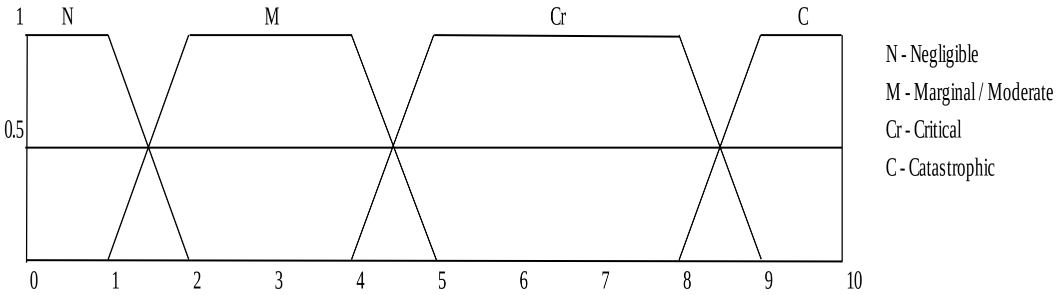

Figure 4.4: Fuzzy Severity Sets Definition

4.4.2 Obtaining the Fuzzy Combine

Crisp to fuzzy combine is used to get the degree of truth. In the maximiser method, when the crisp value corresponds to two neighbouring fuzzy ranges in fuzzy sets, it takes the one having higher membership degrees since it dominates the fuzzy range with lower membership degrees. The average of the two is taken if two actions are having the same degree of membership which is also the maximum. In the case of the Weighted Average Method (WAM), the various actions are averaged out depending on their degree of membership. The centroid method gives the output actions in connection with the centre of mass of the outputs. In this study, all the ranges which represent the crisp values are retained with their corresponding membership degrees. These values are used in the fuzzy inference system. The matrix of fuzzy rules between likelihood and severity for risk estimation is given in Table 4.2.

Table 4.2: Risk Estimation – Fuzzy Rule Matrix

Severity -> Likelihood ↓	Negligible	Marginal	Critical	Catastrophic
Very Low	VL	VL	L	M
Low	VL	VL	L	M
Reasonably Low	VL	L	M	H
Average	L	L	M	H
Reasonably Frequent	L	M	H	VH
Frequent	L	M	H	VH
Highly Frequent	L	H	VH	VH

VL - Very Low
L - Low
M - Medium
H - High
VH - Very High

4.4.3 Estimating the Risk of the System

The risk associated with all the factors obtained by the fuzzy inference rule is synthesised using DST of evidential reasoning. The result of the ER approach is distributed assessment such as,

$Risk\ Level = \{Low, Medium, High, Very\ High\}$.

The flow diagram of the model is given in Figure 4.5.

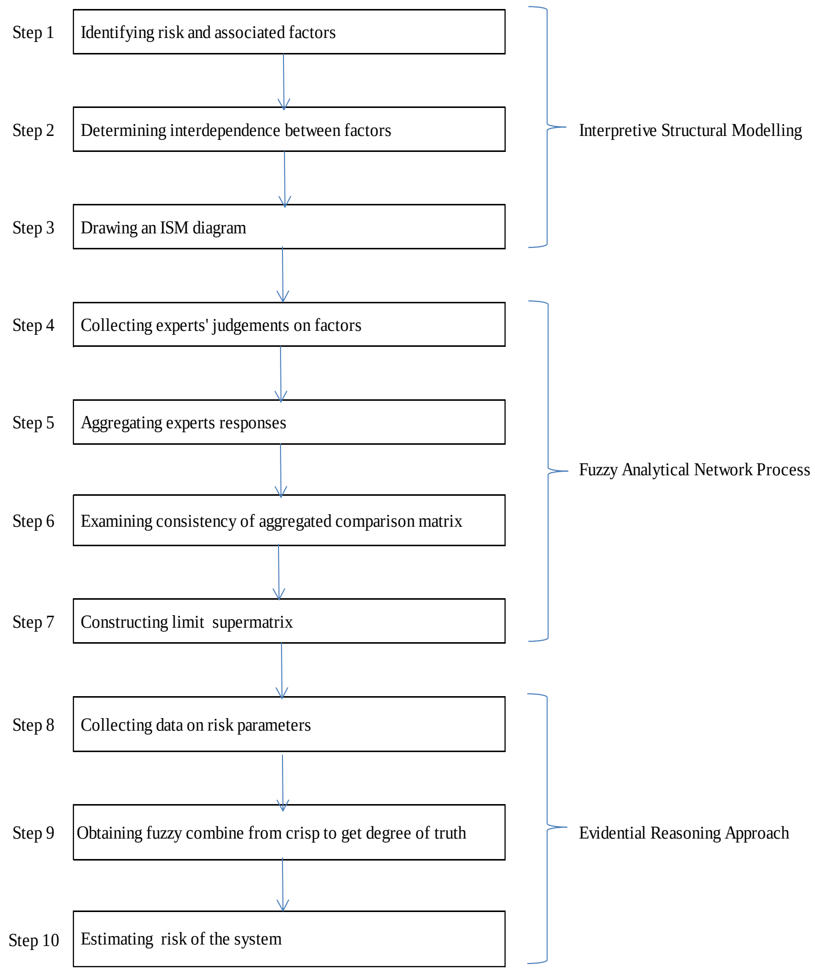

Figure 4.5: The Flow Diagram of the Model

4.5 Fire Risk onboard the Ship

The risk assessment of fire on board the ship in the machinery space of maritime transportation is presented in this section. The data showed that the Oil/Fuel leakages in machinery involved in almost 48% of the accidents, Electrical failures amount to 18%, Explosion/Overheating amount to 14% and the other causes for fires were not known clearly and amounts to the remaining. The areas and systems which are prone to such three critical incidents are identified. The three incidents are identified as three-factor groups/clusters and all the probable causes responsible for the faults to occur are labelled as factors. Three-factor groups/clusters and respective factors identified for fire are given below in Table 4.3.

Table 4.3: Factors for Fire Risk

Sr No	Criteria	Factors
1	Oil / Fuel Leakage (C1)	Damaged 'O' ring (F1)
2		Improper Maintenance (F2)
3		Hot Work Accidents (F3)
4	Electrical Faults (C2)	Chafing (F4)
5		Short Circuit (F5)
6		Overloading of Switches (F6)
7		Static Electricity (F7)
8	Overheating / Explosion (C3)	Turbocharger Explosion (F8)
9		Boiler Explosion (F9)
10		Cargo Fire (F10)
11		Crankcase Explosion (F11)

SSIM, IRM, FRM and partitioned matrix of factors are given in Table 4.4, Table 4.5, Table 4.6 and Table 4.7.

Table 4.4: Structural Self Interaction Matrix

Sr No	Factors	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
1	Damaged 'O' ring (F1)	X	A	V	O	O	O	O	O	O	O	O
2	Improper Maintenance (F2)		X	V	V	V	V	O	O	O	O	O
3	Hot Work Accidents (F3)			X	A	A	O	O	O	O	O	O
4	Chafing (F4)				X	V	V	O	O	O	O	O
5	Short Circuit (F5)					X	A	A	O	O	O	O
6	Overloading of Switches (F6)						X	O	O	O	O	O
7	Static Electricity (F7)							X	O	O	O	O
8	Turbocharger Explosion (F8)								X	O	O	O
9	Boiler Explosion (F9)									X	O	O
10	Cargo Fire (F10)										X	O
11	Crankcase Explosion (F11)											X

Table 4.5: Initial Reachability Matrix

Sr No	Factors	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
1	Damaged 'O' ring (F1)	1	0	1	0	0	0	0	0	0	0	0
2	Improper Maintenance (F2)	1	1	1	1	1	1	0	0	0	0	0
3	Hot Work Accidents (F3)	0	0	1	0	0	0	0	0	0	0	0
4	Chafing (F4)	0	0	1	1	1	1	0	0	0	0	0
5	Short Circuit (F5)	0	0	1	0	1	0	0	0	0	0	0
6	Overloading of Switches (F6)	0	0	0	0	1	1	0	0	0	0	0
7	Static Electricity (F7)	0	0	0	0	1	0	1	0	0	0	0
8	Turbocharger Explosion (F8)	0	0	0	0	0	0	0	1	0	0	0
9	Boiler Explosion (F9)	0	0	0	0	0	0	0	0	1	0	0
10	Cargo Fire (F10)	0	0	0	0	0	0	0	0	0	1	0
11	Crankcase Explosion (F11)	0	0	0	0	0	0	0	0	0	0	1

Table 4.6: Final Reachability Matrix

Sr No	Factors	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
1	Damaged 'O' ring (F1)	1	0	1	0	0	0	0	0	0	0	0
2	Improper Maintenance (F2)	1	1	1	1	1	1	0	0	0	0	0
3	Hot Work Accidents (F3)	0	0	1	0	0	0	0	0	0	0	0
4	Chafing (F4)	0	0	1	1	1	1	0	0	0	0	0
5	Short Circuit (F5)	0	0	1	0	1	0	0	0	0	0	0
6	Overloading of Switches (F6)	0	0	1*	0	1	1	0	0	0	0	0
7	Static Electricity (F7)	0	0	1*	0	1	0	1	0	0	0	0
8	Turbocharger Explosion (F8)	0	0	0	0	0	0	0	1	0	0	0
9	Boiler Explosion (F9)	0	0	0	0	0	0	0	0	1	0	0
10	Cargo Fire (F10)	0	0	0	0	0	0	0	0	0	1	0
11	Crankcase Explosion (F11)	0	0	0	0	0	0	0	0	0	0	1

Table 4.7: Partitioned Matrix of Factors

Sr No	Factors	Reachability Set	Antecedent Set	Intersection Set	Level
1	F1	F1, F3	F1, F2	F1	II
2	F2	F1, F2, F3, F4, F5, F6	F2	F2	V
3	F3	F3	F1, F2, F3, F4, F5, F6, F7	F3	I
4	F4	F3, F4, F5, F6	F2, F4	F4	IV
5	F5	F3, F5	F2, F4, F5, F6, F7	F5	II
6	F6	F3, F5, F6	F2, F4, F6	F6	III
7	F7	F5, F7	F7	F7	III
8	F8	F8	F8	F8	I
9	F9	F9	F9	F9	I
10	F10	F10	F10	F10	I
11	F11	F11	F11	F11	I

The initial digraph and ISM model are shown in Figure 4.6 and Figure 4.7.

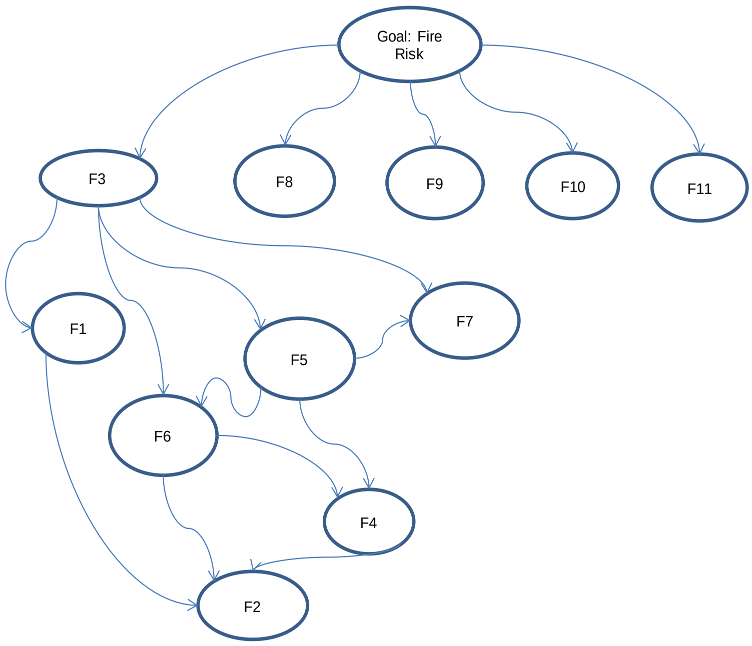

Figure 4.6: Digraph

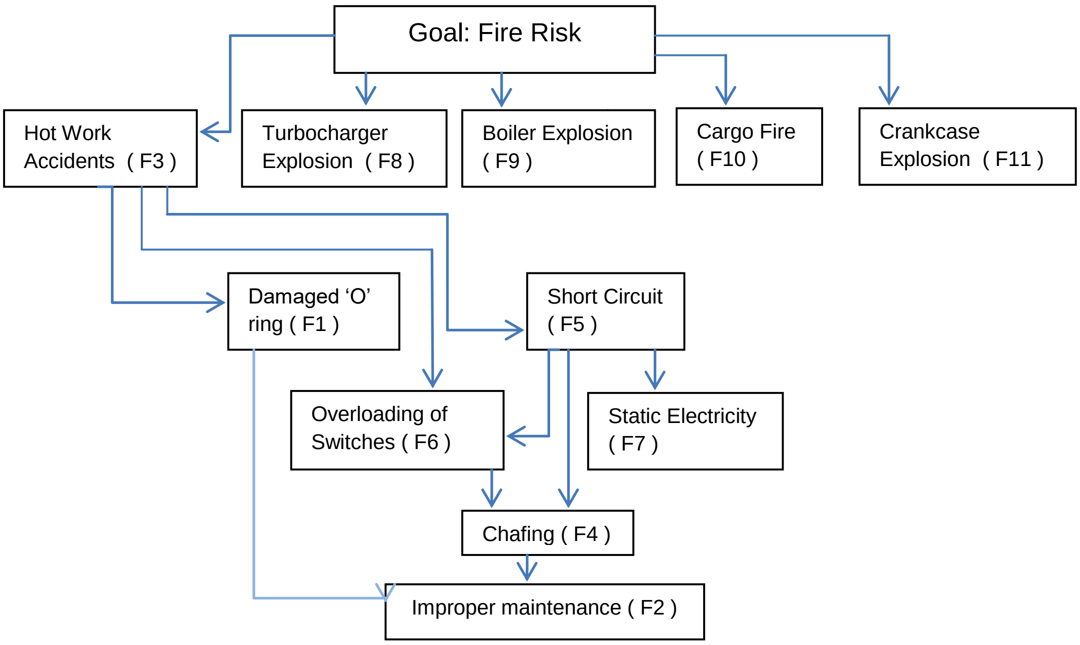

Figure 4.7: ISM Model

The General ANP model for weighting the factors is obtained from the above ISM model and shown in Figure 4.8. The model consists of three phases. Goal i.e. Fire Risk is at the first phase. Three-factor groups viz. Oil/Fuel leakage, Electrical faults and Overheating/Explosion represent the second phase while the third phase consists of all the qualitative factors (eleven in this case) identified within the factor groups. Within the model, there is interdependency between all or some of the factor groups. The qualitative factors also have interdependency within themselves. Arrows are used to indicate such interdependencies between factors. The Overheating/Explosion factor group has no inter-dependency on the other two factor groups. Likewise, factors of the Overheating/Explosion factor group also do not have any inter-dependency between them.

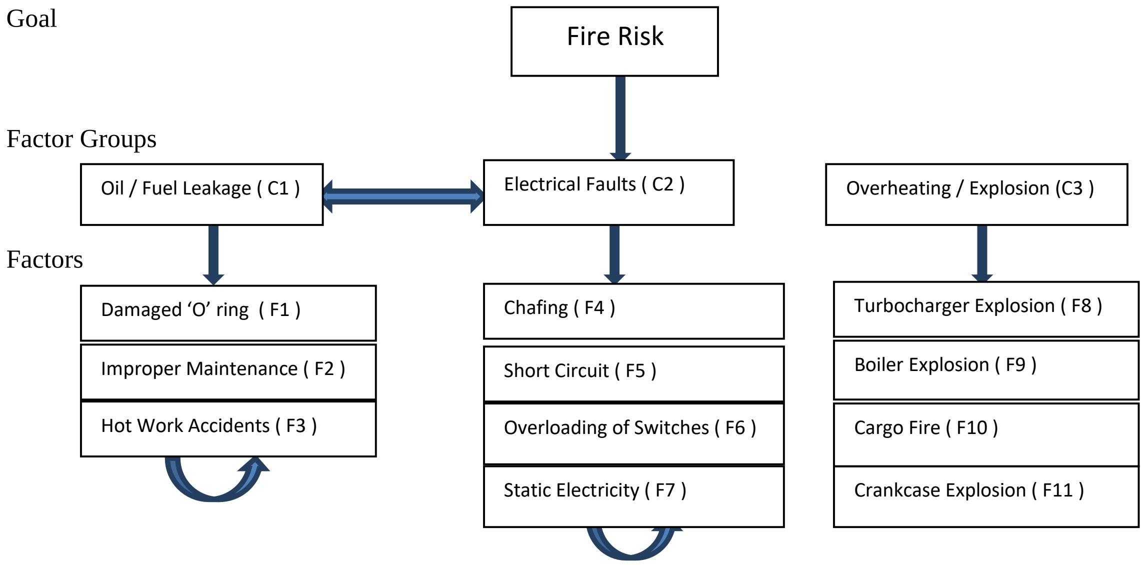

Figure 4.8: The General ANP Model

Unweighted, Weighted and Limit super matrices giving priority weights of factors 1 to 7, priority weights of factors 8 to 11 and that of factor groups are shown in Appendix – I. Global weights so obtained are given in Table 4.8.

Table 4.8: Global Weights of Factors

Factor Groups	Weights	Factors	Weights	Global Weights
Oil / Fuel Leakage and electrical Failures	0.762	Damaged 'O' ring (F1)	0.2151	0.164
		Improper Maintenance (F2)	0.3078	0.235
		Hot Work accidents (F3)	0.08465	0.064
		Chafing (F4)	0.132	0.1
		Short Circuit (F5)	0.1861	0.142
		Overloading of Switches (F6)	0.0644	0.049
		Static Electricity (F7)	0.01	0.008
Explosion	0.238	Turbocharger Explosion (F8)	0.055	0.013
		Boiler Explosion (F9)	0.23	0.055
		Cargo Fire (F10)	0.421	0.1
		Crankcase Explosion (F11)	0.295	0.07

The experts' judgements on likelihood and severity for all the factors and their aggregated membership values are presented in Appendix–I. Applying the rule matrix on aggregated membership values provides the corresponding BBA's of risk. These BBA's are given in Table 4.9.

Table 4.9: Basic Belief Assignments of Risk Factors

	Very Low	Low	Medium	High	Very High
F1	0	0.148	0.852	0	0
F2	0	0.056	0.944	0	0
F3	0	0.5	0	0	0
F4	0.491	0	0	0	0
F5	0	0	0.225	0.313	0.456
F6	0	0.5	0	0	0
F7	0.511	0.452	0	0	0
F8	0.511	0.489	0	0	0
F9	0.60375	0	0	0	0
F10	0	0	0.5	0	0
F11	0	0.60325	0	0	0

Using the ER algorithm and the global weights calculated by FANP, BBA's of all the factors are synthesised to arrive at the fire risk onboard the ship. The final values of levels of risks are Very Low (0.0958), Low (0.1626), Medium (0.6193), High (0.0498), Very High (0.0725). The distributed assessment of the fire risk on board ship is estimated to be medium with 61.93%, Low with 16.26 %, Very Low with 9.58%, Very High with 7.25 % and High with 4.98%. The main reason for accidents onboard the ship including the fire is attributed to negligence from the human being, improper maintenance and creating an unsafe situation which may lead to accidents. The global weights calculated from FANP also assign maximum weightage to improper maintenance amounting to 0.235 among all the eleven factors. This strengthens the belief that human error is one of the prime factors towards the initiation of accidents.

The distributed assessment of fire risk obtained is

$$\{(Very\ Low, 9.58\%), (Low, 16.26\%), (Medium, 61.93\%), (High, 4.98\%), (Very\ High, 7.25\%)\}$$

4.6 An Alternative Approach to D-S Theory

DST is often criticised [120] for giving illogical results when sources of evidence have a high degree of conflict. Suppose a patient is seen by two physicians regarding the patient's neurological symptoms. The two physicians' diagnoses about the patient's symptoms are given below.

$m_1(M) = 0.99$ $\qquad$ $m_1(T) = 0.01$

$m_2(C) = 0.99 \qquad m_2(T) = 0.01$

where M, C and T stand for Meningitis, Brain Tumor and Concussion. Combining the above pieces of evidence by D-S theory gives,

$m_{12}(M) = m_{12}(C) = 0 \qquad m_{12}(T) = 1.0$

This result shows that the D-S rule for combination supports the diagnosis which physicians have given the least probability to occur. This is illogical. To overcome this limitation, many alternative rules are proposed [121-124].

Consider multiple sources of evidence are taken to evaluate the hypotheses. If even one such source of evidence assigns zero belief mass to a particular hypothesis, then despite the higher share of weights assigned by other remaining pieces of evidence to the same hypothesis, the DST on the combination of evidence gives zero probability of that hypothesis being true. This is also highly illogical. In this scenario, there is room to believe that while collecting the evidence, some errors might have crept in. Such error has to be accommodated in the evidence before applying the DST. A new alternative rule is proposed in this study in which possible error while judging the hypothesis is considered.

Consider, $'k'$ sources of evidence on the frame Θ. The proposed steps to consider Error in Judgement (EIJ) are given below.

Step 1: The total focal elements (β) from all the sets of k sources of evidence are identified.

Step 2: The mean (ψ) of the masses of the elements is calculated for individual sources of evidence.

$$\psi_i = \frac{\sum m_i(X)}{\beta}, \qquad i = 1, 2, \dots, k \tag{4.7}$$

where X is the focal element

Step 3: The standard deviation σ of the masses is calculated based on the assumption that the standard deviation of a probability is the same as the standard deviation of a random variable.

$$\sigma_i = \sqrt{\frac{\sum\left(\psi_i - m_i(X)\right)^2}{\beta - 1}}, \qquad i = 1, 2, \dots, k \tag{4.8}$$

Step 4: The EIJ (δ) is calculated for each source of evidence,

$$\delta_i = \frac{\sigma_i}{\sqrt{\beta}}, \qquad i = 1, 2, \dots, k \tag{4.9}$$

Step 5: The revised masses (m') for all the sources of evidence are obtained considering the error and normalising.

$$m'_i = \frac{(m_i(X) + \delta_i)}{(1 + \beta \times \delta_i)}, \qquad i = 1, 2, \dots, k \tag{4.10}$$

Comparative results for physicians' diagnoses about patient's neurological symptoms using Dempster rule, Yager's combination rule of evidence [121], Murphy's average combination rule [122], Deqiang's evidence combination approach [123], Ali's rule of a combination of evidence [124] and our EIJ rule is given in Table 4.10.

Table 4.10: Results of Different Combination Rules (patient's symptoms example)

Combination Rules	m(M)	m(C)	m(T)	m (Θ)
Dempster Rule	0	0	1	0
Yager Rule	0	0	0.0001	0.9999
Murphy's Average combination Rule	0.4999	0.4999	0.0002	0
Deqiang Rule	0.495	0.495	0.01	0
Tazid Ali Rule	0.4975	0.4975	0.0051	0
Proposed EIJ Rule	0.4416	0.4416	0.1168	0

The proposed EIJ method is validated by taking two examples from [124]. Example 1 and its results are given in Table 4.11 and Table 4.12. Example 2 and its results are given in Table 4.13 and Table 4.14.

Table 4.11: Example-1(BBAs obtained from four different bodies of evidence)

Evidence	A	B	C
m1	0.98	0.01	0.01
m2	0	0.01	0.99
m3	0.9	0.01	0.09
m4	0.9	0.01	0.09

Table 4.12: Results of Different Combination Rules (Example-1)

Combination Rules	m12	m123	m1234
Dempster Rule	m(A) =0, m(B)=0.01, m(C)=0.99, m(Θ)=0	m(A) =0, m(B)=0.0011, m(C)=0.9989, m(Θ)=0	m(A) =0, m(B)=0.0001247, m(C)=0.9998753, m(Θ)=0
Yager Rule	m(A) =0, m(B)=0.0001, m(C)=0.0099, m(Θ)=0.99	m(A) =0, m(B)=0.000001, m(C)=0.000891, m(Θ)=0.999108	m(A) =0, m(B)=0.00000001, m(C)=0.00008019, m(Θ)=0.9999198
Murphy's Average Combination Rule	m(A) =0.4898, m(B)=0.0002, m(C)=0.51	m(A) =0.8369, m(B)=0.0000034, m(C)=0.1631	m(A) =0.96856, m(B)=0.0000000415, m(C)=0.03144
Deqiang Rule	m(A) =0.4703, m(B)=0.01, m(C)=0.5197, m(Θ)=0	m(A) =0.7431, m(B)=0.01, m(C)=0.2469, m(Θ)=0	m(A) =0.8358, m(B)=0.01, m(C)=0.1542, m(Θ)=0
Tazid Ali Rule	m(A) =0.4924, m(B)=0.005151, m(C)=0.50245, m(Θ)=0	m(A) =0.701565, m(B)=0.005908, m(C)=0.292528, m(Θ)=0	m(A) =0.807426, m(B)=0.006846, m(C)=0.185728, m(Θ)=0
Our EIJ Rule	m(A) =0.4366, m(B)=0.1151, m(C)=0.4483, m(Θ)=0	m(A) =0.7194, m(B)=0.0471, m(C)=0.2335, m(Θ)=0	m(A) =0.8938, m(B)=0.0145, m(C)=0.0917, m(Θ)=0

Table 4.13: Example-2 (BBAs obtained from five different sources of evidence)

Evidence	A	B	C
m1	0.5	0.2	0.3
m2	0	0.9	0.1
m3	0.55	0.1	0.35
m4	0.55	0.1	0.35
m5	0.55	0.1	0.35

Table 4.14: Results of Different Combination Rules (Example-2)

Combination Rules	m12	m123	m1234	m12345
Dempster Rule	m(A) =0, m(B)=0.8571, m(C)=0.1429	m(A) =0, m(B)=0.6316, m(C)=0.3684	m(A) =0, m(B)=0.3288, m(C)=0.6712	m(A) =0, m(B)=0.1228, m(C)=0.8772
Yager Rule	m(A) =0, m(B)=0.1800, m(C)=0.03, m(Θ)=0.7900	m(A) =0, m(B)=0.0018, m(C)=0.0105, m(Θ)=0.9715	m(A) =0, m(B)=0.0018, m(C)=0.0037, m(Θ)=0.9945	m(A) =0, m(B)=0.0002, m(C)=0.0013, m(Θ)=0.9985
Murphy's Average Combination Rule	m(A) =0.1543, m(B)=0.7469, m(C)=0.0988	m(A) =0.3500, m(B)=0.5224, m(C)=0.1276	m(A) =0.6027, m(B)=0.2627, m(C)=0.1346	m(A) =0.7958, m(B)=0.0932, m(C)=0.1110
Deqiang Rule	m(A) =0.132857, m(B)=0.7140, m(C)=0.153143	m(A) =0.321859, m(B)=0.435805, m(C)=0.242336	m(A) =0.447721, m(B)=0.250546, m(C)=0.301733	m(A) =0.504066, m(B)=0.167611, m(C)=0.328323
Tazid Ali Rule	m(A) =0.236042, m(B)=0.603218, m(C)=0.16074	m(A) =0.388764, m(B)=0.377132, m(C)=0.234103	m(A) =0.479636, m(B)=0.237536, m(C)=0.282828	m(A) =0.530041, m(B)=0.15895, m(C)=0.311009
Our EIJ Rule	m(A) =0.2545, m(B)=0.5187, m(C)=0.2269	m(A) =0.4312, m(B)=0.2974, m(C)=0.2714	m(A) =0.5960, m(B)=0.1391, m(C)=0.2649	m(A) =0.7180, m(B)=0.0567, m(C)=0.2253

From the above examples, it is seen that the Dempster rule gives illogical results when bodies of evidence with a high degree of conflict are combined. Yager's rule assigns conflict mass to an unknown base set and it increases with an increase in bodies of evidence. This is not the idea of combining bodies of evidence. Deqiang's rule uses ambiguity measure to reduce the effect of conflict and the method is slightly complicated as compared to the proposed EIJ approach. Murphy's average combination rule and Ali's rule give reasonable results. The limitation of Murphy's rule is that the series of evidence to be combined should be available at the start while Ali's rule did not give any proper justification for the formula.

Table 4.15 shows comparative results when Dempster's rule, Yager's combination rule of evidence, Murphy's average combination rule, Deqiang's evidence combination approach, Ali's rule of a combination of evidence and our EIJ rule are used for example in section 4.5. The assessment of fire risk on board ship with the new alternative approach is estimated to be Medium with 40.81 %, Low with 18.55 %, Very Low with 14.92 %, Very High with 13.66 % and High with 12.06 %.

Table 4.15: Comparative Results for Example in Section 4.5

Combination Rules	Very Low	Low	Medium	High	Very High
Dempster Rule	0.0958	0.16	0.6193	0.05	0.0725
Yager Rule	0	0	0	0	0
Murphy's Average Combination Rule	0.1058	0.17	0.6015	0.05	0.0726
Deqiang Rule	0.1389	0.61	0.2459	0	0.0016
Tazid Ali Rule	0.0057	0.02	0.9697	0	0.0008
Our EIJ Rule	0.1492	0.19	0.4081	0.12	0.1366

4.7 Summary

In this chapter, the effectiveness of the tools such as BBN, ER approach, ISM and FANP are discussed. The new model using ISM, FANP and ER is proposed and implemented for risk assessment and efficient reasoning under uncertainty. This model is suited for complex engineering systems with interconnected factors and when ascertaining causal relationships between them is difficult. Since most of the factor and factor groups are interdependent, FANP is used to obtain the global weights of factors. Fuzzy inference rules are used to estimate the risks of factors due to the structural complexity and the presence of uncertainty in the data. The model assessed the system risk using the D-S evidential reasoning approach. A suitable alternative is also proposed to overcome the criticism for giving illogical results when there exists a high degree of conflict in various sources of evidence. The model is tested with well developed previous methods and our proposed EIJ approach and comparative results are given in Table 4.15.

Chapter 5

Framework For Risk Assessment

Risk assessment in maritime transportation is carried out here by analysing the safety of the systems. Initial risk parameters are obtained by experts' judgements and uncertainty due to qualitative/subjective human knowledge is dealt with by neutrosophic/plithogenic set theories. The safety of systems in the marine industry is analysed with appropriate illustrations. The validity and sensitivity analysis of the models is carried out wherever applicable.

This chapter forms the second part of the problem statement. Three cases have been formulated for the present study using neutrosophic logic, neutrosophic set theory and plithogenic set theory.

5.1 Decision Making in an Uncertain Environment

Smarandache [41] proposed and developed the concept of neutrosophic sets derived from a new branch of philosophy, neutrosophy. It has the potential to deal with uncertainty, indeterminacy (hesitancy) and inconsistency in the information sought from the human valuation. Wang et al. [42] created SVNS to solve practical, scientific and engineering-related problems. Because of its superiority in handling uncertainty and indeterminacy, an attempt is made to apply neutrosophic/plithogenic set theory in this study.

5.2 Risk Assessment Framework

In this section, detailed procedures for analysing the safety of systems and assessing risk in maritime transportation are explained considering three different models based on various approaches to deal with uncertainty.

1. Model I: Using neutrosophic logic
2. Model II: Using neutrosophic set theory
3. Model III: Using plithogenic set theory

5.3 Model I: Using Neutrosophic Logic

The risk assessment method should be robust enough to process any kind of information be it qualitative, quantitative, subjective or objective in a very transparent and easy way. In this chapter, an efficient and powerful neutrosophic IF-THEN rules method with a comprehensive assessment of identified risk factors under an uncertain environment is proposed to elicit the experts' judgements. The proposed method consists of two parts. Initially, risk parameters are collected from experts in linguistic terms and expressed quantitatively using membership functions of neutrosophic numbers. Then, neutrosophic IF-THEN rules are constructed consisting of two parts –namely Antecedent and Consequent. All the fired rules are aggregated and combined for estimating and systematising the risk factors. An example to illustrate the application of a proposed model is given in subsection 5.3.7.

Neutrosophic set given by Smarandache [41] with the inclusion of the indeterminacy component is an extension of a fuzzy set and represents the real world (full of uncertainty) better than the highest version of fuzzy set i.e. Interval Valued Intuitionistic Fuzzy Set (IVIFS). Neutrosophic logic employing IF-THEN rules is proposed using linear single valued trapezoidal neutrosophic numbers. Neutrosophic AND and OR are used for implication from antecedent to consequent and aggregating consequent across all the firing rules. The novelty of the study is threefold. First, the study presents the risk parameters in neutrosophic numbers with linear membership functions which are easy to understand and model risks in a better way. Second, it proposes a new method for neutrosophication of a crisp input value. AND operator is applied to get a single antecedent value for a given rule. Third, it recognises and analyses the risk of the system from diversified dimensions of personnel, organisational and environmental perspectives.

5.3.1 Deneutrosophication of Single Valued Trapezoidal Number

Consider $\tilde{A}_{Neu}(a,b,c,d;e,f,g,h;i,j,k,l)$ be the linear trapezoidal neutrosophic number. The pictorial view is shown in Figure 5.1. Consider a real number $\varepsilon \in R$ and fuzzy numbers $\tilde{A}$, $\tilde{B}$ and $\tilde{C}$ in the lower trapezium (a, b, c, d), in the left-most upper trapezium (e, f, g, h) and in the right most upper trapezium (i, j, k, l) respectively. A linear trapezoidal single valued neutrosophic number is explained in section 3.6.4.2 and presented in Figure 5.1. Chakraborty et al. [104, 105] used area removal method for deneutrosophication of single valued triangular/trapezoidal neutrosophic number and is given by,

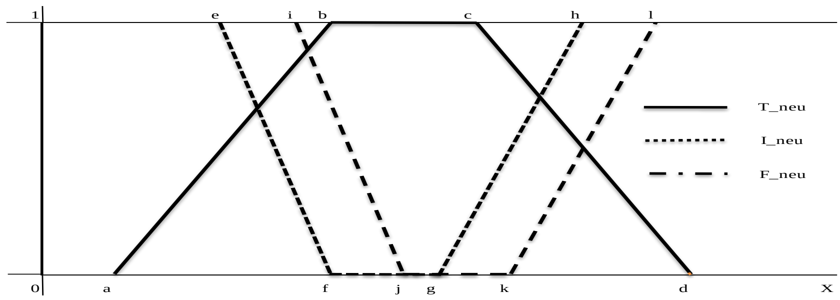

Figure 5.1: Linear Trapezoidal Neutrosophic Number

$$R(\widetilde{D},\varepsilon)=\frac{R(\tilde{A},\varepsilon)+R(\tilde{B},\varepsilon)+R(\tilde{C},\varepsilon)}{3} \tag{5.1}$$

For $\alpha = 0$,

$$R(\widetilde{D},0)=\frac{a+b+c+d+e+f+g+h+i+j+k+l}{12} \tag{5.2}$$

$R(\tilde{A},\varepsilon)$, $R(\tilde{B},\varepsilon)$ and $R(\tilde{C},\varepsilon)$ are mean areas of the three trapeziums (truth, indeterminacy and falsity) in Single Valued Trapezoidal Neutrosophic Number (SVTNN). $R(\widetilde{D},\varepsilon)$ is the deneutrosophic value of the SVTNN. Illustration of deneutrosophication is shown in Table 5.1 for selected SVTNN.

Table 5.1: Deneutrosophic Values of Trapezoidal Neutrosophic Number

Sr. No.	Neutrosophic number	Deneutrosophic value
1	(0.5, 2, 3, 4.5; 1.25, 2, 2.75, 3.75; 1.75, 2.5, 3.25, 4.25)	2.625
2	(4.5, 6, 7, 8.5; 5.25, 6, 6.75, 7.75; 5.75, 6.5, 7.25, 8.25)	6.625
3	(6.5, 8, 9, 9.5; 7.25, 8, 8.75, 9.25; 7.75, 8.5, 9.25, 9.75)	8.4583

5.3.2 Identifying Risk Parameters

As seen in chapter 4, it is difficult to get accurate past data on risk parameters (FL and CS). Moreover, experts' opinions are unclear when expressed in natural languages. Linguistic variables in neutrosophic sets provide experts to opine with ease. Trapezoidal neutrosophic numbers having linear membership functions for FL and CS (personnel, environmental and organisational related) are given in Appendix II and shown in Figure 5.2 and Figure 5.3.

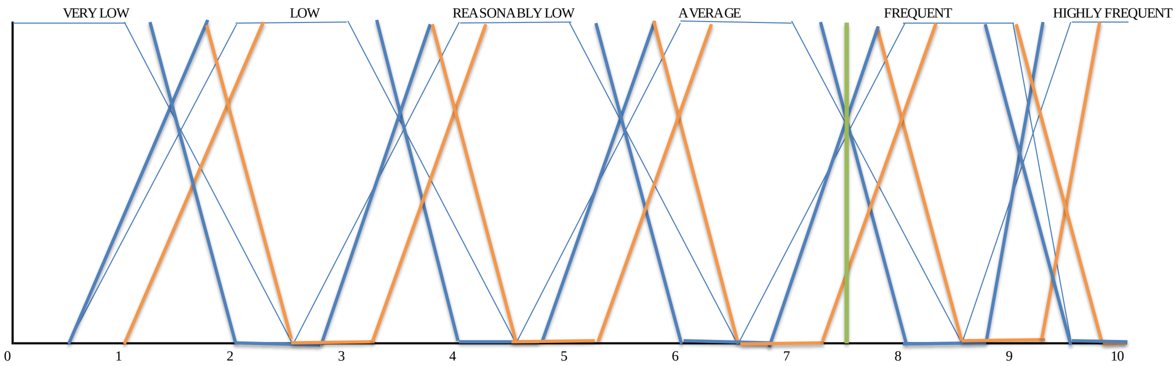

Figure 5.2: Neutrosophic FL Sets Definition

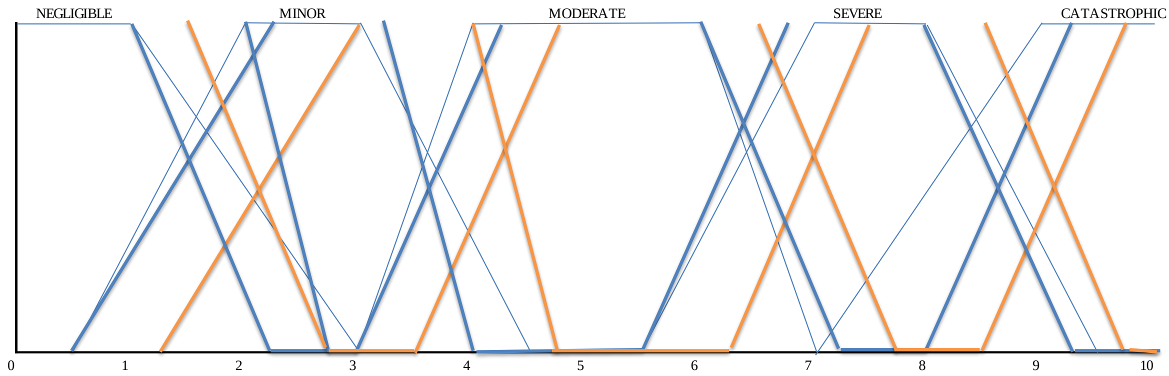

Figure 5.3: Neutrosophic CS Sets Definition

5.3.3 Neutrosophication of Input Parameters

Membership degree (γ_n) of crisp input from experts is determined using membership functions within the universe of discourse containing N linguistic variables. Consider h_n be the crisp deneutrosophic value of the n^{th} linguistic variable (n=1, 2,…, N). The membership degree (γ_n) of the crisp input value h, is given by,

$$\gamma_n = \frac{h_{n+1} - h}{h_{n+1} - h_n}, \qquad \gamma_{n+1} = 1 - \gamma_n \qquad \text{if } h_n \le h \le h_{n+1} \tag{5.3}$$

$$\gamma_1 = 1 \qquad \text{if } h < h_1 \tag{5.4}$$

and

$$\gamma_n = 1 \text{ if } h \ge h_n \tag{5.5}$$

5.3.4 Neutrosophic Logic based IF-THEN Model

The experience and knowledge of experts are used to formulate the neutrosophic logic based IF–THEN rules. These neutrosophic rules are derived from experts' judgements and domain knowledge. The belief rule expressions in the neutrosophic rule based system can represent expert knowledge in compact form when enough evidence is not available and experts are not 100 % sure of their opinions but provide partial trustworthiness towards judgements. The Risk Level (RL) is a trapezoidal neutrosophic number with a linear membership degree (given in Appendix II) and shown in Figure 5.4. The neutrosophic IF-THEN rules are given in Appendix II. Min (AND operator) is used to give the output single truth value. The neutrosophic logic diagram is shown in Figure 5.5.

$$\mu_r = min(\mu_{FL,r}, \mu_{CS,r}) \tag{5.6}$$

$\mu_r \rightarrow$ single truth value for the r^{th} rule

$\mu_{FL,r}, \mu_{CS,r} \rightarrow$ membership values for FL and CS for r^{th} rule respectively.

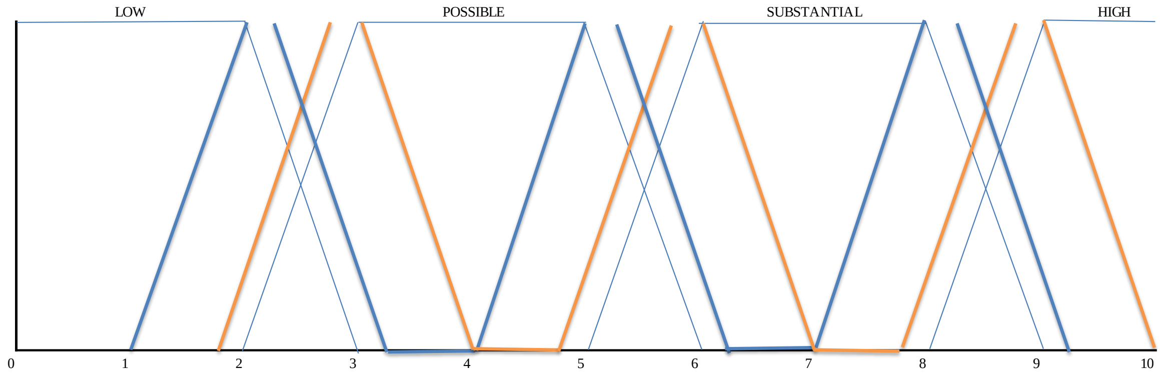

Figure 5.4: Neutrosophic RL Sets Definition

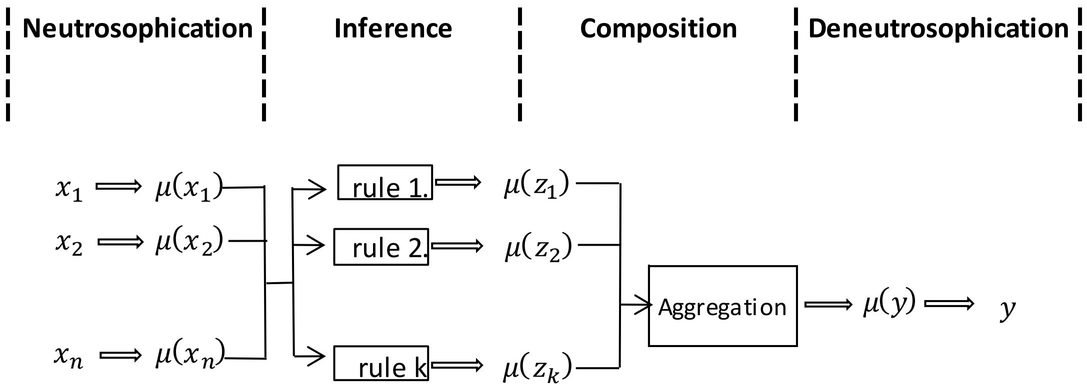

Figure 5.5: Neutrosophic Logic Diagram

5.3.5 Aggregation of Consequents Across the Rules

The outputs obtained from all the fired rules are aggregated to get the single neutrosophic risk level. Max (OR operator) aggregates all the values.

$$RL = \{max(\mu_{1,r}, Low), max(\mu_{2,r}, Possible), max(\mu_{3,r}, Substantial), max(\mu_{4,r}, High)\} \tag{5.7}$$

5.3.6 Deneutrosophication

System failure may impact multiple categories (say m) and CS is expressed for all these m categories. In such cases, the deneutrosophication process is applied after the aggregation process. To assign output values proportionately to adjacent RL sets, these are normalised before deneutrosophication. The overall risk considering all these categories is given by,

$$RL = \sum_{i=1}^{m} R_i w_i$$

and

$$\textstyle\sum_{i=1}^{m} w_i = 1 \tag{5.8}$$

$R_i \rightarrow RL$ of the i^{th} category and $w_i \rightarrow$ weighting factor of the i^{th} category, obtained by any of the weighing techniques such as AHP. The region of the overall risk is identified by mapping it with RL expressions. The flowchart of the model is given in Figure 5.6.

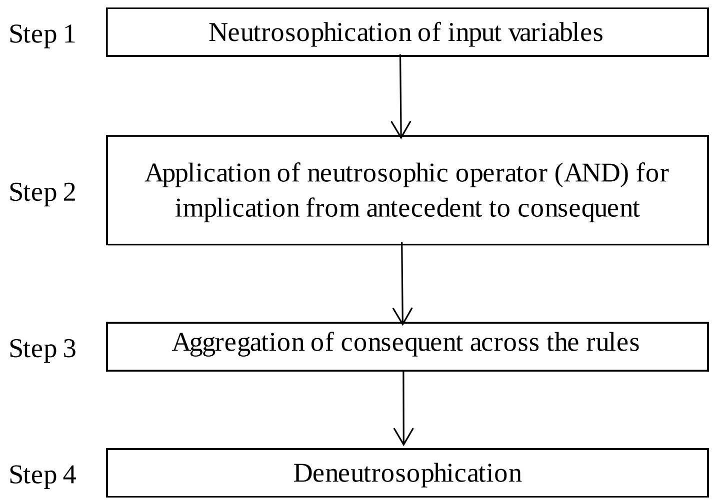

Figure 5.6: The Flowchart for Neutrosophic Logic Model

5.3.7 Safety Modelling of Marine Systems

A numerical example from [72] is revisited to validate the proposed model. Safety modelling of the fuel oil system, one of the critical systems onboard vessels is chosen. Three categories namely personnel related risks, environmental related risks and organisational related risks are considered. The input values for FL, CS for three categories with their priority weights, are given in Table 5.2.

Table 5.2: Input Values for FL and CS

Parameters	Crisp Input value	Priority weights
Oil System failure rate (FL)	7.5	---
Personnel related risk (CS)	8.5	0.31
Environmental related risk (CS)	5.5	0.48
Organisational related risk (CS)	3	0.21

Crisp deneutrosophic output values for different categories are,

$\mu\left(RL_{personnel\ risk}\right) = 8.184206$, $\mu(RL_{environmental\ risk}) = 7$ and

$\mu\left(RL_{organisational\ risk}\right) = 5.431818$

The overall risk of the system,

$$RL_{system} = 8.184206 \times 0.31 + 7 \times 0.48 + 5.431818 \times 0.21 = 7.03779$$

Referring to risk level expressions (Appendix II), the crisp value (7.03779) of the overall risk of the system lies between substantial and high regions. Neutrosophication of the crisp value evaluates the overall risk of the system to be 98.4625% in the substantial region and 1.53705% in the high risk region on the risk expression scale. The result of [72] obtained using fuzzy logic based approach evaluates the risk to be 100 % in the substantial region.

5.4 Model II: Using Neutrosophic Set Theory

A model is proposed using NST and DST for risk assessment of marine systems onboard ships. NST is used because of its capability in handling uncertainty due to hesitancy. The model is combined with the ER approach. SVNS is used in the model to assess the risk. In the neutrosophic set, three components are used to represent uncertainty i.e., truth ($T_A(x)$, degree of belongingness), falsity ($F_A(x)$, degree of non- belongingness) and indeterminacy ($I_A(x)$, degree of hesitancy).

5.4.1 Neutrosophic Set and its Operations

Neutrosophic sets are described in section 1.6.

If $P = \langle a_1, b_1, c_1 \rangle$ and $Q = \langle a_2, b_2, c_2 \rangle$ be two SVNN. The product of two SVNN is defined as [42],

$P \cup Q = \langle max(a_1, a_2), min(b_1, b_2), min(c_1, c_2) \rangle$

$P \cap Q = \langle min(a_1, a_2), max(b_1, b_2), max(c_1, c_2) \rangle$

$$P \otimes Q = \langle a_1 + a_2 - a_1 a_2, b_1 b_2, c_1 c_2 \rangle \quad (5.9)$$

5.4.2 ER Approach for Synthesising Evidence

BBA is the core of evidential reasoning. Like fuzzy sets, neutrosophic sets can be used to gather linguistic data from experts. But to use neutrosophic sets, in evidential reasoning, experts' judgments in neutrosophic numbers need to be suitably converted into corresponding BBAs. A simple method is proposed in this section to obtain the BBAs of a single valued neutrosophic number. ER approach is then used to combine more than one piece of evidence. The result is compared with the new alternative approach proposed to DST in section 4.6.

Consider an SVNN,

$P = \{\langle T_P(x),\ I_P(x), F_P(x)\rangle; x \in X\}$

BBA's are given by,

$$m_P(T) = \frac{T_P(x)}{\left(T_P(x) + \ I_P(x) + F_P(x)\right)}$$

$$m_P(F) = \frac{F_P(x)}{\left(T_P(x) + \ I_P(x) + F_P(x)\right)}$$

$$m_P(T, F) = \frac{I_P(x)}{\left(T_P(x) + \ I_P(x) + F_P(x)\right)} \tag{5.10}$$

$m_P(T)$, $m_P(F)$ and $m_P(T, F)$ represent belief in (T), (F) and $(T \cup F)$

$$m_P(T) + m_P(F) + m_P(T, F) = 1 \tag{5.11}$$

and

$$m_P(T) = m_P(F) = m_P(T, F) = 0 \quad \text{for } P = \langle 0, 0, 0\rangle \tag{5.12}$$

5.4.3 Obtaining Risk Parameters

First, identify critical failure modes of the system. Obtain risk parameters (FL and CS) for identified failure modes using neutrosophic terms from Table 5.3.

5.4.4 Neutrosophic Safety Score and BBA

The neutrosophic risk/safety score of the system is obtained by the traditional definition of risk, $R = FL \times CS$. The safety score is then converted into BBAs.

Table 5.3: Linguistic Terms for Risk Parameters

Linguistic Terms	SVNN
Absolute High (AH)	< 1, 0, 0 >
Very Very High (VVH)	< 0.9, 0.1, 0.1 >
Very High (VH)	< 0.8, 0.15, 0.2 >
High (H)	< 0.7, 0.25, 0.3 >
Fairly High (FH)	< 0.6, 0.35, 0.4 >
Medium (M)	< 0.5, 0.5, 0.5 >
Fairly Low (FL)	< 0.4, 0.65, 0.6 >
Low (L)	<0.3, 0.75, 0.7 >
Very Low (VL)	< 0.2, 0.85, 0.8 >
Very Very Low (VVL)	< 0.1, 0.9, 0.9 >
Absolute Low (AL)	< 0, 1, 1 >

5.4.5 Obtaining Safety Level of the System

The safety score of every failure mode is combined using the ER approach to get the safety level of the system. The correlation coefficient described in section 3.6.7.3 is used to get the similarity between safety level and safety expressions. Safety expressions expressed in linguistic terms are given in Table 5.4. The correlation coefficient gives a distributed assessment of the safety level.

Table 5.4: Linguistic Terms for Safety Expressions

Linguistic Terms	SVNN
Poor (P)	< 1, 0, 0 >
Average (A)	< 0.7, 0.25, 0.3 >
Good (G)	< 0.3, 0.75, 0.7 >
Excellent (E)	< 0, 1, 1 >

5.4.6 Illustrative Example: A System Onboard the Ship

A typical system onboard a ship is shown in Figure 5.7. Three failure modes of a system are identified. Risk parameters as given by experts are shown in Table 5.5. The neutrosophic safety score and BBAs of failure modes are given in Table 5.6 and Table 5.7 while BBAs of safety expressions are shown in Table 5.8.

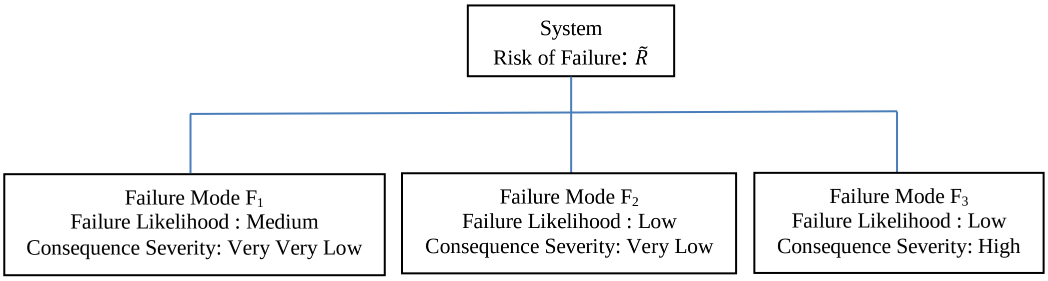

Figure 5.7: A Typical System-I Onboard Ship

Table 5.5: Risk Parameters as given by Experts

Failure Modes	FL	CS
F1	M (< 0.50, 0.50, 0.50 >)	VVL (< 0.10, 0.90, 0.9 >)
F2	L (< 0.30, 0.75, 0.70 >)	VL (< 0.20, 0.85, 0.80 >)
F3	L (< 0.30, 0.75, 0.70 >)	H (< 0.79, 0.25, 0.30 >)

Table 5.6: Neutrosophic Safety Score of Failure Modes

Failure Modes	Safety Score
F1	< 0.55, 0.45, 0.45 >
F2	< 0.44, 0.6375, 0.56 >
F3	< 0.79, 0.1875, 0.21 >

Table 5.7: BBAs of Failure Modes

Failure Modes	BBAs		
	m(T)	m(F)	M(T, F)
F1	0.37931	0.310345	0.310345
F2	0.268702	0.341985	0.389313
F3	0.665263	0.176842	0.157895

Table 5.8. BBAs of Safety Expressions

Linguistic Terms	BBAs		
	m(T)	m(F)	M(T, F)
Poor (P)	1	0	0
Average (A)	0.56	0.24	0.2
Good (G)	0.171429	0.4	0.428571
Excellent (E)	0	0.5	0.5

Correlation coefficients for the system safety are,

$S_r(\alpha^*, 'Poor') = 0.930722$, $S_r(\alpha^*, 'Average') = 0.983024$,

$S_r(\alpha^*, 'Good') = 0.754486$ and $S_r(\alpha^*, 'Excellent') = 0.598074$.

After normalising the values, the system is evaluated to be 30.10 % Average, 28.49 % Poor, 23.10 % Good and 18.31 % Excellent. The result in graphical form is shown in Figure 5.8.

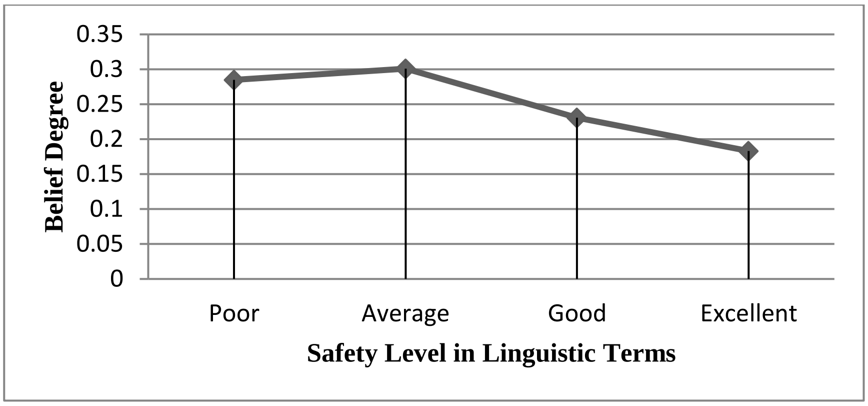

Figure 5.8: Safety Level of the System

The new alternative approach to DST described in section 4.6 is applied to the above example to see the impact on the results after considering the possible error in judgements by experts. New correlation coefficients obtained are,

$S_r(\alpha^*, 'Poor') = 0.977483,$ $S_r(\alpha^*, 'Average') = 0.983664,$

$S_r(\alpha^*, 'Good') = 0.849068$ and $S_r(\alpha^*, 'Excellent') = 0.779572.$

After normalising the values, the system is evaluated to be 27.40 % Average, 27.23 % Poor, 23.65 % Good and 21.72 % Excellent. The result in graphical form is shown in Figure 5.9. It is seen that the safety level curve is flat in the region of Average-Good-Excellent and system level appears to be better than that provided when a possible error from experts is ignored.

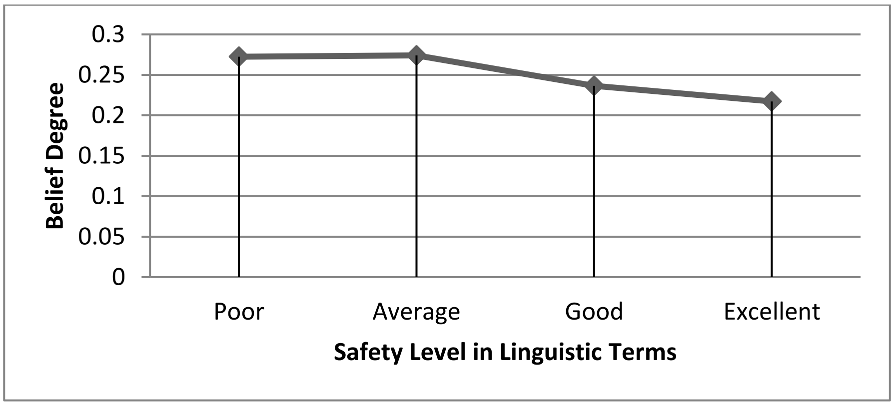

Figure 5.9: Safety Level of the System (with alternative approach)

5.5 Model III: Using Plithogenic Set Theory

In this study, PST is used to carry out a risk assessment. The Plithogenic sets [43, 44] are discussed in section 1.7. These are the extended versions of neutrosophic sets. The peculiarity of these sets is the contradiction degrees created between the attribute values and the dominant attribute value identified by experts amongst the given attribute set. Plithogenic set concept is recently floated by Smarandache [43, 44] and used in multi-criteria decision making models in combination with well-established methods such as TOPSIS [125], VIKOR [126] and QFD [127]. As per the author's knowledge, plithogenic sets are tried for the first time in risk assessment in this study in conjunction with the ER approach. The model is applied for the risk assessment of marine systems. The sensitivity analysis is carried out to show the suitability of the model.

5.5.1 Plithogenic Set and its Operations

Plithogenic aggregation operators are linear combinations of the fuzzy t_{norm} (denoted $\wedge_F$), and fuzzy t_{conorm} (denoted $\vee_F$). Let cd_i be the contradiction degree between the most important (dominant) attribute value and the attribute values d_A and d_B. If t_{conorm} is applied between two attribute values of criteria i, then the aggregation of two attributes is given by [126],

$$
\begin{aligned}
d_{AB}(x, v_T) = (T, I, F) \\
&= \Big((1 - cd_i) \cdot [d_A(x, v_T) t_{conorm} d_B(x, v_T)] + cd_i \\
&\cdot [d_A(x, v_T) t_{norm} d_B(x, v_T)], \frac{1}{2}\big(d_A(x, v_I) t_{norm} d_B(x, v_I) \\
&+ d_A(x, v_I) t_{conorm} d_B(x, v_I)\big), (1 - cd_i) \cdot [d_A(x, v_F) t_{norm} d_B(x, v_F)] \\
&+ cd_i [d_A(x, v_F) t_{conorm} d_B(x, v_F)]\Big)
\end{aligned}
$$

Using symbols,

$$
\begin{aligned}
&d_{AB}(x, v_T) = (T, I, F) = \Big((1 - cd_i) \cdot [d_A(x, v_T) \vee_F d_B(x, v_T)] + cd_i \cdot \\
&[d_A(x, v_T) \wedge_F d_B(x, v_T)], \tfrac{1}{2}\big(d_A(x, v_I) \wedge_F d_B(x, v_I) + d_A(x, v_I) \vee_F d_B(x, v_I)\big), (1 - cd_i) \cdot \\
&[d_A(x, v_F) \wedge_F d_B(x, v_F)] + cd_i [d_A(x, v_F) \vee_F d_B(x, v_F)]\Big) \qquad (5.13)
\end{aligned}
$$

If t_{norm} is applied between two attribute values of criteria i, then the aggregation of two attributes is given by,

$$d_{AB}(x, v_T) = (T, I, F)$$
$$= \Big((1 - cd_i) \cdot [d_A(x, v_T) t_{norm} d_B(x, v_T)] + cd_i \cdot [d_A(x, v_T) t_{conorm} d_B(x, v_T)], \frac{1}{2}\big(d_A(x, v_I) t_{norm} d_B(x, v_I) + d_A(x, v_I) t_{conorm} d_B(x, v_I)\big), (1 - cd_i) \cdot [d_A(x, v_F) t_{conorm} d_B(x, v_F)] + cd_i [d_A(x, v_F) t_{norm} d_B(x, v_F)]\Big)$$

Using symbols,

$$d_{AB}(x, v_T) = (T, I, F) = \Big((1 - cd_i) \cdot [d_A(x, v_T) \wedge_F d_B(x, v_T)] + cd_i \cdot [d_A(x, v_T) \vee_F d_B(x, v_T)], \frac{1}{2}\big(d_A(x, v_I) \wedge_F d_B(x, v_I) + d_A(x, v_I) \vee_F d_B(x, v_I)\big), (1 - cd_i) \cdot [d_A(x, v_F) \vee_F d_B(x, v_F)] + cd_i [d_A(x, v_F) \wedge_F d_B(x, v_F)]\Big) \quad (5.14)$$

5.5.2 Identifying Experts' Weights and Failure Modes

Let $E = \{E_1, E_2, \ldots, E_k\}$ and $F = \{F_1, F_2, \ldots, F_m\}$ be the sets of k experts and m failure modes respectively. The importance of experts is chosen from Table 5.9. Let $E_t = \langle a_t, b_t, c_t \rangle$ be a plithogenic number and represents the importance of t^{th} expert. Its crisp value is obtained by [126],

$$\bar{S}(E_t) = \frac{(2 + a_t - b_t - c_t)}{3} \quad (5.15)$$

The weight vector W_E^T of experts is obtained by normalising the crisp value $\bar{S}(E)$.

$$W_E^T = (w_1, w_2, \ldots, w_k) \quad (5.16)$$

Consider $L = \{L_1, L_2, \ldots, L_m\}$ and $C = \{C_1, C_2, \ldots, C_m\}$ be the sets of FL and CS for the failure mode. The linguistic expressions for FL and CS are shown in Table 5.10.

Table 5.9: Linguistic Expressions for Expert's Weights

Linguistic expressions	Plithogenic numbers < T, I, F >
Very Important (VI)	< 0.9, 0.1, 0.1 >
Important (I)	< 0.75, 0.25, 0.2 >
Medium (M)	< 0.5, 0.5, 0.5 >
Unimportant (UI)	< 0.35, 0.75, 0.80 >
Very unimportant (VUI)	< 0.1, 0.9, 0.9 >

Table 5.10: Linguistic Expressions for FL and CS

Linguistic expressions	Plithogenic numbers <T, I, F >
Very Very High (VVH) / Catastrophic (CS)	< 0.90, 0.10, 0.10 >
High (H) / Critical (C)	< 0.70, 0.25, 0.30 >
Moderate (Mo)	< 0.50, 0.50, 0.50 >
Low (L) / Marginal (M)	< 0.30, 0.75, 0.70 >
Very Very Low (VVL) / Negligible (N)	< 0.10, 0.90, 0.90 >

5.5.3 Constructing Plithogenic Risk Parameter Matrix

Suitable contradiction degrees cd_j are assigned by experts to each failure mode.

$cd_j = \{cd_1, cd_2, \dots, cd_m\}$

The plithogenic data provided by experts on FL and CS of failure mode are presented in the matrix $\widetilde{D}$.

$$\widetilde{D} = \begin{array}{cc} & \begin{array}{ccccccccc} F_1 & F_2 & \cdots & F_m & \vdots & F_1 & F_2 & \cdots & F_m \end{array} \\ \begin{array}{c} Contradiction\ degrees \\ E_1 \\ E_2 \\ \vdots \\ E_k \end{array} & \begin{bmatrix} cd_1 & cd_2 & \cdots & cd_m & \vdots & cd_1 & cd_2 & \cdots & cd_m \\ L_{11} & L_{12} & \cdots & L_{1m} & \vdots & C_{11} & C_{12} & \cdots & C_{1m} \\ L_{21} & L_{22} & \cdots & L_{2m} & \vdots & C_{21} & C_{22} & \cdots & C_{2m} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ L_{k1} & L_{k2} & \cdots & L_{km} & \vdots & C_{k1} & C_{k2} & \cdots & C_{km} \end{bmatrix} \end{array} \quad (5.17)$$

$L_{ij} = \left(T_{ij}^L, I_{ij}^L, F_{ij}^L\right)$ and $C_{ij} = \left(T_{ij}^C, I_{ij}^C, F_{ij}^C\right)$ are plithogenic numbers for likelihood and severity of i^{th} expert for j^{th} failure mode.

5.5.4 Estimating Plithogenic Risk Score of Failure Modes

Plithogenic risk score of failure modes is obtained by plithogenic product of their corresponding FL and CS.

$$R_{ij} = (L)_{ij}(t_{norm})(C)_{ij} \quad (5.18)$$

$i = 1, 2, \dots, k$ and $j = 1, 2, \dots, m$

$$\tilde{R} = \begin{array}{cc} & \begin{array}{cccc} F_1 & F_2 & \cdots & F_m \end{array} \\ \begin{array}{c} E_1 \\ E_2 \\ \vdots \\ E_k \end{array} & \begin{bmatrix} R_{11} & R_{12} & \cdots & R_{1m} \\ R_{21} & R_{22} & \cdots & R_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ R_{k1} & R_{k2} & \cdots & R_{km} \end{bmatrix} \end{array} \quad (5.19)$$

where $R_{ij} = \left(T_{ij}^R, I_{ij}^R, F_{ij}^R\right)$

5.5.5 Obtaining Combined Risk Score of Failure Modes

BBA of the plithogenic risk score is obtained in a similar way described in section 5.4.2. The ER approach is then used to combine the risk score for individual failure mode generated by all the experts.

5.5.6 Ranking of Failure Modes

The ranking is done by mapping the risk score with the plithogenic risk expressions given in Table 5.11. Consider,

$R = \{R_1, R_2, R_3, R_4, R_5\} = \{'Very\ High', 'High', 'Medium', 'Low', 'Very\ Low'\}$ be the set of risk expressions. The similarity response of different failure modes is obtained by normalising the correlation coefficient,

$$\tilde{S} = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ R_4 \\ R_5 \end{array} \begin{array}{c} \begin{array}{cccc} F_1 & F_2 & \cdots & F_m \end{array} \\ \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1m} \\ S_{21} & S_{22} & \cdots & S_{2m} \\ S_{31} & S_{32} & \cdots & S_{3m} \\ S_{41} & S_{42} & \cdots & S_{4m} \\ S_{51} & S_{52} & \cdots & S_{5m} \end{bmatrix} \end{array} \tag{5.20}$$

The weighted risk score is given by,

$$[RS]_{1\times m} = [W]_R^T \times [\tilde{S}]_{5\times m} \tag{5.21}$$

$[W]_R^T \rightarrow$ weight vector of risk expressions.

The weighted risk score is used to rank the failure modes. The higher the weighted score, the more critical is the failure modes. The proposed steps in the flowchart are shown in Figure 5.10.

Table 5.11: Linguistic Expressions for Risk Level

Linguistic expressions	Plithogenic numbers < T, I, F >	Crisp	Normalised Weight	BBA's		
				m(T)	m(T, F)	m(F)
Very High (VH)	< 0.90, 0.10, 0.10 >	0.9	0.36	0.8182	0.0909	0.0909
High (H)	< 0.70, 0.25, 0.30 >	0.72	0.29	0.56	0.2	0.24
Medium (Me)	< 0.50, 0.50, 0.50 >	0.5	0.2	0.3333	0.3333	0.3333
Low (L)	< 0.30, 0.75, 0.70 >	0.28	0.11	0.1714	0.4286	0.4
Very Low (VL)	< 0.10, 0.90, 0.90 >	0.1	0.04	0.0526	0.4737	0.4737

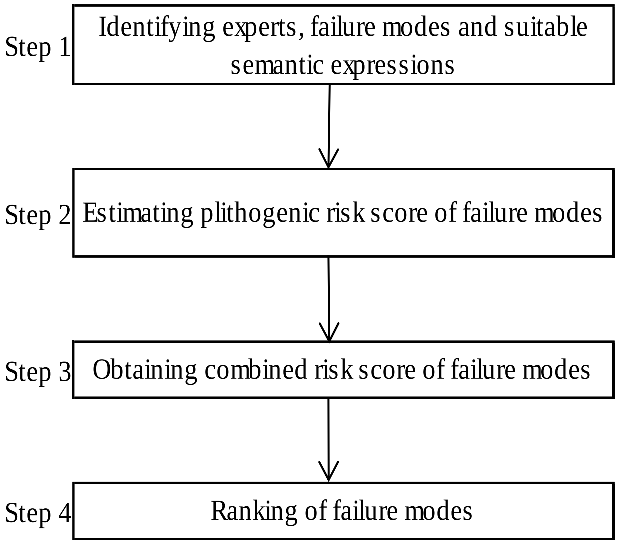

Figure 5.10: The Flowchart for Plithogenic Model

5.5.7 Illustration of the Model

A model is applied to estimate the risk associated with a typical system onboard the ship. Four experts ($k = 4$) from the maritime field identified five failure modes ($m = 5$) of a typical system onboard a ship. The experts proposed the contradiction degrees of failure modes as $cd = \{cd_1, cd_2, \dots, cd_5\} = \{0,0.25,0.50,0.75,1.00\}$. The importance given to four experts based on their experience and knowledge is, $E = \langle(0.9, 0.1, 0.1), (0.75, 0.25, 0.2), (0.9, 0.1, 0.1), (0.5, 0.5, 0.5)\rangle$. The weight vector obtained for the experts is, $W_E^T = (0.294, 0.25, 0.294, 0.162)$. A typical system on the ship is shown in Figure 5.11. The plithogenic data provided by experts on the likelihood and consequences of failure modes are presented in the matrix $\widetilde{D}$.

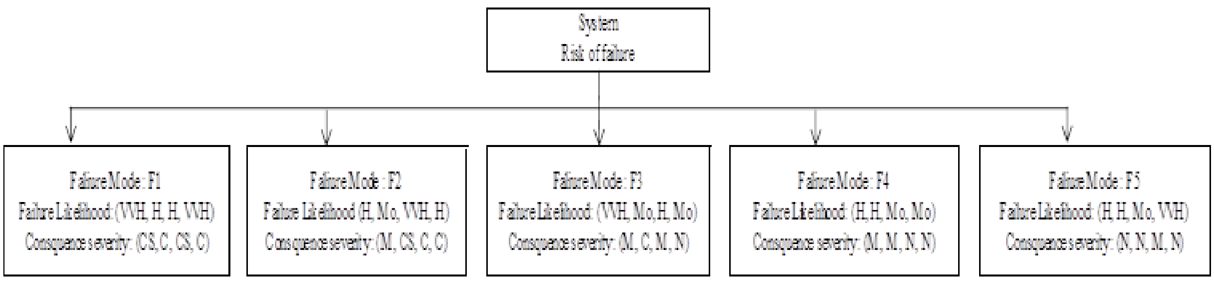

Figure 5.11: A Typical System-II Onboard Ship

$$\widetilde{D} = \begin{array}{c} \\ Contradiction\ degrees \\ E_1 \\ E_2 \\ E_3 \\ E_4 \end{array} \begin{array}{c} \begin{array}{ccccccccccc} F_1 & F_2 & F_3 & F_4 & F_5 & & F_1 & F_2 & F_3 & F_4 & F_5 \end{array} \\ \begin{bmatrix} 0 & 0.25 & 0.50 & 0.75 & 1.0 & \vdots & 0 & 0.25 & 0.50 & 0.75 & 1.0 \\ VVH & H & VVH & H & H & \vdots & CS & M & M & M & N \\ H & Mo & Mo & H & H & \vdots & C & CS & C & M & N \\ H & VVH & H & Mo & Mo & \vdots & CS & C & M & N & M \\ VVH & H & Mo & Mo & VVH & \vdots & C & C & N & N & N \end{bmatrix} \end{array}$$

Plithogenic risk score, BBA's of risk score and normalised similarity score are given in Appendix-III.

The weight vector obtained for plithogenic risk expressions is $W_R^T = (0.36, 0.29, 0.2, 0.11, 0.04)$. The weighted risk score is, $[RS] = (0.211178, 0.202089, 0.197743, 0.198414, 0.209815)$. The final ranking of failure modes in decreasing order of criticality is $F_1 > F_5 > F_2 > F_4 > F_3$.

The result shows that F_1 is the most critical failure mode and requires immediate attention. This is mainly because FL of F_1 is very very high. If this failure mode occurs, the resulting severity is also catastrophic/critical. F_5 is at second place. F_2, F_4 and F_3 follow in that order to be next critical failure modes.

5.5.8 Sensitivity Analysis

Sensitivity analysis is performed to see the effect of risk control options. New ranking order is obtained when the likelihood of a highly sensitive failure mode criterion is reduced when the model is run repeatedly. The result is given in Table 5.12.

Table 5.12: Sensitivity Analysis

Sr. No.	Critical failure mode	Revised likelihood values of critical failure mode	New ranking order
1	F1	(H, Mo, H, H)	F5 > F2 > F1 > F4 > F3
2	F5	(VVH, Mo, H, Mo)	F2 > F1 > F5 > F4 > F3
3	F2	(H, Mo, H, H)	F1 > F5 > F2 > F4 > F3
4	F1	(H, Mo, Mo, Mo)	F5 > F2 > F4 > F3 > F1
5	F5	(Mo, Mo, L, Mo)	F2 > F4 > F3 > F5 > F1

Sensitivity analysis shows that by attending the critical failure mode on priority, the likelihood of occurrence of that failure mode can be reduced. This can lower the chances of failure and improve the safety of the system.

5.6 Summary

In this chapter, three different models for assessing risk and the safety of the system in maritime transportation are proposed. First, neutrosophic IF-THEN rules are constructed to elicit the experts' judgements and assess the risk from diversified dimensions such as personnel, organisational and environmental perspectives. The proposed model is validated using an example [72]. The result is reasonably better and in line with [72]. Second, neutrosophic sets in combination with the ER approach are proposed for precise risk assessment. The model is illustrated taking a contrived example from the ship system. The results show that the safety of the system is evaluated as average and can be improved further to good and excellent by reducing the values of risk parameters. The results are also verified w.r.t the proposed alternative approach to DST. Third, the model using plithogenic sets is created and its effectiveness is demonstrated in risk assessment. The model ranked the failure modes in descending order as per their criticality. The sensitivity analysis performed on the model showed how the criticality of failure modes changed with the change in the risk parameters. A comparative study of three proposed models and their suitability for different types of applications is given in Table 5.13. The usefulness of neutrosophic sets in risk assessment in dynamic conditions is shown in chapter six.

Table 5.13: A comparative Study of Three Models

Sr. No.	Model	Suitability
1	Model-I Using Neutrosophic Logic	1. Useful in dealing with uncertainties
		2. Suitable when data collected are in semantic expressions
		3. Works well when IF-THEN rules are accurately framed
		4. Useful when data are imprecise and incomplete
		5. Useful in dealing with non-linearity in complex situations
2	Model-II Using Neutrosophic Set Theory	1. Useful in dealing with uncertainties
		2. Suitable when data collected are in semantic expressions
		3. Suitable in solving MCDM problems when uncertainty arises due to hesitancy
		4. Model can be used with ER to solve MCDM problems if suitable methods can be designed to convert SVNN into BBA's
3	Model-III Using Plithogenic Set Theory	1. Useful in dealing with uncertainties
		2. Suitable when data are collected in semantic expressions
		3. Beneficial when dissimilarity or contradiction degree is properly defined between attribute values and dominant attribute value

Chapter 6

Dynamic Decision Making Model

Most of the decision making theories are devised considering static data. Such data are believed to be available at the start. In the real world, decisions are required in dynamic conditions wherein the factors influencing the decisions change periodically. Decision making in dynamic conditions requires a fusion of information gathered at different periods and different operating conditions. This necessitates the data to be captured dynamically in varying periods and assessed periodically. This is necessitated because the decisions taken at a particular time influence the decisions taken in the subsequent period. In this study, Interval Neutrosophic Number (INN) and DSmT are used for decision making in a dynamic environment.

6.1 Dynamic Interval Valued Neutrosophic Set (DIVNS)

The neutrosophic set and its set theoretic operations are described in section 1.6. A dynamic interval valued neutrosophic set is defined as [128],

Let U be a universe of discourse,

$x([T_x^L(t), T_x^U(t)], [I_x^L(t), I_x^U(t)], [F_x^L(t), F_x^U(t)])$

where $t \geq 0$ and $x \in U$

$T_x^L(t) < T_x^U(t)$, $I_x^L(t) < I_x^U(t)$, $F_x^L(t) < F_x^U(t)$

and

$$[T_x^L(t), T_x^U(t)], [I_x^L(t), I_x^U(t)], [F_x^L(t), F_x^U(t)] \subseteq [0, 1] \tag{6.1}$$

In DIVNS, all intervals are changing w.r.t. time (t).

6.1.1 Set Theoretic Operations of DIVNS

Consider two Dynamic Interval Valued Neutrosophic Numbers (DIVNN):

$$a(t) = \{\langle T_x^A(t_1), I_x^A(t_1), F_x^A(t_1)\rangle, \dots, \langle T_x^A(t_k), I_x^A(t_k), F_x^A(t_k)\rangle\}$$

$$b(t) = \{\langle T_x^B(t_1), I_x^B(t_1), F_x^B(t_1)\rangle, \dots, \langle T_x^B(t_k), I_x^B(t_k), F_x^B(t_k)\rangle\} \tag{6.2}$$

where $t = \{t_1, t_2, \dots, t_k\}$ is a time sequence at each time $t_l, 1 \leq l \leq k$

Thong et al. [128] defined the following operations.

a) Addition of two DIVNN

$$a(t) \oplus b(t) = \left\{\begin{matrix} \langle T_x^A(t_1) + T_x^B(t_1) - T_x^A(t_1) \times T_x^B(t_1), I_x^A(t_1) \times I_x^B(t_1), F_x^A(t_1) \times F_x^B(t_1)\rangle, \dots, \\ \langle T_x^A(t_k) + T_x^B(t_k) - T_x^A(t_k) \times T_x^B(t_k), I_x^A(t_k) \times I_x^B(t_k), F_x^A(t_k) \times F_x^B(t_k)\rangle \end{matrix}\right\} \tag{6.3}$$

b) Multiplication of two DIVNN

$$a(t) \otimes b(t) = \left\{\begin{matrix} \langle T_x^A(t_1) \times T_x^B(t_1), I_x^A(t_1) + I_x^B(t_1) - I_x^A(t_1) \times I_x^B(t_1), F_x^A(t_1) + F_x^B(t_1) - F_x^A(t_1) \times F_x^B(t_1) \rangle, \dots, \\ \langle T_x^A(t_k) \times T_x^B(t_k), I_x^A(t_k) + I_x^B(t_k) - I_x^A(t_k) \times I_x^B(t_k), F_x^A(t_k) + F_x^B(t_k) - F_x^A(t_k) \times F_x^B(t_k) \rangle \end{matrix}\right\} \tag{6.4}$$

c) Scalar multiplication of two DIVNN

$$\alpha \times a(t) = \left\{\begin{matrix} \langle 1 - \left(1 - T_x^A(t_1)\right)^\alpha, I_x^A(t_1)^\alpha, F_x^A(t_1)^\alpha \rangle, \dots, \\ \langle 1 - \left(1 - T_x^A(t_k)\right)^\alpha, I_x^A(t_k)^\alpha, F_x^A(t_k)^\alpha \rangle \end{matrix}\right\} \tag{6.5}$$

d) Power of the DIVNN

$$a(t)^\alpha = \left\{\begin{matrix} \langle T_x^A(t_1)^\alpha, 1 - \left(1 - I_x^A(t_1)\right)^\alpha, 1 - \left(1 - F_x^A(t_1)\right)^\alpha \rangle, \dots, \\ \langle T_x^A(t_k)^\alpha, 1 - \left(1 - I_x^A(t_k)\right)^\alpha, 1 - \left(1 - F_x^A(t_k)\right)^\alpha \rangle \end{matrix}\right\} \tag{6.6}$$

6.2 Basic Belief Assignment of Interval Neutrosophic Number (INN)

Consider an INN. $BBAO(\cdot)$ function converts any INN into its corresponding BBA.

$$m(\cdot) \equiv BBAO(\cdot) = \frac{mean(\cdot)}{sum\_of\_the\_mean(\cdot)} \tag{6.7}$$

where $(\cdot)$ finds the mean of the neutrosophic component interval given by,

$$mean(\cdot) = \frac{(\cdot)^L + (\cdot)^U}{2} \tag{6.8}$$

and $sum\_of\_the\_mean(\cdot)$ gives the summation of the means of all the three components of INN.

6.2.1 Dynamic Basic Belief Assignment of Interval Neutrosophic Number

Consider a decision maker D_q, $(q = 1, 2, \dots, h)$, evaluate the alternative A_a, $(a = 1, 2, \dots, v)$ w.r.t. criterion C_p, $(p = 1, 2, \dots, n)$, in time t_l, $(l = 1, 2, \dots, k)$. The evaluation characteristic is given by,

$$X_{apq}(t_l) = \{[T^L_{apq}(X_{t_l}), T^U_{apq}(X_{t_l})], [I^L_{apq}(X_{t_l}), I^U_{apq}(X_{t_l})], [F^L_{apq}(X_{t_l}), F^U_{apq}(X_{t_l})]\} \quad (6.9)$$

Dynamic Basic Belief Assignment Operator (DBBAO) and DSmT of information fusion are combined to get the Dynamic Basic Belief Assignment (DBBA). Belief components of $T \cup F$ and $T \cap F$ are assigned to $T \cup F$ as DSmT is closed on $\cup$ and $\cap$.

Dynamic basic belief mass,

$$m_{D_{ap}}(C) \equiv DBBAO(C) = \sum_{\substack{x_1,x_2,\dots,x_l \in D^\Theta \\ x_1 \cap x_2 \cap \dots \cap x_l = C}} \left[\prod_{l=1}^{k} \left[\sum_{\substack{x_1,x_2,\dots,x_q \in D^\Theta \\ x_1 \cap x_2 \cap \dots \cap x_q = C_a}} \prod_{q=1}^{h} m_{lq}(X_{t_l})\right]\right] \quad (6.10)$$

for $a = 1, 2, \dots, v$ and $p = 1, 2, \dots, n$

6.2.2 Dynamic Weight Vector

Evaluation of alternatives is done w.r.t. the laid criteria. These criteria are assessed by different experts in different periods. The importance of criteria is expressed in linguistic terms. These are converted into neutrosophic numbers and aggregated to get the dynamic weight vector (DWV). A dynamic weight vector operator (DWVO) is proposed to get the DWV.

The evaluation characteristic of a criterion C_p by the decision maker D_q in time t_l is,

$$X_{pq}(t_l) = \{[T^L_{pq}(X_{t_l}), T^U_{pq}(X_{t_l})], [I^L_{pq}(X_{t_l}), I^U_{pq}(X_{t_l})], [F^L_{pq}(X_{t_l}), F^U_{pq}(X_{t_l})]\} \quad (6.11)$$

The averaged aggregation characteristic is,

$$\bar{X}_p = \{[\bar{T}^L_p(X), \bar{T}^U_p(X)], [\bar{I}^L_p(X), \bar{I}^U_p(X)], [\bar{F}^L_p(X), \bar{F}^U_p(X)]\}$$

where,

$$\bar{T}_p(X) = \left[\langle 1 - \left[\prod_{i=1}^{k}\left[1 - \left[1 - \prod_{q=1}^{h}\left(1 - T^L_{iq}(X)\right)^{1/h}\right]\right]^{1/k}\right\rangle, \langle 1 - \left[\prod_{i=1}^{k}\left[1 - \left[1 - \prod_{q=1}^{h}\left(1 - T^U_{iq}(X)\right)^{1/h}\right]\right]^{1/k}\right\rangle\right]$$

$$\bar{I}_p(X) = \left[\langle \prod_{i=1}^{k}\left[\prod_{q=1}^{h}[I^L_{iq}(X)]^{1/h}\right]^{1/k} \rangle, \langle \prod_{i=1}^{k}\left[\prod_{q=1}^{h}[I^U_{iq}(X)]^{1/h}\right]^{1/k} \rangle\right]$$

and

$$\bar{F}_p(X) = \left[\langle \prod_{i=1}^{k}\left[\prod_{q=1}^{h}[F^L_{iq}(X)]^{1/h}\right]^{1/k} \rangle, \langle \prod_{i=1}^{k}\left[\prod_{q=1}^{h}[F^U_{iq}(X)]^{1/h}\right]^{1/k} \rangle\right] \quad (6.12)$$

DWV is a column vector,

$W = (\bar{w}_d)_{n\times 1}$

$$\bar{w}_d \equiv DWVO(\bar{X}_p) = \frac{mean(\bar{T}_p(X))+mean(\bar{I}_p(X))+mean(\bar{F}_p(X))}{\sum_{p=1}^{n}[sum\_of\_the\_mean(\bar{X}_p)]} \tag{6.13}$$

6.3 Dynamic Information Fusion

Information collected in a dynamic, complex and uncertain environment is fused to rank the alternatives. The model is further developed to assess the safety of the system. The steps for both above methods are presented in the next sub sections.

6.3.1 Method to Evaluate and Rank the Alternatives

Step 1: Every alternative is evaluated by a team of experts w.r.t. criteria in different periods. Suitability ratings for evaluation are given in Table 6.1. The evaluation is represented as a characteristic matrix $\left(X_{apq}(t_{t_l})\right)_{v\times k}$.

Table 6.1: Suitability Ratings as Linguistic Variables

Linguistic Terms	INS
Very_Poor (Ve_Po)	([0.1, 0.2], [0.6, 0.7], [0.7, 0.8])
Poor (Po)	([0.2, 0.3], [0.5, 0.6], [0.6, 0.7])
Medium (Me)	([0.3, 0.5], [0.4, 0.6], [0.4, 0.5])
Good (Go)	([0.5, 0.6], [0.4, 0.5], [0.3, 0.4])
Very_Good (Ve_Go)	([0.6, 0.7], [0.2, 0.3], [0.2, 0.3])

Step 2: DSmT is applied on the evaluated characteristic matrix using DBBAO to get the dynamic mass.

Step 3: The importance of criteria is evaluated in different periods. Linguistic variables are given in Table 6.2.

Table 6.2: Importance Weights as Linguistic Variables

Linguistic Terms	INS
Unimportant (U_IPA)	([0.1, 0.2], [0.4, 0.5], [0.6, 0.7])
Ordinary_Important (O_IPA)	([0.2, 0.4], [0.5, 0.6], [0.4, 0.5])
Important (IPA)	([0.4, 0.6], [0.4, 0.5], [0.3, 0.4])
Very_Important (V_IPA)	([0.6, 0.8], [0.3, 0.4], [0.2, 0.3])
Absolutely _Important (A_IPA)	([0.7, 0.9], [0.2, 0.3], [0.1, 0.2])

Step 4: The averaged aggregation of all the criteria is found out.

Step 5: The DWV is obtained.

Step 6: The Weighted Dynamic Basic Belief Assignment (WDBBA) (m_{wD}) is obtained for all the alternatives using DBBA (m_D) and DWV ($\overline{w}_D$) of the criteria.

$$m_{wD_{ap}}(X) = \overline{w}_d \times m_{D_{ap}}(X) \tag{6.14}$$

For $\forall a = 1, 2, \dots, v$

Step 7: The information is synthesized using m_{wD} and applying the classic DSmT to get the dynamic belief masses for all the alternatives. The obtained dynamic belief masses are normalised to get the final belief masses.

$$m_{D_a}(C) = \sum_{\substack{X_1, X_2, \dots, X_n \in D^{\Theta} \\ X_1 \cap X_2 \cap \dots \cap X_n = C}} \left[\prod_{p=1}^{n} m_{d_a}(X)\right] \tag{6.15}$$

For $\forall a = 1, 2, \dots, v$

Step 8: The final BBAs of all alternatives are compared with the ideal alternative $\langle(1,1),(0,0),(0,0)\rangle$ using the similarity measure proposed by Jiang [116]. The alternatives are ranked as per their correlation coefficients. The flowchart of the model for alternatives is shown in Figure 6.1.

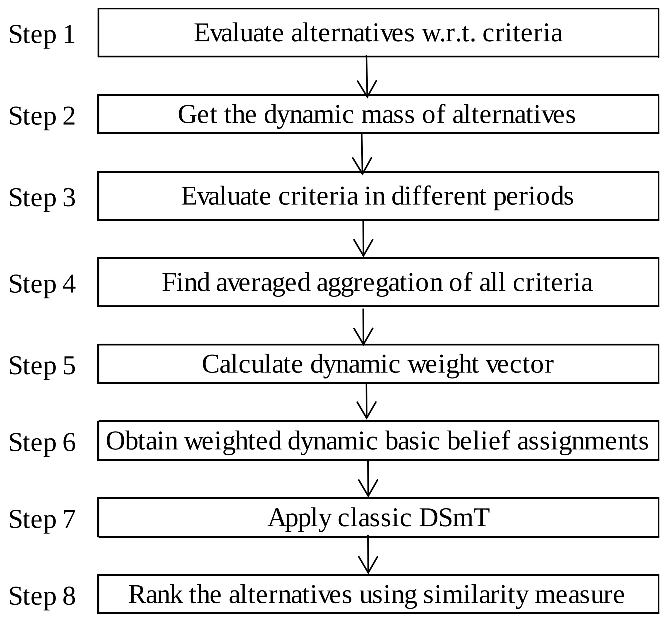

Figure 6.1: The Flowchart to Evaluate and Rank the Alternatives

6.3.2 Method to Assess the Safety of the System

Step 1: The different failure modes are identified.

Step 2: The evaluated characteristic matrix by $'q'$ decision maker on a^{th} failure mode is obtained in l^{th} period.

$$\left(X_{aq}(t_l)\right)_{v\times k}=\{[T_{aq}^{L}(X_{t_l}),T_{aq}^{U}(X_{t_l})],[I_{aq}^{L}(X_{t_l}),I_{aq}^{U}(X_{t_l})],[F_{aq}^{L}(X_{t_l}),F_{aq}^{U}(X_{t_l})]\} \tag{6.16}$$

$a=1,2,\dots,v;\quad q=1,2,\dots,h$ and $l=1,2,\dots,k$

Step 3: The horizontal integration using DBBAO and DSmT is carried out on the characteristic matrix to get dynamic belief masses of all failure modes.

Step 4: The vertical integration using DSmT and dynamic belief masses is carried out to get the dynamic belief masses of the system.

Step 5: The dynamic belief masses of the system are mapped back to the risk expressions using similarity measures [116]. The safety expressions are given in Table 6.3.

Table 6.3: Safety Expressions to Evaluate the System

Linguistic Expressions	INS
Poor (P)	([0.1, 0.2], [0.2, 0.3], [0.8, 0.9])
Average (A)	([0.4, 0.5], [0.4, 0.5], [0.6, 0.7])
Good (G)	([0.6, 0.7], [0.4, 0.5], [0.4, 0.5])
Excellent (E)	([0.8, 0.9], [0.2, 0.3], [0.1, 0.2])

The flowchart of the model for assessing the safety of the system is shown in Figure 6.2.

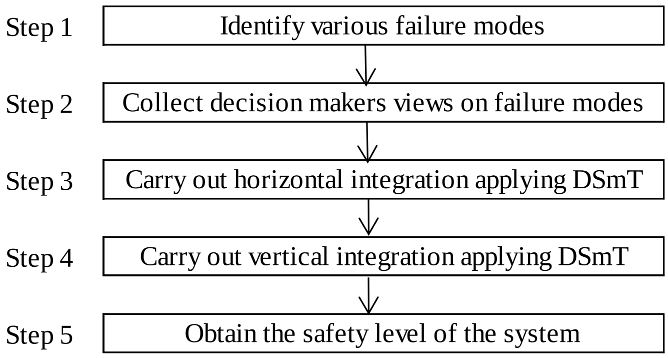

Figure 6.2: The Flowchart to Assess the Safety of the System

6.4 Applications

Two examples are given to validate and demonstrate the proposed methods of ranking the alternatives and assessing the safety of the system.

6.4.1 Example 1: The Proposed Ranking Model

The example is taken from [128] to evaluate lecturers' performance in the case study of ULIS-VNU. Consider five lecturers i.e. $A_1, A_2, \dots, A_5$ and three decision-makers i.e.

D_1, D_2, D_3. Five lecturers are evaluated with respect to 6 criteria: total publications (C_1), teaching student evaluations (C_2), personality characteristics (C_3), professional society (C_4), teaching experience (C_5), fluency of foreign language (C_6). The evaluated matrix along with their dynamic basic belief masses and the evaluation of criteria for their importance along with the dynamic weight vector are given in Appendix-IV. Normalised weighted dynamic belief masses and normalised correlation coefficients are given in Table 6.4 and Table 6.5.

Table 6.4: Normalised Weighted Dynamic Belief Masses

Lecturers	Normalised Weighted Dynamic Belief masses
A1	(0.697808, 0.078287, 0.223905)
A2	(0.760933, 0.050429, 0.188578)
A3	(0.796668, 0.042129, 0.161202)
A4	(0.701103, 0.077390, 0.221507)
A5	(0.662146, 0.097506, 0.240348)

Table 6.5: Normalised Correlation Coefficient

Lecturers	Normalised Correlation Coefficients
r1(α*, A1)	0.198675
r2(α*, A2)	0.202459
r3(α*, A3)	0.204062
r4(α*, A4)	0.198903
r5(α*, A5)	0.195901

The ranking order of five lecturers is $A_3 > A_2 > A_4 > A_1 > A_5$. The ranking order as given by [128] is $A_2 > A_3 > A_4 > A_1 > A_5$. The ranking order is in line with [128] except for the first two alternatives.

6.4.2 Example 2: The Proposed Model for Assessing the Safety of the System

An example of Steering Gear failure onboard ship is taken to illustrate the model. Two experts from the marine field having over 20 years of sailing experience identified the failure modes of the system. Equal weights are assigned to both experts. The steering gear system with failure modes is shown in Figure 6.3. The evaluated characteristic matrix for two different periods is given in Table 6.6.

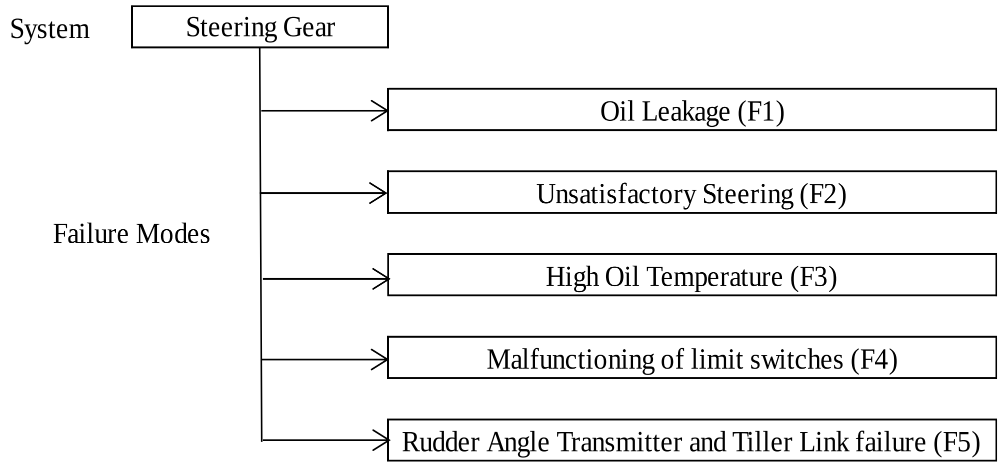

Figure 6.3: Steering Gear System with Failure Modes

Table 6.6: Evaluated Characteristic Matrix with Dynamic Belief Masses

Failure Modes	Experts				Dynamic Basic Belief masses
	t1		t2		
	D1	D2	D1	D2	
F1	Me	Me	Go	Go	(0.379971, 0.281706, 0.338324)
F2	Go	Go	Go	Go	(0.473601, 0.212394, 0.314005)
F3	Me	Go	Me	Go	(0.38612, 0.283486, 0.330394)
F4	Po	Po	Me	Me	(0.194758, 0.481636, 0.323606)
F5	Me	Me	Me	Go	(0.341035, 0323677, 0.335288)

By vertical integration of all the masses using DSmT, we get the system's dynamic belief masses as,

$m(T) = 0.325928,\quad m(F) = 0.340302$ and $m(T,F) = 0.33377$

These dynamic masses are mapped back to the safety expressions using similarity measures. After normalising, the safety level of the system obtained is,

$\beta_{Poor} = 0.23539,\quad \beta_{Average} = 0.266823,\quad \beta_{Good} = 0.265923$ and $\beta_{Excellent} = 0.231864$

The steering gear system is assessed as 'Average' with a belief of 26.68 %, as 'Good' with a belief of 26.59 %, as 'Poor' with a belief of 23.54 % and as 'Excellent;' with a belief of 23.19%. The result is shown in Figure 6.4.

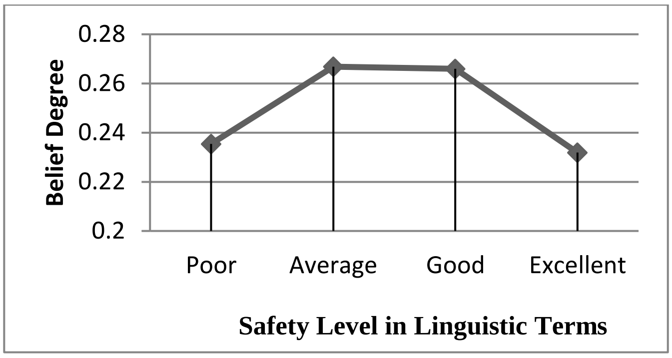

Figure 6.4: Safety Level of the System

The safety level of the system is assessed for one more period. The data for the third period is collected after taking risk control options which reduced the likelihood of occurrence of failure mode. The data for the third period is given in Table 6.7.

With the incorporation of new data, the safety level of the system obtained is shown in Figure 6.5. $\beta_{Poor} = 0.1907$, $\beta_{Average} = 0.2550$, $\beta_{Good} = 0.2771$ and $\beta_{Excellent} = 0.2772$

The steering gear system with the inclusion of the third period is assessed as 'Excellent' with a belief of 27.72 %, as 'Good' with a belief of 27.71 %, as 'Average' with a belief of 25.50 % and as 'Poor' with a belief of 19.07%. From Figure 6.4 and Figure 6.5, it is seen that by considering the data in subsequent periods and assessing the safety level of the system periodically, the performance of the system can be monitored dynamically.

Table 6.7: Experts Data for Third Period

Failure Modes	Experts	
	t3	
	D1	D2
F1	Ve_Go	Go
F2	Ve_Go	Ve_Go
F3	Go	Ve_Go
F4	Go	Go
F5	Go	Ve_Go

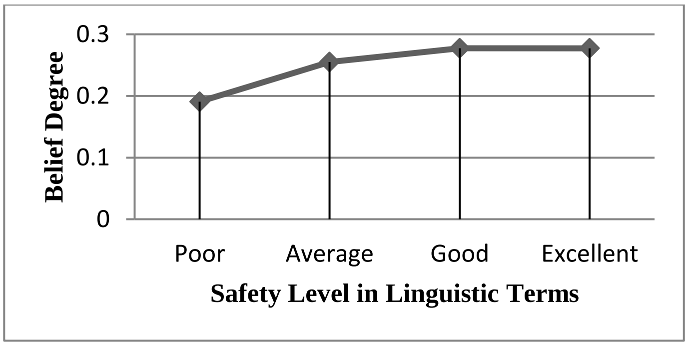

Figure 6.5: Safety Level of the System (Including the Third Period)

6.5 Summary

This chapter dealt with the last part of the problem statement. A dynamic decision making model is proposed using neutrosophic sets. Three operators BBAO, DBBAO and DWVO are proposed to facilitate the decision making when information is collected at different periods. Two methods are proposed namely the method to rank the alternatives and the method to assess the safety of the system. DSmT of information fusion is used to integrate and fuse the information collected from experts using INS. Linguistic expressions for evaluation of alternatives, importance weight criteria and safety expressions are provided using INS. For the illustrative example safety level of the system is showed as average. The model showed that the safety of the system can be increased from average to good and further to excellent by incorporating the new data once proper measures are taken to reduce the effect of critical parameters.

Chapter 7

Summary and Conclusions

This concluding chapter presents the extract of the work done in this thesis under the title "Risk Assessment and Dynamic Decision Making in Maritime Transportation". Limitations and future scope in this area are presented in the end.

7.1 Discussion

The research problem, its solution and the research work are mainly carried out in three stages.

- Checking the effectiveness of tools like Bayesian Belief Network, Evidential reasoning and Fuzzy multi criteria methods suitable for efficient reasoning under uncertainty.
- Creating a framework for estimating the risk in maritime transportation.
- Introducing a framework for dynamic decision making in integrated approach/method.

Major work is the development of novel risk assessment models for the safety of maritime transportation. It involved collecting the data from professionals having quite a lot of seagoing experience, devising various operators required to execute the model, validating the model qualitatively and quantitatively wherever applicable, carrying out a sensitivity analysis of the model to ascertain the impact of input parameters on the outcome of the model. Experts are not chosen randomly but those who have quite experience and knowledge from the related field to draw meaningful conclusions. The experts are chosen to represent the population of interest. The research has resulted in several contributions in the field of risk assessment and decision making.

The research work carried out in this thesis is summarised as follows.

1. A general method using ISM is proposed when the past data for hazards and failure likelihood of hazards are scarce and not available in totality. It is difficult to accurately measure these parameters due to the complexity of the system. Therefore, hazard identification and their causable interrelationships associated with the given problem are done using experts' judgements. An ISM model is built using the collected information. The hazards of similar nature are grouped in factor groups and the model is developed and networked in these factor groups.

2. The factors identified for the given problem may not be independent of each other and may have a dependence on other factors. Any of these factors may trigger accidents. To assess the risk of a system, we require the appropriate weights of these factors. To obtain the precise weights in such a complex networked structure is quite difficult. The best suited method under such circumstances is FANP. This method is used to get the weights of factors and assess the risk of the system.
3. Experts expressed the importance of factors, factor groups and risk parameters (FL and CS) using linear triangular/trapezoidal fuzzy numbers. In crisp to fuzzy combine, all the ranges representing crisp values are retained with their corresponding membership degrees. Fuzzy IF–THEN rules are created to get the risk due to these factors. These risks are synthesised using the ER approach to get the overall risk of the system.
4. In real life, reliable statistical data for risk assessment are not available and one has to rely heavily on subjective judgements provided by experts. Such data collected being qualitative are fuzzy and contain a lot of uncertainty. Unless this uncertainty is handled properly in the initial stages, the model may give false results and not represent reality. Neutrosophic sets because of the inclusion of indeterminacy components help to incorporate this uncertainty. A novel model using neutrosophic IF-THEN rules is employed for handling the uncertainty in the data. A model developed is validated taking an example from Sii [72] and the result is found to be more convincing than that of Sii [72].
5. A neutrosophic set because of its superiority in handling uncertainty is used to develop a hybrid model for risk assessment in combination with the ER approach. A simple novel method is proposed to convert the SVNN to the corresponding BBA. ER approach is then used to synthesise the safety scores of every failure mode using the obtained BBAs to get the risk level of the system.
6. A plithogenic set that can contain more than one attribute, is an extension of the neutrosophic set. With the introduction of contradiction degrees, better accuracy in the aggregation operators is expected in this type of set. A model using a plithogenic set and ER approach is developed by introducing a novel method to convert the plithogenic number to its BBA. Sensitivity analysis performed on an illustrative example based on this model affirmed the superiority of this method of iteratively reducing the risk associated with the factors and enhancing the safety of the system.
7. Risk assessment in dynamic conditions demands the collection of data dynamically in varying periods. A model using INN is developed to dynamically assess the safety of the

system. Combining the data dynamically using the ER approach requires the dynamic belief masses. First, BBAO is designed to obtain the BBA of INN which is further extended (DBBAO) to get the DBBA of INN.

8. For assessing safety in dynamic conditions, various alternatives are evaluated with respect to each criterion. The importance of criteria expressed in linguistic terms are converted to INN and aggregated to get DWV using DWVO. The suitability of DWVO is to properly assign the weights of the criteria according to their importance.
9. The risk assessment model with DSmT using DBBA and DWV in dynamic conditions is carried out. The classic model of DSmT is used for the first time in risk assessment to check its suitability in such cases. DSmT has overcome the basic limitations of DST as highlighted in section 3.6.3.2. The two models are proposed, one for the ranking of alternatives and the other to assess the safety of the system. The model is validated using a well-established example from Thong [128] and shown its application in assessing safety.
10. DST is often criticised for giving illogical results when sources of evidence have a high degree of conflict. A new alternative rule is proposed in which possible error from an expert while judging the hypotheses is considered. The new approach proposed in DST is applied to the models to highlight its superiority.

7.2 Conclusions

The conclusions of this research work are listed below:

1. The risk and safety level of the system can be computed even when the data of risk parameters are available in qualitative form.
2. If the past data is not available, the model can still be constructed to incorporate the subjective judgements of experts to get reliable results.
3. ISM is more suitable for drawing a directed graph and building an interconnected network of factors when the past data on factors (causes) of accidents are not available and the only source is the experts' judgements.
4. FANP is the most suited and appropriate method to get the weights of factors when they are interconnected and influence each other.
5. Neutrosophic sets can provide ease (over fuzzy sets) to experts for judgements. The hesitancy component in the neutrosophic sets can remove the uncertainty associated while evaluating a particular hypothesis.

6. Neutrosophic logic can be employed for assessing the safety level of the system by carefully constructing IF-THEN rules.
7. Plithogenic set, an extension of the neutrosophic set, is a recent development in set theory. The peculiarity of these sets is the contradiction degrees created between the attribute values and the dominant attribute value. With the inclusion of contradiction degrees, the results obtained using plithogenic sets are better and close to reality.
8. Neutrosophic and plithogenic sets in combination with the ER approach can model the scenario of risk assessment in a better way. A suitable method is required to get the BBA from the neutrosophic and plithogenic numbers.
9. In real life, we need to make decisions dynamically with periodically changing data. A dynamic model can capture this data that can help to improve the safety level of the system.
10. An alternative approach is proposed to D-S theory considering the EIJ of the experts. This model when applied to a given problem gives better results with a conflicting piece of evidence.

7.3 Contributions

The contributions of this research work are as follows:

1. The hybrid model using ISM, FANP and ER approach is developed to get the data from experts' judgements, build the causable model and assess the risk. The model is suitable when the past data are not available, the system is complex with several influencing factors and exact interrelationships between factors are not known.
2. The model using neutrosophic logic is constructed with IF-THEN rules. The model is suitable for analysing the risk of the system from diversified dimensions such as personnel, organisational and environmental perspectives.
3. An integrated model using the neutrosophic set theory and ER approach is proposed for precise assessment of risk in a complex environment. A simple novel method to convert SVNN to its BBA is developed.
4. A decision making model using the D-S theory of evidential reasoning is developed for assessing the risk and ranking criteria in a complex system.
5. The model for dynamic decision making is developed by creating three operators BBA, DBBAO and DWVO to get BBA, DBBA and DWV for the hazards. The model used DSmT and interval neutrosophic numbers that collected criteria values at different

periods to solve the decision making problems in a neutrosophic environment. The model is effectively utilised for assessing the safety of the system in dynamic conditions.

6. The models developed illustrate their usability in assessing the performance of the system periodically. The models help to monitor and enhance the performance of the system by running the model iteratively after executing proper risk control options.
7. A new alternative is added in DST to overcome its limitations when the series of evidence to be combined are in a high degree of conflict. The proposed alternative incorporated the possibility of error from experts while making judgements.

7.4 Limitations of the Work

This academic research that is carried out and reported in this thesis is mainly to enhance the risk assessment and decision making techniques by developing newer models and methodologies by employing fuzzy/neutrosophic/plithogenic set theory and evidential reasoning. The research has achieved its aims of providing an integrated framework for estimating risk and dynamic decision making in maritime transportation. However, due to time constraints, some of the problems cannot be fully explored and needs further investigation in the future. While attempting this, it is inevitable to carry a few limitations in the work. These limitations are as follows.

1. Almost all models (except two) are tested with contrived data.
2. Two models are validated taking examples from the previous research work. The results are compared and the proposed models showed improved performance.
3. Prominent arguments from experts, decision makers and stakeholders are used to validate the research models through the inferential qualitative technique. Model validity is tested with regard to the understanding of the theoretical bases by the experts. The experts participated and appreciated the methodological aspects of the study and its validity in the implementation.
4. Partial validation of one model is done by carrying out sensitivity analysis.
5. The membership grades in some models are assumed to be linear triangular/trapezoidal which may not be the case in practice and may take other shapes such as bell shaped, pentagonal, cylindrical and so on.
6. Only a few criteria are considered while developing models. In real life, there may be more criteria as constraints.
7. The identified risk factors may not have clear interrelationships and may be difficult to ascertain. In the present study, in certain cases the risk factors are considered independent

(except in one case), where it is considered that some factors may influence others but still the exact relationship is unclear.

8. The identified factors, affecting (triggering) the accidents, for developing the model may not be exhaustive. In complex systems, there may be more factors not fitting in the model.
9. The experts' judgements may not be perfect and accurate. The expert may sometimes inadvertently give the wrong judgement. The error from the expert may also creep in if the information required cannot be adequately expressed/processed and the expert is incoherent.
10. The traditional risk matrices used for evaluation are not full proof and require experts' judgements for validation. Moreover, the number of experts chosen for the study may be insufficient for proper evaluation. The horizontal expansion can be done by increasing the number of experts with a stretch of varying experience.
11. While developing a model on dynamic decision making, only dynamicity of varying periods is considered assuming other surrounding conditions remain the same which may not be the case in reality.

7.5 Future Scope

The limitations discussed in the previous section offer scope for the future. The following work could be considered as possible extensions and scope for future work.

1. The models developed in this study can be tested with more practical data for checking their suitability in varied scenarios.
2. The models developed can be applied to a full-fledged case study of a maritime transportation accident.
3. The model can be suitably modified using membership functions such as pentagonal, cylindrical, normal and so on. The results and performance of the models may be verified.
4. The refined neutrosophic and plithogenic sets can be used for further developing the existing models for refined and more precise risk assessment.

This research work has resulted in the development of risk assessment models for maritime transportation, safety analysis of maritime transportation in dynamic conditions and development of the new alternative approach to Dempster-Shafer theory of evidential reasoning to overcome its limitations of giving illogical and counterintuitive results especially when the series of evidence provided by various experts are in a high degree of conflict.

Appendix I

ANP Matrices and Experts' Judgements

Unweighted Supermatrix

			Oil Leakage			Electrical Faults			
	Oil Leakage	Electrical Faults	F1	F2	F3	F4	F5	F6	F7
Oil Leakage	1	0	0	0	0	0	0	0	0
Electrical Faults	0	1	0	0	0	0	0	0	0
F1	0.2887439	0	1	0.8628277	0.673207	0	0	0	0
F2	0.6223279	0	0.8687735	1	0.326793	0.8071371	0.78866	0.8457707	0
F3	0.0889283	0	0.1312265	0.1371723	1	0.1928629	0.21134	0.1542293	1
F4	0	0.3598041	0	0.251772	0.3119842	1	0.6207346	0.6917151	0
F5	0	0.4839005	0	0.6482228	0.4990046	0.7615188	1	0.3082849	1
F6	0	0.0982142	0	0.1000052	0.1393649	0.2384812	0.2940082	1	0
F7	0	0.0580811	0	0	0.0496464	0	0.0852572	0	1

Weighted Supermatrix

			Oil Leakage			Electrical Faults			
	Oil Leakage	Electrical Faults	F1	F2	F3	F4	F5	F6	F7
Oil Leakage	0.5	0	0	0	0	0	0	0	0
Electrical Faults	0	0.5	0	0	0	0	0	0	0
F1	0.1443719	0	0.5	0.2876092	0.2244023	0	0	0	0
F2	0.3111639	0	0.4343868	0.3333333	0.108931	0.2690457	0.2628867	0.2819236	0
F3	0.0444641	0	0.0656132	0.0457241	0.3333333	0.0642876	0.0704467	0.0514098	0.3333333
F4	0	0.1799021	0	0.083924	0.1039947	0.3333333	0.2069115	0.2305717	0
F5	0	0.2419503	0	0.2160743	0.1663349	0.2538396	0.3333333	0.1027616	0.3333333
F6	0	0.0491071	0	0.0333351	0.046455	0.0794937	0.0980027	0.3333333	0
F7	0	0.0290406	0	0	0.0165488	0	0.0284191	0	0.3333333

Limit Supematrix

	Oil Leakage	Electrical Faults	Oil Leakage			Electrical Faults			
			F1	F2	F3	F4	F5	F6	F7
Oil Leakage	5.421E-20	0	0	0	0	0	0	0	0
Electrical Faults	0	5.421E-20	0	0	0	0	0	0	0
F1	0.2150562	0.2150562	0.2150562	0.2150562	0.2150562	0.2150562	0.2150562	0.2150562	0.2150562
F2	0.3078224	0.3078224	0.3078224	0.3078224	0.3078224	0.3078224	0.3078224	0.3078224	0.3078224
F3	0.0846495	0.0846495	0.0846495	0.0846495	0.0846495	0.0846495	0.0846495	0.0846495	0.0846495
F4	0.1319755	0.1319755	0.1319755	0.1319755	0.1319755	0.1319755	0.1319755	0.1319755	0.1319755
F5	0.1860807	0.1860807	0.1860807	0.1860807	0.1860807	0.1860807	0.1860807	0.1860807	0.1860807
F6	0.064382	0.064382	0.064382	0.064382	0.064382	0.064382	0.064382	0.064382	0.064382
F7	0.0100336	0.0100336	0.0100336	0.0100336	0.0100336	0.0100336	0.0100336	0.0100336	0.0100336

Priority Vectors for Overheating / Explosion factor groups

	F8	F9	F10	F11	Weights
F8	1	0.186	0.165	0.186	0.0548
F9	5.382	1	0.565	0.565	0.2296
F10	6.07	1.769	1	1.925	0.4208
F11	5.384	1.769	0.519	1	0.2948

Experts' Judgements - Likelihood of factors

Factors	Expert1	Expert2	Expert3	Expert4	Expert5	Expert6
Damaged 'O' ring (F1)	Average	Reasonably Frequent	Frequent	Average	Low	Average
Improper Maintenance (F2)	Frequent	Average	Frequent	Frequent	Frequent	Average
Hot Work accidents (F3)	Reasonably Frequent	Very Low	Reasonably Low	Low	Average	Very Low
Chafing (F4)	Reasonably Low	Low	Average	Reasonably Low	Average	Very Low
Short Circuit (F5)	Reasonably Frequent	Average	Reasonably Frequent	Reasonably Frequent	Reasonably Frequent	Frequent
Overloading of Switches (F6)	Low	Frequent	Frequent	Average	Average	Low
Static Electricity (F7)	Average	Average	Reasonably Frequent	Reasonably Low	Average	Low
Turbocharger Explosion (F8)	Low	Low	Low	Reasonably Low	Average	Average
Boiler Explosion (F9)	Very Low	Average	Reasonably Frequent	Average	Very Low	Very Low
Cargo Fire (F10)	Reasonably Frequent	Low	Average	Average	Reasonably Frequent	Average
Crankcase Explosion (F11)	Average	Reasonably Low	Reasonably Low	Very Low	Low	Reasonably Low

Experts' Judgements – Consequence severity of factors

Factors	Expert1	Expert2	Expert3	Expert4	Expert5	Expert6
Damaged 'O' ring (F1)	Critical	Catastrophic	Catastrophic	Marginal	Marginal	Marginal
Improper Maintenance (F2)	Critical	Catastrophic	Critical	Critical	Negligible	Catastrophic
Hot Work accidents (F3)	Catastrophic	Catastrophic	Marginal	Marginal	Catastrophic	Critical
Chafing (F4)	Marginal	Marginal	Critical	Marginal	Negligible	Negligible
Short Circuit (F5)	Catastrophic	Catastrophic	Critical	Catastrophic	Catastrophic	Catastrophic
Overloading of Switches (F6)	Marginal	Marginal	Critical	Marginal	Critical	Negligible
Static Electricity (F7)	Negligible	Negligible	Negligible	Marginal	Marginal	Critical
Turbocharger Explosion (F8)	Marginal	Marginal	Negligible	Critical	Critical	Marginal
Boiler Explosion (F9)	Critical	Marginal	Critical	Marginal	Catastrophic	Negligible
Cargo Fire (F10)	Catastrophic	Critical	Marginal	Catastrophic	Critical	Marginal
Crankcase Explosion (F11)	Critical	Critical	Critical	Critical	Critical	Catastrophic

Membership Values of Likelihood and Consequence Severity of factors

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
μ (Severity)	Marginal (0.148), Critical (0.852)	Marginal (1.0)	Critical (1.0)	Negligible (0.277), Marginal (0.723)	Critical (0.313), Catastrophic (0.687)	Marginal (1.0)	Negligibl e (0.567), Marginal (0.433)	Marginal (1.0)	Marginal (1.0)	Critical (1.0)	Critical (1.0)
μ (Likelihood)	Average (1.0)	Average (0.056), Reasonabl y Frequent (0.944)	Very Low (0.2195), Low (0.7805)	Very Low (0.241), Low (0.8795)	Average (0.225), Reasonably Frequent (0.775)	Reasonabl y Low (0.369), average (0.631)	Reasonab ly Low (0.511), Average (0.489)	Low (0.511), Reasonably Low (0.489)	Very Low (0.415), Low (0.7925)	Reasonably Low (0.023), Average (0.977)	Very Low (0.413), Low (0.7935)

Appendix II

Model I: Neutrosophic Logic Data

Model I: Failure Likelihood

Linguistic terms	Trapezoidal neutrosophic number	meaning	Failure rate (1/year)	Crisp values
Very Low	(0, 0, 1, 2.5; 0, 0, 0.5, 1.75; 0, 0, 1, 2.25)	Very less chance of failure	$<10^{-8}$	0.75
Low	(0.5, 2, 3, 4.5; 1.25, 2, 2.75, 3.75; 1.75, 2.5, 3.25, 4.25)	May happen at the most once in lifetime	10^{-7} - 10^{-6}	2.625
Reasonably Low	(2.5, 4, 5, 6.5; 3.25, 4, 4.75, 5.75; 3.75, 4.5, 5.25, 6.25)	Between low and average	10^{-5} - 10^{-4}	4.625
Average	(4.5, 6, 7, 8.5; 5.25, 6, 6.75, 7.75; 5.75, 6.5, 7.25, 8.25)	occasional failure	10^{-3} - 10^{-2}	6.625
Frequent	(6.5, 8, 9, 9.5; 7.25, 8, 8.75, 9.25; 7.75, 8.65, 9.25, 9.75)	Repeated failure	10^{-2} - 10^{-1}	8.45833
Highly Frequent	(8.5, 9.5, 10, 10; 8.25, 9.5, 10, 10, 9, 9.75, 10, 10)	Failure is almost inevitable	>1	9.54167

Model I: Consequence Severity (personnel related risk)

Linguistic terms	Trapezoidal neutrosophic number	Meaning	Crisp values
Negligible	(0, 0, 1, 3; 0, 0, 0.5, 2.25; 0, 0, 1.25, 3)	No Injury	0.91667
Minor	(0.5, 2, 3, 4.5; 1, 2.25, 3, 4.25; 1.5, 2.75, 3.5, 4.75)	Single or minor injury	2.75
Moderate	(3, 4, 6, 7; 3.25, 4, 5.5, 6.75; 4, 4.75, 6.25, 7.5)	Multiple injuries	5.16667
Severe	(5.5, 7, 8, 9.5; 6, 7.25, 8, 9.25; 6.5, 7.75, 8.5, 9.75)	Single death or several severe injuries	7.75
Catastrophic	(7, 9, 10, 10; 8, 9.25, 10, 10; 8.5, 9.75, 10, 10)	Large number of fatalities	9.29167

Model I: Consequence Severity (environmental related risk)

Linguistic terms	Trapezoidal neutrosophic number	Meaning	Crisp values
Negligible	(0, 0, 1, 3; 0, 0, 0.5, 2.25; 0, 0, 1.25, 3)	No environmental degradation caused	0.91667
Minor	(0.5, 2, 3, 4.5; 1, 2.25, 3, 4.25; 1.5, 2.75, 3.5, 4.75)	Minor damage due to discharge of materials	2.75
Moderate	(3, 4, 6, 7; 3.25, 4, 5.5, 6.75; 4, 4.75, 6.25, 7.5)	Intermittent discharge of oil, chemicals etc.	5.16667
Severe	(5.5, 7, 8, 9.5; 6, 7.25, 8, 9.25; 6.5, 7.75, 8.5, 9.75)	Long term damage due to discharge of oil, chemicals etc.	7.75
Catastrophic	(7, 9, 10, 10; 8, 9.25, 10, 10; 8.5, 9.75, 10, 10)	Significant damage due to heavy discharge of oil, chemicals etc.	9.29167

Model I: Consequence Severity (organisational related risk)

Linguistic terms	Trapezoidal neutrosophic number	Meaning	Crisp values
Negligible	(0, 0, 1, 3; 0, 0, 0.5, 2.25; 0, 0, 1.25, 3)	Insignificant damage property	0.91667
Minor	(0.5, 2, 3, 4.5; 1, 2.25, 3, 4.25; 1.5, 2.75, 3.5, 4.75)	Minor damage	2.75
Moderate	(3, 4, 6, 7; 3.25, 4, 5.5, 6.75; 4, 4.75, 6.25, 7.5)	Significant damage requiring outside support for repair	5.16667
Severe	(5.5, 7, 8, 9.5; 6, 7.25, 8, 9.25; 6.5, 7.75, 8.5, 9.75)	Major damage to ship	7.75
Catastrophic	(7, 9, 10, 10; 8, 9.25, 10, 10; 8.5, 9.75, 10, 10)	Total loss of ship	9.29167

Model I: Risk Level Expressions

Linguistic terms	Trapezoidal neutrosophic number	Crisp values
Low	(0,0,2,3;0,0,1,2.25;0,0,1.75,2.75)	1.04167
Possible	(2,3,5,6;2.25,3.25,4,5;3,4,4.75,5.75)	4
Substantial	(5,6,8,9;5.25,6.25,7,8;6,7,7.75,8.75)	7
High	(8,9,10,10;8.25,9.25,10,10;9,10,10,10)	9.45833

Model I: Neutrosophic IF-THEN Rules

Rule	Antecedent (FL)	Antecedent (CS)	Consequent
#1	'Very Low'	'Negligible'	'Low'
#2	'Very Low'	'Minor'	'Low'
#3	'Very Low'	'Moderate'	'Possible'
#4	'Very Low'	'Severe'	'Possible'
#5	'Very Low'	'Catastrophic'	'Possible'
#6	'Low'	'Negligible'	'Low'
#7	'Low'	'Minor'	'Possible'
#8	'Low'	'Moderate'	'Possible'
#9	'Low'	'Severe'	'Possible'
#10	'Low'	'Catastrophic'	'Substantial'
#11	'Reasonably Low'	'Negligible'	'Possible'
#12	'Reasonably Low'	'Minor'	'Possible'
#13	'Reasonably Low'	'Moderate'	'Possible'
#14	'Reasonably Low'	'Severe'	'Substantial'
#15	'Reasonably Low'	'Catastrophic'	'Substantial'
#16	'Average'	'Negligible'	'Possible'
#17	'Average'	'Minor'	'Possible'
#18	'Average'	'Moderate'	'Substantial'
#19	'Average'	'Severe'	'Substantial'
#20	'Average'	'Catastrophic'	'Substantial'
#21	'Frequent'	'Negligible'	'Possible'
#22	'Frequent'	'Minor'	'Substantial'

#23	'Frequent'	'Moderate'	'Substantial'
#24	'Frequent'	'Severe'	'Substantial'
#25	'Frequent'	'Catastrophic'	'High'
#26	'Highly Frequent'	'Negligible'	'Substantial'
#27	'Highly Frequent'	'Minor'	'Substantial'
#28	'Highly Frequent'	'Moderate'	'Substantial'
#29	'Highly Frequent'	'Severe'	'High'
#30	'Highly Frequent'	'Catastrophic'	'High'

Appendix III

Model III: Plithogenic Model Data

Model –III: Plithogenic risk score

$$\tilde{R} = \begin{array}{c} \\ E_1 \\ E_2 \\ E_3 \\ E_4 \end{array} \begin{array}{c} \begin{array}{ccccc} F_1 & F_2 & F_3 & F_4 & F_5 \end{array} \\ \begin{bmatrix} 0.810,0.1000,0.190 & 0.355,0.500,0.645 & 0.600,0.425,0.400 & 0.645,0.500,0.355 & 0.730,0.575,0.270 \\ 0.490,0.250,0.510 & 0.575,0.300,0.425 & 0.600,0.375,0.400 & 0.645,0.500,0.355 & 0.730,0.575,0.270 \\ 0.630,0.175,0.370 & 0.715,0.175,0.283 & 0.500,0.500,0.500 & 0.425,0.700,0.575 & 0.650,0.625,0.350 \\ 0.630,0.175,0.370 & 0.595,0.250,0.405 & 0.300,0.700,0.700 & 0.425,0.700,0.575 & 0.910,0.500,0.090 \end{bmatrix} \end{array}$$

Model –III: BBA's of risk score

	F1			F2			F3			F4			F5		
	m(T)	m(T,F)	m(F)	m(T)	m(T,F)	m(F)	m(T)	m(T,F)	m(F)	m(T)	m(T,F)	m(F)	m(T)	m(T,F)	m(F)
E1	0.7364	0.0909	0.1727	0.2367	0.3333	0.43	0.4211	0.2982	0.2807	0.43	0.3333	0.2367	0.4635	0.3651	0.1714
E2	0.392	0.2	0.408	0.4423	0.2308	0.3269	0.4364	0.2727	0.2909	0.43	0.3333	0.2367	0.4635	0.3651	0.1714
E3	0.5362	0.1489	0.3149	0.6085	0.1489	0.2426	0.3333	0.3333	0.3333	0.25	0.4118	0.3382	0.4	0.3846	0.2154
E4	0.5362	0.1489	0.3149	0.476	0.2	0.324	0.1765	0.4118	0.4118	0.25	0.4118	0.3382	0.6067	0.3333	0.06

Model –III : Normalised similarity score

$$\tilde{R} = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ R_4 \\ R_5 \end{array} \begin{array}{c} \begin{array}{ccccc} F_1 & F_2 & F_3 & F_4 & F_5 \end{array} \\ \begin{bmatrix} 0.214225 & 0.189777 & 0.17817 & 0.180078 & 0.21093 \\ 0.224551 & 0.213485 & 0.208053 & 0.208697 & 0.222267 \\ 0.209691 & 0.212939 & 0.214494 & 0.214258 & 0.21019 \\ 0.186631 & 0.199509 & 0.205768 & 0.204942 & 0.189011 \\ 0.164902 & 0.18429 & 0.193514 & 0.192025 & 0.167601 \end{bmatrix} \end{array}$$

Appendix IV

Dynamic Decision Making Model Data

Example -1: The evaluated matrix along with their dynamic basic belief masses

Criteria	Lecturers	Decision Makers									Dynamic Basic Belief Masses (T, F, T∪F)
		t1			t2			t3			
		D1	D2	D3	D1	D2	D3	D1	D2	D3	
C1	A1	Me	Go	Go	Go	Go	Go	Go	Ve_Go	Go	(0.537456, 0.167772, 0.294773)
	A2	Go	Go	Ve_Go	Ve_Go	Go	Ve_Go	Ve_Go	Go	Ve_Go	(0.677230, 0.089733, 0.233037)
	A3	Me	Go	Go	Go	Go	Go	Go	Go	Ve_Go	(0.551952, 0.157914, 0.290134)
	A4	Go	Me	Go	Go	Go	Go	Go	Go	Go	(0.506046, 0.189117, 0.304836)
	A5	Me	Go	Me	Go	Go	Me	Go	Go	Go	(0.445630, 0231638, 0.322731)
C2	A1	Go	Go	Go	Ve_Go	Go	Go	Go	Go	Go	(0.545188, 0.161556, 0.293256)
	A2	Ve_Go	Go	Ve_Go	Me	Go	Go	Ve_Go	Go	Go	(0.587106, 0.137222, 0.275673)
	A3	Ve_Go	Go	Go	Go	Me	Go	Go	Me	Go	(0.495164, 0.194219, 0.310617)
	A4	Go	Go	Go	Go	Ve_Go	Go	Go	Go	Ve_Go	(0.592985, 0.134266, 0.272749)
	A5	Ve_Go	Go	Go	Go	Ve_Go	Go	Go	Go	Me	(0.516687, 0.172812, 0.310501)
C3	A1	Ve_Go	Ve_Go	Go	Go	Ve_Go	Go	Go	Me	Go	(0.547366, .152625, 0.300009)
	A2	Go	Ve_Go	Go	Ve_Go	Go	Ve_Go	Go	Go	Ve_Go	(0.639759, 0.107299, 0.252942)
	A3	Go	Ve_Go	Ve_Go	Go	Go	Go	Go	Ve_Go	Go	(0.605431, 0.125957, 0.268611)
	A4	Go	Go	Go	Ve_Go	Go	Go	Ve_Go	Go	Go	(0.577997, 0.142833, 0.279170)
	A5	Ve_Go	Go	Go	Go	Ve_Go	Go	Go	Go	Go	(0.564545, 0.147920, 0.287535)
C4	A1	Me	Go	Me	Go	Go	Me	Me	Go	Me	(0.374181, 0.293782, 0.332038)
	A2	Go	Me	Go	Go	Me	Go	Go	Me	Go	(0.456588, 0.224954, 0.318457)
	A3	Go	Go	Go	Go	Go	Me	Go	Go	Ve_Go	(0.542148, 0.163564, 0.294288)
	A4	Me	Po	Me	Go	Me	Me	Go	Go	Me	(0.335600, 0.325733, 0.338667)
	A5	Me	Me	Po	Me	Me	Me	Me	Go	Me	(0.279417, 0.384679, 0.335904)
C5	A1	Me	Go	Me	Me	Go	Go	Go	Me	Go	(0.427180, 0.248386, 0.324434)
	A2	Go	Ve_Go	Go	Ve_Go	Go	Go	Go	Ve_Go	Go	(0.597962, 0.130556, 0.271483)
	A3	Go	Go	Me	Go	Go	Go	Go	Ve_Go	Go	(0.527769, 0.173730, 0.298501)
	A4	Ve_Go	Go	Go	Ve_Go	Go	Go	Ve_Go	Go	Go	(0.597962, 0.130556, 0.271483)
	A5	Go	Go	Go	Go	Go	Go	Go	Ve_Go	Go	(0.557417, 0.155493, 0.287090)
C6	A1	Ve_Go	Go	Go	Ve_Go	Go	Ve_Go	Ve_Go	Go	Ve_Go	(0.668533, 0.094153, 0.223732)
	A2	Go	Go	Go	Go	Ve_Go	Go	Go	Go	Ve_Go	(0.592985, 0.134266, 0.272749)
	A3	Ve_Go	Go	Ve_Go	Ve_Go	Go	Ve_Go	Ve_Go	Go	Ve_Go	(0.693488, 0.081472, 0.225040)
	A4	Go	Ve_Go	Go	Go	Ve_Go	Go	Go	Go	Go	(0.564545, 0.147920, 0.287535)
	A5	Go	Go	Go	Ve_Go	Go	Go	Go	Ve_Go	Go	(0.577997, 0.142833, 0.279170)

Example-1: The evaluated matrix along with their dynamic basic belief masses

Criteria	Decision Makers									Dynamic weight vector
	t1			t2			t3			
	D1	D2	D3	D1	D2	D3	D1	D2	D3	
C1	IPA	IPA	IPA	IPA	V_IPA	IPA	V_IPA	IPA	V_IPA	0.166934
C2	V_IPA	V_IPA	IPA	V_IPA	V_IPA	V_IPA	A_IPA	V_IPA	V_IPA	0.16657
C3	IPA	IPA	V_IPA	IPA	IPA	V_IPA	V_IPA	IPA	V_IPA	0.167202
C4	IPA	V_IPA	IPA	IPA	O_IPA	IPA	IPA	IPA	IPA	0.165894
C5	IPA	IPA	IPA	V_IPA	IPA	V_IPA	IPA	IPA	IPA	0.166197
C6	V_IPA	V_IPA	IPA	IPA	IPA	IPA	V_IPA	V_IPA	IPA	0.167202

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LIST OF PUBLICATIONS

International Journals

[1] "Combining belief functions taking into consideration error in judgement", *International Journal of General Systems.* vol. 49, no. 4, pp. 438-448, May 2020 (**SCI/SCIE/SCOPUS**)

[2] "Safety modelling of marine systems using neutrosophic logic", *Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment,* vol. 235, no. 1, pp. 225-235, January 2021 (**SCIE/SCOPUS**)

[3] "Using Interpretive Structural Modelling, Fuzzy Analytical Network Process, and Evidential Reasoning to Estimate Fire Risk Onboard Ships", *International Journal of Performability Engineering (IJPE),* vol. 16, no. 9, pp. 1321-1331, September 2020 (**SCOPUS**)

[4] "The safety assessment in dynamic conditions using interval neutrosophic sets", *Neutrosophic Sets and Systems,* vol. 40, pp. 68-85, February 2021 (**SCOPUS**)

[5] "Risk assessment using comprehensive plithogenic evaluation method", *International Journal of General Systems* (**SCI/SCIE/SCOPUS**) (Under Review)

International Conferences

[1] "Modelling uncertainty using neutrosophic sets for precise risk assessment of marine systems", **Presented** in *International Conference on Maintenance and Intelligent Asset Management (ICMIAM-2020), Bengaluru, 17-18 January, 2020*. **Published** in *International Journal of System Assurance Engineering and Management,* doi:10.1007/s13198-021-01496-y

[2] "Risk assessment using evidential reasoning in plithogenic environment", **Presented** in *International Conference on the Recent Advances in Mechanical Engineering Research and Development (ICRAMERD-2020), Bhubaneswar, 24-26 July, 2020.* **Published** in *Current Advances in Mechanical Engineering, Springer Nature,* pp. 949-962