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Analysis of the human factor contribution to the risk of navigation in restricted waters

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RESUMO

A navegação em águas restritas apresenta um conjunto de desafios adicionais quando comparada à navegação em mar aberto. As dimensões reduzidas das vias navegáveis, tráfego intenso e a dinâmica de obstáculos como bancos de areia tornam a entrada e saída em portos e as singraduras em rios propensas a acidentes como colisões, abalroamentos e encalhes. Adicionalmente, a navegação em águas restritas é realizada sem o apoio de sistemas de controle automatizados, o que a torna significativamente dependente do desempenho dos operadores humanos envolvidos, tais como os práticos, o comandante do navio com sua tripulação, e os comandantes de rebocadores.

Não obstantes os riscos inerentes à navegação em águas restritas, a pressão comercial força as margens de segurança aos seus limites. O efeito do ganho de escala faz com que navios cada vez maiores cheguem aos portos que, por sua vez, não conseguem adaptar em tempo seus canais de acesso à demanda. Com isso, fica a cargo dos operadores humanos a responsabilidade de executar a navegação de maneira segura, mesmo quando as margens de segurança são reduzidas.

Dada a importância que os operadores humanos desempenham hoje nas operações de navegação em águas restritas, torna-se interessante conhecer quais os principais fatores que influenciam seu desempenho, a fim de garantir altos níveis de confiabilidade humana. Neste contexto, este trabalho tem como objetivo o desenvolvimento e a aplicação da Análise de Confiabilidade Humana para investigação de como o fator humano contribui para o risco da navegação em águas restritas e quais os principais fatores de desempenho que afetam a probabilidade de erro humano. A análise se apoia num modelo de rede Bayesiana (quantitativo), que mapeia as relações causais entre as tarefas desenvolvidas pelos operadores e suas habilidades necessárias, além de fatores internos, ambientais e organizacionais. A análise é desenvolvida para três cenários diferentes: a) com um prático a bordo; b) com dois práticos a bordo; e c) sem prático a bordo (isenção de praticagem). A quantificação do modelo é realizada com base nas probabilidades de erro humano derivadas por um modelo prospectivo de desempenho humano – a TECHR (*Technique for Early Consideration of Human Reliability*).

Os resultados incluem um ranqueamento dos fatores que mais influenciam os operadores em cada caso, o qual é gerado a partir da comparação entre a probabilidade de erro humano em diferentes cenários, além de uma análise de sensibilidade da rede. Entre outros aspectos, os resultados revelam a importância de garantir a proficiência dos operadores humanos no que diz respeito ao conhecimento das condições locais mediante trabalho contínuo reforçado por leis e treinamentos, além da necessidade de boa coordenação da equipe a bordo.

Palavras-chave: Redes Bayesianas. Confiabilidade Humana. TECHR. Navegação. Águas Restritas. Portos.

ABSTRACT

The navigation in restricted waters presents a number of additional challenges when compared to open sea navigation. The reduced size of waterways, congested waters and the dynamics of obstacles such as underwater shoals make the port entering and departure and river navigation prone to accidents, such as collisions, contacts and groundings. Additionally, restricted water navigation is performed without the support of automated control systems, which makes it significantly dependent on the performance of the human operators involved, such as maritime pilots, the captain of the ship with his/her crew, and the tug masters.

Notwithstanding the risks inherent to the restricted water navigation, commercial pressure forces safety margins to their limits. The effect of the gain of scale causes larger ships to reach ports which, in turn, often cannot adapt their access channels to the demand. As a result, human operators are responsible for ensuring the safety of the navigation even when the safety margins are reduced.

Given the importance that human operators play today in restricted water navigation, it is interesting to know which key factors influence their performance in order to ensure high levels of human reliability. In this context, this work aims at the development and application of the Human Reliability Analysis to investigate how the human factor contributes to the risk of restricted water navigation and which are the main performance factors that affect the probability of human error. The analysis is based on a Bayesian network model (quantitative), which maps the causal relationships between the tasks performed by operators and their necessary skills, as well as internal, environmental, and organizational factors. The analysis is developed for three different scenarios: a) with one Pilot on board; b) with two Pilots on board; and c) without Pilot on board (pilotage exemption). The quantification of the model is performed based on the probabilities of human error derived by a prospective human performance model – the Technique for Early Consideration of Human Reliability (TECHR).

The results include a ranking of the factors that most influence the operators in each case, which is generated from a comparative analysis of human error probabilities in different scenarios and a network sensitivity analysis. Among other things, the results reveal the importance of ensuring the fitness for duty of human operators in what refers to knowledge of local conditions through continuous work reinforced by laws and training, as well as the need for good coordination of the crew on board.

Keywords: Bayesian Networks. Human Reliability. TECHR. Navigation. Restricted waters. Ports.

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LIST OF ABBREVIATIONS

BN	Bayesian network
CAP	Ship's captain
CMPA	Canadian Marine Pilots' Association
CODESP	São Paulo State Docks Company
CPT	Conditional probability table
FSA	Formal Safety Assessment
GHA	Generic human action
HEL	Helmsman
HEP	Human error probability
HRA	Human reliability analysis
HTA	Hierarchical task analysis
IMO	International Maritime Organization
MOF	Management & organizational factor
PIL	Pilotage
PIL1	1st pilot
PIL2	2nd pilot
PSF	Performance shaping factor
SOW	Ship owner
TECHR	Technique for Early Consideration of Human Reliability
TMA	Tug master
TOW	Tugboats owner
VTS	Vessel Traffic Service

SUMMARY

1. Introduction

The maritime transportation plays a significant role in countries with broad coastal regions and navigable rivers, as well as island countries. As these countries' economies grow, the necessity for importation/exportation of goods increases and this tendency directly influences the demand for ports. However, ports and the related infrastructure (e.g., waterways) require huge investments and their construction and maintenance may need long periods of time. Frequently, due to commercial pressure, excessively large ships, with dimensions above those the navigational infrastructure is designed to support, are allowed to enter the port or navigable river, thus increasing the risk of accidents (GOMES, 2015).

In fact, the open sea and restricted water navigations are inherently risky activities. Their several benefits – such as employment, support for international trade and economies of scale – do not come without negative effects. The typical accidents[1] associated with the maritime industry are presented and described in Table 1.

Table 1 – Typical accidents associated with maritime and inland navigation

Type of accident	Description
Collision	Striking between ships
Contact/impact	Striking between ship and other surface objects
Grounding and stranding	Hitting the seabed or shore
Foundering and flooding	Opening and flooding of hull
Hull and machinery failure[2]	Hull or machinery failure is directly responsible for the accident
Fire and explosion	Fire, explosion or dangerous goods release

Source: Kristiansen (2005, p. 22)

In comparison with the open sea scenario, the navigation in restricted waters imposes additional challenges to the ship's crew. The distance among ships and obstacles is reduced, as is the depth; there are many vessels in the vicinity; and the maneuverability of the ship is reduced due to the lower speeds imposed. Additionally,

[1] An accident is defined as "an undesirable event that results in damage to humans, assets and/or the environment" (KRISTIANSEN, 2005, p. 19)
[2] From a more conventional perspective, the hull and machinery failure can be interpreted as initiating events, i.e., occurrences that start a chain of events leading to an undesired loss (accident).

elements such as underwater sandbanks may change their characteristics over time without being updated in nautical charts in a timely manner, making each transit unique. Therefore, the chances (per hour of navigation) of collision, contact and grounding accidents in these areas are higher in relation to the open sea navigation.

In order to partially overcome these difficulties, local experienced pilots (often referred to as maritime pilots) get on board to support the ship's crew wherever the navigation is considered hazardous or whenever the crew (specially, the captain) is proven not experienced with the area. These pilots contribute not only with their knowledge, but also with advanced communication capability with tugboats and the local Vessel Traffic Service (VTS), if available. Also, it is important to emphasize that the navigation supported by pilots occurs in areas where the ship auto pilot system is generally not used, therefore making this task success highly dependent on the human performance.

In the maritime industry, as in other industrial sectors, the human factor stands out as one of the main causes of accidents. According to the Allianz Global Corporate & Specialty[3] (n.d., apud ALLIANZ GLOBAL CORPORATE & SPECIALTY, 2017, p. 13), about 75% to 96% of maritime accidents can be attributed to human errors. One way to address this problem in the context of a risk analysis is through the human reliability analysis (HRA), which is included in the International Maritime Organization (IMO) Guidelines for Formal Safety Assessment (IMO, 2018).

Given the importance of the human factor in the maritime industry and related activities, several works in the literature proposed the HRA as an analysis technique, encompassing different problems such as diverse ship operations (AKYUZ; CELIK, 2016; ISLAM et al., 2017; AKYUZ et al., 2018), human integration with dynamic positioning systems (HOGENBOOM et al., 2018), and offshore platform emergency procedures (DiMATTIA; KHAN; AMYOTTE, 2005; MUSHARRAF et al., 2013), including data acquisition initiatives through virtual simulations (MUSHARRAF et al., 2014). In what concerns the navigation, the majority of works focus on open sea navigation (MARTINS; MATURANA, 2010; MARTINS; CHAUVIN et al., 2013; MATURANA, 2013; SOTIRALIS et al., 2016), which do not account for factors exclusive to the navigation in restricted waters.

[3] ALLIANZ GLOBAL CORPORATE & SPECIALTY. **Safety & Shipping 1912-2012 From Titanic to Costa Concordia**. n. d.

There are several methods proposed in the literature to perform the HRA, generally divided into three generations. Some examples are presented in Table 2.

The first-generation methods were developed for the nuclear industry and are concerned with calculating the human error probability (HEP) in specific situations through binary trees (DROGUETT; MENÊZES, 2007; MATURANA, 2010). However, these techniques presented some limitations, notably, the restrictions regarding modelling the context in which the human actions occurs and the dependencies among performance shaping factors (PSFs) and events.

Table 2 – HRA methods examples

Name		Objective
	First generation	
THERP	Technique for Human Error Rate Prediction	Assess failure in task or action sequence. It is applied in maintenance, operational, or incident analysis with complex graphic representation (1975).
OAT	Operator Action Trees	Assess failure in task or action sequence. It is applied in maintenance, operational, or incident analysis with simple graphic representation (1982).
SLIM	Success Likelihood Index Methodology	Assess failure in task or action sequence. It is applied in maintenance, operational, or incident analysis and regards human factors performance based on specialist opinion (1984).
SHARP	Systematic Human Action Reliability Procedure	Assess cognitive human process failure (detection, understanding, decision, and action), being applied in maintenance, operational, or incident analysis (1984).
STAHR	Sociotechnical Assessment of Human Reliability	Assess failure in task or action sequence and is applied in maintenance, operational, or incident analysis and regards human factors performance-based or expert opinion (1983).
	Second generation	
ATHEANA	A Technique for Human Error Analysis	Assess cognitive human process of failure (detection, understanding, decision, and action), being applied in maintenance, or incident analysis (1996).
CREAM	Cognitive Reliability and Error Analysis	Assess cognitive human process of failure (detection, understanding, decision, and action), being applied in maintenance, or incident analysis (1998).
	Third generation	
Bayesian networks		Assess failure in task or action sequence and is applied in maintenance, operational, or incident analysis and regards human factors performance based on specialist opinion; in addition, such methods regard human factors performance dependency (2005).

Source: Calixto (2016)

The second-generation methods included some advances in terms of mapping the cognitive process behind the operator/crew's performance. On the other hand, these models do not take into account dynamic contexts. Additionally, they suppose independence between the PSFs, what accounts for another limitation (DROGUETT; MENÊZES, 2007). At this point, the modelling of causality within the human actions' context became the main challenge for the HRA.

Finally, the third-generation methods, allowed overcoming the challenges faced by the first- and second-generation methods, mainly based on the use of methodologies supported by Bayesian networks (BNs) (GROTH; MOSLEH, 2012b; CAI et al., 2013; BANDEIRA; CORREIA; MARTINS, 2017; ABRISHAMI et al., 2020). This type of data structure is able to model causal relations, estimate probabilities, identify errors in a contextual manner, represent the dynamic nature of the man-nature systems and, notably, provide prognostics and diagnostics (DROGUETT; MENÊZES, 2007). The BN-based models received attention in the last years due to their versatility.

Looking forward to improving the understanding of how the human factors influence the risk of navigation in restricted waters, this Thesis presents the application of a third generation HRA technique to the navigation in restricted waters. Through this approach, it is possible to express not only qualitatively, but also quantitatively the influence of elements such as skills and management & organizational factors on the human performance.

This Thesis is organized as follows. Chapter 2 summarizes the main concepts regarding BN theory, which composes the basic data structure to the HRA model. Chapter 3 presents the methodology of HRA applied to build the BN model, describing it in four steps – familiarization, qualitative analysis, quantitative analysis, and incorporation. Chapter 4 shows the application of the aforementioned methodology to the navigation in restricted waters. Finally, chapter 5 presents and discusses the results derived from the application described in chapter 4 and chapter 6 is dedicated to the conclusion and final considerations.

2. Bayesian networks: fundamental concepts

The BNs are, essentially, graphical models capable of representing sets of stochastic variables and their dependence relationships in the form of conditional probabilities. They are, among other attributes, adequate to perform prognostic analysis – i.e., given the causes, compute the likelihood of the effects – and diagnostic analysis – i.e., given the effects, compute the likelihood of the causes. These capacities find application in a vast field of areas, such as medicine and healthcare, software engineering and risk analysis (TOSUN; BENER; AKBARINASAJI, 2017).

Specifically, in this work, the main interests towards BNs is associated to their application in HRA, mainly motivated by their capacity of representing dependence relationships among factors that influence the human performance. Thus, this section is dedicated to present the fundamental concepts of BNs to an extent that is sufficient to the stated purpose. A broader explanation about this theme is presented by Russel and Norvig (2010).

2.1. Basics of Probability Theory

Before presenting and explaining the structure of BNs, it is important to review the basics of Probability Theory, as well as formalize some of the notations for the rest of this Thesis. The objective of this subsection is to accomplish this task. The main reference for the definitions depicted below is Neapolitan (2003).

Given a sample space, Ω, containing n distinct elements, i.e., $\Omega = \{e_1, e_2, \dots, e_n\}$, a function that attributes a real number $\mathrm{Pr}(E)$ to each element of Ω is called a probability function on the set of subsets of Ω if it satisfies the following conditions:

$$0 \leq \mathrm{Pr}(\{e_i\}) \leq 1, \qquad for\ 1 \leq i \leq n \tag{1}$$

$$\sum_{i=1}^{n} \mathrm{Pr}(\{e_i\}) = 1 \tag{2}$$

$$\mathrm{Pr}(E \cup F) = \mathrm{Pr}(E) + \mathrm{Pr}(F) - \mathrm{Pr}(E \cap F) \tag{3}$$

If two events, E and F are mutually exclusive, then $E \cap F = \emptyset$ and, consequently, $\mathrm{Pr}(E \cap F) = 0$. In this case, Equation 3 is reduced to:

$$\Pr(E \cup F) = \Pr(E) + \Pr(F) \tag{4}$$

The principle of indifference, firstly attributed to Pierre-Simon Laplace in 1816 (RUSSEL; NORVIG, 2010) and popularized by John Maynard Keynes in 1921 (NEAPOLITAN, 2003), states that the elementary events[4] are to be considered equiprobable if there is no reason to believe the opposite. In other words, it is equivalent to say that, if the set Ω has n elements, the probability of each of them is given by $1/n$. However, if there is lack of symmetry in the analyzed problem, then this principle is not applicable.

There are basically two approaches to obtain probabilities: the frequentist and subjectivist. According to the frequentist approach, a probability is a measure obtained from a sequence of trials. In this case, the ratio between the outcomes favorable to a given event and the total number of trials represents the probability of this event. On the limit of infinite trials, this ratio gives the exact probability. Therefore:

$$\Pr(E) = \lim_{m \to \infty} \frac{\#E}{m} \tag{5}$$

Where $\#E$ indicates the number of times the event E occurs in m trials.

However, not all types of events can be subjected to repetitive trials in order to compute their probability. For instance, a gambler would like to know the probability of a team winning a soccer game, despite the fact that this game (in the exact same conditions) will occur only once. It is impossible to repeat the game several times in order to evaluate the ratio between wins (or defeats) and the total number of trials. In this context, emerges the concept of subjective probability, which is essentially based on a person's judgment of the likelihood of uncertain events (KAHNEMAN; TVERSKY, 1972), i.e., the degree of belief. When it is possible to compute ratios or relative frequencies of an event, the belief of a person is expected to be similar to these values (NEAPOLITAN, 1996).

[4] An elementary event is a subset of Ω consisting of exactly one element

Another important probability concept is that of conditional probabilities. Assuming two events, E and F, the conditional probability of E given F is denoted by $\Pr(E|F)$ and is mathematically expressed by:

$$\Pr(E|F) = \frac{\Pr(E \cap F)}{\Pr(F)}, \qquad \text{where } \Pr(F) \neq 0 \tag{6}$$

This definition is based on the ratio between the elements of the sample space that are pertaining mutually to E and F and the whole collection of elements pertaining to F. Additionally, the events E and F are said to be independent if one of the two following conditions are observed:

a) $\Pr(E|F) = \Pr(E)$, when $\Pr(E) \neq 0$ and $\Pr(F) \neq 0$; or

b) $\Pr(E) = 0$ or $\Pr(F) = 0$.

The concept of conditional probabilities is the basis of the Bayes' theorem. The Bayes' theorem states that, given two events E and F, with $\Pr(E) \neq 0$ and $\Pr(F) \neq 0$, then:

$$\Pr(E|F) = \frac{\Pr(F|E)\Pr(E)}{\Pr(F)} \tag{7}$$

Specific nomenclature applies to the probabilities that compose Equation 7:

a) $\Pr(E)$ and $\Pr(F)$ are, respectively, the priori probabilities of E and F, independent of each other;

b) $\Pr(E|F)$ is called the conditional probability of E given F;

c) $\Pr(F|E)$ is called the conditional probability of F given E.

In addition, and more generically, given n mutually exclusive and exhaustive events, $E_1, E_2, \dots, E_n$, if $\Pr(E_i) \neq 0$ for all i, then for every $i = 1, \dots, n$:

$$\Pr(E_i|F) = \frac{\Pr(F|E_i)\Pr(E_i)}{\Pr(F|E_1)\Pr(E_1) + \Pr(F|E_2)\Pr(E_2) + \dots + \Pr(F|E_n)\Pr(E_n)} \tag{8}$$

The process of updating a probability given some evidence using Equations 7 or 8 is called "Bayesian inference" and plays an important role in statistical analysis.

2.2. *The structure of a Bayesian network*

The concept of BN was introduced in 1986 by Pearl, under the nomenclature of “belief networks”. According to Pearl (1986, p. 241),

> Belief networks are directed acyclic graphs in which the nodes represent propositions (or variables), the arcs signify direct dependencies between the linked propositions, and the strengths of these dependencies are quantified by conditional probabilities.

To sum up, BNs constitute data structures adequate to map dependencies among random variables, due to their ability to represent essentially any type of joint probability distribution. This type of data structure allows modelling the humans’ inferential reasoning, which is a subjective, uncertain and incomplete process (PEARL, 1986).

The full specification of a BN satisfies the following (RUSSEL; NORVIG, 2010):

a) each node represents a random variable, which may be discrete or continuous;

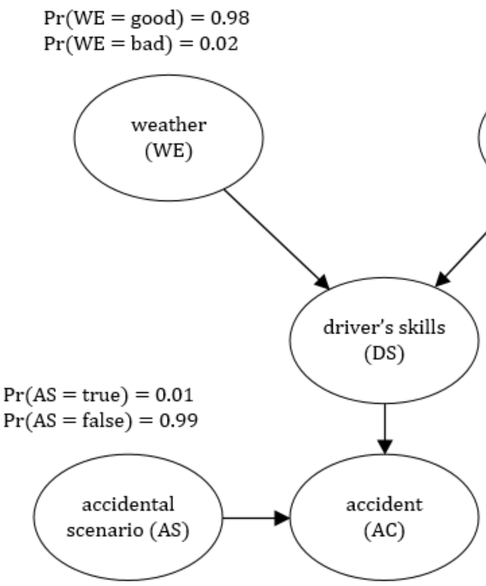
b) a set of directed arrows represents the connections between pair of nodes;

c) if there is an arrow from node X to node Y, X is said to be a parent of Y, and each node X_i has a conditional probability distribution $\Pr\left(X_i \middle| parents(X_i)\right)$ that quantifies the effects of the parents on the node;

d) the graph is directed and acyclic.

In order to illustrate this, Figure 1 presents a didactic BN example, dedicated to model the probability of a driving accident. In this example, each node has two discrete states, but in a generic case the nodes could have any number of discrete states, or otherwise, assume a value in a continuous domain. The BN models the probability of an accident (AC) given the driver’s skills (DS) and the probability of an accidental scenario (AS) happening. The main assumption here is that given an accidental scenario, the driver’s skill will determine if he/she will avoid the accident or not with some probability. Additionally, the driver’s skill is conditioned to two factors: the local weather (WE) and the driver’s mental state (MS).

Figure 1 – Example of a Bayesian network



Pr(DS = good)	Pr(DS = bad)	WE	MS
0.99	0.01	good	good
0.90	0.10	good	bad
0.85	0.15	bad	good
0.70	0.30	bad	bad

Pr(AC = true)	Pr(AC = false)	AS	DS
0.05	0.95	true	good
0.35	0.65	true	bad
0.00	1.00	false	good
0.00	1.00	false	bad

A priori probabilities are attributed directly to the states of the nodes that have no parents – i.e., WE, MS and AS. On the other hand, the child nodes – i.e., DS and AC – need the specification of a joint probability distribution associated with each possible combination of their parent nodes' states. For the case of discrete variables, this joint probability distribution is expressed in the form of a conditional probability table (CPT). In this example, the CPTs are presented next to the nodes they are related to. It is important to observe that for any node the sum of the probabilities of all their states must be unitary.

Observing the CPT for the driver's skill node, one may note that if there is good weather ($\mathrm{WE} = \mathrm{good}$) and the mental state of the driver is good ($\mathrm{MS} = \mathrm{good}$), then there is a high belief, of 0.99, that the driver's skill is good ($\mathrm{DS} = \mathrm{good}$). The evidence of bad weather alone ($\mathrm{WE} = \mathrm{bad}$), however, reduces the aforementioned belief to 0.85. Similarly, the evidence of a bad mental state ($\mathrm{MS} = \mathrm{bad}$) alone also reduces this belief, to a value of 0.90. The fact that the evidence of bad weather reduces the belief more than a bad mental state suggests that the causal relation of the former is stronger than the causal relation of the latter. Finally, the combined belief of having both bad weather and a bad mental state reduces the belief that the driver's skill is good to 0.70, representing the joint effect of both factors.

It is also interesting to observe the CPT of the node "accident", which is slightly different than the driver's skill node. It contains also logical information, what is quite common for some types of BN. When there is no accidental scenario ($\mathrm{AS} = \mathrm{false}$) it is certain that the accident will not occur ($\mathrm{AC} = \mathrm{false}$), i.e., the belief is 1. On the other hand, if the accidental scenario exists ($\mathrm{AS} = \mathrm{true}$), then the belief of an accident occurring ($\mathrm{AC} = \mathrm{true}$) is equal to 0.05 if the driver's skill is good ($\mathrm{DS} = \mathrm{good}$) and 0.35 if the driver's skill is bad ($\mathrm{DS} = \mathrm{bad}$).

2.3. Joint probability distribution and the Bayesian network complexity

The subsection 2.2 presents how the BN can be a good way to represent causal relations among variables, due to their visual appeal. Furthermore, they conveniently support probabilistic information in order to quantify the strength of the relations. Though, what is the real advantage of using this specific type of model in detriment of other alternatives such as, for instance, the direct application of the Bayes' theorem?

The answer for this question lies in the joint probability distribution and its consistency property. However, it is important to firstly understand the source of inconsistency when dealing with conditional probabilities and this is made clear through an example presented by Charniak (1991). Suppose a system in which we consider the following probabilities: $\Pr(E|F) = 0.70$, $\Pr(F|E) = 0.30$ and $\Pr(F) = 0.50$. Apparently, there is nothing wrong in doing this, but by simply applying the Bayes' theorem, it is possible to observe an inconsistency regarding $\Pr(E)$, which turns out to be greater than one, as presented in Equation 9:

$$\Pr(E) = \frac{\Pr(E|F)\Pr(F)}{\Pr(F|E)} = \frac{0.70 \times 0.50}{0.30} = \frac{0.35}{0.30} > 1 \tag{9}$$

This example is quite simple, but enough to illustrate how easily a mistake can be made when computing joint probability distributions. In systems with more variables, defining consistent conditional probabilities along its entire domain could mean a problem without special-purpose techniques to handle these inconsistencies (CHARNIAK, 1991). The BNs are especially adequate to deal with this type of problem due to their implicit consideration of joint probability distributions, which takes into account the dependence relationships among all variables within a domain in a structured form.

The joint probability distribution for a set of n random variables, $X_1, \dots, X_n$, ordered in an arbitrary order, will be denoted by $\Pr(x_1, \dots, x_n)$ where $x_1, \dots, x_n$ denotes a specific combination of values for $X_1, \dots X_n$. For a given sample space, Ω, a random variable, X, is a function that attributes a unique value, x, to each element of Ω (NEAPOLITAN, 2003). Mathematically:

$$\Pr(x_1, \dots x_n) = \Pr(x_n | x_{n-1}, \dots, x_1) \dots \Pr(x_2 | x_1) \Pr(x_1) \tag{10}$$

This is obtained by applying exhaustively the chain-rule[5] to the following relation:

$$\Pr(x_1, \dots x_n) = \Pr(x_n | x_{n-1}, \dots, x_1) \Pr(x_{n-1}, \dots, x_1) \tag{11}$$

In order to keep Equation 11 consistent (and, consequently, Equation 10 also), for each combination $x_{n-1}, \dots, x_1$ one should specify the corresponding probability distribution of the random variable X_n. In practice, for the discrete case, considering that X_n may assume m states, the total number of values to be specified for each combination $x_{n-1}, \dots, x_1$ is equal to $m - 1$, since the sum of probabilities for the complete set of states should be unitary, thus reducing the number of degrees of freedom by 1. Therefore, the total number of values that should be informed, N, is given by:

$$N = \sum_{i=1}^{n} (m_i - 1) k_i \tag{12}$$

Where m_i is the number of states for the random variable X_i and k_i represents the number of combinations of possible states for all random variables prior to X_i (according to the adopted variable ordering). Thus, k_i is calculated through the following expression:

$$k_i = \prod_{j=1}^{i-1} m_j \tag{13}$$

[5] The chain-rule is based on the relation $\Pr(E \cap F) = \Pr(E, F) = \Pr(E|F) \Pr(F)$

Where, $k_1 = m_1 - 1$.

A joint probability distribution can be attributed to a BN respecting the following conditions:

a) the variables $x_1, \dots, x_n$ should be ordered in a manner that every child node comes after all its parents;

b) the right side of the conditioning bar of each term refers only to the parent nodes of the variable on the left side of the conditioning bar.

The second condition mentioned above implies that, in the specific case of a BN, Equation 10 can be written as:

$$\Pr(x_1, \dots x_n) = \prod_{i=1}^{n} \Pr\big(X_i \big| Parents(X_i)\big) \tag{14}$$

For instance, a possible ordering for the joint probability distribution of the BN in Figure 1 is:

$$\{X_1, X_2, X_3, X_4, X_5\} = \{\mathrm{MS}, \mathrm{WE}, \mathrm{DS}, \mathrm{AS}, \mathrm{AC}\} \tag{15}$$

Note that the child nodes necessarily come after their parents and such ordering is only possible because the BN is acyclic. Therefore, AC should be positioned after AS and DS, as well as DS is positioned after WE and MS. Once this condition is satisfied, the positioning of the nodes AS, WE and MS is indifferent, since they have no parent nodes.

Additionally, denoting by $\{\mathrm{ms}, \mathrm{we}, \mathrm{ds}, \mathrm{as}, \mathrm{ac}\}$ a specific set of states for $\{\mathrm{MS}, \mathrm{WE}, \mathrm{DS}, \mathrm{AS}, \mathrm{AC}\}$ and applying Equation 14:

$$\Pr(\mathrm{ms}, \mathrm{we}, \mathrm{ds}, \mathrm{as}, \mathrm{ac}) = \Pr(\mathrm{ac}|\mathrm{as}, \mathrm{ds}) \Pr(\mathrm{as}) \Pr(\mathrm{ds}|\mathrm{we}, \mathrm{ms}) \Pr(\mathrm{we}) \Pr(\mathrm{ms}) \tag{16}$$

By inspecting Equation 16 and comparing it with Equation 10, it is possible to notice the compactness provided by the BN data structure in relation to the full specification of the joint probability distribution. Since each node for this BN has two states, according to Equation 12, the total number of values to be specified is equal to 31. However, to fill every CPT and a priori probabilities of the BN presented in Figure 1 only 11 values were needed. In fact, the number of values to be specified within a BN structure is always equal or less to the number of values needed for the joint probability distribution (which can be calculated using Equation 12).

In summary, the BN models take advantage of the consistency provided by the joint probability distribution and, additionally, are compact in terms of the number of values to be specified. Specifically, in the case where the numbers of arcs per node is fixed, the amount of data needed to fill a BN grows linearly with the number of nodes, while the full specification of the joint probability distribution grows exponentially (MATURANA, 2010).

2.4. Conditional independence

The quantification procedure of a BN presented in subsection 2.3 reveals an important feature of this type of data structure, regarding the conditional independence among the nodes. Specifically, Equation 14 reveals that a node is conditionally independent of all its successors given its parents. Furthermore, it is interesting to observe that the topology of a BN also reveals other conditional independence relations, and not only for the successor nodes, but also in the other direction.

Once the topology of a BN is determined (i.e., the complete set of nodes and arcs), conditional independence relations can be inferred from two specific conditions (RUSSEL; NORVIG, 2010):

a) a node is conditionally independent of all its non-descendants, given its parents, as illustrated in Figure 2;

b) a node is conditionally independent of all other nodes in the network, given its Markov blanket, which is composed by its parents, children, and children's parents, as illustrated in Figure 3.

Knowing the independence relations is an important step to perform probabilistic inferences by the BN. The next subsection is dedicated to discussing this specific topic.

Figure 2 – Conditional dependency of node Z given its parents

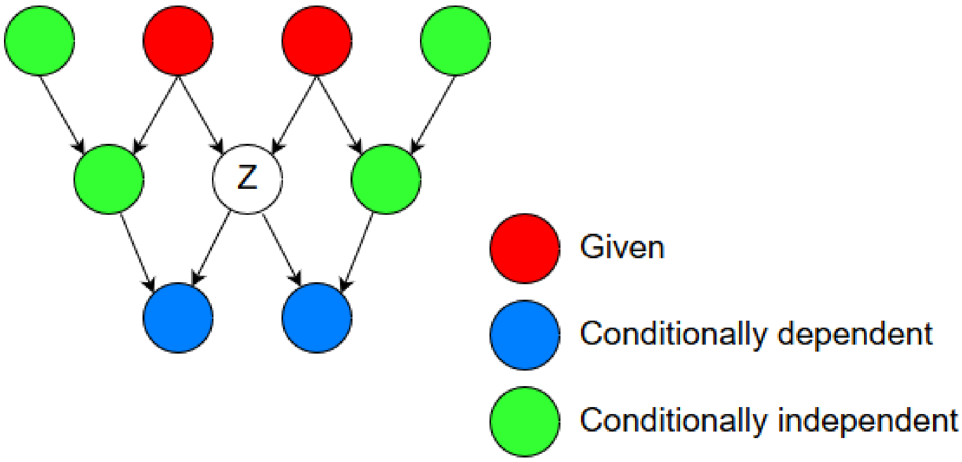
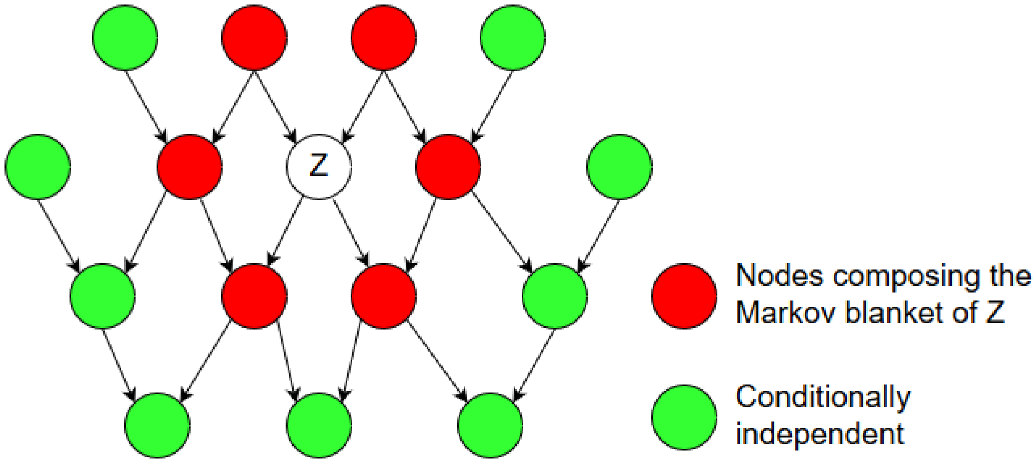


Figure 3 – Markov blanket for the node Z and the conditionally independent nodes regarding it



2.5. *Marginalization and inference*

Common interests when dealing with BNs relate to performing two specific processes, called marginalization and inference. The former refers to extracting the probability distribution of one or multiple variables within the network. The later involves computing the posteriori probability of variables given some evidence in the network. In this context, evidence can be interpreted as having certainty that one or more variables are in specific states.

The marginalization process, also known as "summing out", allows computing the probability distribution of any variable in the BN. For instance, in the BN of Figure 1, the priori probability distribution over the states of the nodes WE, MS and AS are known. But what are, for instance, the probability distributions over the states of the node DS? In other words, what is the marginal probability of DS?

For any sets of variables Y and Z, the marginalization rule is written by (RUSSEL; NORVIG, 2010):

$$\Pr(Y) = \sum_{z \in Z} \Pr(Y, z) \tag{17}$$

Where Y is the variable(s) we want to compute the probability distribution, and Z includes all the remaining variables of the network. Therefore, the marginalization process involves performing the sum over all the possible combinations of states of variables in Z. By using the product rule, Equation 17 can be rewritten as:

$$\Pr(Y) = \sum_{z \in Z} \Pr(Y|z) \Pr(z) \tag{18}$$

Therefore, to compute the marginal probabilities of DS:

$$\begin{gathered}\Pr(\mathrm{DS}) = \Pr(\mathrm{DS}|\mathrm{WE} = \mathrm{good}, \mathrm{MS} = \mathrm{good}) \Pr(\mathrm{WE} = \mathrm{good}) \Pr(\mathrm{MS} = \mathrm{good}) + \\ \Pr(\mathrm{DS}|\mathrm{WE} = \mathrm{good}, \mathrm{MS} = \mathrm{bad}) \Pr(\mathrm{WE} = \mathrm{good}) \Pr(\mathrm{MS} = \mathrm{bad}) + \\ \Pr(\mathrm{DS}|\mathrm{WE} = \mathrm{bad}, \mathrm{MS} = \mathrm{good}) \Pr(\mathrm{WE} = \mathrm{bad}) \Pr(\mathrm{MS} = \mathrm{good}) + \\ \Pr(\mathrm{DS}|\mathrm{WE} = \mathrm{bad}, \mathrm{MS} = \mathrm{bad}) \Pr(\mathrm{WE} = \mathrm{bad}) \Pr(\mathrm{MS} = \mathrm{bad})\end{gathered} \tag{19}$$

Replacing the terms by the values provided by Figure 1:

$$\begin{gathered}\Pr(\mathrm{DS}) = [\Pr(\mathrm{DS} = \mathrm{good}), \Pr(\mathrm{DS} = \mathrm{bad})] = \\ [0.99, 0.01] \times 0.98 \times 0.95 + [0.90, 0.10] \times 0.98 \times 0.05 + \\ [0.85, 0.15] \times 0.02 \times 0.95 + [0.70, 0.30] \times 0.02 \times 0.05\end{gathered} \tag{20}$$

From which results:

$$\Pr(\mathrm{DS}) = [0.983, 0.017] \tag{21}$$

Therefore, the probability of the driver’s skill being good is of 98.3% while 1.7% is the probability of the driver’s skill being bad. These are probabilities based only on prior information, i.e., a kind of prior probability for the node “driver’s skill”. At this point, we may ask what the probabilities would be if more knowledge were available or, in other words, if we had evidence. This problem motivates the inference process.

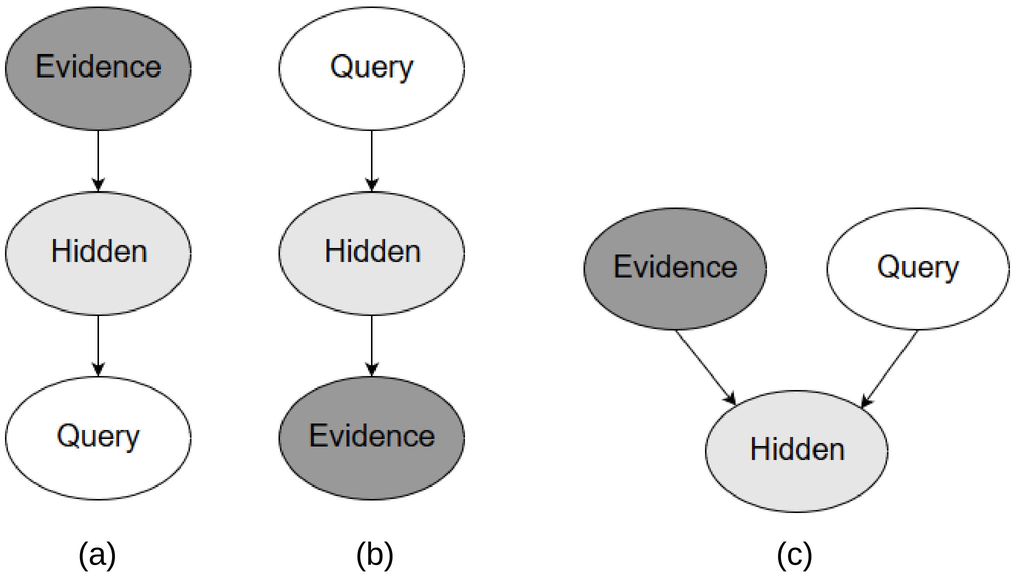
When performing an inference, the variable for which we want information is called “query variable”. The variables that we have knowledge about are called “evidence variables”. Furthermore, the remaining variables that are not included in those two categories are called “hidden variables”. Then, basically three types of inferences can be performed (MATURANA; 2010):

a) Prognosis: given the causes, obtain the probability of the effects – see Figure 4a;

b) Diagnosis: given the effects, obtain the probability of the causes – see Figure 4b;

c) Intercausal: given the evidence of one cause, find the probability of the other cause – see Figure 4c.

Figure 4 – Types of inference: (a) prognosis; (b) diagnosis; (c) intercausal



Source: adapted from Maturana (2010)

In summary, the objective of the inference consists of determining $\Pr(X|e)$, where X denotes the query variable and e denotes an observed event related to a set of k evidence variables, $E = \{E_1, \dots E_k\}$. Also, the set of l hidden variables will be denoted by $Y = \{Y_1, \dots Y_l\}$. The query $\Pr(X|e)$ can be answered by summing terms from the full joint probability distribution (RUSSEL; NORVIG, 2010):

$$\Pr(X|e) = \alpha \Pr(X, e) = \alpha \sum_{y \in Y} \Pr(X, e, y) \tag{22}$$

Where y denotes a specific state of a hidden variable and, as indicated by Equation 22, it is necessary to perform the sum over all possible combinations of states of the hidden variables. The Greek letter α represents a normalization factor, which is equal to $1/\Pr(e)$.

Back to the example of Figure 1, suppose we want to compute the probability of the driver's skill being good given the evidence of bad weather. Then:

$$\Pr(\mathrm{DS} = \mathrm{good}|\mathrm{WE} = \mathrm{bad}) = \\ \alpha \sum_{\substack{\mathrm{ac} \in \mathrm{AC} \\ \mathrm{as} \in \mathrm{AS} \\ \mathrm{ms} \in \mathrm{MS}}} \Pr(\mathrm{ac}|\mathrm{as}, \mathrm{DS} = \mathrm{good}) \Pr(\mathrm{as}) \Pr(\mathrm{DS} = \mathrm{good}|\mathrm{WE} = \mathrm{bad}, \mathrm{ms}) \Pr(\mathrm{WE} = \mathrm{bad}) \Pr(\mathrm{ms}) \tag{23}$$

Where:

$$\alpha = \frac{1}{\Pr(\mathrm{WE} = \mathrm{bad})} \tag{24}$$

From which results:

$$\Pr(\mathrm{DS} = \mathrm{good}|\mathrm{WE} = \mathrm{bad}) = 0.842 \tag{25}$$

In this calculation, $\Pr(\mathrm{WE} = \mathrm{bad})$, which refers to the evidence, is a common term in the sum. Thus, the terms α and $1/\Pr(\mathrm{WE} = \mathrm{bad})$ are cancelled. This leads to the conclusion that the posteriori probability is independent of the evidence node's priori probabilities.

3. Application of Bayesian networks to the human reliability analysis

In the area of risk analysis and related, the popular definition of reliability is traditionally associated with the concept of component or system reliability. It refers to "an item's ability to successfully perform an intended function" (MODARRES; KAMINSKIY & KRIVTSOV, 1999). Accordingly, the definition of human reliability derives from this general concept. Swain and Guttmann (1983) define human reliability as "the probability that a person (1) correctly performs some system-required activity in a required time period (if time is a limiting factor) and (2) performs no extraneous activity that can degrade the system".

On the other hand, the HRA has several definitions, which coincide with its different purposes. The term "analysis" itself is broad and designates the "process of studying or examining something in an organized way to learn more about it, or a particular study of something" (CAMBRIDGE UNIVERSITY, n.d.). Therefore, the HRA may be defined in a straightforward manner as "the method by which human reliability is estimated" (SWAIN; GUTTMANN, 1983) or, in a broader manner, as a process that "aims at systematically identifying and analyzing the causes, consequences and contributions of human failures in socio-technical systems" (MKRTCHYAN; PODOFILLINI; DANG, 2015). This latter definition matches the purpose of this Thesis, since its primary focus is the study of the main factors influencing the human reliability (causes of human failures).

The majority of HRA studies consider the influence of PSFs on the HEP. The early proposed methodologies – supported by first- and second-generation techniques – postulated that the HEP is a function of the PSFs (DROGUETT; MENÊZES, 2007), which is a concept that still pertinent nowadays. However, these first models considered assumptions of independency among the PSFs, which imply limitations to the HRA.

Due to their ability to overcome this specific limitation and other capabilities, the HRA modelling based on BN received special attention. Their main features include, but are not limited to (DROGUETT; MENÊZES, 2007):

a) good representation of causal relations, through their graphical structures;

b) error identification in a contextual manner (through the causal relations graphically expressed in the network) and estimation of probabilities (due to the conditional probabilities between nodes);

c) realistic representation of the man-machine interactions, through scenarios and cause-effect relations in a given context;

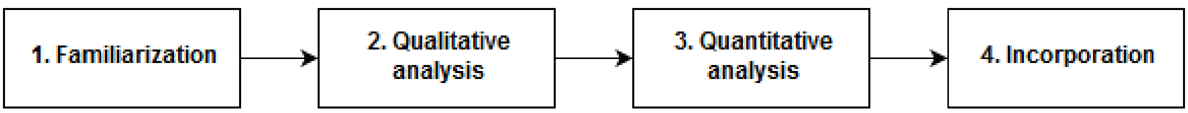
d) ability to represent different contexts;

e) better representation of currently observed scenarios, through the updating based on subjective and empirical evidence.

Given all the advantages highlighted above, the HRA modelling using BN was adopted in this work. Specifically, the methodology adopted to build the BN follows the proposal of Martins and Maturana (2013). This methodology was applied effectively not only to analyze problems correlated the navigation in restricted waters (e.g., the collision of oil tankers), but also found application in other areas, such as the emergency evacuation of an aircraft (BAYMA; MARTINS, 2017) and the evaluation of aircraft pilots' performance (BANDEIRA; CORREIA; MARTINS, 2017).

The methodology postulates a generic dependency model, which maps the main factors influencing the human performance when executing some action. This model is useful to simplify the building of a BN, since it defines categories of factors that can only influence or be influenced by other specific categories, to the detriment of an approach that allows any type of relations among factors. It also establishes four steps to perform the analysis, as illustrated in Figure 5.

Figure 5 – Steps for Human Reliability Analysis using Bayesian Networks



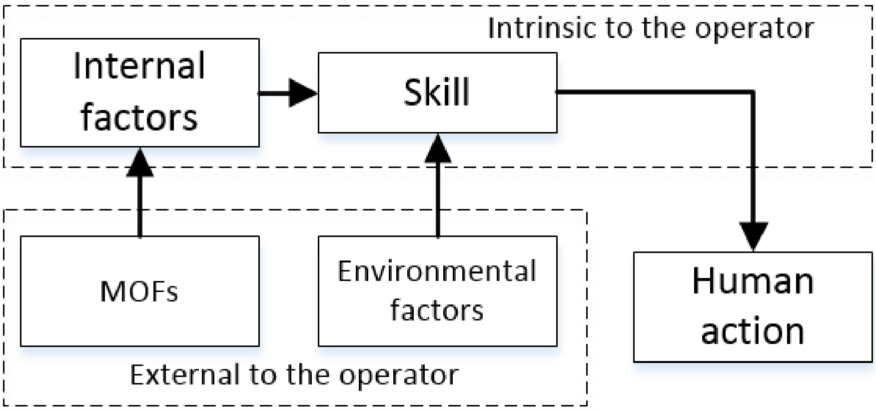
The remainder of this section is dedicated to describing the adopted methodology for HRA using BN. Firstly, the generic dependency model is presented, then the four steps highlighted above. Notably, the step 2, qualitative analysis, is highly dependent on the relations established by the generic dependency model, but it is also recommended to keep these relations in mind during the step 1, familiarization, guiding the process of gathering information.

3.1. The generic dependency model

When an operator performs a task, we can derive several measures of his/her performance, such as fastness, efficiency, and likelihood of success. This latter measure is of special interest for HRA. Regardless of the measure it depends essentially on skills (e.g., concentration, motor control), internal factors (e.g., quality of sleep, stress), environmental factors (e.g., temperature, noise) and management & organizational factors (e.g., training, work coordination). In other words, the human performance depends on the performance shaping factors (PSFs), some of which are intrinsic to the operator, while others are external (SWAIN; GUTTMANN, 1983).

The human tasks in complex systems include cognitive, psychomotor and affective tasks. Knowing the behavioral mechanism behind each type of task is currently one of the main challenges for the HRA models (PAN; LIN; HE, 2017). However, when building such models, it is necessary to develop a framework that incorporates the most significant factors to the system operation under analysis (MATURANA, 2010). The generic dependency model proposed, presented in Figure 6, allows advancing in this direction, by mapping the influences among four groups of PSFs and their impact on the human actions.

Figure 6 – Generic dependency model



Source: adapted from Martins and Maturana (2013)

The model postulates that the human actions performance is directly affected only by the skills of the operator. On their turn, the skills are influenced by the environmental factors (external to the operator) and internal factors. Finally, the internal factors are influenced by the management & organizational factors (MOFs). The environmental factors and MOFs are external to the operator, while the internal factors and skills are intrinsic[6] to the operator.

The generic dependency model is a simplification of the human behavioral mechanisms, based on two independence assumptions:

a) the MOFs are not capable of modifying the skills in the short period when the operation occurs;
b) the environmental factors are transitional and, therefore, do not influence the long-term state of the operator, represented by the internal factors.

Each element of the generic dependency model is briefly explained below.

3.1.1. Human actions

The human actions are the observable or reportable activities developed by the operators when performing their functions. They are the basic elements to which the human errors can be attributed.

In a high level, the human actions can be classified according to three levels of performance, which are proposed by the SRK model (RASMUSSEN; DUNCAN; LEPLT, 1987):

a) skill level;
b) rule level;
c) knowledge level.

The skill level is the simplest one, involving automated actions and routines. The rule level is more complex than the skill level, and involves following a given procedure, but in a familiar environment, with well-defined rules. Finally, the knowledge level is the highest in terms of complexity, referring to all those actions developed in an unprecedented scenario for which there is no definite or defined procedure.

There are proposals of human actions taxonomies that go further into each of these three levels. One popular example is the Bloom's taxonomy (BLOOM et al., 1956),

[6] Martins and Maturana (2013) classify internal factors and skills as "internal to the operator". In this Thesis, the term "intrinsic to the operator" is adopted instead, in order to avoid ambiguity.

which explore lower-level actions such as basic movements, non-verbal communication, interpretation and planning.

3.1.2. Skills

Despite having different connotations (ATTEWELL, 1990), from the point of view of the generic dependency model, skills should be interpreted as abilities essential to the good performance of the human actions. How well the operator develops some skill is essentially related to his/her internal condition. However, the skills may also be affected momentarily by factors on the surrounding – namely, the environmental factors.

This is made clear with an example. Suppose an operator should read a set of numbers (e.g., readings from gauges) and transform it into useful information for decision making. This cognitive process is a human action that depends on the operator's ability to interpret the set of values. Therefore, the interpretation skill defines how well the operator will perform this activity. An individual's ability to interpret something depends basically on how well he/she was educated to read numbers, but also on the mental state at the moment the information comes by. On the other hand, despite the individual's ability, the interpretation capacity can be influenced, for instance, by the local luminosity modifying the readings.

As depicted above, the definition of which skills are necessary for each action is a straightforward process, strongly based on the human perception of their own performance. The results, however, tend to be better when eliciting experts. This is also true when dealing with the other factors of the generic dependency model.

3.1.3. Internal factors

Any sociotechnical system depends on roles developed by humans. As highlighted by Swain and Guttmann (1983), the ideal scenario is the one with standardized operators, since it would be easier to predict their performance and design the man-machine interface to overcome their deficiencies. Since this is not possible, an attempt to evaluate the particulars of each operator is made through the definition of internal factors.

The operators start their jobs with a very particular set of characteristics, which will ultimately determine how well they perform their functions, i.e., the quality of their skills. This includes factors such as intelligence, team identification and knowledge. These factors can be continuously improved by organizational measures, aiming at modifying the operator’s fitness for the job.

Therefore, in the generic dependency model, the internal factors should be interpreted as those that directly influence the operator’s skills to perform their functions. These factors are subject to change through the quality of organizational policies or, in other words, they can be influenced by MOFs.

3.1.4. Environmental factors

Environmental factors are transitional elements, external to the operator, that directly influence their skills when performing some task. Since they are situational, in their absence the operators tend to return to their normal working conditions. The environmental factors are not capable of modifying the operator’s condition permanently.

These factors include the forces of nature, such as wind, temperature and precipitation, as well as elements of the working environment, such as noise, vibration and luminosity.

3.1.5. Management & organizational factors

The MOFs are the continuous factors external to the operators and capable of influencing their internal states permanently from the point of view of the operation. This means that these factors change in an extent of time much larger than the period in which the operation occurs.

These factors include a wide range of elements. Examples of MOFs include:

a) infrastructure, such as the machine layouts and accommodations;

b) job instructions, such as checklists and formal procedures;

c) strategic elements of the organization and its organizational culture;

d) information networks;

e) rules and the enforcement of laws;

f) time and commercial pressures.

The impact of the MOFs on the human performance is one of the most interesting results to decision makers, since they can serve as input to the planning of improvement policies. Additionally, once the critical MOFs are identified, they can be followed up through key performance indicators or other measures.

3.2. Steps for the human reliability analysis using Bayesian networks

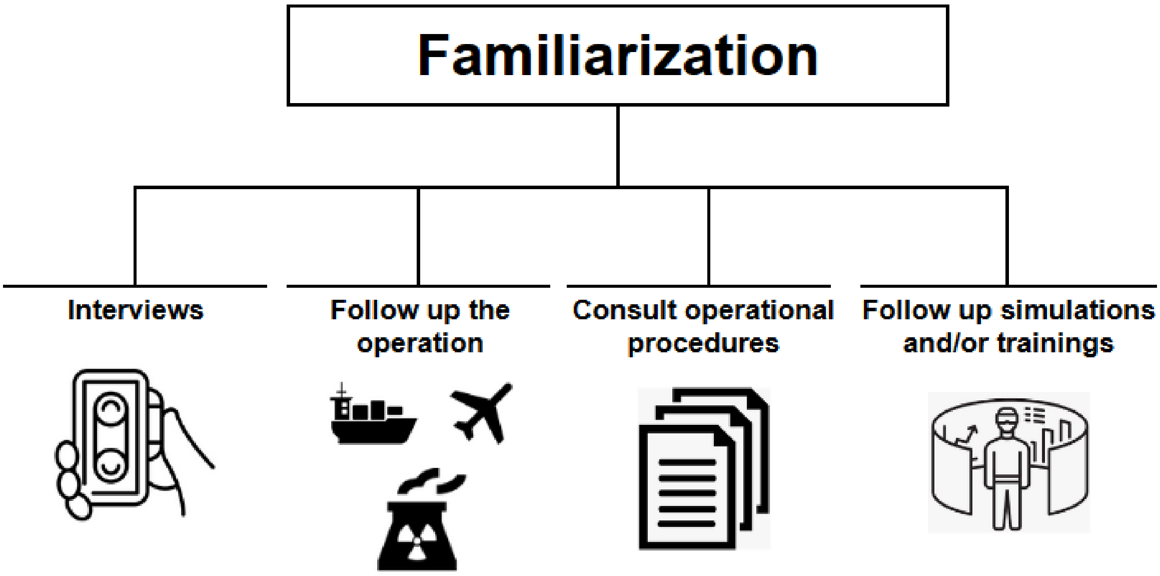
This section describes each of the four steps for HRA using BNs, which are (see Figure 5): familiarization, qualitative analysis, quantitative analysis, and incorporation.

3.2.1. Step 1: familiarization

The objective of the familiarization step is to gather useful information about the problem being analyzed. At this phase of the HRA process, it is important to identify hazardous events, as well as unsafe human actions that can lead to hazardous situations and safety actions that can prevent them. There are several ways to acquire such information, as illustrated in Figure 7.

One of the most common ways to acquire information during the familiarization phase is by interviewing experts, commonly, experienced operators that currently perform the operation under analysis. These interviews can assume basically two forms: structured, in which the operators answer predetermined questions; or unstructured conversations, in which the operators are free to relate their perceptions. The former option has as advantage the possibility of comparing the answers and store them in a structured manner. However, the format with predetermined questions can miss important aspects, since it is elaborated by an analyst that generally has poor knowledge about the daily aspects of the operation. On its turn, the unstructured conversation lacks formality, but the freedom to the interviewee can reveal aspects not covered by structured forms. A combination of both – i.e., the use of predetermined questions with space for free speeches – is generally an interesting option.

Figure 7 – Methods of familiarization for the human reliability analysis



Visiting the plant and following up the operation is another common way of acquiring information. Through this method, it is possible to observe phenomena not revealed by the interviews, such as unsafe actions that are omitted by the operators or aspects that were not clear to the operators to be described verbally. When performed along with the interviews, following up the operation can lead to conclusions free of the biases intrinsic to the operator. However, the analyst biases may take place.

A third way to acquire information is to consult the operational procedures, if they exist. This process may not reveal the exact actions performed by the operators, since they can diverge from the formal procedures in organizations with poor supervision or procedures that are not adequate to the operational reality. However, the comparison between operational procedures and the real dynamics of the operation can reveal important deviations to feed the HRA.

The last source of information included in the familiarization phase refers to the process of following up of simulations and/or trainings. These activities have been popularized in the last decades with the increased accessibility of virtual reality environments. Even though simulations do not reproduce exactly the real world, they are capable of reproducing, at least, the main aspects. Notably, simulations are one of the only ways by which analysts can observe the operators' behavior under emergency.

To sum up, the familiarization step can be performed through several procedures, each with their own advantages and limitations. It is up to the analysts to choose the best procedure or combination of procedures to perform their familiarization, always keeping in mind the objectives of the HRA and the resources available. Despite being listed as the first step in the HRA process – and it should be – the familiarization phase can be revisited at any time to gather missing information.

3.2.2. Step 2: qualitative analysis

In the second step of the methodology – qualitative analysis – the analysts should register in a structured manner the information gathered during the familiarization phase. The aim of this step is to build the topology of the BN, indicating the main factors contributing to the human performance and the causal relations among them, according to the generic dependency model – see Figure 6.

Martins and Maturana (2013) point out some of the sub steps for the qualitative analysis:

a) determine the required performance;
b) task analysis;
c) isolate possible human errors in the task performance;
d) development of the task BN topology[7];
e) definition of the relevant performance factors for good task execution and associated dependencies; and
f) development of the performance factors network topology.

The required performance refers to the function of the operators within the sociotechnical system they are inserted. It can be registered, for instance, in terms of the minimum accomplishments for the operation to be considered successful.

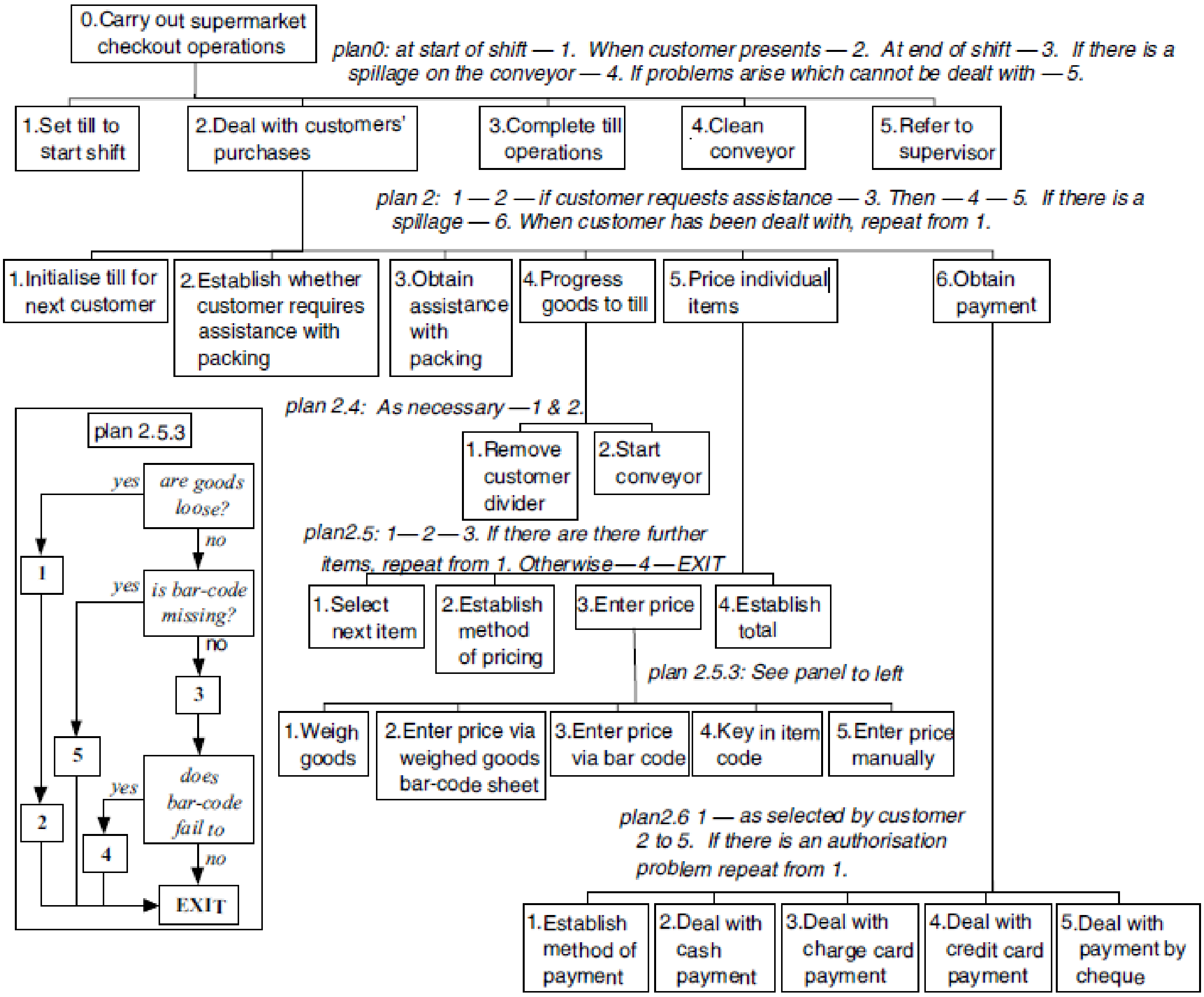
Once the required performance is defined, the tasks necessary to satisfy it should be detailed. It is a process of breaking down high level tasks into lower-level elementary tasks, until it is considered adequate for the purpose of the HRA or manageable. An overdetailed task analysis may turn out to be intractable, while a under detailed

[7] Also referred to as "Task dynamic network" in Martins and Maturana (2013)

analysis may not reveal important aspects of the operation being studied. Therefore, it is important to be judicious at this part.

One typical way of performing the task analysis is through the hierarchical task analysis (HTA). In the HTA, a task is decomposed into subtasks to any desired level of details and the relations among them are detailed in terms of a plan (ANNET, 2003). Figure 8 presents a didactic example of an HTA diagram for the task of carrying out supermarket operations.

Figure 8 – Example of hierarchical task analysis

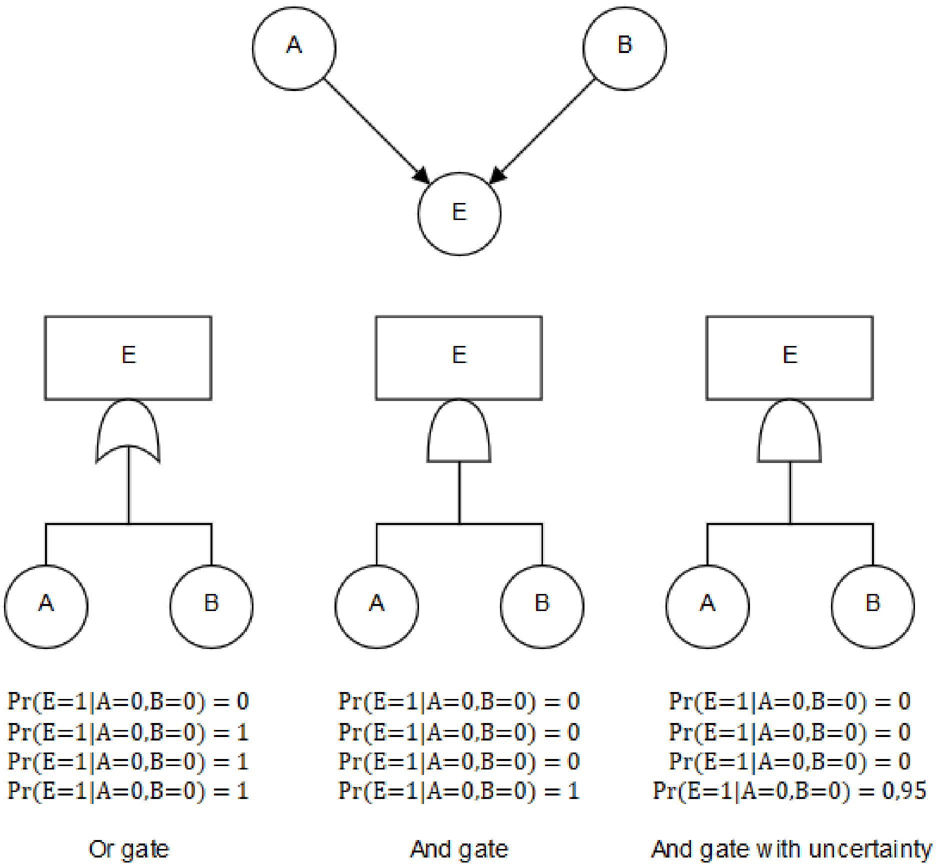


Source: Shepherd (2001).

Each task identified in the task analysis is prone to errors. These errors lead to the system failure or its performance degradation. Thus, for each task, the possible errors should be listed. There are several types of error, such omission (when an action is necessary, but not taken) and commission (undesired consequences after an action is taken) errors. One way to properly identify the human errors is through taxonomies that interrelate them with types of human actions (MATURANA, 2017).

After the tasks and their respective errors were identified and listed, it is possible to build the topology of a BN that reproduces the dynamics of the operation. These dynamics may be described, for instance, by the plans within the HTA. This BN is composed mainly by logical nodes that indicate combinations of errors leading to the task failure. This sub step can be achieved by converting existing fault trees or event trees into BNs (MARTINS; MATURANA, 2013). Figure 9 illustrates how to convert the main fault tree gates into a BN and how to consider uncertainty within the structure of an "and" gate.

Figure 9 – Conversion of typical fault tree gates to Bayesian networks

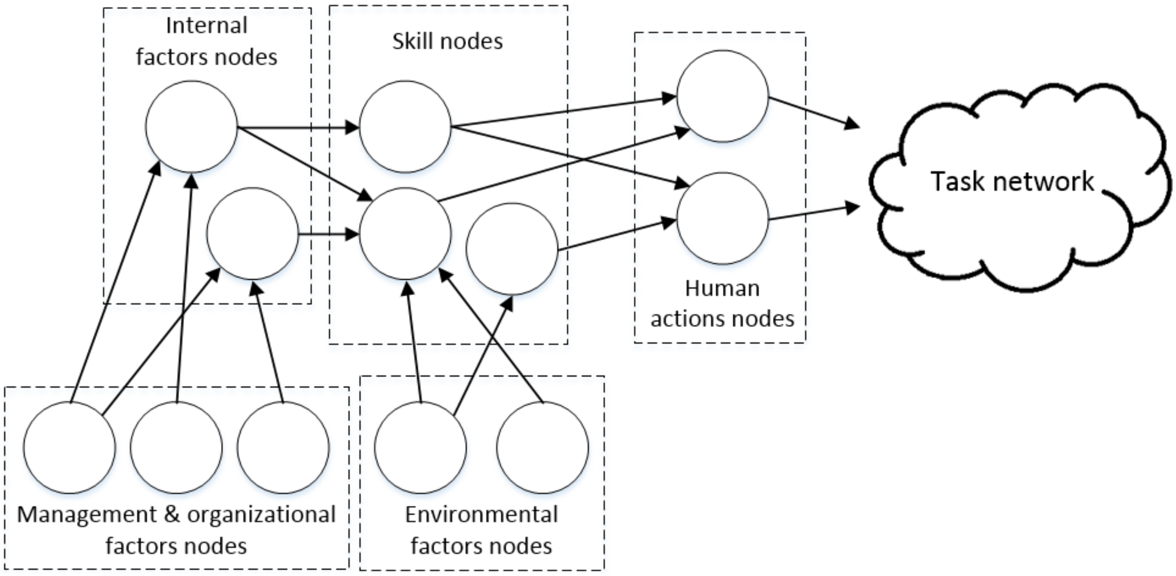


Source: Martins, Schleder and Droguett (2014)

The second part of the BN complements the task network. It refers to the human performance network. To build it, the analyst should identify the main factors influencing the human performance, following the generic dependency model (Figure 6) – mainly using the information gathered during the familiarization step. If required, a new familiarization step focusing on identifying such factors may be developed. The registration of this information is generally written in a tabular format, by simply pointing out which factors influence one another.

Each node of the human performance BN represents a node within one of the five categories: MOFs, environmental factors, internal factors, skills or human actions. Then, the relations among these nodes will be represented by the BN arcs, always following the causal relations postulated by the generic dependency model. Finally, the human actions should be associated to the task network, in order to connect both parts of the BN for HRA. Figure 10 illustrates the scheme for building the network, omitting the task network.

Figure 10 – Mapping of the generic dependency model into a BN



At the end of the qualitative analysis, the resulting BN contains the main tasks developed by the operators, the logical relations among them, focusing on accident sequences and the relations among factors influencing the human performance. Despite being adequate to visually identify the relations, at this point the BN is not able to support quantitative analysis, since its CPTs are not filled yet. The CPT filling is the next step's objective, which constitutes the quantitative analysis.

3.2.3. Step 3: quantitative analysis

The third step of the methodology consists of quantifying the dependency relationships among the nodes of the BN built during the qualitative analysis. This quantification will indicate the strength of the causal relations represented by the arcs connecting the nodes. There are several methods for performing the quantification – most of them based on eliciting[8] experts, given the scarcity of specific empiric data to build the CPTs.

Since the number of fields to be filled in a CPT for a given child node tends to increase exponentially with the number of states and/or parent nodes, the methods commonly rely on interpolation rules. This is possible because in the HRA context, the states of the BN nodes have an increasing sense in their meaning (MKRTCHYAN; PODOFILLINI; DANG, 2016) – with respect to the human performance aspect. On its turn, the task network quantification generally does not represent a challenge, since the CPTs mainly represent logical relations, as suggested by the zeros and ones presented in Figure 9. The existence of an increasing sense means that the states of any node may be sorted according to a crescent order in terms of improving (or worsening) the human performance. For instance, suppose that there is a node named “Training” with three states – “bad”, “regular” and “good”. It is possible to claim that, from the left to the right, the ordering “bad”, “regular” and “good” indicate an increasing contribution to improve the human performance.

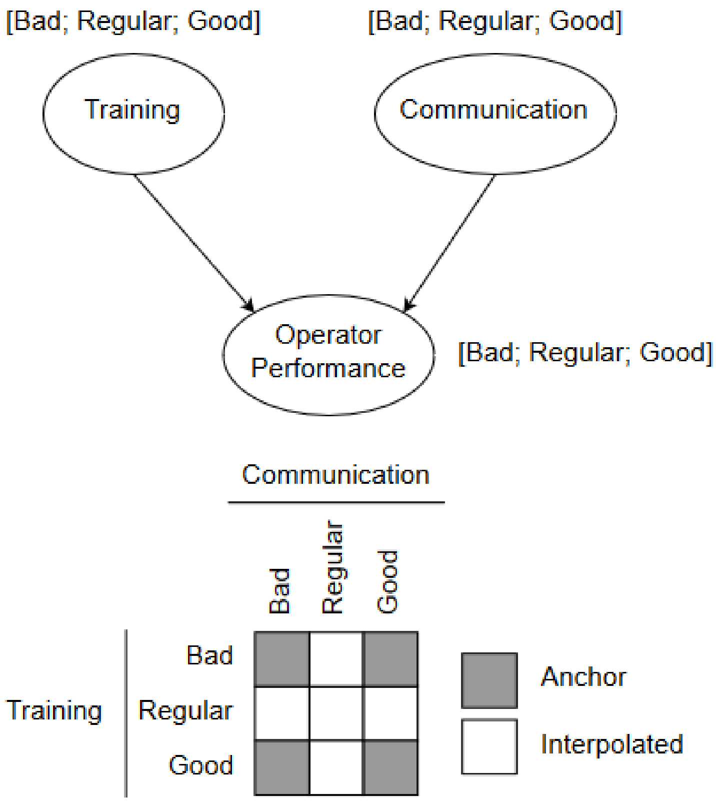
The interpolation process is based on establishing the conditional probabilities for specific combinations of the parent nodes states – known as anchors – and then expanding the results for the remaining combinations. Any combinations of states can be chosen as anchors but, generally, extreme combinations are chosen, such as all parent nodes in their worst state or one parent node on its best state and the others on their worst state.

Figure 11 presents a simplified human performance BN containing one child node – “operator performance” – with two parent nodes – “training” and “communication”. Each node has three states sortable in an increasing sense. The complete filling of

[8] Elicitation is the process of obtaining opinions about a specific subject through an interviewing process (PESTANA, 2017).

the CPT would demand eliciting $3 \times 3 \times (3 - 1) = 18$ values[9]. However, by choosing the four anchors highlighted in the figure and interpolating the remaining values, the total number of values to be elicited is equal to $4 \times (3 - 1) = 8$, which is less than a half of the quantity needed previously.

Figure 11 – Anchors selection for a typical human performance BN



In the literature, there are different proposal of interpolation methods for filling the CPTs (CAIN, 2001; WISSE et al., 2008; RØED et al., 2009; MARTINS; MATURANA, 2013; PODOFILLINI; MKRTCHYAN; DANG, 2015) and also methods that reduce the elicitation burden with no interpolation at all (FENTON; NEIL; CABALLERO, 2007). When quantifying the BN, the analyst should choose the method based on their adequacy for the study purpose and the available resources to perform the quantification.

[9] The term $(3 - 1)$ indicates that for the child node, once the probability for two states is known, the probability for the third state is automatically defined, since their sum is unitary.

3.2.4. Step 4: incorporation

The last step, namely, the incorporation phase, relates to including the HRA model and results into a larger risk analysis model and/or performing sensitivity analysis to compute which factors most contribute to the risk. Additionally, prognosis, diagnosis and intercausal inferences can be made through the BN model (see section 2.5 for a discussion on these topics).

There are several measures that indicate the importance of a given PSF. Martins and Maturana (2013) suggest two types of inferences that can be made through the human performance model:

a) prognosis, i.e., given the evidence that a PSF is on its negative state, compute the impact on the task error probability;

b) diagnosis, i.e., compute the likelihood of a PSF negative state, given the evidence of task failure.

In the first case – prognosis – the impact is the relative difference between the task failure probability given the evidence of a PSF on its negative state and the task failure marginal probability. Denoting by δ this difference, we have:

$$\delta = \frac{\Pr(task|psf) - \Pr(task)}{\Pr(task)} \tag{26}$$

Where $task$ and psf indicate, respectively, a task error and the negative state of a given PSF (skill, internal factor, environmental factor, or MOF).

In the second case – diagnosis –, δ is the relative difference between the PSF's negative state probability given the evidence of a task failure and the PSF's negative state marginal probability. Therefore:

$$\delta = \frac{\Pr(psf|task) - \Pr(psf)}{\Pr(psf)} \tag{27}$$

It is important to note that this formulation assumes that the tasks nodes have only two states – success and failure –, as well as the PSFs nodes, which can assume only a negative or a positive state. The analogous analysis can be performed using the positive/success states and any combinations among positive/success and negative/failure states.

The sensitivity measures proposed by Martins and Maturana (2013) are applicable for human performance networks – what do not limit their use exclusively for this type of network. In addition, there are other two more sophisticated sensitivity measures, widely used among BNs built with different purposes.

The variance reduction sensitivity measure indicates the reduction in the variance of the expected real value of a given variable, Q, due to the values of another variable, F (MARCOT, 2012). Following its conception, it is adequate to rank the nodes according to their importance in networks whose variables are defined in continuous domain (HOSHINO et al., 2016). The expected value of Q prior to any findings, $E(\mathrm{Q})$, is given by:

$$E(\mathrm{Q}) = \sum_{\mathrm{q} \in \mathrm{Dom}(\mathrm{Q})} \mathrm{Pr}(\mathrm{q}) \cdot \mathrm{X_q} \tag{28}$$

Where $\mathrm{Pr}(\mathrm{q})$ is the marginal probability of a specific state q that the variable Q may assume and X_{q} is the real value attributed to q. Moreover, the variance of Q, namely $V(\mathrm{Q})$, can be calculated using the following expression:

$$V(\mathrm{Q}) = \sum_{\mathrm{q} \in Dom(\mathrm{Q})} \mathrm{Pr}(\mathrm{q}) \cdot \left[X_{\mathrm{q}} - E(\mathrm{Q})\right]^2 \tag{29}$$

If there is evidence that the variable F assumes any of its specific states, denoted by f, then the updated expected value of Q, $E(\mathrm{Q}|\mathrm{f})$ is given by:

$$E(\mathrm{Q}|\mathrm{f}) = \sum_{\mathrm{q} \in Dom(\mathrm{Q})} \mathrm{Pr}(\mathrm{q}|\mathrm{f}) \cdot X_{\mathrm{q}} \tag{30}$$

Finally, the average variation of Q given any finding associated with F, $V(\mathrm{Q}|\mathrm{F})$ is:

$$V(\mathrm{Q}|\mathrm{F}) = \sum_{\mathrm{f} \in Dom(\mathrm{F})} \mathrm{Pr}(\mathrm{f}) \sum_{\mathrm{q} \in Dom(\mathrm{Q})} \mathrm{Pr}(\mathrm{q}|\mathrm{f}) \cdot \left[X_{\mathrm{q}} - E(\mathrm{Q}|\mathrm{f})\right]^2 \tag{31}$$

Therefore, the variance reduction, VR, can be expressed as the difference between the variance of Q before any findings and its variance due to findings in F:

$$VR = V(\mathrm{Q}) - V(\mathrm{Q}|\mathrm{F}) \tag{32}$$

If the variables within a network are defined in discrete domains, then the mutual information sensitivity measure can be used (SHANNON, 1948). The mutual information is based on the measure of uncertainty regarding any variable Q that is characterized by a probability distribution (PEARL, 1988). This uncertainty is denoted by $H(\mathrm{Q})$ and is represented by the entropy function, as follows:

$$H(\mathrm{Q}) = -\sum_{\mathrm{q} \in Dom(\mathrm{Q})} \mathrm{Pr(q)} \cdot \log_2 \mathrm{Pr(q)} \tag{33}$$

Where q represents a specific state of the variable Q. The base 2 of the logarithm is associated to the basic unit of information, the bit, which can assume only two values – 0 and 1, associated with the statements “false” and “true”.

Additionally, assuming another variable, F and an evidence of one of its specific states, f, the residual uncertainty regarding the true value of Q can be expressed as:

$$H(\mathrm{Q|f}) = -\sum_{\mathrm{q} \in Dom(\mathrm{Q})} \mathrm{Pr(q|f)} \cdot \log_2 \mathrm{Pr(q|f)} \tag{34}$$

Then, the average residual uncertainty associated with all possible states of F is given by (PEARL, 1988):

$$H(\mathrm{Q|F}) = \sum_{\mathrm{f} \in Dom(\mathrm{F})} H(Q|\mathrm{f}) \cdot \mathrm{Pr(f)} \tag{35}$$

Developing Eq. 35:

$$H(\mathrm{Q|F}) = -\sum_{\mathrm{f} \in Dom(\mathrm{F})} \sum_{\mathrm{q} \in Dom(\mathrm{Q})} \mathrm{Pr(q,f)} \cdot \log_2 \mathrm{Pr(q|f)} \tag{36}$$

Finally, by subtracting $H(\mathrm{Q})$ from $H(\mathrm{Q|F})$, we have the total potential of entropy reduction of F regarding Q. This potential is named “Shannon’s mutual information”, denoted by $I(\mathrm{Q,F})$, and given by:

$$I(Q,F) = H(Q|F) - H(Q) = -\sum_{\mathrm{f} \in Dom(\mathrm{F})} \sum_{\mathrm{q} \in Dom(\mathrm{Q})} \mathrm{Pr(q,f)} \cdot \log_2 \left[\frac{\mathrm{Pr(q,f)}}{\mathrm{Pr(q)} \cdot \mathrm{Pr(f)}}\right] \tag{37}$$

In practice, the larger the entropy reduction, the stronger is the influence between the variables (HOSHINO et al., 2016). Therefore, the mutual information allows ranking quantitatively the nodes within a BN, according to their importance regarding another specific node. The same is true for the variance reduction.

4. Human reliability analysis applied to the navigation in restricted waters

Aiming at understanding how the human factor contributes to the risk of navigation in restricted waters, the HRA methodology described was applied to a port entering operation. This type of maneuver is generally characterized by a strict navigation area with smaller depths and breadths, as well as higher traffic density when compared to open sea navigation. Additionally, the navigation channel may be subjected to complex dynamics due to underwater shoals' movement. Because of all these challenges, tugboats are employed to provide additional maneuverability to the ship and local experienced pilots go onboard to support the captain.

The research questions to be answered based on the developed model are:

a) what are the PSFs that have most influence on the human error probability?

b) how the employment of one pilot, two pilots, or pilotage exemption impacts the human error probability?

Figure 12 summarizes the group of important operators to the port entering operation and illustrates their positioning during the maneuver. The human operators considered in this work include:

a) the 1st pilot, who supports the captain with his/her enhanced local knowledge;

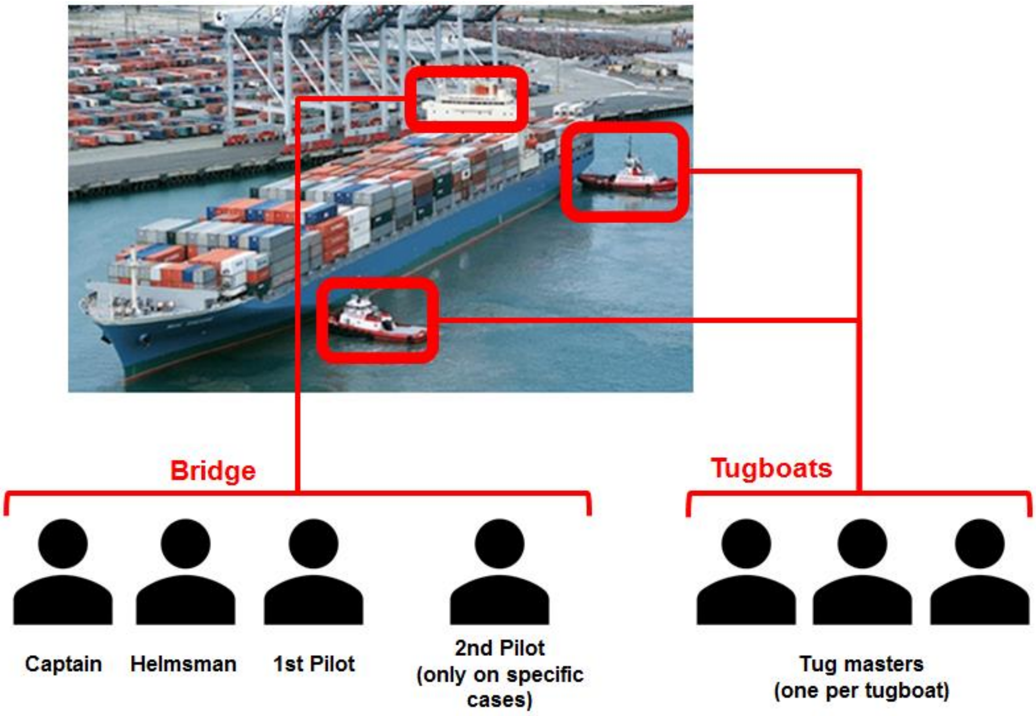
b) the 2nd pilot, who supports the captain and the 1st pilot when a second pilot is required (generally, in special types of maneuvers);

c) the ship captain, representing the maximum authority onboard and responsible for assuming the pilot functions in the pilotage exemption case;

d) the helmsman, responsible for executing the steering commands;

e) the tug masters, who are responsible for controlling the tugboats.

Figure 12 – Human operators that generally take part in a ship maneuver



The remainder of this section details the walkthrough to build the HRA model following the steps depicted in section 3. The familiarization phase was conducted through informal interviews and observations in person at the Numerical Offshore Tank's Maritime Simulator at University of São Paulo – Brazil and at the Port of Santos – Brazil, by following up real ship maneuvers. On its turn, the qualitative analysis allowed building the task sequence models using fault trees and event trees, which were converted in BN models and integrated with the human performance model. The quantitative analysis included the results of generic human error probabilities provided by a prospective human performance model, the TECHR. Finally, the incorporation phase includes the manipulation of the BN model in order to answer quantitatively the research questions mentioned above.

4.1. Familiarization with the port entering operation

The port entering operation is a specific part of a cargo ship's voyage. As the ship approaches the port coastal area, it generally heads to an anchorage area, where it drops the anchor and waits until there is a vacancy on the terminal to perform the loading/unloading operation. The ships at the anchorage area form a kind of queue.

Once a vacancy is available on the terminal, the next ship on this queue receives a calling and is instructed to leave the anchorage area to berth at the terminal, navigating through a navigation channel. Some specific ships should wait not only the vacancy, but also adequate tide conditions if their draft is larger than the port's navigation channel maximum allowed depth at a given period of the day. After receiving the calling, if the ship is on an area subjected to pilotage – what is common to most of the world's ports – they can only navigate from the anchoring area to the terminal with a pilot on board (at least the 1st Pilot, as pointed out in Figure 12). The Pilot gets on board near the (with the ship already in motion), supported by the pilot boat and the pilot ladder on the ship, and disembark only after the ship is berthed.

While the pilot is on board, he/she supports the ship's captain with local knowledge about the navigation channel particularities and coordinates the control of the ship giving steering orders to the helmsman and to the tug masters onboard the tugboats. The captain is responsible to inform the ship's condition to the pilot (e.g., current draft, ship particulars, relevant machinery failures/limitations) and follows up the navigation, being able to intervene whenever he/she judges necessary. The helmsman stays on his/her specific position controlling the engine speed and the rudder according to the pilot orders. Finally, the tug masters, based on the pilot orders, control the tugboats pushing and pulling the ship to perform specific maneuvers and assist the speed reduction. Currently, there is not any type of automation applicable to conventional ships[10] entering a port – the auto-pilot is always turned off for this specific period of the navigation.

During the port entering, the operators develop several types of tasks, whose performance are influenced by several PSFs. With the objective of understanding the operation as a whole and identifying every relevant task to the success of a ship's port entering, the familiarization phase of this work included in person observations of simulations at the Numerical Offshore Tank's Maritime Simulator at University of São Paulo – Brazil, as well as real ship maneuvers in the Port of Santos – Brazil.

The simulator – illustrated in Figure 13 – is composed of hardware structures, such as screens, steering wheel and navigation instruments, and software, such as graphical interface and hydrodynamics models, disposed in an integrated environment inside a simulation room. It includes information about several Brazilian ports and coastal regions and is widely used to reproduce maneuvers that have

[10] Dynamic Positioning vessels may perform port entering with some degree of automation, but this case is out of scope for this Thesis.

never been tried before in the reality or that already occur but need further understanding. Experienced operators are always invited to take part in the simulations. With this, the stakeholders may acquire important insights to support their decision making.

Figure 13 – Numerical Offshore Tank's Maritime Simulator in the University of São Paulo – Brazil

Source: Numerical Offshore Tank (2019).

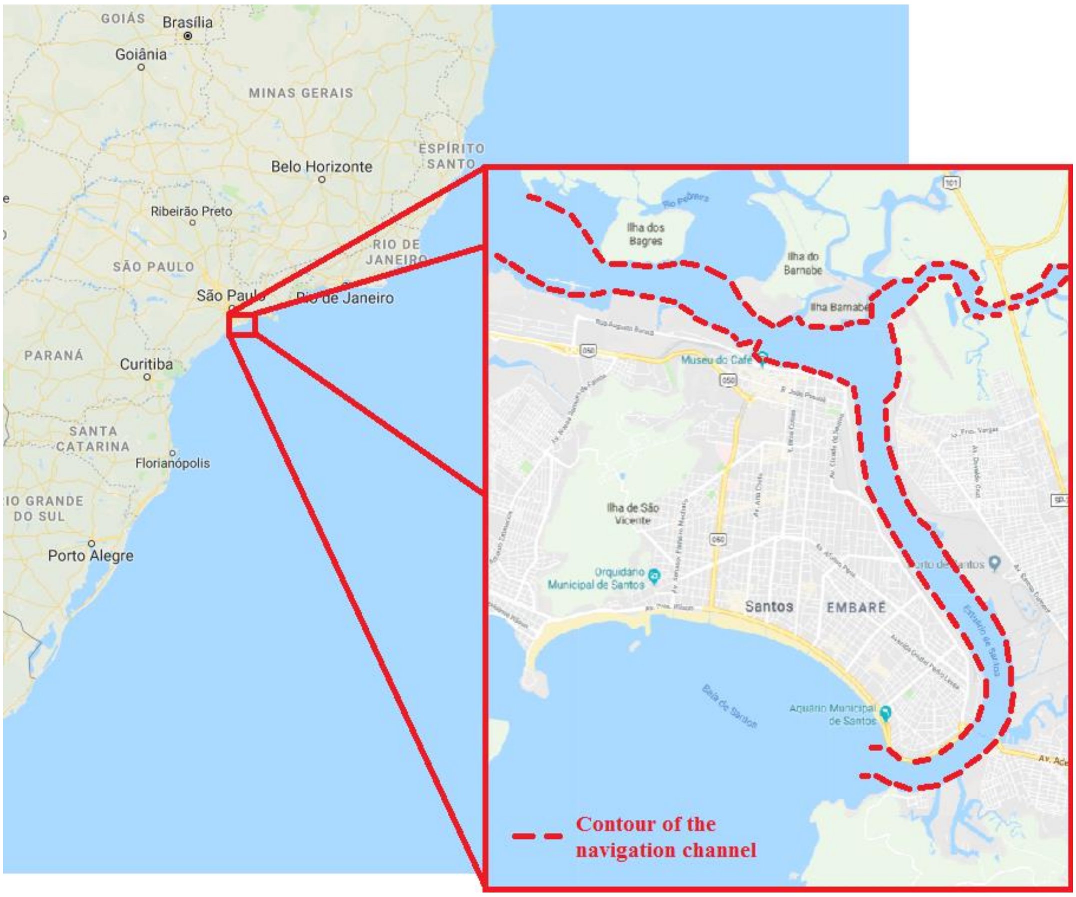
The other field study environment, the Port of Santos, is the largest port in the Latin America in terms of cargo tonnage movement. It is located in the city of Santos, in the state of São Paulo, Brazil. In 2018, the total cargo movement in this port was of approximately 133 million tons, which demanded 4853 ship berths[11], according to the São Paulo State Docks Company (CODESP) (CODESP, 2018). Figures 14 and 15 illustrate, respectively, a photo of the Port of Santos navigation channel and its geographical localization, highlighting the navigable contour. As shown in the figures, the navigation channel contains many small leisure craft in addition to the larger ocean-going vessels and contains some sharp curves.

[11] This number includes 92 passenger ship berths also

Figure 14 – View of the Port of Santos' navigation channel

Source: CODESP (2019).

Figure 15 – Port of Santos localization and part of the navigation channel



The activities developed during the familiarization phase can be divided into two parts: a) unstructured interviews with the operators involved (limited to those operators depicted in Figure 12); and b) direct observation of the operations in real time while they were occurring. In total, 112 hours of simulations and seven real ship maneuvers were followed up during the familiarization phase. The latter category included bulker and container ships, at day and nighttime and, specially, one maneuver employing two pilots.

In the case of simulations, both parts – interviews and observations – were developed separately. This is because generally only one simulation room was being used, but several operators were taking turns with each other. Therefore, there was always one operator available for the interviewing process outside the simulation room. During the observation opportunities at the simulator, only pilots and tug masters were interviewed (no captain or helmsman took part in the simulations).

In contrast, during the real ship maneuvers followed up in the Port of Santos, the observations and interviews were developed simultaneously, since the time available to be onboard the ships was limited to the navigation period. Additionally, since the real operations were occurring, the researchers exercised caution to not interfere negatively the performance of human operators. At this category, the focus was to interview the Captain and Helmsman, since these operators did not participate in the simulations. However, some Pilots were also interviewed during this part of the study.

The direct observations allow identifying certain behaviors and environmental conditions relevant to the problem under analysis (YIN, 2005). Specially, for the HRA purposes, this type of observation contributed to the mapping of the main tasks developed by the operators and the context in which they occur. Also, the direct observations constitute an interesting unbiased form of information gathering, since it do not depends on the description offered by informants, as occurs with the interviews. The disadvantages of the direct observations include the large time consumption, the excessive costs in the case of real ship maneuvers (travel and accommodation costs) and partial coverage of the aspects of interests. The direct observations alone did not allow recognizing exhaustively the set of PSFs influencing the human performance, but some important factors such as those related to communication quality and human-machine interface were identified.

On their turn, the unstructured interviews are a form of gathering relevant information from stakeholders without predetermined questions or answers and that depends on the social interaction between the researcher and the informant (MINICHIELLO et al., 1990). It is necessary to exercise caution when performing the interviews to not allow biases of the informants influence the information quality. During the familiarization, the interviews served as a complement to the direct observations, since they allowed gathering not directly observable information, including the PSFs influencing the operators and narratives of near-misses or accidents they witnessed.

As highlighted by Yin (2005), the direct observations are limited in terms of gathering historical information. Specially, when it refers to rare events, as are the near-misses and accidents in navigation, the factors influencing these occurrences may not be witnessed during the period of observation. Fortunately, one particularity regarding the simulations is the possibility of stressing the environmental conditions to extreme scenarios, in which the likelihood of errors is relatively high. Therefore, during the simulations, it was possible to identify factors influencing the human performance during near-misses and accidents through the direct observations, despite this method not being preconized as the most adequate in the literature.

Summarizing, the familiarization phase consisted of two methodologies to gather information, which are complementary to each other. The results of this step provided inputs to the following step of the HRA methodology – the qualitative analysis –, described in the next section.

4.2. Qualitative analysis

As depicted in section 3.2.2, the objective of the qualitative analysis is to build the topology of the BN for HRA. Firstly, this process involves the development of task networks, which maps the sequence of actions taken by the operators and allows identifying how accidental scenarios potentially occur. Then, once the human actions are known, the analyst is able to develop the human performance network, which interrelates the PSFs causality according to the generic dependency model (as presented previously in Figure 6, section 3.1).

In this Thesis, the task performance network was developed using a model combining event trees and fault trees. The event trees are adequate to represent a sequence of events that are needed for the success of a given event. For instance, it is particularly useful to represent the actions executed by the pilot and the ship crew in order to avoid an accident, given an accidental scenario (e.g., the ship heading to an underwater sandbank). On its turn, the fault trees are useful to model the causes leading to an undesirable event, which postulated as the top event. The potential causes behind each event in the event tree were developed using fault trees. Particularly the human errors were included as basic events of the fault trees and follow the TECHR taxonomy. Afterwards, both models were converted into BNs and integrated to constitute the task network.

The remainder of this section is dedicated to present the development of the task BN and the performance BN.

4.2.1. Task network: event tree modeling

The event trees are a popular model adopted in the probabilistic risk assessment. They can represent the sequence of events necessary to the success of an operation. The typical structure of an event tree includes:

a) an initiating event, which triggers off the following events of the tree;

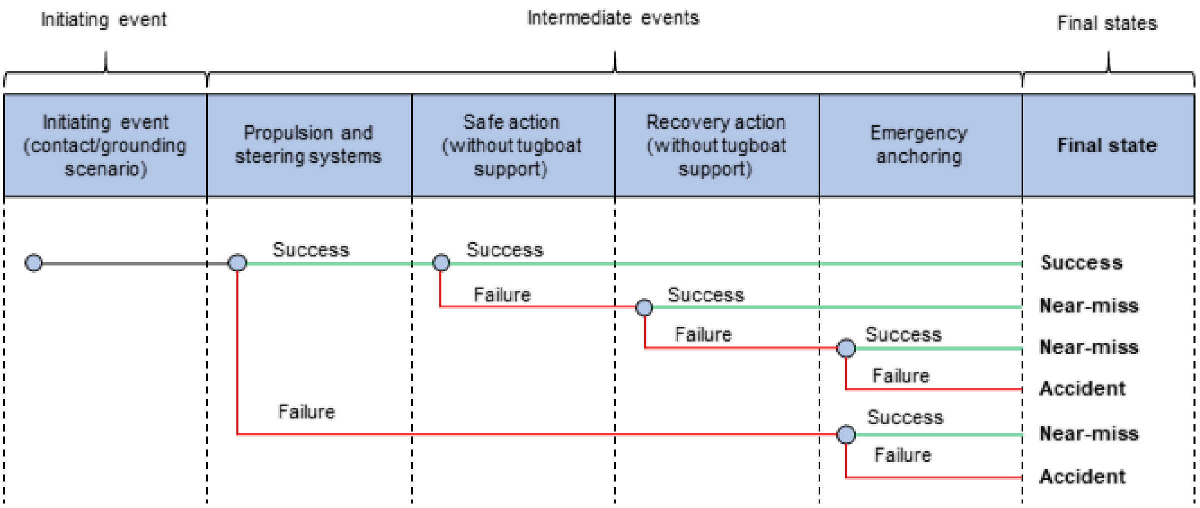
b) intermediate events, which may have success or fail in response to the initiating event or other intermediate events;

c) final states, resulting from the combinations of success and failures of the intermediate events.

Figure 16 present and event tree example. The initiating event generally represents an undesired event for which barriers should exist to prevent an accident. In this sense, each intermediate event can be interpreted as one barrier. Below each intermediate event there are two possible branches: success and failure, indicating the outcome of each barrier in a given scenario. The final states are the result of the combination among the initiating event and the possible outcomes of each intermediate events.

Note that the event tree does not need to be exhaustive, i.e., take into account every possible combination of intermediate events outcomes. Instead, only the plausible combinations are considered. For instance, for the event tree of Figure 16, if the propulsion and steering systems fail, it is not possible to perform safe and recovery actions (since they depend on the proper functioning of the propulsion and steering systems). Therefore, the success and failure branches under these intermediate events do not need to be specified.

Figure 16 – Event tree example



It is always possible to convert an event tree model into a BN model. Figure 17 presents the BN equivalent of the event tree model of Figure 16. There is one node representing the final states among its possible states – success, near-miss and accident. Each intermediate event is modelled as a parent node of the final state node, with two possible states – success and failure – representing the two possible outcomes. Finally, the CPT of the final state node is filled with zeros and ones, representing the logic behind the corresponding event tree. Table 3 presents the CPT for the final state node.

Figure 17 – BN corresponding to the event tree of Figure 16

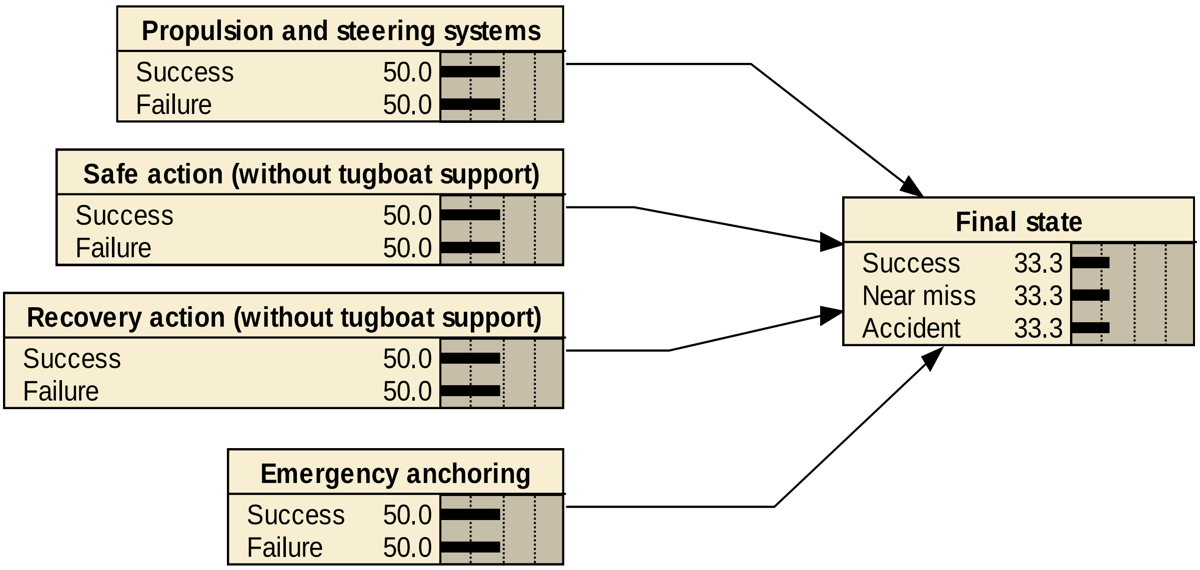
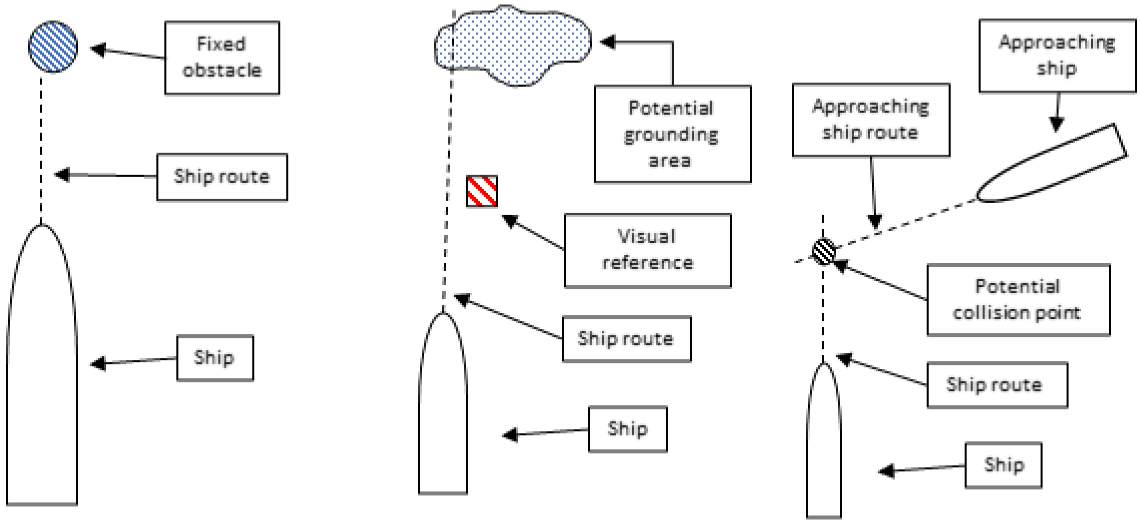


Table 3 – CPT for the node “Final state” of the Figure 17 BN

Propulsion and steering systems	Safe action (w/o tugboat support)	Recovery action (w/o tugboat support)	Emergency anchoring	Final state		
				Success	Near-miss	Accident
Success	Success	Success	Success	1	0	0
Success	Success	Success	Failure	1	0	0
Success	Success	Failure	Success	1	0	0
Success	Success	Failure	Failure	1	0	0
Success	Failure	Success	Success	0	1	0
Success	Failure	Success	Failure	0	1	0
Success	Failure	Failure	Success	0	1	0
Success	Failure	Failure	Failure	0	0	1
Failure	Success	Success	Success	0	0	0
Failure	Success	Success	Failure	0	0	1
Failure	Success	Failure	Success	0	1	0
Failure	Success	Failure	Failure	0	0	1
Failure	Failure	Success	Success	0	1	0
Failure	Failure	Success	Failure	0	0	1
Failure	Failure	Failure	Success	0	1	0
Failure	Failure	Failure	Failure	0	0	1

In this work, the event trees were adopted to model the sequence of actions needed to avoid three specific accidental scenarios illustrated in Figure 18 and described previously in Table 1: contact, grounding, and collision. The contact scenario refers to the ship heading to a fixed obstacle. If no corrective action is taken by the pilot and/or the ship’s crew, then the impact is expected to occur. The grounding scenario involves the ship heading to an area with small depth (less than the ship’s draft). As in the contact scenario, an evasive action is needed to avoid touching the waterway bottom. When navigating restricted waters, the potential grounding area can be identified through navigation equipment indicating the local depths or through visual references. In this latter case, it is assumed that the low depth area is known a priori and is associated with nearby visual references. Finally, the collision scenario refers to the risk of impact between two vessels with concurrent routes. In this case, the evasive action involves detecting the approaching ship, formulate the evasive strategy along with the approaching ship crew, and performing the evasive action effectively.

Figure 18 – Accidental scenarios: a) contact; b) grounding; c) collision



(a) (b) (c)

A total of four event trees were developed, considering the following scenarios:

a) contact/grounding scenario during the waterway navigation phase;

b) contact/grounding scenario during the terminal approaching & berthing or unberthing & terminal departure phases;

c) collision scenario during the waterway navigation phase;

d) collision scenario during the terminal approaching & berthing or unberthing & terminal departure phases.

Initially, the contact and collision scenario were developed separately, since the former refers to the avoidance of visible obstacles above the waterline and the latter refers to underwater obstacles. However, during the familiarization phase, the pilots highlighted that the underwater obstacles are often associated with visual references above the waterline. This fact motivated the development of a single event tree for both types of accident, since the HRA level of resolution did not allow to differentiate them.

Furthermore, the accidents were analyzed according to the different phases of maneuver: a) waterway navigation; and b) terminal approaching & berthing or unberthing & terminal departure. In the first case, the ship is navigating using its own resources, while in the second case the ship's speed is reduced and it has support of tugboats.

The following assumptions were made when building each scenario:

a) the propulsion and steering systems need to be properly working in order to allow the evasive actions;

b) given an accidental scenario, the human operators need to perform a safe action to avoid the accident;

c) if the safe action fails, the human operators have the opportunity to perform a recovery action;

d) if any of the barriers mentioned above fail (propulsion system, steering system, safe action, or recovery action), the last barrier is the emergency anchoring;

e) in the collision scenario, the approaching ship needs to be identified and the evasive maneuver should be performed;

The final states were divided into three categories: success, near-miss, and accident. A “success” final state indicates that every barrier functioned successfully. A “near-miss” final state indicates that the accident did not occur, despite the failure of at least one barrier. An “accident” final state indicates that all the barriers failed and the accidental scenario resulted in one of the undesired consequences (collision, contact, or grounding).

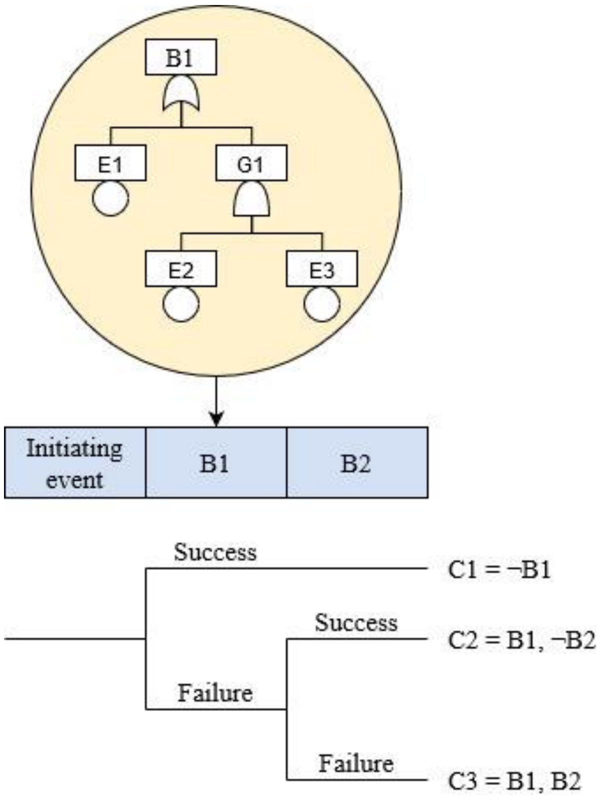
Whenever applicable (e.g., safe action, recovery action), the barrier failure probabilities are computed for three pilotage conditions: a) one pilot onboard; b) two pilots onboard; and c) no pilot onboard (i.e., pilotage exemption). For each intermediate event, a fault tree model is developed and integrated in the BN format. The next section presents the fault tree modelling.

4.2.2. Task network: fault tree modeling

The barrier failures in the event tree models presented in section 4.2.1 were modelled using fault trees. The failure of an intermediate event was postulated as the top event of a fault tree, for which the possible causes were deduced. Figure 19 illustrates the proposed model integration. This approach was particularly interesting to map the human errors and their integration with physical system failures (e.g., propulsion and steering system failures, radar failure). Furthermore, by combining multiple human errors, it is possible to evaluate the chain of errors leading to an accident. For a deeper discussion regarding the fault tree modelling along with its benefits and limitations can be found in Modarres, Kaminskiy and Krivstov (1999).

The Appendix B presents all the fault tree models developed in this work. Except by the “Propulsion or steering system failure” fault tree (see section B.1), which is exclusively dedicated for modelling physical system failures, the remaining fault trees are developed considering one pilot onboard, two pilots onboard, and no pilot onboard. Each fault tree was converted into a BN model following the rules presented previously in section 3.2.2 (see Figure 9).

Figure 19 – Integration of fault tree models on event tree models

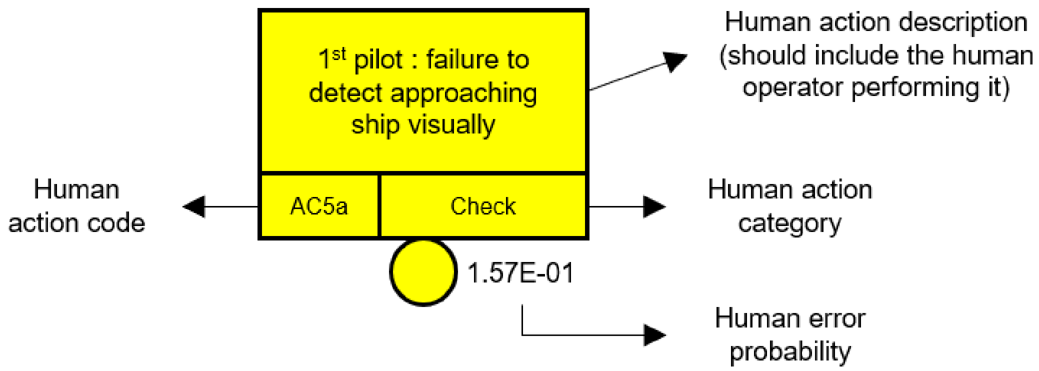


Source: Abreu et al. (2020)

For the fault tree models, the basic events representing human errors are associated with the best fitting human error category considering the TECHR taxonomy (MATURANA, 2017). Appendix C presents the complete taxonomy of human actions and their brief descriptions. The advantage of establishing such relationships is made clear during the quantitative analysis phase: once the human action category is known, it is possible to quantify the HEP using the generic probabilities from the TECHR.

As presented in Figure 20, a special basic event symbology was adopted in the fault tree models in order to indicate the corresponding human action categories adopted for each identified human action. The basic event description box includes the action under consideration and the operator performing it. Under this box, there are the human action code, according to the Appendix C, and the corresponding human action category. Finally, the associated HEP are also indicated below the basic event box (section 4.3 details the quantification procedures).

Figure 20 – Human error basic event symbology



Once both, the event tree and the fault tree models are complete, integrated and converted into the corresponding BN, they constitute the task network (see Figure 10). The remainder of the qualitative analysis involves developing the performance network (developed as a BN from the very beginning) and integrating it with the task network. This integration allows relating PSFs and human actions, therefore allowing computing the influence of each PSF on the overall HEPs. The following two sections present the development of the performance network. Section 4.2.3 introduces and discusses the PSFs adopted in this work, while section 4.2.4 presents the development of the performance network topology.

4.2.3. Performance shaping factors

In the field of HRA, there is no consensus regarding which or how many PSFs should be used to build a model. In fact, the number of PSFs among different techniques varies from 1 to up to 60 (BORING, 2010), aiming at satisfying several different purposes.

In this Thesis, the initial set of PSFs proposed was identical to those presented by Maturana (2010), mainly because of two reasons: a) similar area of study (maritime navigation); and b) similar purpose of analysis. However, during the development of the qualitative analysis, the feedback of the experts (i.e., the operators interviewed) suggested that the description of the PSFs could be improved in order to better represent their contexts.

Therefore, the initial set of PSFs was modified to fit the pilotage context. During the implementation of these changes, the principle of covering all necessary factors was observed at all moments. Additionally, definitions were appended to each PSF looking forward to ensuring its comprehension without ambiguity.

The MOFs, environmental factors, internal factors, and skills are presented respectively from Table 4 to 7, each one identified with a code. Each MOF have three codes, representing the three organizations influencing the operators: the local pilot’s organization (prefix “PIL”), the ship owner (prefix “SOW”) and the tug owner (prefix “TOW”).

Table 4 – Definition of the management & organizational factors

Code	MOF	Definition
PIL01, SOW01, TOW01	Work overload	Existence of an amount of workload that exceeds what would be considered adequate for its function.
PIL02, SOW02, TOW02	Low workload	Existence of an amount of workload below what would be considered adequate for its function.
PIL03, SOW03, TOW03	Work standardization	Existence of well-defined procedures for the execution of a specific task, such as step-by-step instructions and emergency checklist.
PIL04, SOW04, TOW04	Work coordination	Use of strategies and behavioral patterns aimed at integrating actions, knowledge and objectives of interdependent members of a team, aiming at a common goal. Coordination of work makes the operators work as a unit.
PIL05, SOW05, TOW05	Organizational culture	Set of values of an organization that contribute to an overall view around its objectives and, if proven valid, is taught to later generations (RICO at al., 2011).
PIL06, SOW06, TOW06	Awards, acknowledgements, and benefits	Existence of bonuses and honors to the operators that stand out in the context of the work, motivated by good performance and/or remarkable attitudes.
PIL07, SOW07, TOW07	Life quality	Set of factors internal to the work environment (e.g., non-monotony, autonomy, participation in the business, perception of significance) that promote the operator satisfaction.

Table 4 – Definition of the management & organizational factors (continuation)

Code	MOF	Definition
PIL08, SOW08, TOW08	Performance evaluation	Feedback from leaders and managers on operator performance.
PIL09, SOW09, TOW09	Personnel selection	Adequacy of the selective process of human resources selection, regarding choosing the individuals of better qualification for the function to be performed.
PIL10, SOW10, TOW10	Personnel turnover	Diversification of work environments in which the operator performs his/her functions.
PIL11, SOW11, TOW11	Training	Measures that increase the operator's proficiency in relation to his/her function.
PIL12, SOW12, TOW12	Commercial pressure	The relation between the commercial pressure that seeks system efficiency versus commercial pressure that overlooks safety.
PIL13, SOW13, TOW13	Enforcement of laws and regulations	Strength of the actions of regulatory bodies towards the function performed. It is associated not only with the existence of rules, laws and penalties, but also their practical application.
PIL14, SOW14, TOW14	Time management	Adequacy of scheduling of the organization activities in relation to the time needed for its fulfillment.
PIL15, SOW15, TOW15	Organizational learning	Ability of the organization to apply its operational experience in the context of the operation. It includes learning with errors and the implementation of continuous improvement policies.
PIL16, SOW16, TOW16	Communication capacity	Quality and quantity of communication means within an organization and between organizations. It also covers the ability of the members in the standard language of communication and/or codified languages.
PIL17, SOW17, TOW17	Infrastructure	Quality of the physical installations and adequacy of the machines & equipment layouts.

Table 5 – Definition of the environmental factors

Code	Environmental factor	Definition
EF01	Temperature	Adequacy of local temperature in terms of thermal comfort to operators. High or low temperatures can negatively impact human performance.
EF02	Humidity	Adequacy of the humidity of the air to the healthy levels for the human being. Both dry and wet weather can negatively impact human performance.
EF03	Luminosity	Illumination level of the place of execution of the task12 (differs, therefore, from the visibility) - natural or artificial.
EF04	Noise	Continuous or intermittent presence of unpleasant sounds to the hearing.

[12] Usually, the ship’s bridge

Table 5 – Definition of the environmental factors (continuation)

Code	Environmental factor	Definition
EF05	Vibration	Regular and repetitive movement whose intensity or frequency causes annoyance to operators.
EF06	Cleaning	Level of impurities at the place of execution of the task, focusing on the impact on the well-being of the operators.
EF07	Visibility	Visibility conditions of the external environment to the place of execution of the task (differs, therefore, from the luminosity). Influenced, for example, by the presence of precipitation or fog.
EF08	Current, winds and waves	Factors that may add difficulty to the maneuver by directly influencing the behavior of the ship.

Table 6 – Definition of the internal factors

Code	Internal factor	Definition
IF01	Physical stress	Physical strain caused by a stressor (SWAIN; GUTTMANN, 1983).
IF02	Mental stress	Mental strain caused by a stressor (SWAIN; GUTTMANN, 1983).
IF03	Influence of third parties	Tendency to perform deviations due to the influence of people or organizations that do not take part in the developed task.
IF04	Identification with the team	Perspective of the individual in relation to a work group, in terms of a unit with a common goal (CAMPION; PAPPER; MEDSKER, 1996).
IF05	Personality and intelligence	The mental capacity of the operator (GOTTFREDSON, 1997) and the set of individual characteristic patterns that contribute to the good execution of the task (SAUCIER, 2009).
IF06	Motivation and attitude	Activating, targeting and sustaining behavior towards a goal (ROBERTS; SADLER, 2019).
IF07	Knowledge of standards	Level of knowledge regarding the standards and rules that regulate the activity performed.
IF08	Experience and training	Time of experience of an operator, as well as the attendance to trainings, amount of time spent since last training session and knowledge regarding the systems relevant to the task (BLACKMAN; GERTMAN; BORING, 2008).
IF09	Inactivity and state of practice	Impact of long periods without action on the operator's proficiency regarding the activity performed.
IF10	Time pressure	Impact of the time pressure on the operator’s cognitive ability.
IF11	Fatigue	Tiredness or exhaustion (usually verbalized), with decreased ability to perform habitual activities and lack of relief for these manifestations with the application of usual energy recovery strategies (MOTA; CRUZ; PIMENTA, 2005).
IF12	Pain and discomfort	Sensorial and emotional unpleasant experience associated with actual or potential physical damage or described in terms of such damages (MERSKEY et al., 2002).
IF13	Sedentary lifestyle	No physical activity or persistent inactivity. Do not engage in moderate or high intensity physical activity at least five times a week (RICCIARDI, 2005).

Table 6 – Definition of the internal factors (continuation)

Code	Internal factor	Definition
IF14	Emotional state	Psychological and physiological state in which emotions and behaviors are interconnected and appreciated in a context (KIM et al., 2013).
IF15	Sleep quality	Feeling of restoration upon waking and during the day, in addition to the continuity of sleep at night (do not wake up often during sleep) (HARVEY et al., 2008).
IF16	Risk sensitivity	Measure how much the operator is disposed to accept.
IF17	Monotony	A transient affective state in which an individual feels he has nothing, little or something uninteresting in the moment to do, or does not feel like doing something, but wishes to be entertained (FISHER, 1987).
IF18	Distractions	Deviation of attention from an individual in relation to their main task. It can be caused by conversation, meals, manipulating navigation system, cell phone usage, and other.
IF19	Conflicts about performance	Conflicts about which is the best result of a given task, generally involving tradeoffs (e.g., safety vs. productivity).

Table 7 – Definition of the skills

Code	Skill	Definition
SKL01	Interpretation	Ability to perceive information and transform it into parameters for decision making.
SKL02	Calculations	Ability to perform operations with numerical quantities.
SKL03	Concentration	Ability to keep focus on a single task.
SKL04	Knowledge of procedures	Knowledge of the operator regarding the pre-established procedures to carry out the task performed.
SKL05	Long-term and short-term memory	Ability to retrieve from memory information relevant to the task performed.
SKL06	Physical resistance	Stamina; ability to stand for long periods of time activities with aerobic and muscular demands.
SKL07	Motor control	Ability to precisely perform commands that require motor functions.
SKL08	Team and communication	Ability to interact with the work team in order to favor the harmonious execution of group tasks.
SKL09	Frequency and repeatability	Skill associated with the proficiency acquired around a given task due to its repetition.
SKL10	Perception	Ability to acquire information and/or receive stimuli from the senses or the mind.
SKL11	Planning	Ability to organize a set of procedures and actions in order to successfully serve a goal or tasks that contribute to it.
SKL12	Leadership	Ability to lead a task force to achieve a specific goal.
SKL13	Creativity	Ability to establish plausible solutions in unpublished contexts.
SKL14	Flexibility	Ability to adapt to unusual or extraordinary contexts.
SKL15	Empathy	Ability to understand the condition of another individual.

The performance model was initially developed adopting the PSF described above. However, during the quantification phase, it was not possible to compile the full model (integrating the performance and task networks) due to its size. The software used in this work, Netica 4.11, was not able to compute the BN probabilities with all the PSFs considering all the operators (captain, 1st pilot, 2nd pilot, helmsman, and tug master) and all the organizations (pilotage, ship owner, and tugboats owner). Therefore, the qualitative analysis needed to be rebuilt.

The solution adopted to overcome the computational problem was to reduce the number of PSFs included in the model. This reduction was performed by creating higher level PSFs, which encompass the PSFs from the initial set. In fact, some authors such as Groth and Mosleh (2012a) highlight that a PSF set with a large number of factors is adequate for qualitative analysis, but eventually will not be the best for quantitative analysis. The reduced PSF set for each PSF category is presented from Table 8 to Table 11, including the corresponding factors from the initial set that were grouped together. Nonetheless, some additional PSFs were included, referring to factors not covered by the initial set.

Table 8 – Mapping of the MOFs from the initial to the reduced PSF set

Reduced set MOF	Corresponding PSFs from the initial set
Activities scheduling	• Work overload • Time management
Personnel management	• Low workload • Personnel selection • Personnel turnover • Enforcement of laws and regulations
Safety culture	• Safety culture • Performance evaluation • Organizational learning • Enforcement of laws and regulations
Work satisfaction	• Awards, acknowledgements, and benefits • Life quality
Necessary information	• Communication capacity • Infrastructure
Workplace adequacy	• Infrastructure
Commercial pressure	• Commercial pressure • Enforcement of laws and regulations

Table 8 – Mapping of the MOFs from the initial to the reduced PSF set (continuation)

Reduced set MOF	**Corresponding PSFs from the initial set**
Training	• Training program • Enforcement of laws and regulations
Work standardization	(new PSF)

Table 9 – Mapping of the environmental factors from the initial to the reduced PSF set

Reduced set environmental factor	**Corresponding PSFs from the initial set**
Visual conditions	• Visibility • Luminosity
Climate conditions	• Temperature • Humidity
Workplace hospitality	• Noise • Vibration • Cleaning
Navigation impairment factors	• Current, winds, and waves

Table 10 – Mapping of the internal factors from the initial to the reduced PSF set

Reduced set internal factor	**Corresponding PSFs from the initial set**
Physical resources	• Physical stress • Fatigue • Pain and discomfort • Sedentary lifestyle
Mental resources	• Mental stress • Emotional state • Sleep quality • Monotony • Distractions
Perceived situation	• Influence of third parties • Risk sensitivity • Conflicts about performance
Attitude	• Personality and intelligence • Motivation and attitude
Training and experience	• Knowledge of standards • Experience and training • Inactivity and state of practice
Team identification	(new PSF)
Time pressure	(new PSF)

Table 11 – Mapping of the skills from the initial to the reduced PSF set

Reduced set skill	Corresponding PSFs from the initial set
Situation assessment	• Interpretation • Calculations • Memory (short-term)
Situation awareness	• Concentration • Perception
Situation familiarity	• Knowledge of procedures • Memory (long-term) • Frequency and repeatability
Physical skills	• Physical resistance • Motor control
Teamwork	• Team and communication • Leadership • Empathy
Response	• Planning • Creativity • Flexibility
Vision	• Perception

4.2.4. The performance BN topology

Once all human actions necessary to the operation success are identified, as well as the PSFs, it is possible to determine the BN topology according to the generic dependency model (see Figure 6). The following relations should be established:

a) which skills influence each generic human action;

b) which internal factors and environmental factors influence each skill;

c) which MOF influence each internal factor.

The relations are presented in tabular format, from Table 12 to Table 14. They were defined based on the information gathered during the familiarization phase along with the experts. These tables are sufficient to build the performance BN model, since the direction of the arcs should follow strictly the generic dependence model. The performance BN is then integrated with the task BN on the human action level (i.e., for each human action node), giving rise to a single model.

Table 12 – Relations among skills and generic human actions

	Skills						
Generic human actions	Situation assessment	Situation awareness	Situation familiarity	Physical skills	Teamwork	Response	Vision
AC1a: Recognize	X	X	X				
AC1b: Remember			X				
AC2a: Interpret	X		X				
AC2b: Exemplify			X			X	
AC2c: Rank	X		X				
AC2d: To sum up	X		X				
AC2e: Infer	X					X	
AC2f: Compare	X						
AC2g: Explain			X			X	
AC3a: Execute			X				
AC3b: Implement	X					X	
AC4a: Differentiate	X		X				
AC4b: Organize	X					X	
AC4c: Assign	X		X				
AC5a_1: Check (internal)		X	X				
AC5a_2: Check (external)		X	X				X
AC5b: Criticize	X	X					
AC6a: Generate	X					X	
AC6b: Plan			X			X	
AC6c: Produce						X	
AA1: Receptivity		X			X		
AA2: Answer		X			X	X	
AA3: Appreciation			X		X		
AA4: Conceptualization of values					X	X	
AA5: Internalization of values					X	X	
AP1: Reflective motion				X			
AP2: Basic movement				X			
AP3: Perceptive ability				X			X
AP4: Physical ability				X			
AP5: Qualified movement			X	X			
AP6: Nonverbal communication	X			X			

Table 13 – Relations among internal factors & environmental factors and skills

	Internal factors							**Environmental factors**			
Skills	Physical resources	Mental resources	Perceived situation	Attitude	Training and experience	Team identification	Time pressure	Visual conditions	Climate conditions	Workplace hospitality	Navigation impairment factors
Situation assessment		X	X		X		X				
Situation awareness		X	X						X	X	X
Situation familiarity					X						
Physical skills	X									X	
Teamwork				X	X						
Response				X	X		X				
Vision								X			

Table 14 – Relations among MOFs and internal factors

	MOFs								
Internal factors	Activities scheduling	Personnel management	Safety culture	Work satisfaction	Necessary information	Workplace adequacy	Commercial pressure	Training	Work standardization
Physical resources				X		X			
Mental resources	X			X		X	X		
Perceived situation			X		X		X		
Attitude		X	X				X	X	
Training and experience			X					X	
Team identification		X							
Time pressure	X		X				X		X

The resulting BN was developed using the software Netica 4.11. All the necessary information to reproduce it was presented along the section 4.2 and is complemented in section 4.3 (quantitative analysis). However, the size of the visual model is impeditive when trying to reproduce it in this document. As an alternative, Figure 21 presents a “zoomed out” picture of the complete model for the collision accident, highlighting the main categories of nodes. The colored boxes represent the nodes of the network while the black lines represent the arcs.

The event tree nodes map the event tree models as BN. Following the example of Figure 17, there is one node that represents the final states and several parent nodes representing the event tree intermediate events. Each intermediate event is connected to several other nodes representing the fault trees.

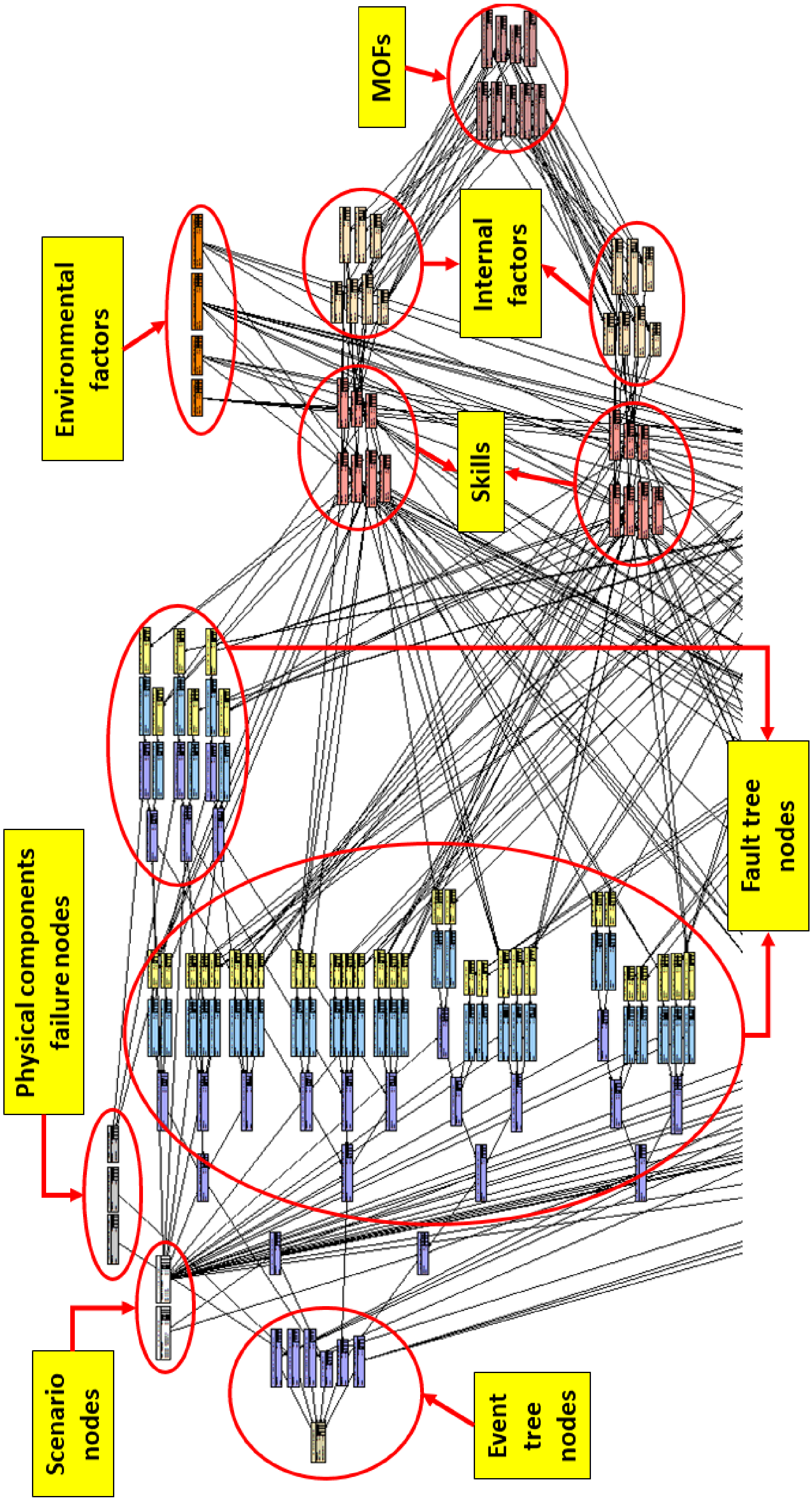
The fault tree nodes are dedicated to convert the fault tree models (presented in Appendix B) into their BN correspondents, following the rules presented in Figure 9 for each type of gate. The basic events are composed by human action nodes (in yellow) and physical components failure nodes (accounting for steering system, propulsion system, and radar failures). The human action nodes are connected to the performance network nodes on the rightmost part of the model.

Scenario nodes were introduced in the model to allow utilizing the same network to represent the different pilotage scenarios (one pilot, two pilots, or no pilots onboard), and the availability of tugboats. By setting the states of these nodes as evidence, it is possible to modify the fault tree nodes (and, consequently, the event tree nodes), in order to consider specific situations, such as “pilotage exemption without tugboat support”, and “one pilot onboard with tugboat support”.

The set of event tree nodes, fault tree nodes, physical components failures nodes, and scenario nodes represent the task network.

The performance network is composed by the PSF nodes representing the skills, environmental factors, internal factors, and MOFs. In Figure 21, the performance network of the 1st and 2nd pilots is presented. They share the same MOFs and environmental factors but have individual sets of internal factors and skills nodes. Other operators would share different MOFs (since they are influenced by other organizations), but always the same environmental factors. As expected, each operator has its own internal factors and skills nodes.

Figure 21 – Excerpt of the complete BN model (performance network + task network)



4.3. Quantitative analysis

Since the proposed BN model for HRA is generic, its quantification should be somehow generalist. Therefore, while the model may not represent accurately the conditions of a specific port, it is adequate to capture the main tendencies towards the operators' performance. This is achieved by using a priori HEP derived from the TECHR, interpolation rules to fill the CPTs and assuming a priori probabilities to the leaf nodes[13]. This section is dedicated to detail the process of quantification, focusing on the performance BN, since the task BN is purely composed of logic relations, therefore leading to CPTs filled with zeros and ones.

The human performance BN nodes represent variables that can assume only two states. The possible states for the nodes in the human action category are "success" and "failure", while for the PSFs the possible states are "positive" and "negative". A positive state indicates a condition in which the PSF contributes to improve the human performance, while a negative state indicates that the PSF is degrading it.

Even though each node have only two possible states, filling the CPT can easily be infeasible due to the large number of possible combinations of parent nodes states. For instance, if a child node has 5 parents, it needs $2^5 = 32$ values to be introduced. Given that the complete performance BN (including all operators) have dozens of nodes, this quantification procedure can quickly become infeasible. Therefore, an alternative method is necessary to fill the CPTs to the detriment of an exhaustive filling. This Thesis uses the interpolation rule proposed by Martins and Maturana (2013). Additionally, a calibration procedure is adopted to ensure that the HEPs computed by the BN are equal[14] to those obtained using the TECHR.

Firstly, regarding the interpolation rule, two reference values are adopted for each CPT, namely the minimum and the maximum, denoted respectively by MIN and MAX. The minimum value represents the probability that the node is in its positive/success state when all the parents are in their negative states. On the other hand, the maximum value represents the probability that the node is in its positive/success state when all the parents are in their positive states. It is enough to determine the values for the positive/success states, since their sum with the negative/failure states

[13] Nodes that have no parents
[14] With a given precision

should be unitary, therefore uniquely defining the latter. The computation of the probabilities of a child node state given a combination of parent nodes states is performed through the following expression:

$$\mathrm{Pr}(+) = \mathrm{MIN} + (\mathrm{MAX} - \mathrm{MIN}) \cdot \frac{k}{N} \tag{38}$$

$$\mathrm{Pr}(-) = 1 - \mathrm{Pr}(+) \tag{39}$$

Where $\mathrm{Pr}(+)$ denotes the probability of the child node positive/success state, $\mathrm{Pr}(-)$ denotes the probability of the child node negative/failure state, k is the number of parent notes on their positive/success states and N is the total number of parent nodes.

The interpolation method can be illustrated through an example. Figure 22 presents an excerpt of the BN for the skill node “SKL01: Interpretation”. Its parents are the internal factor nodes “IF02: Mental stress”, “IF08: Experience and training” and “IF10: Time pressure”. The filling of its CPT is illustrated in Table 15, which indicates the states of the parent nodes, as well as the values of k, $\mathrm{Pr}(+)$ and $\mathrm{Pr}(-)$ for each parent nodes states combination. Since there are three parent nodes, $N = 3$. For this example, the values of 0.20 and 0.80 were adopted for MIN and MAX, respectively.

Figure 22 – Excerpt of the BN illustrating the node “SKL01: Interpretation” and its parents

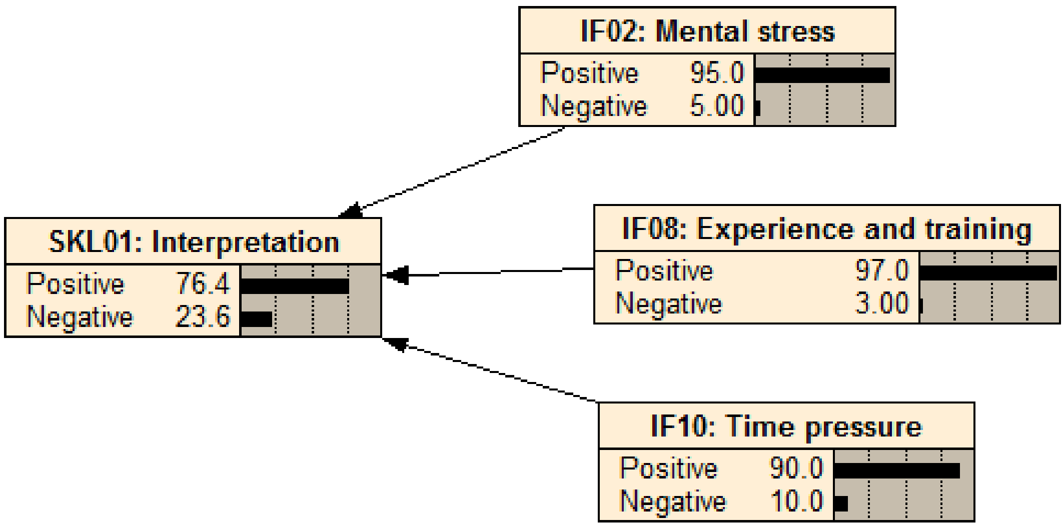


Table 15 – CPT filling for the "SKL01: Interpretation" node with $\mathrm{MIN} = 0.20$ and $\mathrm{MAX} = 0.80$

Interpretation		Mental stress	Experience and training	Time pressure	k
$\mathrm{Pr}(+)$	$\mathrm{Pr}(-)$				
0.80	0.20	Positive	Positive	Positive	3
0.60	0.40	Positive	Positive	Negative	2
0.60	0.40	Positive	Negative	Positive	2
0.40	0.60	Positive	Negative	Negative	1
0.60	0.40	Negative	Positive	Positive	2
0.40	0.60	Negative	Positive	Negative	1
0.40	0.60	Negative	Negative	Positive	1
0.20	0.80	Negative	Negative	Negative	0

To sum up, the interpolation method allows filling the CPTs in a simple manner, making a previously unfeasible problem viable. The idea that an interpolated CPT is representative of the human behavior finds its foundations on the assumption that the PSFs have cumulative effects. In other words, the more positive are the PSFs, the better is the human performance and the inverse is true when dealing with negative states.

However, at this point, a question emerges: how to adequately define the values of MIN and MAX for each CPT? One possible way is to elicit experts, as is generally done when quantifying BN models that deal with rare events or events for which empiric data is scarce or nonexistent (MKRTCHYAN; PODOFILLINI; DANG, 2016). In this work, an alternative method is proposed. using the HEPs derived from a prospective human performance model, the TECHR, which combines values from several consolidated HEP data sources. It is called here the "calibration" of the HRA model.

This calibration process consists of varying the MIN and MAX values of each CPT until the relative difference between the values of HEP calculated by the TECHR and by the BN model is less than a given value of precision, ϵ. Therefore, the calibration process' acceptance criterion is given by:

$$\frac{\left|\mathrm{HEP}_i^{TECHR} - \mathrm{HEP}_i^{model}\right|}{\mathrm{HEP}_i^{TECHR}} \leq \epsilon, \qquad for\ i = 1, \dots, n \tag{40}$$

Where HEP_i^{TECHR} and HEP_i^{model} denote the HEPs for the ith generic human action calculated by the TECHR and the BN model, respectively, and n is the number of generic human actions included in the model. The HEP values extracted from the TECHR are presented in Table 16. For the quantification procedure, this work adopted the mean values of Table 16.

In practice, the calibration process can be written as the following optimization problem:

$$\text{minimize} \sum_{i=1}^{n} \frac{\left|\text{HEP}_i^{TECHR} - \text{HEP}_i^{model}\right|}{\text{HEP}_i^{TECHR}} \tag{41}$$

Subjected to:

$$0 \leq \text{MIN}_j \leq 1, \qquad for\ j = 1, \dots, m \tag{42}$$

$$0 \leq \text{MAX}_j \leq 1, \qquad for\ j = 1, \dots, m \tag{43}$$

$$\text{MIN}_j \leq \text{MAX}_j, \qquad for\ j = 1, \dots, m \tag{44}$$

Where MIN_j and MAX_j indicate the values of MIN and MAX for the jth CPT, assuming a total of m CPTs within the model.

The quantification of the CPTs depends on the existence of a priori probabilities on the model leaf nodes – i.e., the MOFs and environmental factor nodes. Since the proposed model is generic, these values are not determined empirically: instead, reasonable values proposed in the literature are adopted (Martins and Maturana, 2013). This procedure does not interfere in the main purpose of the HRA model, which is computing the influence of each factor on the tasks HEPs. The sensitivity analysis measures are modified, but the ranking among the most important factors is not. Furthermore, the accident marginal probabilities are not influenced either, since they depend only on the HEPs derived from the TECHR.

Adopting the structure of quantification depicted above, the HRA model was quantified using the following conditions:

a) calibration precision: ϵ = 1.00E-04;

b) solver method: Microsoft® Office Excel GRG Nonlinear;

c) initial values: $\text{MIN}_i = 0.00$ and $\text{MAX}_i = 1.00$ for each $i = 1, \dots, n$;

d) a priori probabilities for the environmental factors' nodes: $\Pr(+) = 0.95$ and $\Pr(-) = 0.05$;

e) a priori probabilities for the MOFs' nodes: $\Pr(+) = 0.95$ and $\Pr(-) = 0.05$.

The optimization problem converged without convergence problems.

Table 16 – Generic human actions error probabilities according to the TECHR

Human action code	Human action	Human Error Probability			
		5th percentile	Median	95th percentile	Mean
AC1a	Recognize	1.00E-02	7.00E-02	3.00E-01	9.69E-02
AC1b	Remember	5.00E-03	5.00E-02	2.00E-01	6.41E-02
AC2a	Interpret	9.00E-04	2.00E-02	2.00E-01	4.28E-02
AC2b	Exemplify	1.00E-02	6.00E-02	2.00E-01	7.47E-02
AC2c	Rank	4.00E-03	5.00E-02	2.00E-01	7.03E-02
AC2d	Sum up	6.00E-03	4.00E-02	2.00E-01	5.90E-02
AC2e	Infer	4.00E-02	1.00E-01	3.00E-01	1.39E-01
AC2f	Compare	1.00E-02	6.00E-02	2.00E-01	7.02E-02
AC2g	Explain	3.00E-02	1.00E-01	3.00E-01	1.29E-01
AC3a	Execute	1.00E-02	7.00E-02	3.00E-01	9.38E-02
AC3b	Implement	1.00E-02	9.00E-02	3.00E-01	1.11E-01
AC4a	Differentiate	6.00E-03	4.00E-02	1.00E-01	5.17E-02
AC4b	Organize	2.00E-02	1.00E-01	3.00E-01	1.10E-01
AC4c	Assign	2.00E-03	3.00E-02	2.00E-01	5.29E-02
AC5a	Check	4.00E-02	1.00E-01	4.00E-01	1.57E-01
AC5b	Criticize	7.00E-02	2.00E-01	4.00E-01	2.06E-01
AC6a	Generate	7.00E-02	2.00E-01	4.00E-01	2.06E-01
AC6b	Plan	7.00E-02	2.00E-01	4.00E-01	2.06E-01
AC6c	Produce	7.00E-02	2.00E-01	4.00E-01	2.06E-01
AA1	Receptivity	1.00E-02	7.00E-02	3.00E-01	9.38E-02
AA2	Answer	1.00E-02	9.00E-02	3.00E-01	1.11E-01
AA3	Appreciation	7.00E-02	2.00E-01	4.00E-01	2.06E-01
AA4	Values conceptualization	7.00E-02	2.00E-01	4.00E-01	2.06E-01
AA5	Values internalization	7.00E-02	2.00E-01	4.00E-01	2.06E-01
AP1	Reflective motion	7.00E-04	1.00E-02	1.00E-01	2.69E-02
AP2	Basic movement	8.00E-03	5.00E-02	2.00E-01	7.20E-02
AP3	Perceptive ability	1.00E-03	2.00E-02	1.00E-01	3.69E-02
AP4	Physical ability	1.00E-02	6.00E-02	3.00E-01	8.40E-02
AP5	Qualified movement	1.00E-02	6.00E-02	3.00E-01	8.40E-02
AP6	Nonverbal communication	1.00E-02	6.00E-02	3.00E-01	8.40E-02

Source: Maturana and Martins (2019)

Table 17 presents the resulting values for each node marginal probabilities, as well as the MIN and MAX (if applicable). All the HEPs converged to the desired precision of 1.00E-04 for the generic human actions.

Table 17 – Performance network nodes' marginal probabilities and values adopted for MIN and MAX

Node	Category	Positive/success state marginal probability	Negative/failure state marginal probability	**MIN**	**MAX**
AC1a: Recognize	Generic human action	9.03E-01	9.69E-02	0.46	0.93
AC1b: Remember	Generic human action	9.36E-01	6.41E-02	0.40	0.97
AC2a: Interpret	Generic human action	9.57E-01	4.28E-02	0.37	0.99
AC2b: Exemplify	Generic human action	9.25E-01	7.47E-02	0.31	0.97
AC2c: Rank	Generic human action	9.30E-01	7.03E-02	0.30	0.96
AC2d: Sum up	Generic human action	9.41E-01	5.90E-02	0.31	0.97
AC2e: Infer	Generic human action	8.61E-01	1.39E-01	0.61	0.88
AC2f: Compare	Generic human action	9.30E-01	7.02E-02	0.36	0.96
AC2g: Explain	Generic human action	8.71E-01	1.29E-01	0.06	0.93
AC3a: Execute	Generic human action	9.06E-01	9.38E-02	0.19	0.95
AC3b: Implement	Generic human action	8.89E-01	1.11E-01	0.32	0.92
AC4a: Differentiate	Generic human action	9.48E-01	5.17E-02	0.20	0.99
AC4b: Organize	Generic human action	8.90E-01	1.10E-01	0.25	0.93
AC4c: Assign	Generic human action	9.47E-01	5.29E-02	0.25	0.98
AC5a: Check	Generic human action	8.43E-01	1.57E-01	0.17	0.90
AC5b: Criticize	Generic human action	8.43E-01	1.57E-01	0.58	0.86
AC6a: Generate	Generic human action	7.94E-01	2.06E-01	0.01	0.85
AC6b: Plan	Generic human action	7.94E-01	2.06E-01	0.01	0.84
AC6c: Produce	Generic human action	7.94E-01	2.06E-01	0.07	0.84
AA1: Receptivity	Generic human action	7.94E-01	2.06E-01	0.14	0.84
AA2: Answer	Generic human action	9.06E-01	9.38E-02	0.30	0.97
AA3: Appreciation	Generic human action	8.89E-01	1.11E-01	0.25	0.95
AA4: Values conceptualization	Generic human action	7.94E-01	2.06E-01	0.07	0.85
AA5: Values internalization	Generic human action	7.94E-01	2.06E-01	0.15	0.85
AP1: Reflective motion	Generic human action	7.94E-01	2.06E-01	0.88	0.79
AP2: Basic movement	Generic human action	9.73E-01	2.69E-02	0.48	1.00
AP3: Perceptive ability	Generic human action	9.28E-01	7.20E-02	0.00	0.98
AP4: Physical ability	Generic human action	9.63E-01	3.69E-02	0.14	1.00

Table 17 – Performance network nodes' marginal probabilities and values adopted for MIN and MAX (continuation)

Node	Category	Positive/success state marginal probability	Negative/failure state marginal probability	**MIN**	**MAX**
AP5: Qualified movement	Generic human action	9.16E-01	8.40E-02	0.16	0.96
AP6: Nonverbal communication	Generic human action	9.16E-01	8.40E-02	0.01	0.97
AC1a: Recognize	Generic human action	9.16E-01	8.40E-02	0.06	0.96
Situation assessment	Skill	9.56E-01	4.37E-02	0.21	1.00
Situation awareness	Skill	9.10E-01	9.01E-02	0.05	0.96
Situation familiarity	Skill	9.45E-01	5.52E-02	0.03	0.99
Physical skills	Skill	9.51E-01	4.94E-02	0.12	0.99
Teamwork	Skill	9.09E-01	9.09E-02	0.06	0.97
Response	Skill	9.30E-01	7.02E-02	0.06	0.99
Vision	Skill	9.69E-01	3.10E-02	0.52	0.99
Physical resources	Internal factor	9.58E-01	4.20E-02	0.22	1.00
Mental resources	Internal factor	9.36E-01	6.40E-02	0.11	0.98
Perceived situation	Internal factor	9.51E-01	4.90E-02	0.04	1.00
Attitude	Internal factor	9.17E-01	8.31E-02	0.02	0.96
Training and experience	Internal factor	9.48E-01	5.16E-02	0.05	1.00
Team identification	Internal factor	3.00E-01	7.00E-01	0.11	0.31
Time pressure	Internal factor	9.52E-01	4.80E-02	0.43	0.98
Visual conditions	Environmental factor	9.50E-01	5.00E-02	N/A	N/A
Climate conditions	Environmental factor	9.50E-01	5.00E-02	N/A	N/A
Workplace hospitality	Environmental factor	9.50E-01	5.00E-02	N/A	N/A
Navigation impairment factors	Environmental factor	9.50E-01	5.00E-02	N/A	N/A
Activities scheduling	MOF	9.50E-01	5.00E-02	N/A	N/A
Personnel management	MOF	9.50E-01	5.00E-02	N/A	N/A
Safety culture	MOF	9.50E-01	5.00E-02	N/A	N/A
Work satisfaction	MOF	9.50E-01	5.00E-02	N/A	N/A
Necessary information	MOF	9.50E-01	5.00E-02	N/A	N/A
Workplace adequacy	MOF	9.50E-01	5.00E-02	N/A	N/A
Commercial pressure	MOF	9.50E-01	5.00E-02	N/A	N/A
Training	MOF	9.50E-01	5.00E-02	N/A	N/A
Work standardization	MOF	9.50E-01	5.00E-02	N/A	N/A

Nonetheless, during the quantification phase, it was necessary to define the failure probability of the physical components. The following probabilities were adopted, considering that the port entering/departure operation lasts for 1h30:

- propulsion system failure probability[15]: 2.25E-04;
- steering system failure[16]: 9.45E-05;
- radar failure: 9.50E-04 (PEDERSEN, 1995).

4.4. Incorporation

The incorporation phase is dedicated to computing the HRA results. The results of interest can be divided into two categories:

a) compare the accident probabilities considering the different pilotage scenarios – one pilot onboard, two pilots onboard, and no pilot onboard (pilotage exemption);

b) determine which PSFs are most important to the pilotage operations through the sensitivity analysis.

The first results, referring to the accident probabilities, are easily obtainable by comparing the accident probabilities for each scenario.

The incorporation phase consisted of merging the task and human performance BN models and the development of sensitivity analysis to understand how the PSFs influence the HEP of the port entering operation. Particularly, the sensitivity analysis was performed using the Shannon's mutual information measure – see subsection 3.2.4 – which is implemented in the software Netica 4.11, adopted for this work.

Based on the mutual information value, an importance measure indicator for each factor is proposed, considering the set of nodes within the same category. It is called here the relative sensitivity and is denoted by RS. Let I_i denote the entropy reduction for the ith node, which is computed using Eq. 37. The corresponding relative importance measure of the ith node, RS_i, is given by:

$$RS_i = \frac{I_i}{\sum_{j=1}^{N} I_j} \tag{45}$$

[15] Assuming a frequency of 1.50E-04 per ship per hour (RASMUSSEN et al., 2012)
[16] Assuming a frequency of 6.30E-05 per ship per hour (RASMUSSEN et al., 2012)

Where N is the number of nodes within the same category (e.g., skills, MOFs).

The results obtained from the incorporation phase are presented and discussed in chapter 5.

5. Results and discussion

From the HRA model developed through the steps presented in chapter 4, the probabilities were computed and compared for each type of accidental scenario. The results consider three pilotage conditions of interest: one pilot onboard, two pilots onboard, and no pilot onboard. Additionally, the sensitivity of the accident probabilities to the PSFs was also computed using the relative sensitivity importance measure (defined in section 4.4). The remaining of this chapter is dedicated to present and discuss these results.

5.1. Accidental scenarios probabilities considering one pilot, two pilots, and no pilot onboard

The accident probabilities obtained for the maneuver phases and accidents considered in this work are presented from Table 18 to Table 21. They refer to the probabilities of the potential outcomes given the occurrence of an initiating event that may cause a loss. At this point, it is important to highlight that the probabilities presented are not the final accident probabilities, since they do not consider the initiating event probabilities, which essentially depends on the vessel and waterway characteristics (LI, MENG and QU, 2012). This latter quantification is out of the scope of this work.

Table 18 – Outcome probabilities for the collision accidental scenario during the waterway navigation phase

Outcome	**Pilotage conditions**			**Ratio between probabilities**	
	No pilot onboard (NP)	**1 pilot onboard (1P)**	**2 pilots onboard (2P)**	**NP vs. 1P**	**2P vs. 1P**
Accident	5.3%	1.0%	0.4%	5.1:1	2.5:1
Near-miss	24.0%	13.3%	10.4%	1.8:1	1.2:1
Success	70.8%	85.7%	89.2%	0.8:1	0.9:1

Table 19 – Outcome probabilities for the contact/grounding accidental scenario during the waterway navigation phase

Outcome	Pilotage conditions			Ratio between probabilities	
	No pilot onboard (NP)	1 pilot onboard (1P)	2 pilots onboard (2P)	NP vs. 1P	2P vs. 1P
Accident	5.1%	0.7%	0.2%	7.0:1	3.4:1
Near-miss	20.3%	5.9%	2.0%	3.4:1	3.0:1
Success	74.5%	93.4%	97.8%	0.7:1	0.9:1

Table 20 – Outcome probabilities for the collision accidental scenario during the terminal approaching & berthing/unberthing & terminal departure phase

Outcome	Pilotage conditions			Ratio between probabilities	
	No pilot onboard (NP)	1 pilot onboard (1P)	2 pilots onboard (2P)	NP vs. 1P	2P vs. 1P
Accident	4.7%	0.8%	0.3%	5.7:1	2.3:1
Near-miss	23.2%	13.1%	10.3%	1.7:1	1.2:1
Success	72.2%	86.1%	89.3%	0.8:1	0.9:1

Table 21 – Outcome probabilities for the contact/grounding accidental scenario during the terminal approaching & berthing/unberthing & terminal departure phase

Outcome	Pilotage conditions			Ratio between probabilities	
	No pilot onboard (NP)	1 pilot onboard (1P)	2 pilots onboard (2P)	NP vs. 1P	2P vs. 1P
Accident	4.4%	0.5%	0.1%	8.9:1	3.3:1
Near-miss	19.4%	5.6%	1.9%	3.4:1	2.9:1
Success	76.3%	93.9%	98.0%	0.8:1	0.9:1

The results show that when comparing the scenarios with one pilot onboard and no pilot onboard, the latter condition may increase the accident probability by 5.1 to 8.9 times given the occurrence of an undesired initiating event. For comparison purpose, a study developed by the Canadian Marine Pilots' Association obtained an accident reduction rate between 16 to 87 times, considering the danish Great Belt area[17] (CMPA, 2017). Notably, the values differ significantly between the two works. However, at this point, it is important to state that this work considers that in the pilotage exemption case, the captain is licensed as a pilot, which is not the case of the Great Belt area. Considering a licensed captain represents better the Brazilian context (in which this work was developed), being in accordance with the Brazilian's Navy standard NORMAM-12 (Brazilian Navy, 2011).

The accident probability reduction provided by the employment of one pilot onboard can be attributed to the redundancy that this professional adds to the ship's crew when developing tasks that demand local expertise. These generally cannot be executed by a non-licensed operator (e.g., situation assessment and decision-making).

Regarding the comparison between the scenarios with one pilot onboard versus the scenarios considering two pilots onboard, the results show that employing one additional pilot reduces the accident probabilities even more, by 2.3 to 4.1 times. This reduction is also associated with the redundancy provided by the second pilot when developing tasks that require advanced local expertise. The employment of a second pilot is generally associated with the maneuvers of special types of vessels, particularly those with large dimensions and visibility restrictions. For instance, for container ships with several containers stacked up above the main deck, one pilot alone may struggle to watch the ship's bow and a second pilot can support him/her in this task. When considering the large vessels, the accident probability reduction receives particular importance, since the initiating event probability (i.e., the occurrence of an accidental scenario) is expected to be higher.

5.2. PSF sensitivity analysis

The sensitivity analysis was performed using the approach described in section 4.4, adopting the relative sensitivity as an importance measure indicator. This analysis was carried out focusing on the influence of PSFs on the probability of human error. The sensitivity was assessed on the level of skills, internal factors, MOFs, and environmental factors. The full quantitative results are presented in the Appendix D

[17] The danish Great Belt area is one of the few regions in the world in which the pilotage is facultative

due to its extension. In this section, the main conclusions obtained based on these results will be discussed, presenting the most sensitive factors in each category.

5.2.1. Skills

The full sensitivity for the skills PSFs are presented in the section D.1 of the appendix D.

For all accidental sequences, the sensitivity analysis indicated that the main skill is situation the situation familiarity. In the scenarios employing pilots, it refers to the "situation familiarity" of these professionals, while in the case of pilotage exemption, the "captain's situation familiarity" gains importance. This skill reveals the importance of factors such as knowledge of operational procedures, memory, and frequency and repeatability, which are already recognized as important for the pilotage operation according to the NORMAM-12 (Brazilian Navy, 2011).

The response skill also appears as a preponderant PSF according to the sensitivity analysis. This skill is related to individual characteristics such as planning, creativity and flexibility, which are important for decision making in contexts of uncertainty and imminent accidents.

When evaluating the scenarios of collision accidents, the teamwork skill appears as a relevant contributor to the chances of success of the maneuver. This factor refers to elements such as the ability for interpersonal communication, leadership, and empathy, which are important when establishing favorable and safe conditions for both competing vessels. In other words, in a scenario of potential collision, it is important that the professionals involved (ship's captain or pilot) have good performance in transmitting and receiving information. Furthermore, the leadership and empathy are necessary to understand any limitations of the other vessel (e.g., operational draft restrictions) and try to plan the best evasive maneuver possible.

It is interesting to observe how the relative importance of each skill changes with the employment of qualified professionals to the team, i.e., from the pilot exemption scenario to the case with the employment of one pilot, and from the latter to the case with the employment of two pilots. When employing only one pilot, the skills of this professional assume greater importance (in terms of overall contribution) in relation to the skills of the ship's captain, but the latter is still relevant. This indicates that the quality of the maneuver is expected to be strongly associated with the skills of the pilot, but the presence of a qualified captain also contributes to the successful execution of a maneuver. When a second pilot is employed, the skills of both pilots gain relative importance far superior to the skills of the individual captain and compete on the ranking of the most important skills. Therefore, in this second operational scenario the maneuvering safety is less sensitive to the captain skills.

5.2.2. Internal factors

The full sensitivity for the internal factors PSFs are presented in the section D.2 of the appendix D.

Regarding the internal factors, there is a preponderance of training and experience as the main PSF necessary for the success of the maneuvers. Related to this factor are the knowledge of standards, and the current state of practice. It is interesting to note that this internal factor is important not only for pilots and the ship's captain, but also for the helmsman, since it determines his aptitude to execute the commands received.

Another internal factor revealed as important by the sensitivity analysis is the attitude of the pilots and of the ship's captain. This factor mainly impacts the response of these professionals, which is one of the most important factors in scenarios where evasive actions are needed. In addition, since the attitude is related to the individual's personality and intelligence, its contribution in the interaction with other teams is also relevant, notably scenarios involving the interaction with other vessels.

Finally, the perceived situation is the third most important internal factor among those considered in the HRA. This factor impacts the perception of dangerous situations by the decision maker during the maneuver (pilot or captain, depending on the operational scenario), which is essential for the conscious execution of evasive actions. The elements that contribute to this internal factor include the influence of third parties, risk sensitivity, and conflicts about performance.

For the internal factors, it is possible to observe a trend similar to what happens with skills, as the different operational scenarios are considered. When a single pilot is employed onboard, the condition of its internal factors is of great importance for the success of the maneuver, but a captain with good conditions may also be of relevant importance. When two pilots are employed, their internal states predominate and there is a compensatory dynamic between both professionals. This means that the qualities of one professional tend to compensate for the deficiencies of the other.

5.2.3. MOFs

The full sensitivity for the internal factors PSFs are presented in the section D.3 of the appendix D.

According to the sensitivity analysis, two MOFs predominate as the most important for the success of the maneuvers: training and safety culture. In the case of pilotage exemption, this refers to the quality of these factors in relation to the ship owner, while in the cases with the presence of one or two pilots on board, it is the quality of these factors in relation to the local pilotage.

Training as an organizational factor refers to programs that aim to improve the aptitude of professionals for the specific type of operation addressed – in this case, the maneuvers of ships in ports and waterways. This MOF mainly influences experience and training as internal factors, but it can also affect the attitude of the operator.

On its turn, the safety culture impacts the main internal factors revealed as important to the maneuver (see section 5.2.2), including the perceived situation, attitude, and training and experience of the professionals involved. The safety culture is related to several attributes of the organization, such as organizational culture, performance evaluation and organizational learning. In addition, the safety culture is also influenced by the application of laws and regulations, which encourage organizations to adopt practices that prioritize risk mitigation and contingency even in environments with high commercial pressure.

5.2.3.1. Environmental factors

The full sensitivity for the internal factors PSFs are presented in the section D.4 of the appendix D.

Three environmental factors proved to be important according to the sensitivity analysis, all with approximately the same relevance: climate conditions, navigation impairment factors, and workplace hospitality. These three PSFs impact the professional's attention to the situation. Although this is not one of the main skills listed in section 5.2.1, as the three factors similarly influence it, the contribution of the three becomes uniform.

The fourth environmental factor considered in the model – visual conditions – did not appear as one of the main factors in the sensitivity analysis. At a first glance, this may sound counterintuitive. However, this tendency is justified by the fact that the sensitivity analysis is computed for each factor individually, keeping the others constant. Since visual conditions only impact activities that require external visual perception and these are redundant with instrument monitoring activities (e.g., radar), the individual effect of this environmental factor becomes less important.

6. Conclusion and final considerations

This Thesis aimed at investigating the contribution of the human factor to the risk of maneuvering ships in ports and waterways (restricted waters). The methodology adopted consisted of applying the HRA supported by BN to accidental scenarios typical of these maneuvers during its different phases, such as collision, contact, and grounding. In addition to analyzing the main contributing factors, the results included the comparison between three different operational scenarios, considering the employment of one pilot, two pilots, and pilotage exemption (i.e., no pilot onboard).

The results indicate that in the imminence of an accidental scenario, the accident probabilities are reduced from 5.1 to 8.9 times when comparing the scenario of pilotage exemption with the scenario considering one pilot onboard. Additionally, when comparing the employment of an additional pilot, these probabilities are further reduced, from 2.3 to 4.1 times.

Through BN sensitivity analysis, the main PSFs contributing to the success of the maneuver were evaluated and ranked. These include:

a) in terms of skills, situation familiarity, response, and teamwork;
b) in terms of internal factors: training and experience, attitude, and perceived situation;
c) in terms of MOFs: training, and safety culture; and
d) in terms of environmental factors, climate conditions, navigation impairment factors and workplace hospitality.

Therefore, it is recommended that measures that seek to improve the safety of piloting operations focus on these aspects. Furthermore, the organizations involved must pay attention so that these factors do not degrade over time, compromising security.

In addition to the numerical results, it is noteworthy that the BN models developed in a format compatible with the Netica 4.11 software are a product of the research project. The models developed are generic. However, these can be adapted to specific cases, assisting in the preparation of quantitative risk analyzes and decision making. On the other hand, it is noteworthy that this study was generated based on the analysis of port operations for the arrival and departure of ships, which were observed by simulations at TPN-USP and in person at the Port of Santos. In principle, the results can be extended to other ports and seaports on navigable rivers. However, due to the particularities of the latter, it is understood that adjustments are necessary to better represent these operations – e.g., consideration of the turns between pilots, absence of the captain at the bridge for some moments, absence of constant updating of bathymetry information for the ship's crew, and absence or poor visual references when navigating during the night.

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Appendix A. Event tree models

Figure 23 – Event tree for the contact/grounding scenario during the waterway navigation phase

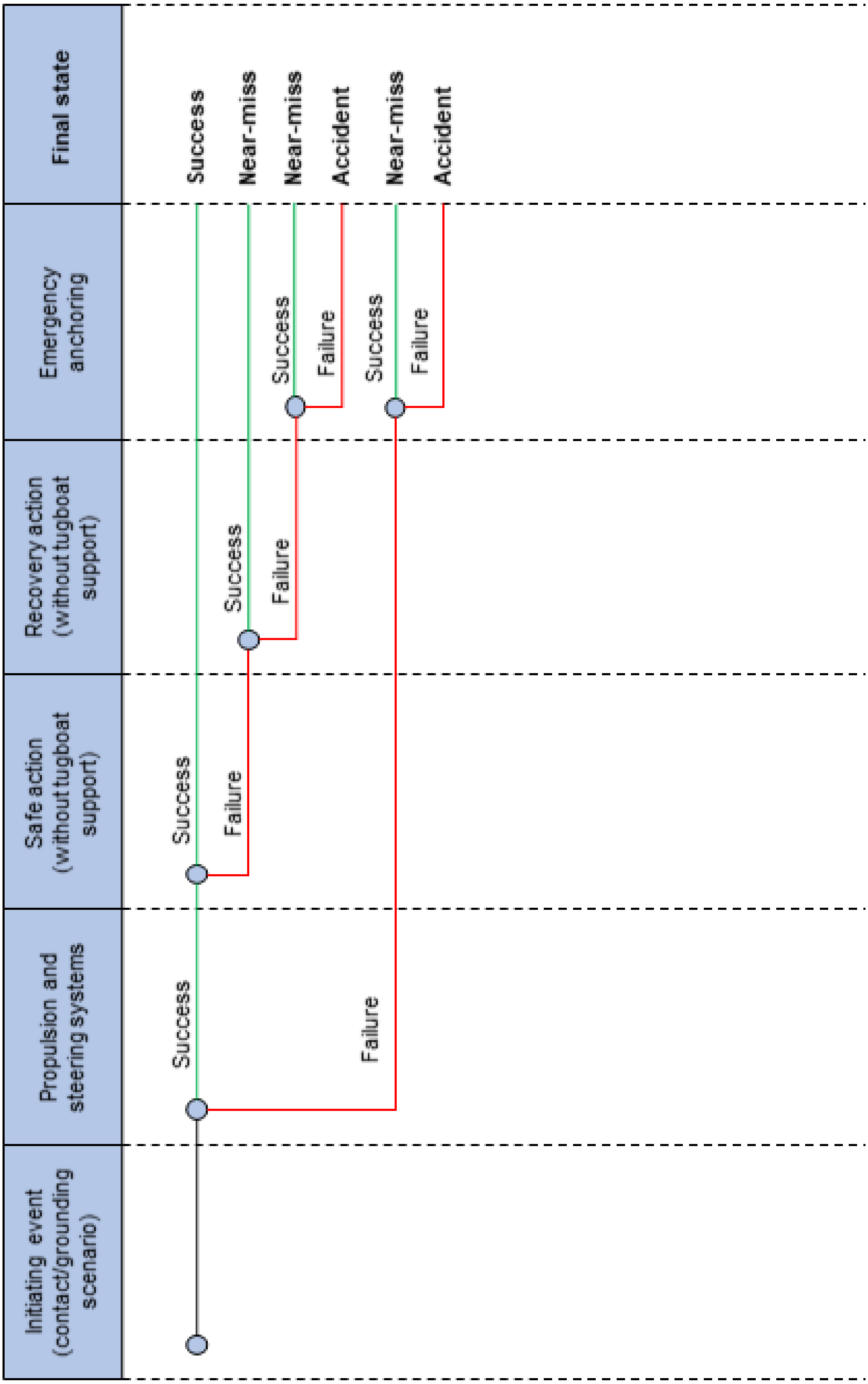


Figure 24 – Event tree for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure phase

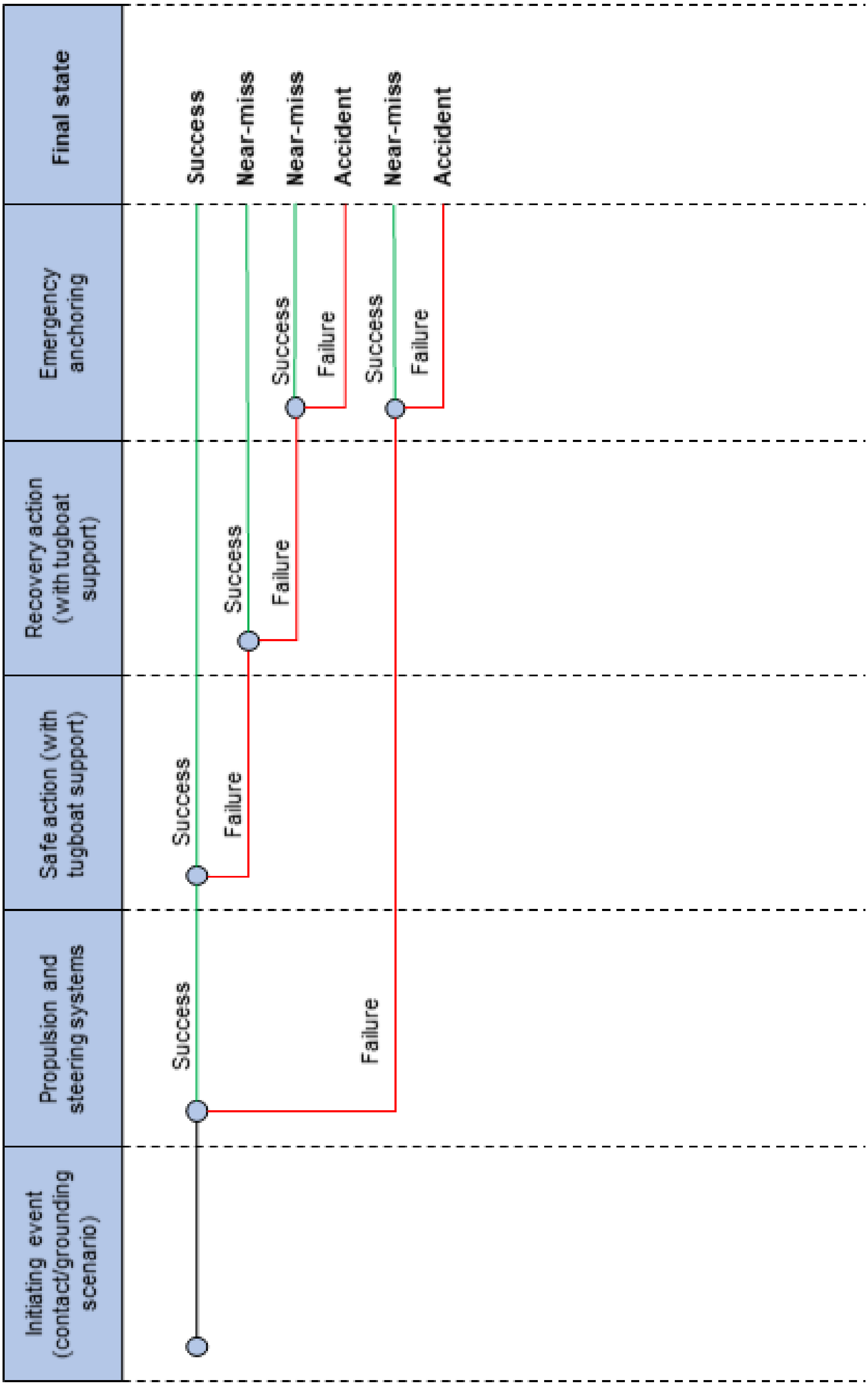


Figure 25 – Event tree for the collision scenario during the waterway navigation phase

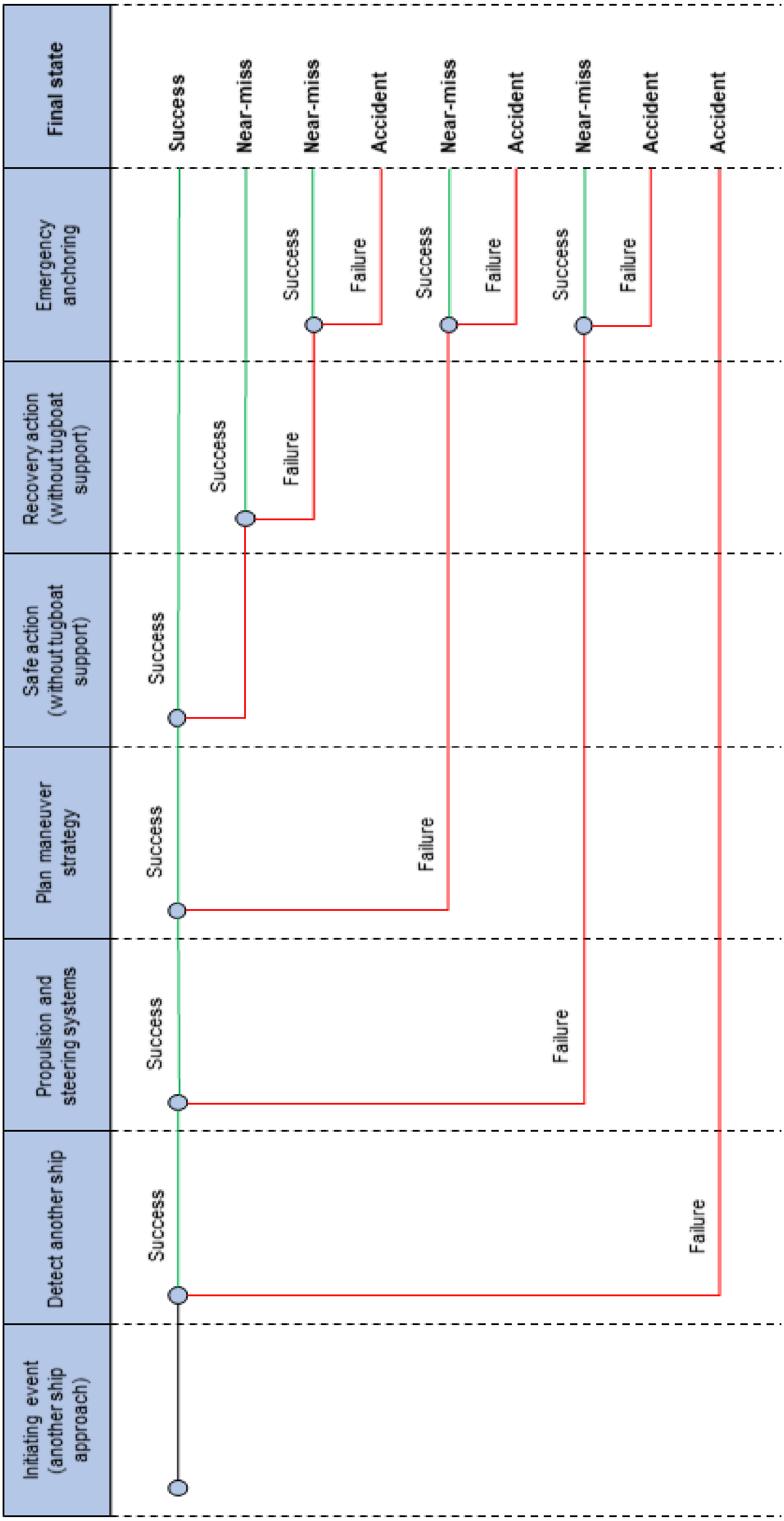
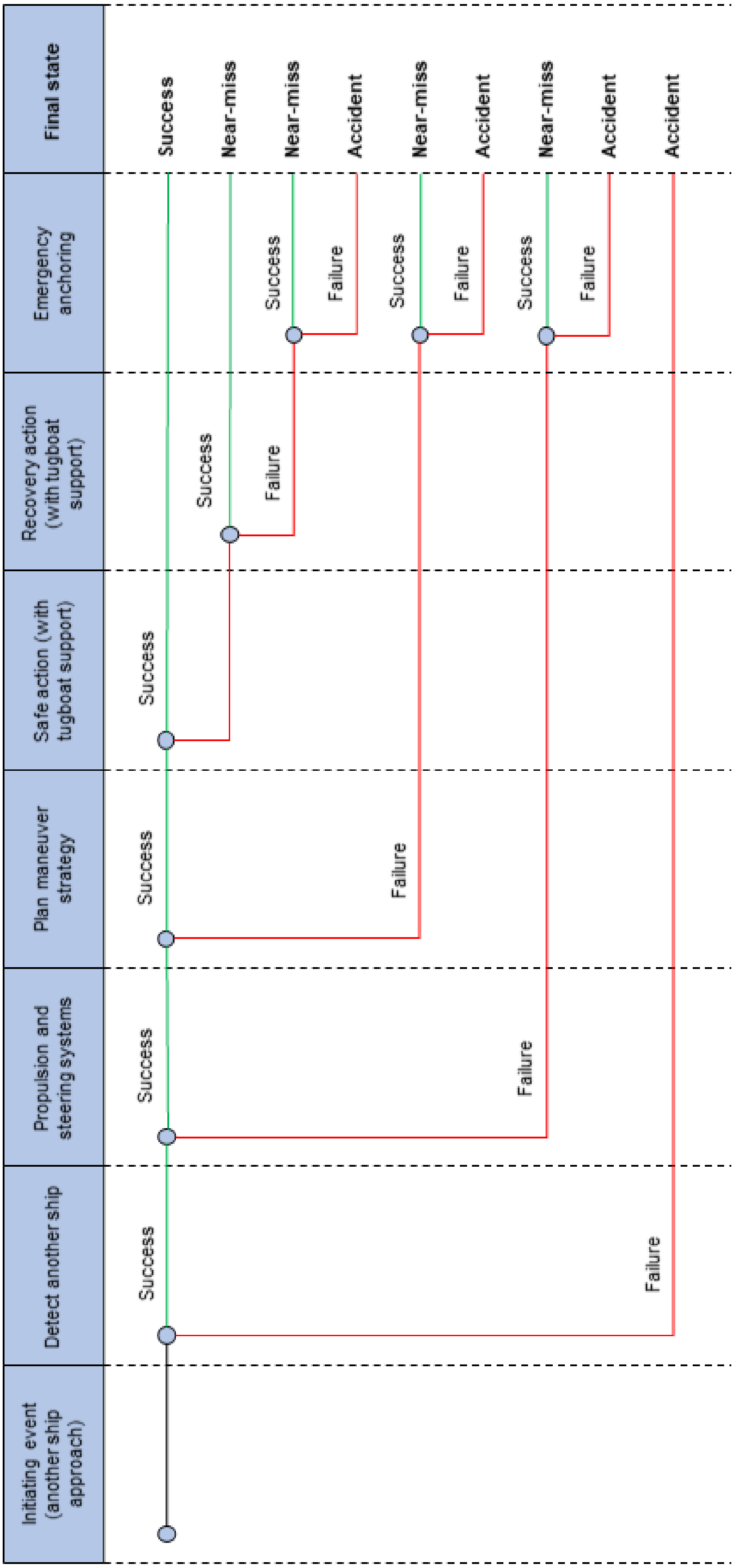


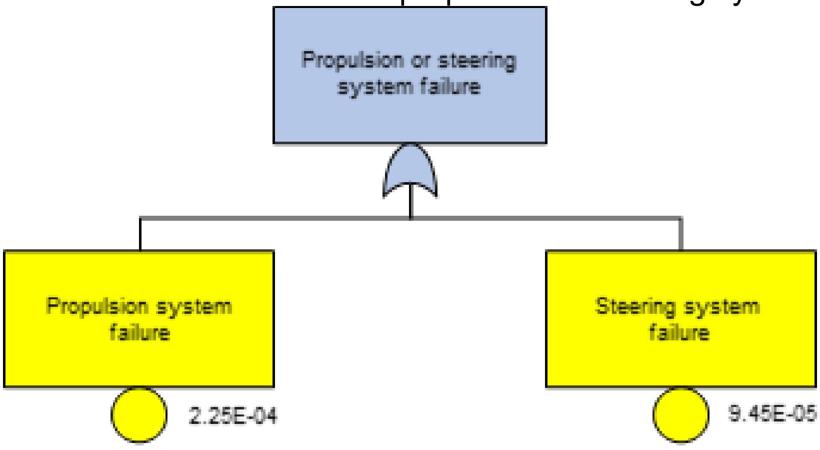
Figure 26 – Event tree for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure phase



Appendix B. Fault tree models

B.1. Fault tree for the event "Propulsion or steering system failure"

Figure 27 – Fault tree for the event "propulsion or steering system failure"



B.2. Fault tree for the event "Safe action failure (without tugboat support) - one pilot onboard"

Figure 28 – Fault tree for the event "Safe action failure (without tugboat support) - one pilot onboard", part 1/4

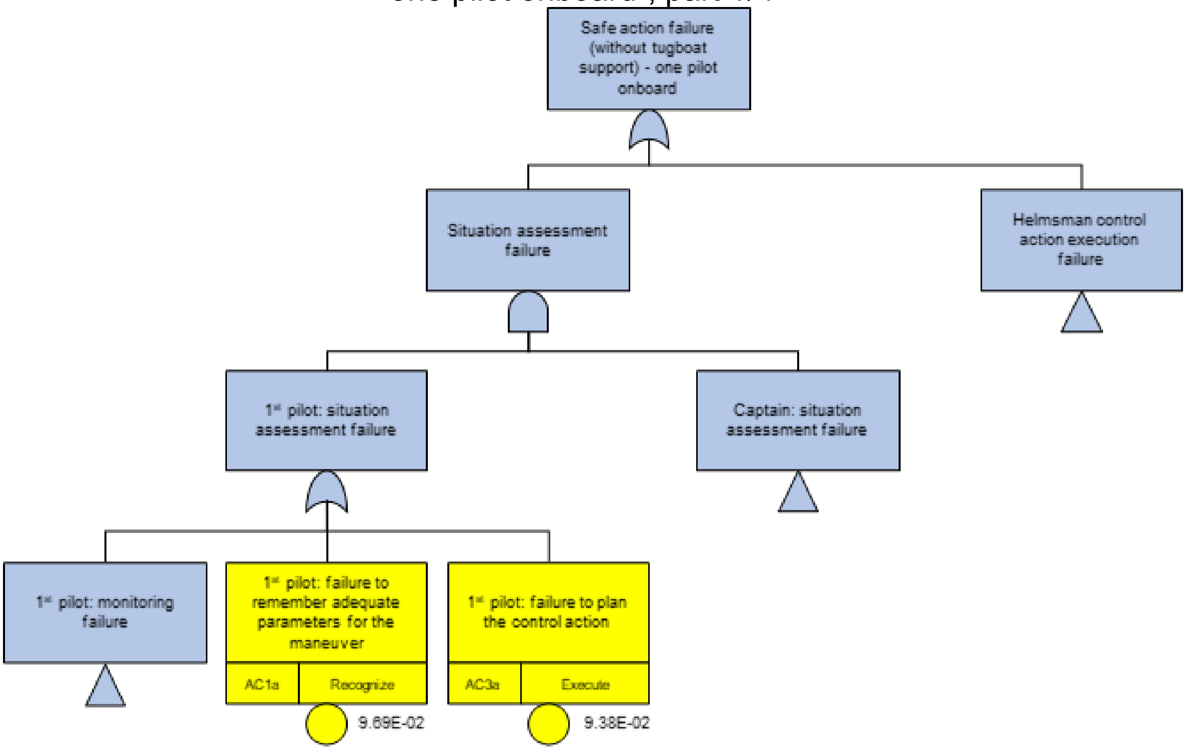


Figure 29 – Fault tree for the event "Safe action failure (without tugboat support) - one pilot onboard", part 2/4

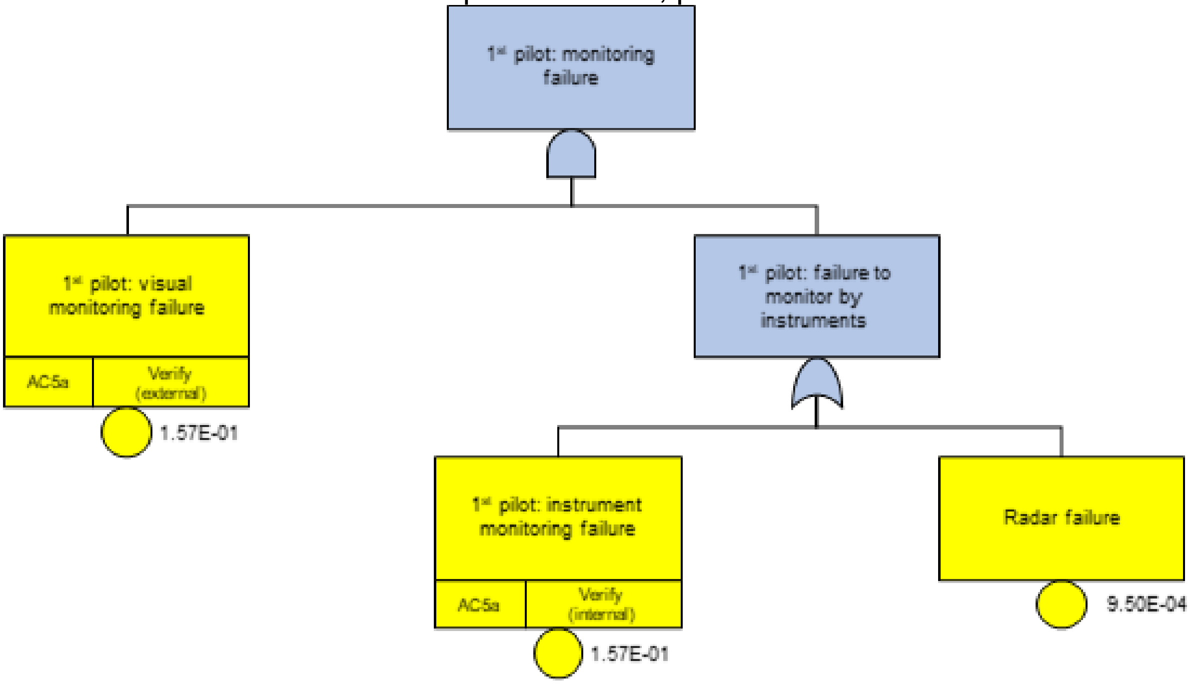


Figure 30 – Fault tree for the event "Safe action failure (without tugboat support) - one pilot onboard", part 3/4

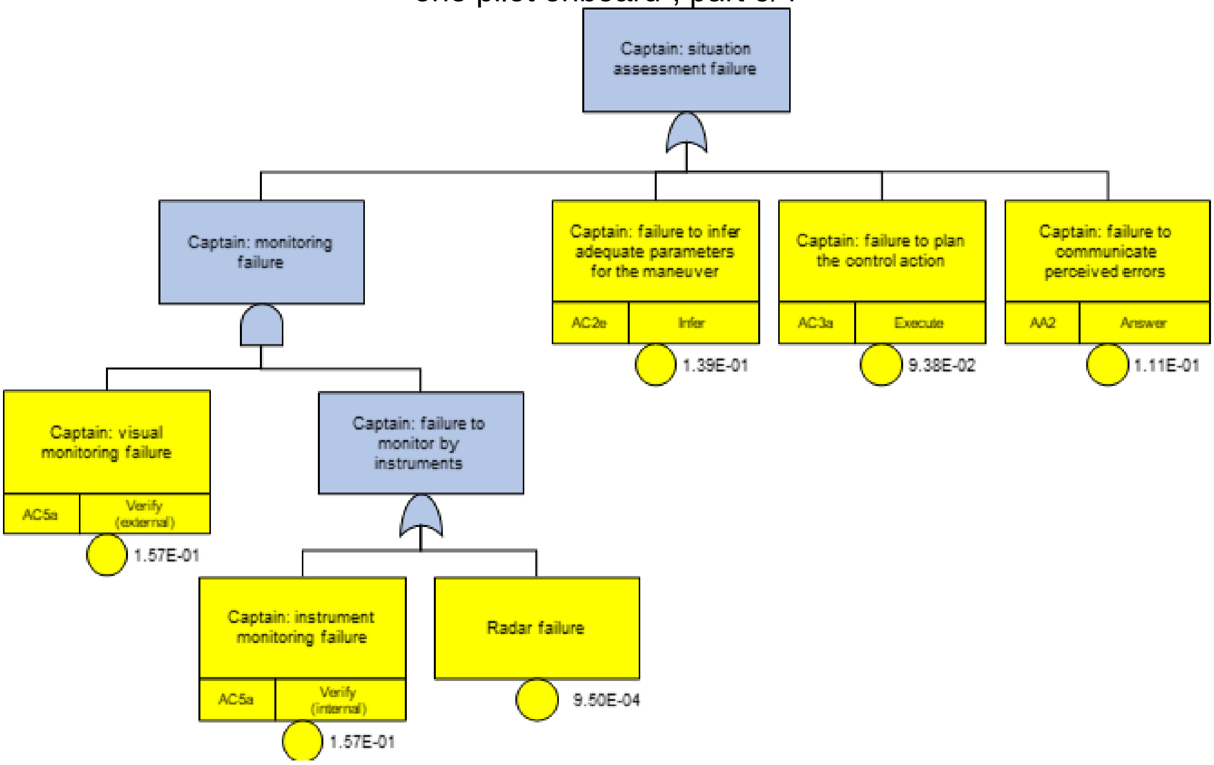
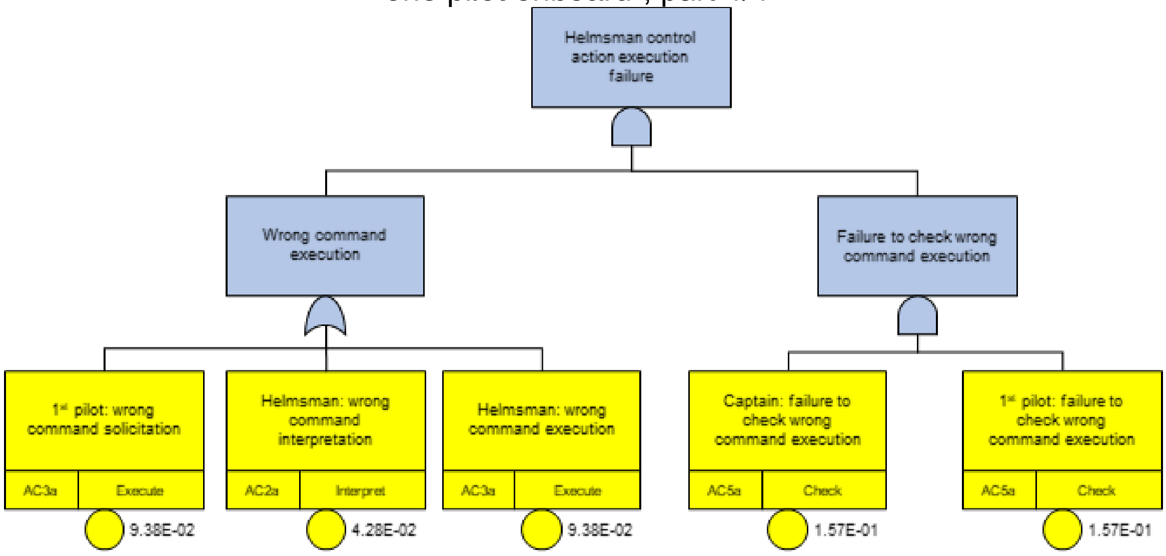


Figure 31 – Fault tree for the event "Safe action failure (without tugboat support) - one pilot onboard", part 4/4



B.3. Fault tree for the event "Safe action failure (without tugboat support) - two pilots onboard"

Figure 32 – Fault tree for the event "Safe action failure (without tugboat support) - two pilots onboard", part 1/5

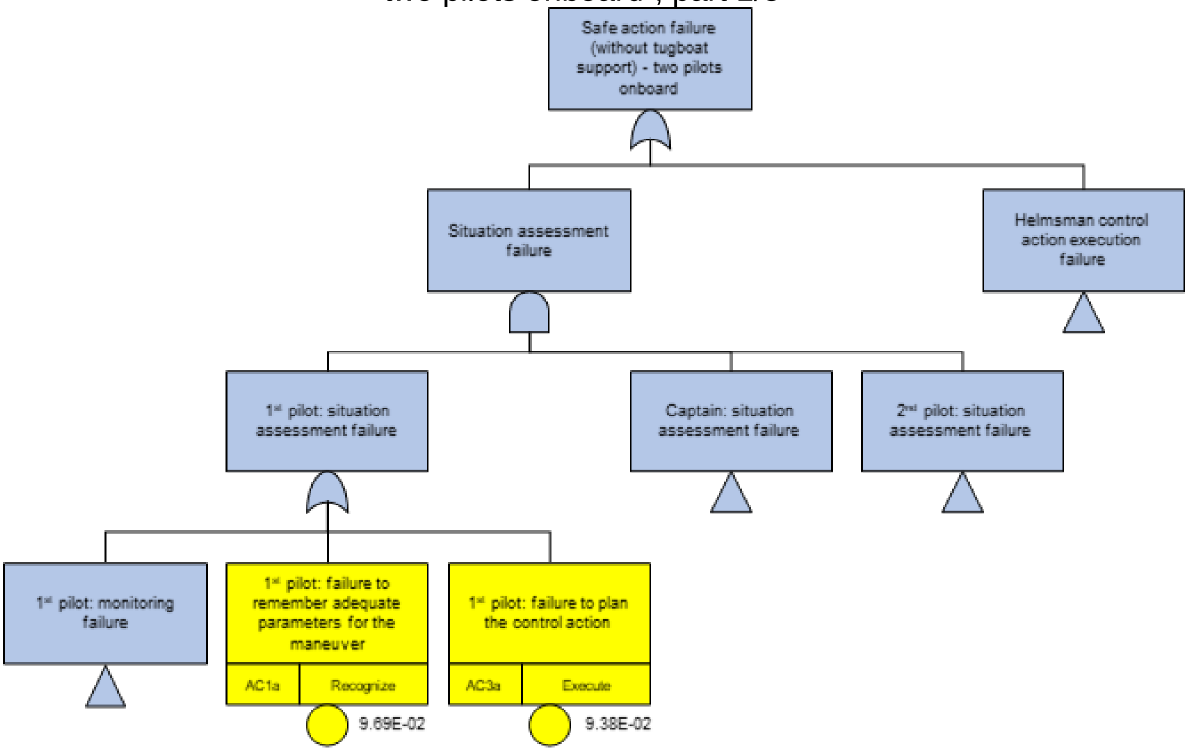


Figure 33 – Fault tree for the event “Safe action failure (without tugboat support) - two pilots onboard”, part 2/5

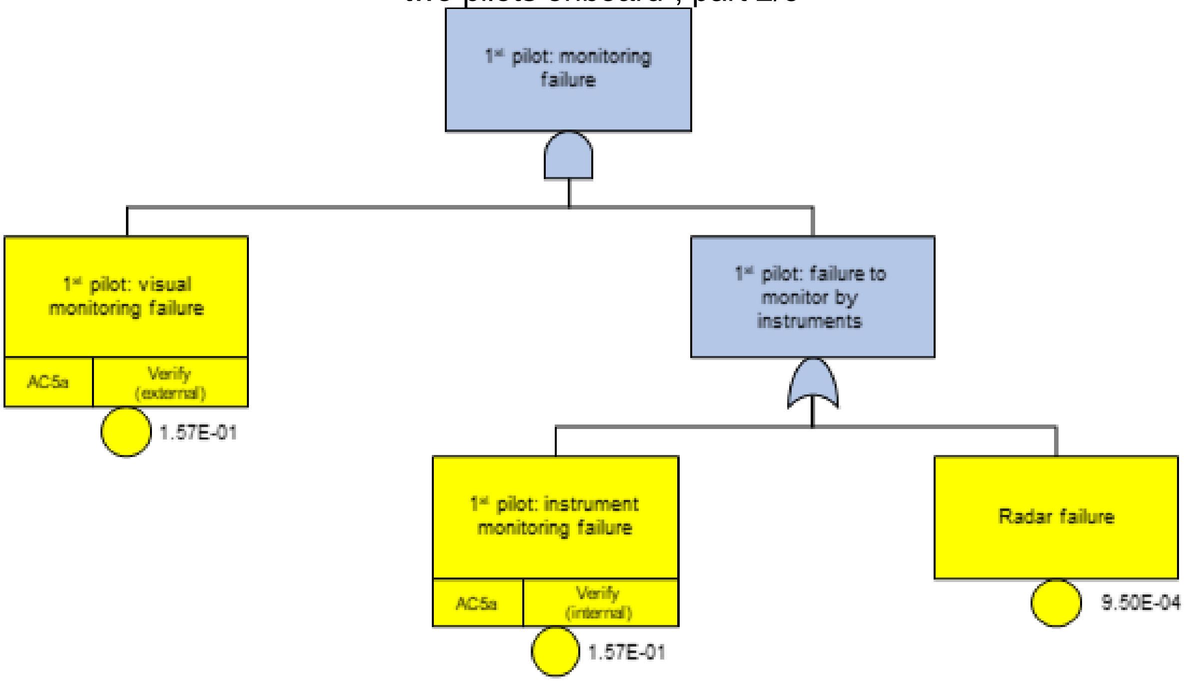


Figure 34 – Fault tree for the event “Safe action failure (without tugboat support) - two pilots onboard”, part 3/5

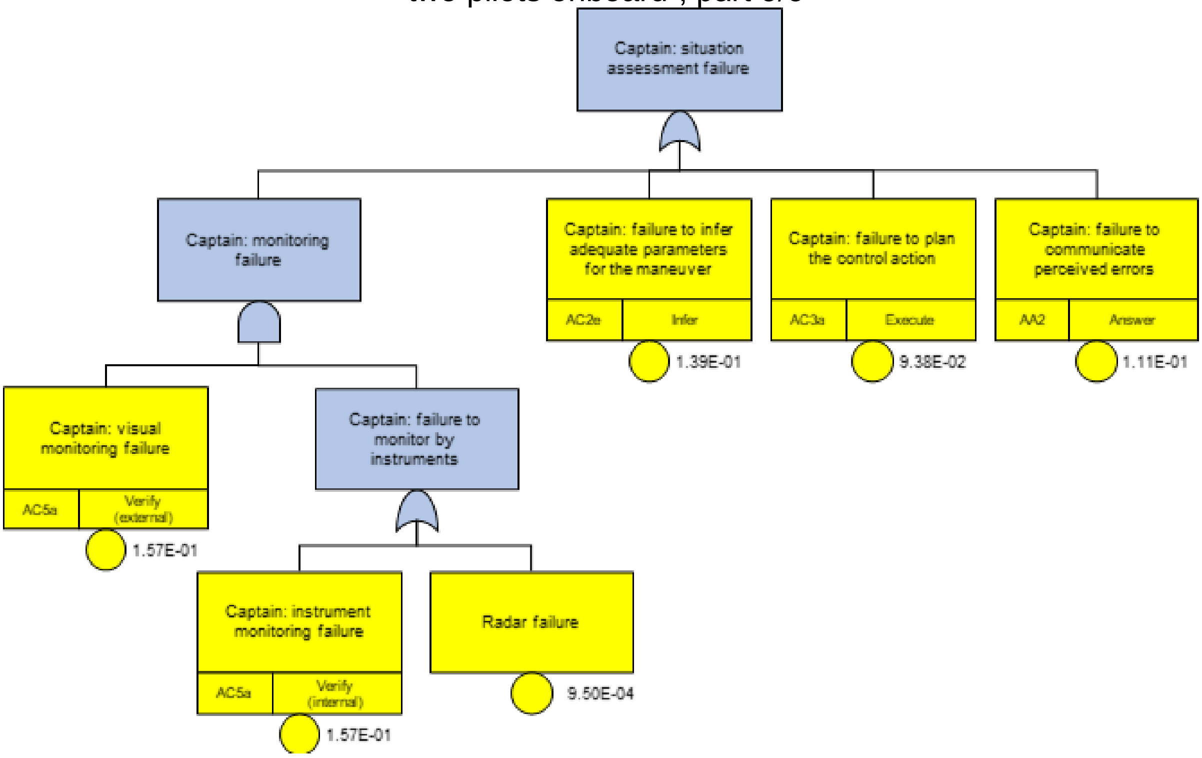


Figure 35 – Fault tree for the event "Safe action failure (without tugboat support) - two pilots onboard", part 4/5

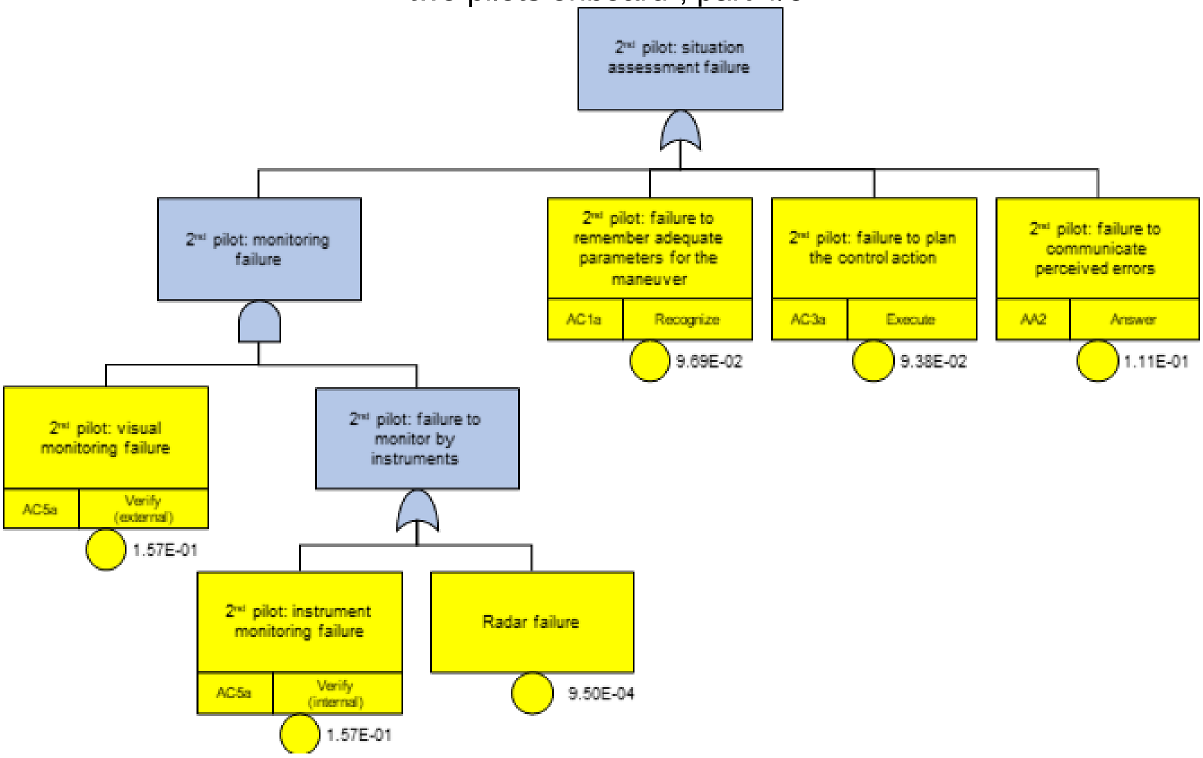
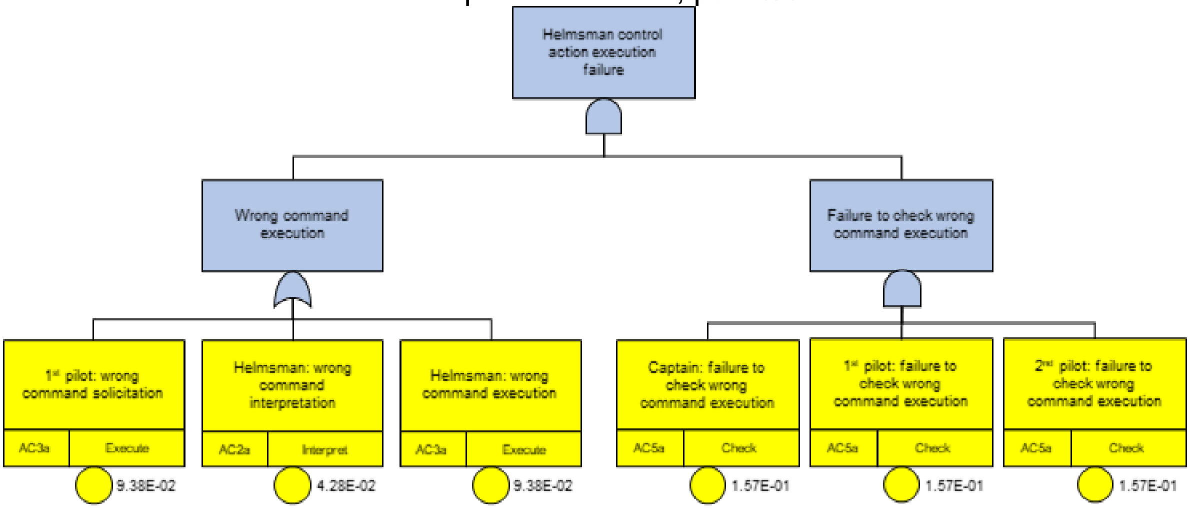


Figure 36 – Fault tree for the event "Safe action failure (without tugboat support) - two pilots onboard", part 5/5



B.4. Fault tree for the event "Safe action failure (without tugboat support) - no pilot onboard"

Figure 37 – Fault tree for the event "Safe action failure (without tugboat support) - no pilot onboard", part 1/4

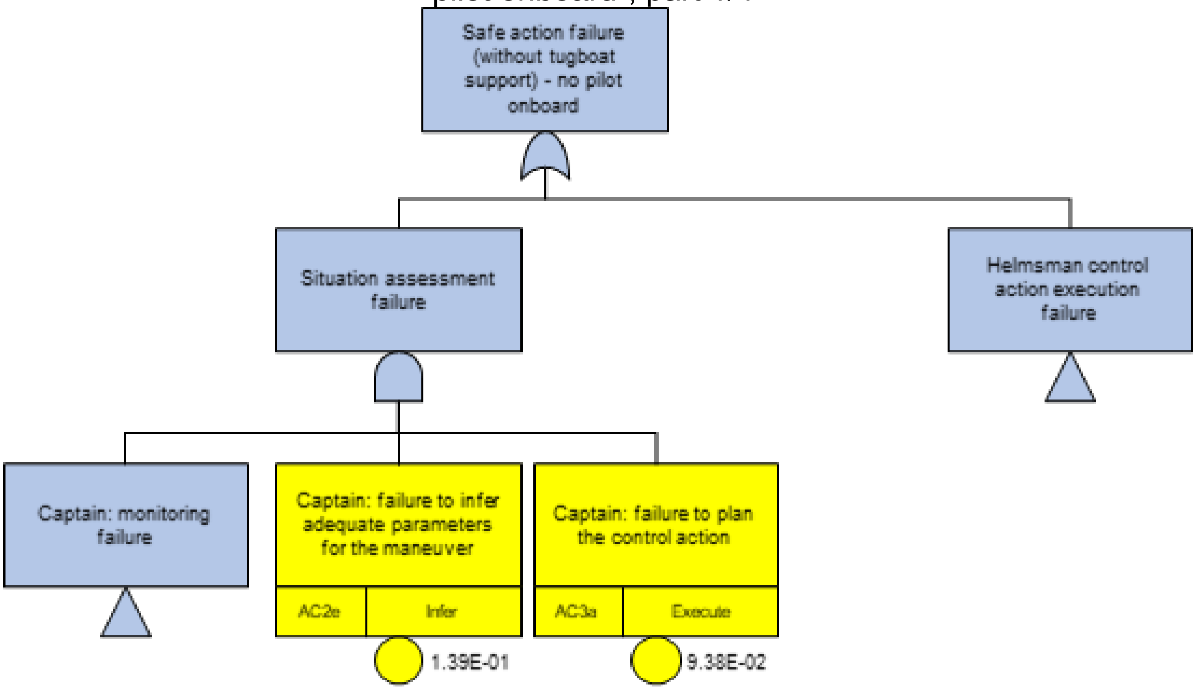


Figure 38 – Fault tree for the event "Safe action failure (without tugboat support) - no pilot onboard", part 2/4

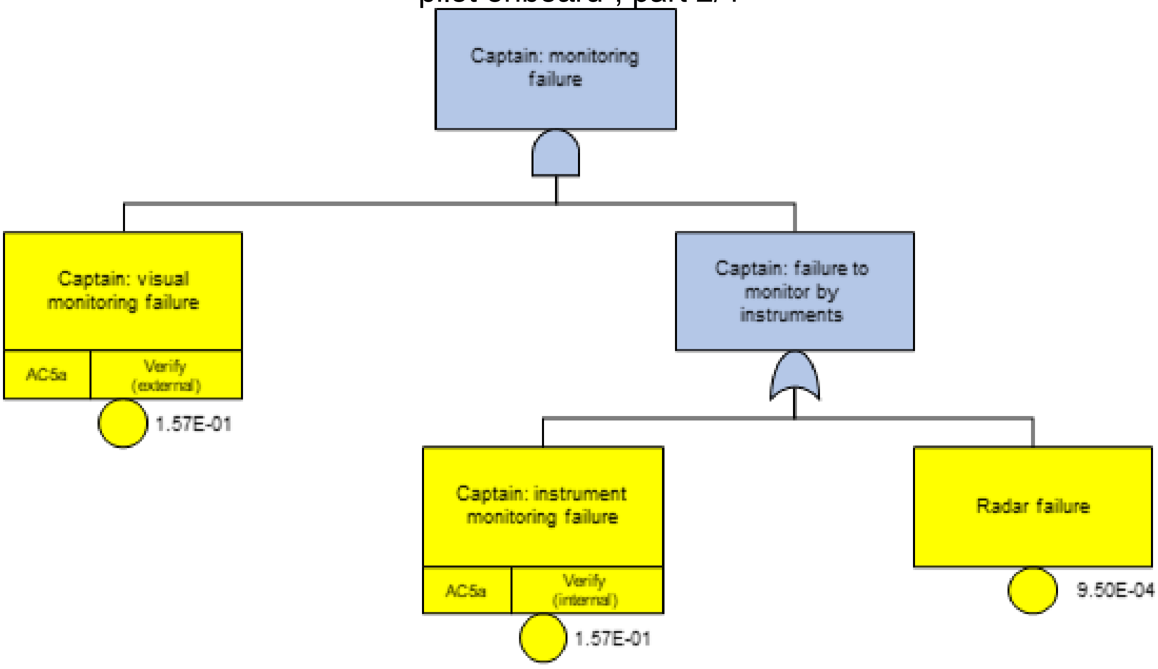


Figure 39 – Fault tree for the event "Safe action failure (without tugboat support) - no pilot onboard", part 3/4

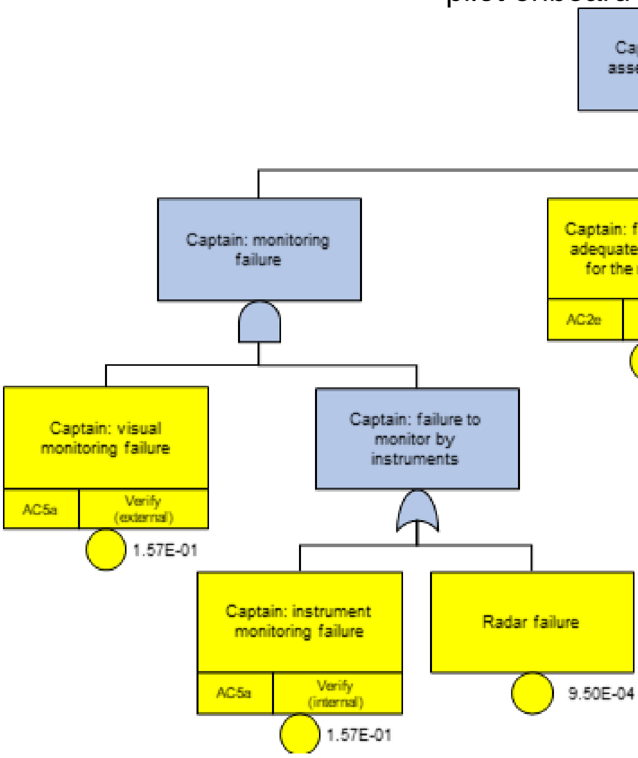
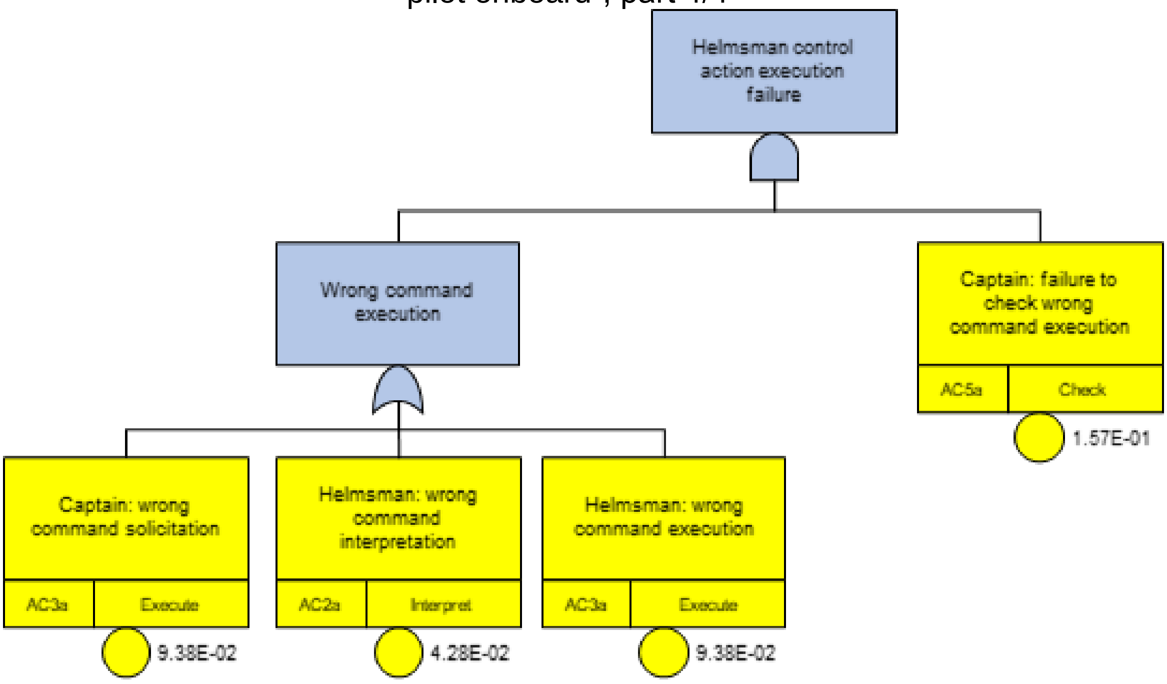


Figure 40 – Fault tree for the event "Safe action failure (without tugboat support) - no pilot onboard", part 4/4



B.5. Fault tree for the event "Safe action failure (with tugboat support) - one pilot onboard"

Figure 41 – Fault tree for the event "Safe action failure (with tugboat support) - one pilot onboard", part 1/5

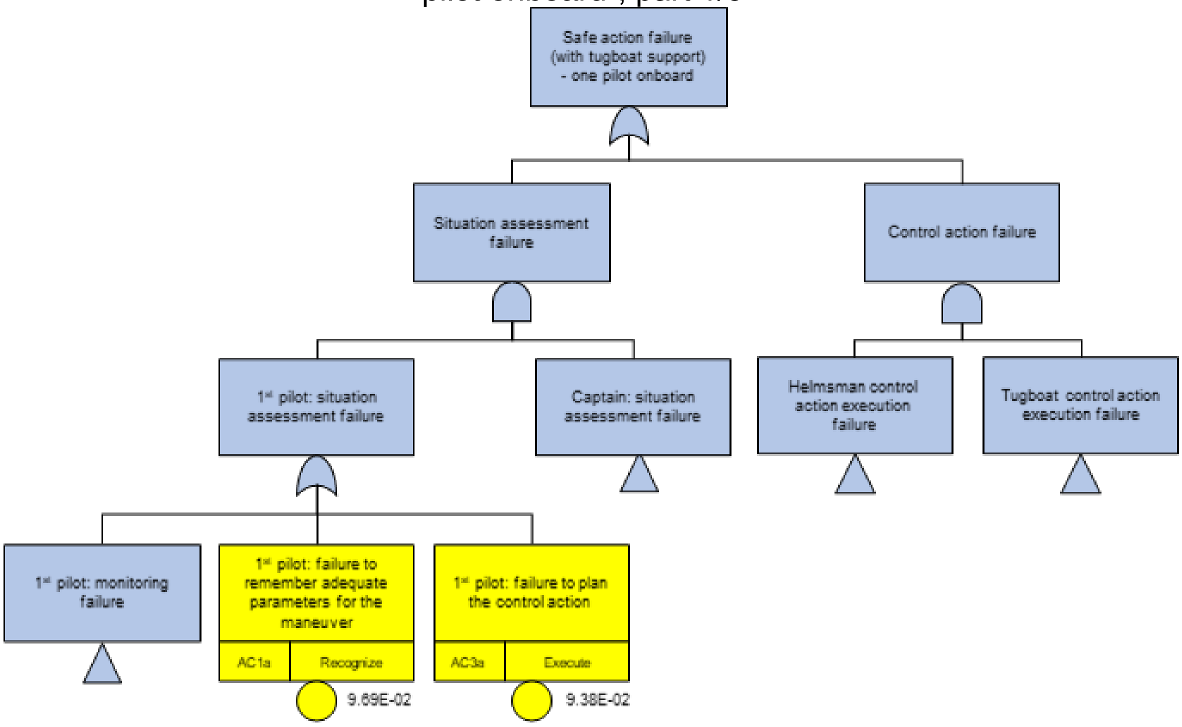


Figure 42 – Fault tree for the event "Safe action failure (with tugboat support) - one pilot onboard", part 2/5

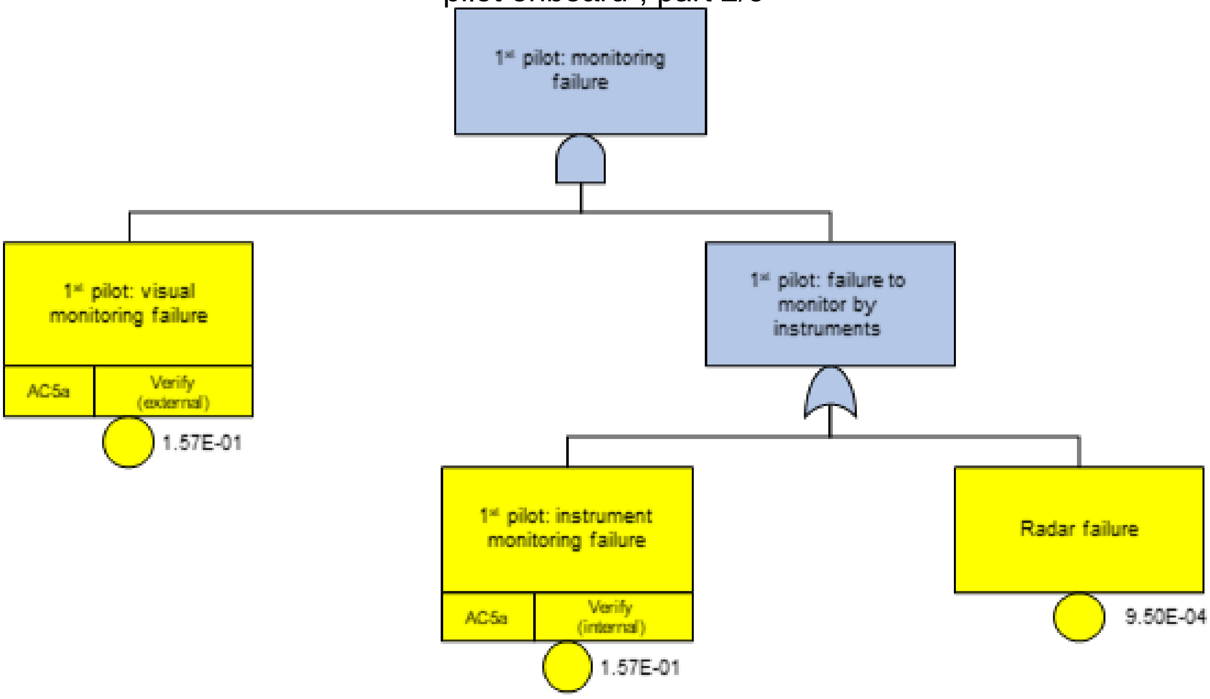


Figure 43 – Fault tree for the event “Safe action failure (with tugboat support) - one pilot onboard”, part 3/5

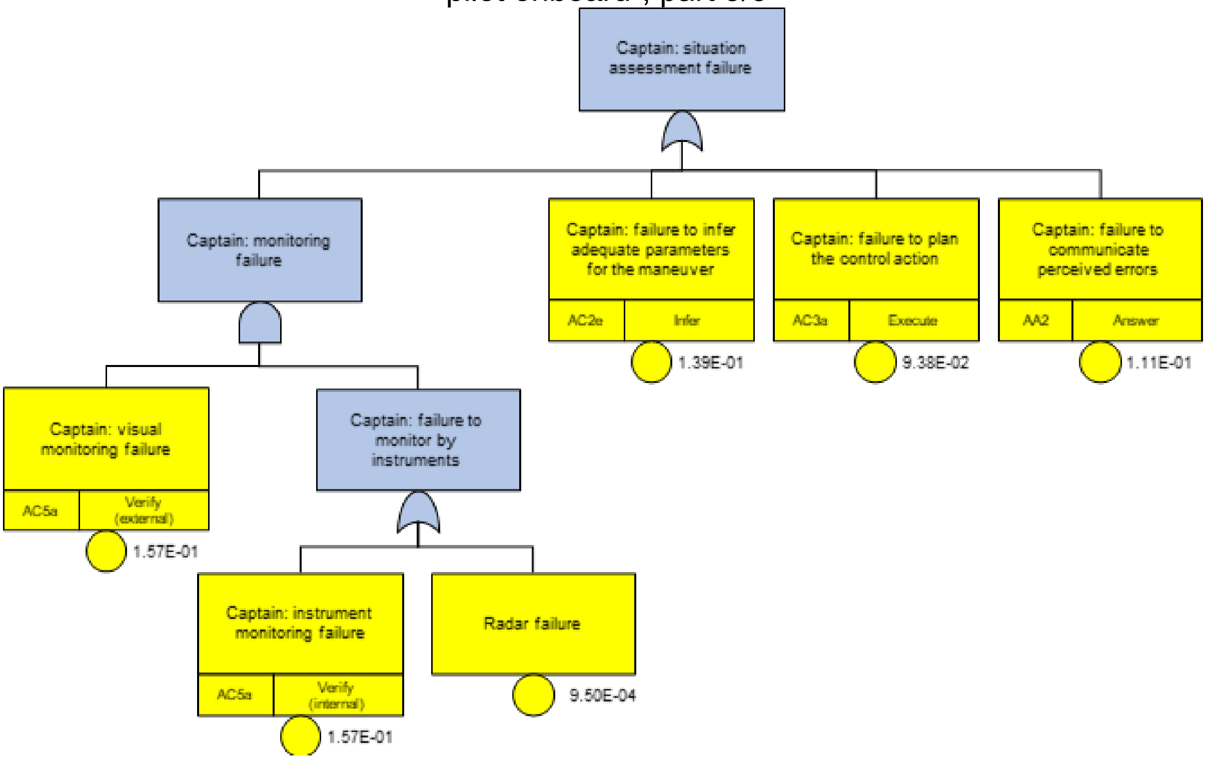


Figure 44 – Fault tree for the event “Safe action failure (with tugboat support) - one pilot onboard”, part 4/5

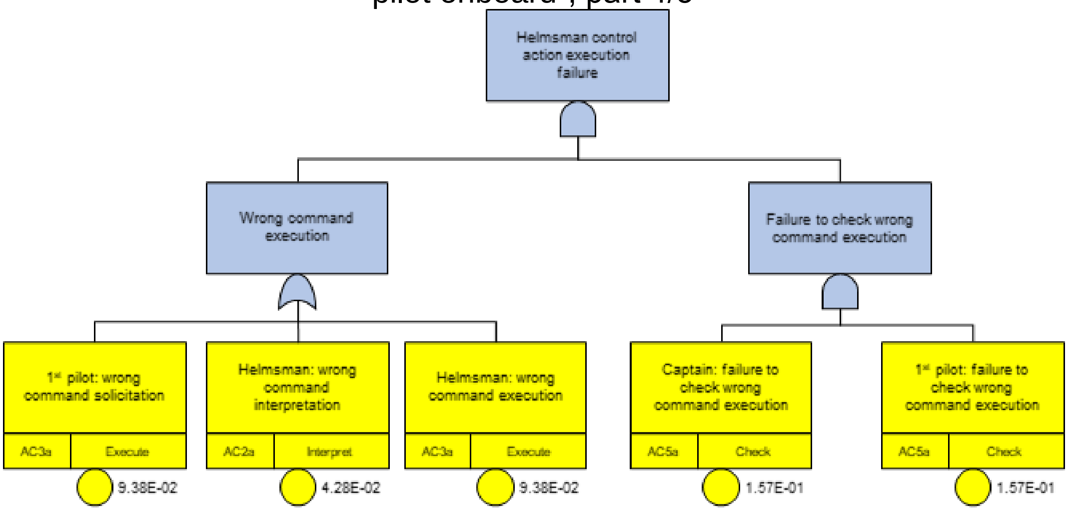
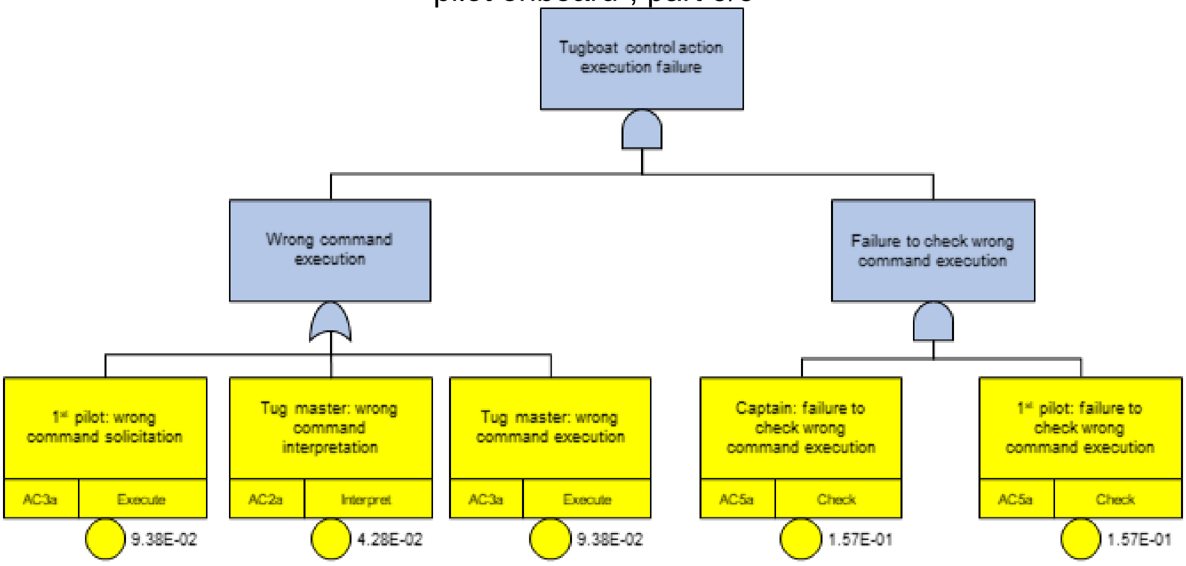


Figure 45 – Fault tree for the event “Safe action failure (with tugboat support) - one pilot onboard”, part 5/5



B.6. Fault tree for the event “Safe action failure (with tugboat support) - two pilots onboard”

Figure 46 – Fault tree for the event “Safe action failure (with tugboat support) - two pilots onboard”, part 1/6

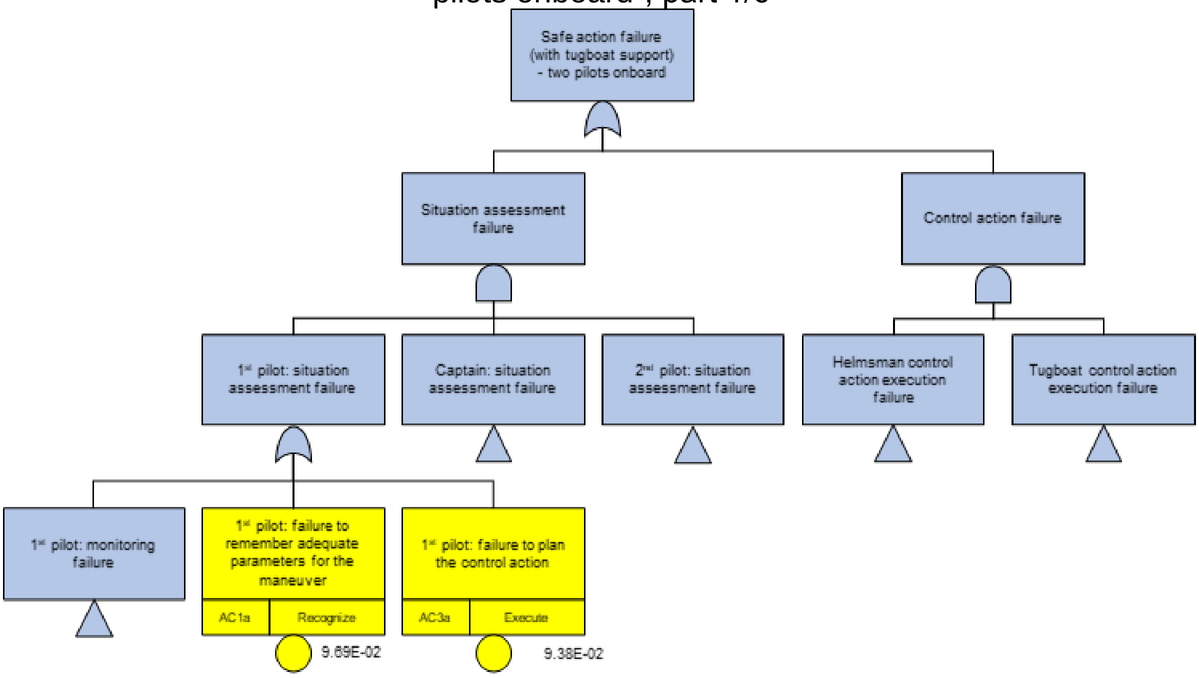


Figure 47 – Fault tree for the event “Safe action failure (with tugboat support) - two pilots onboard”, part 2/6

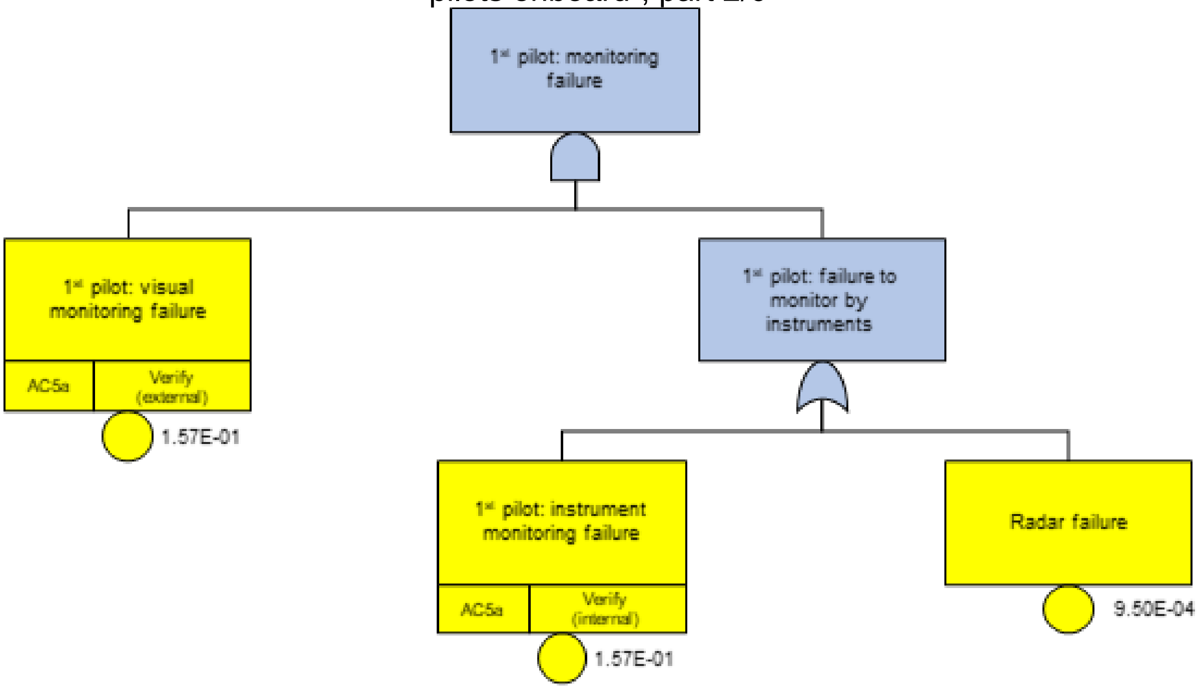


Figure 48 – Fault tree for the event “Safe action failure (with tugboat support) - two pilots onboard”, part 3/6

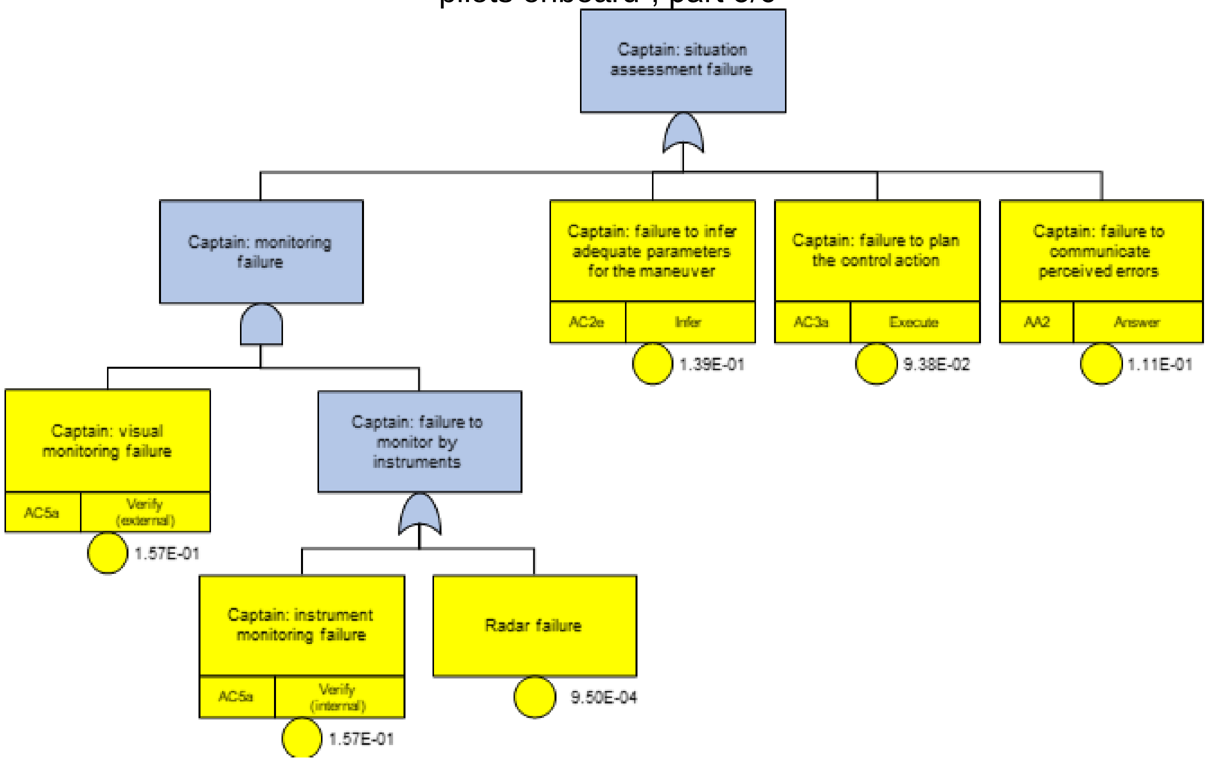


Figure 49 – Fault tree for the event “Safe action failure (with tugboat support) - two pilots onboard”, part 4/6

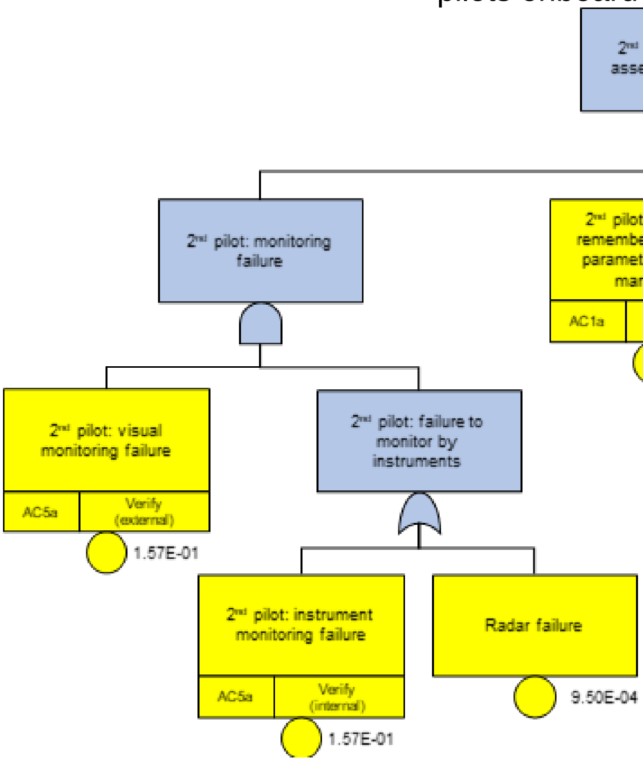


Figure 50 – Fault tree for the event “Safe action failure (with tugboat support) - two pilots onboard”, part 5/6

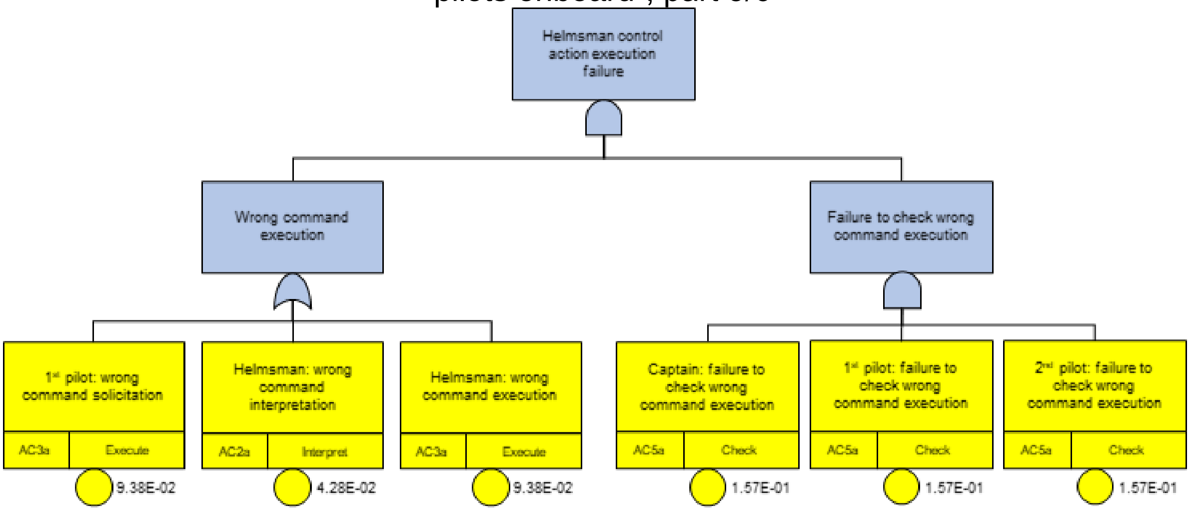
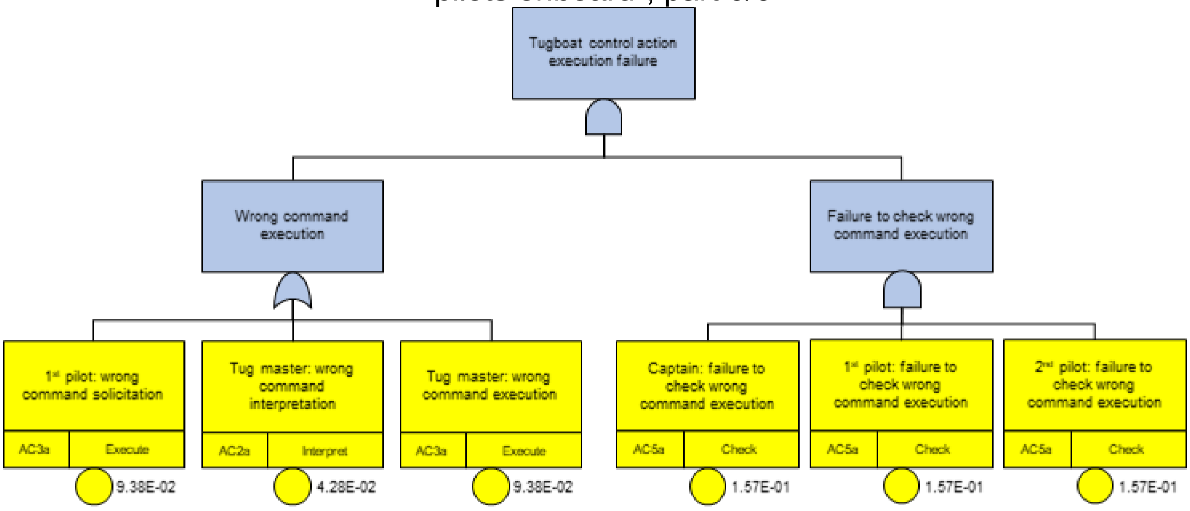


Figure 51 – Fault tree for the event “Safe action failure (with tugboat support) - two pilots onboard”, part 6/6



B.7. Fault tree for the event “Safe action failure (with tugboat support) – no pilot onboard”

Figure 52 – Fault tree for the event “Safe action failure (with tugboat support) - two pilots onboard”, part 1/4

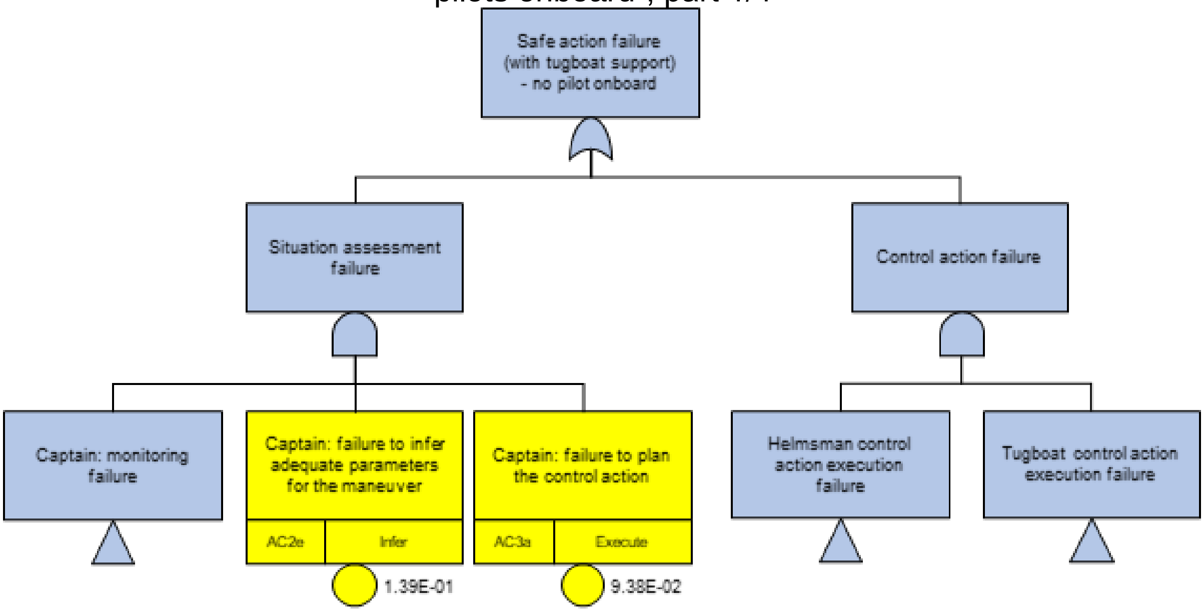


Figure 53 – Fault tree for the event "Safe action failure (with tugboat support) - two pilots onboard", part 2/4

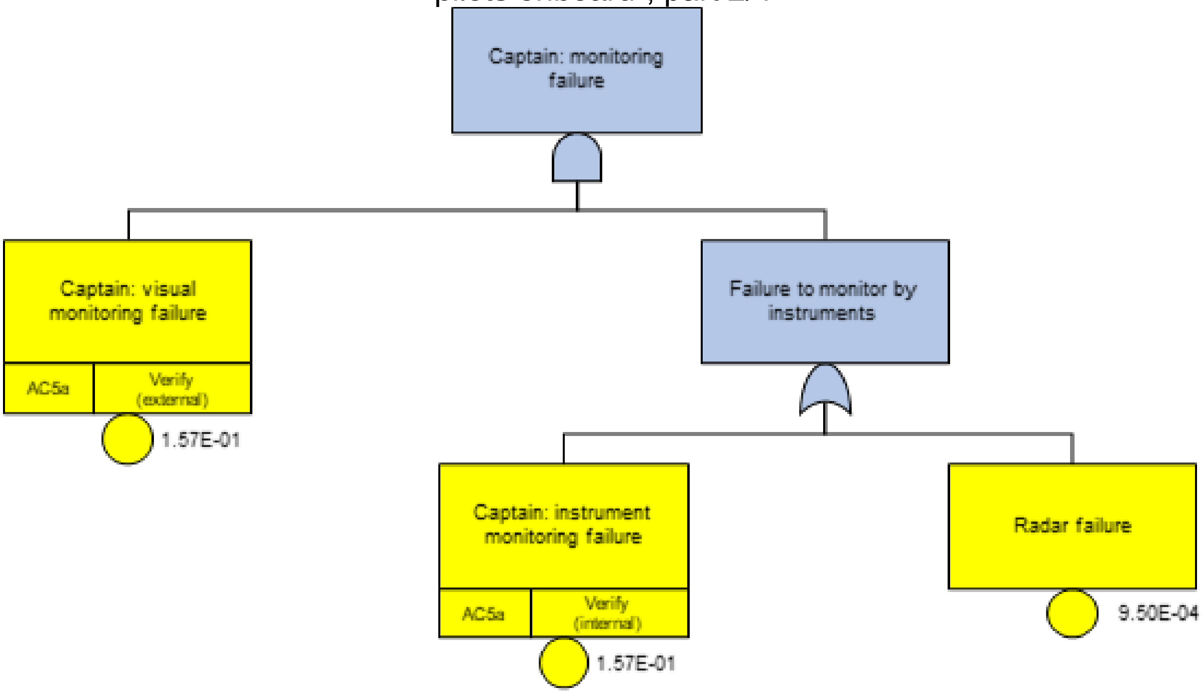


Figure 54 – Fault tree for the event "Safe action failure (with tugboat support) - two pilots onboard", part 3/4

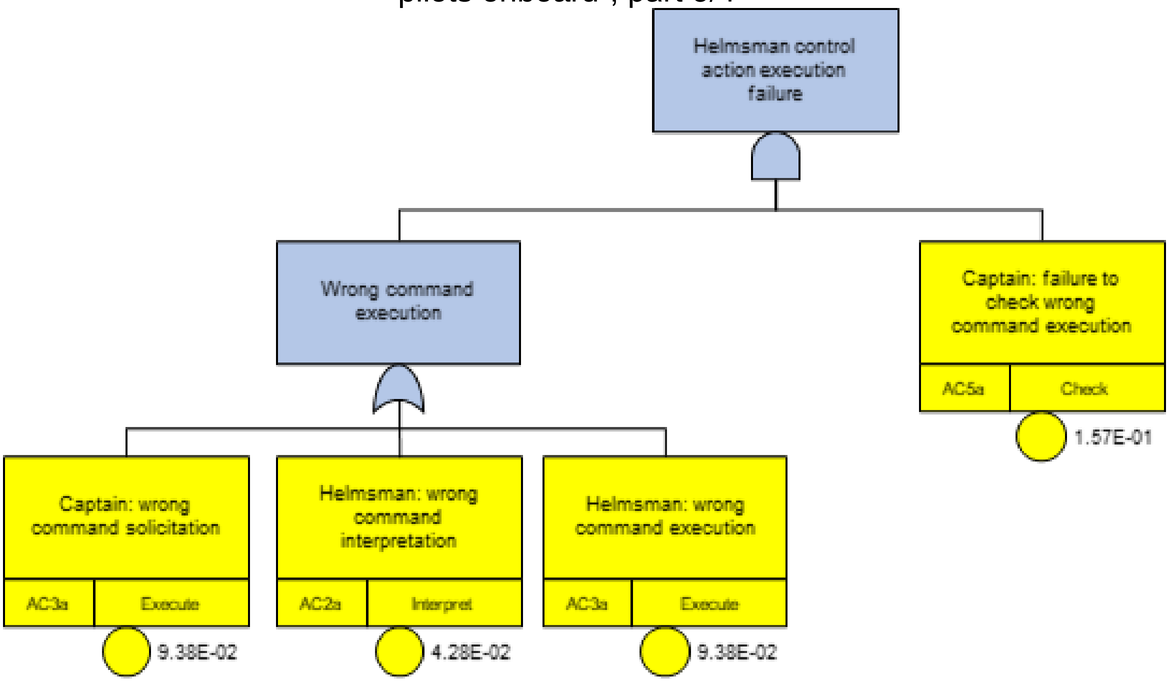
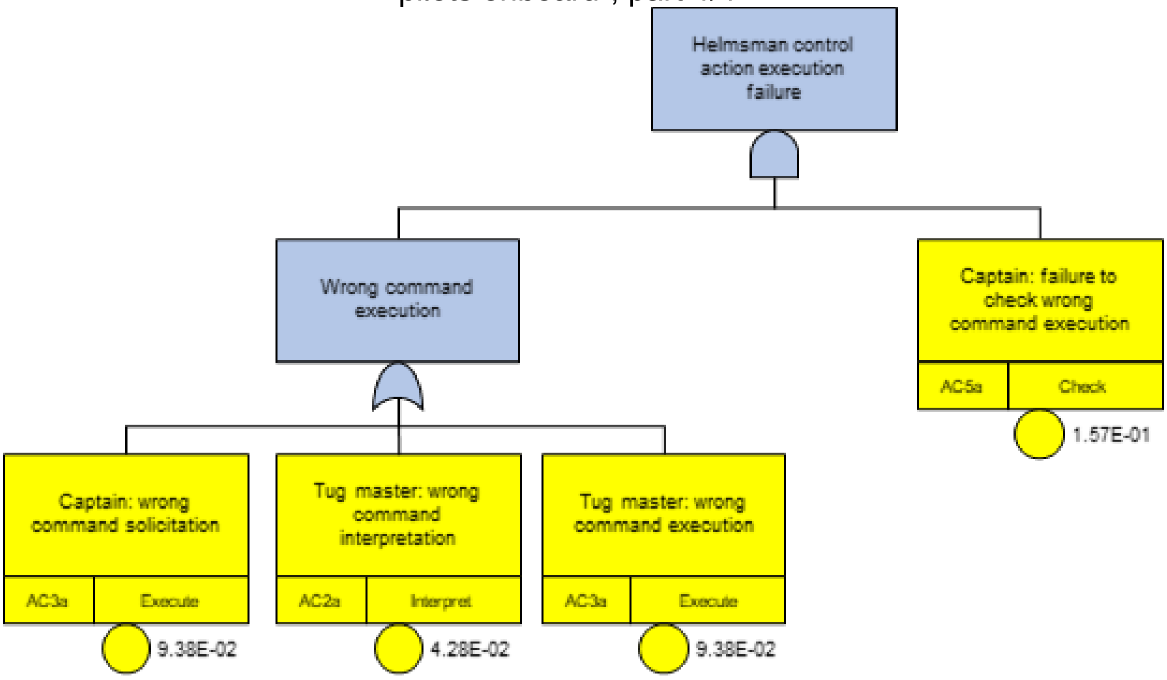


Figure 55– Fault tree for the event "Safe action failure (with tugboat support) - two pilots onboard", part 4/4



B.8. Fault tree for the event "Recovery action failure (without tugboat support) - one pilot onboard"

Figure 56 – Recovery action failure (without tugboat support) - one pilot onboard, part 1/4

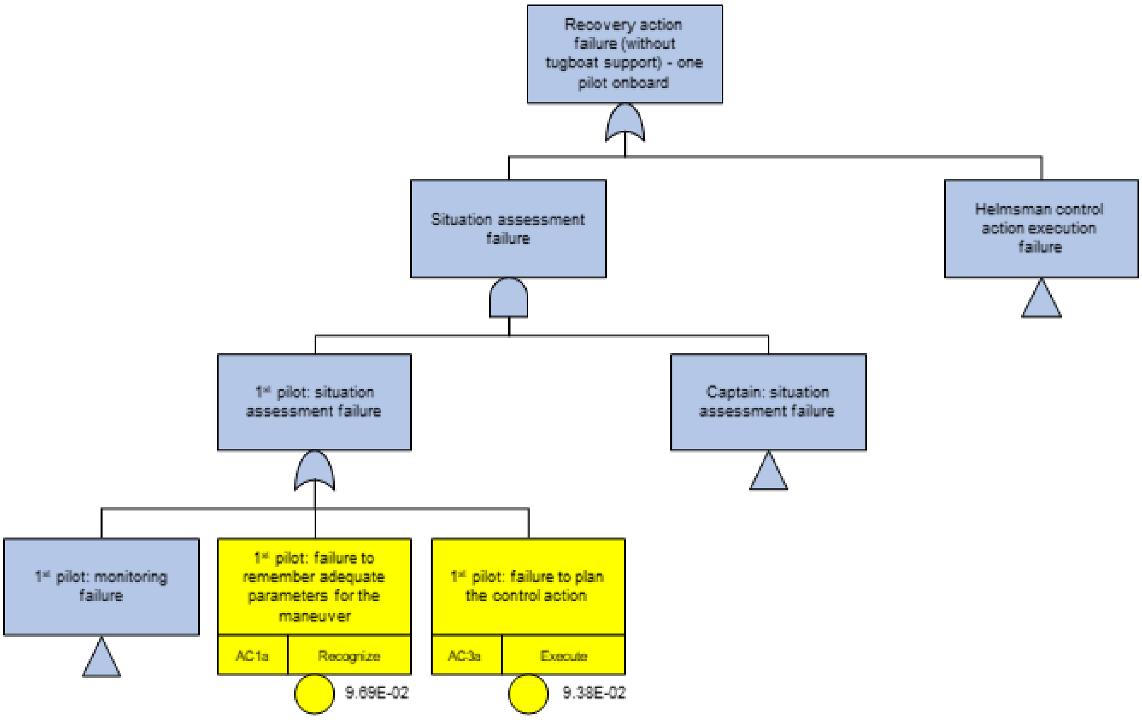


Figure 57 – Recovery action failure (without tugboat support) - one pilot onboard, part 2/4

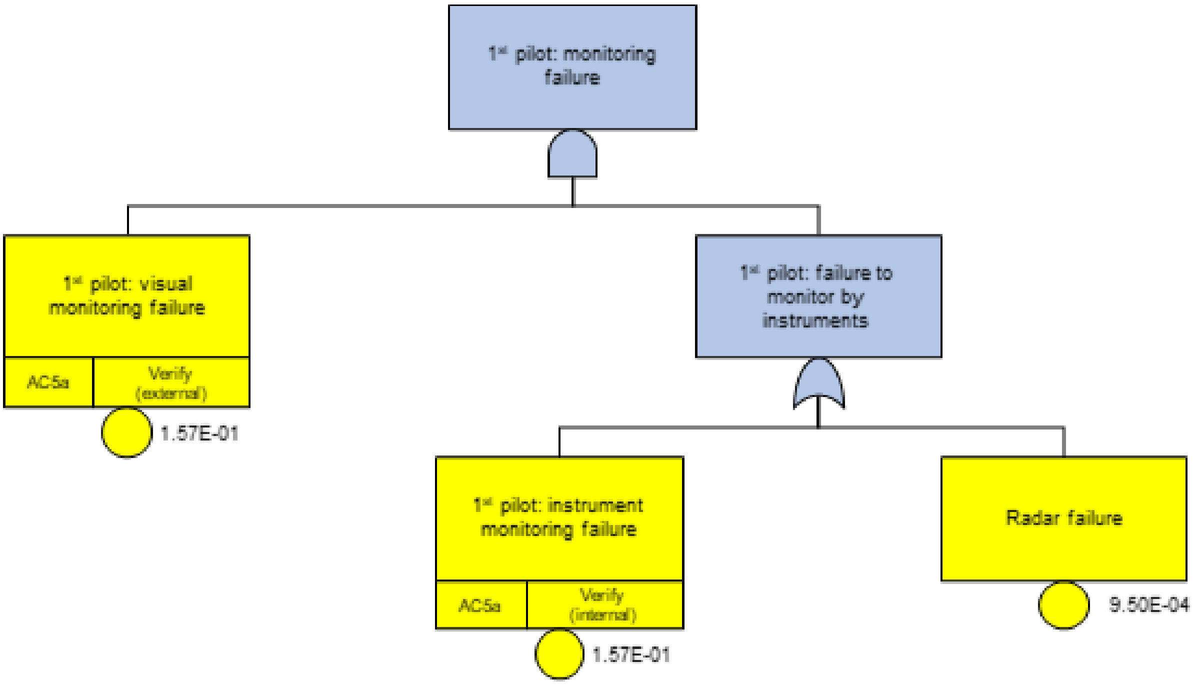


Figure 58 – Recovery action failure (without tugboat support) - one pilot onboard, part 3/4

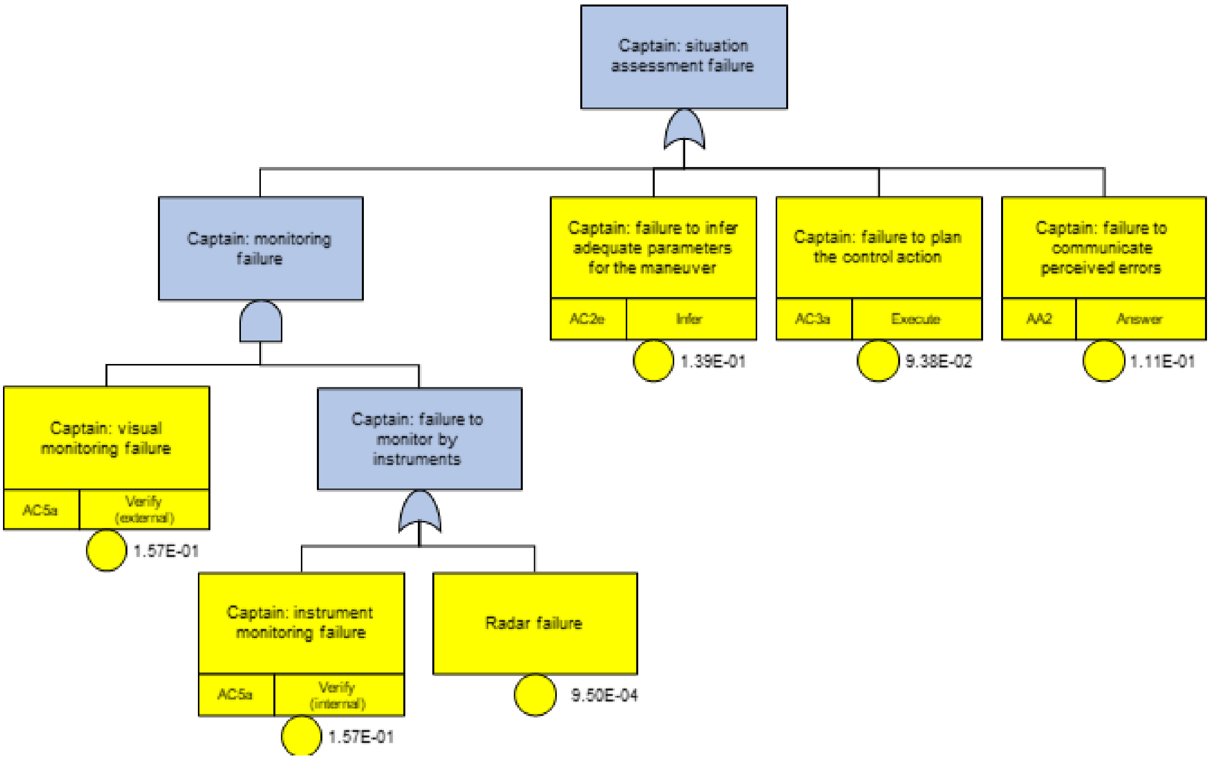
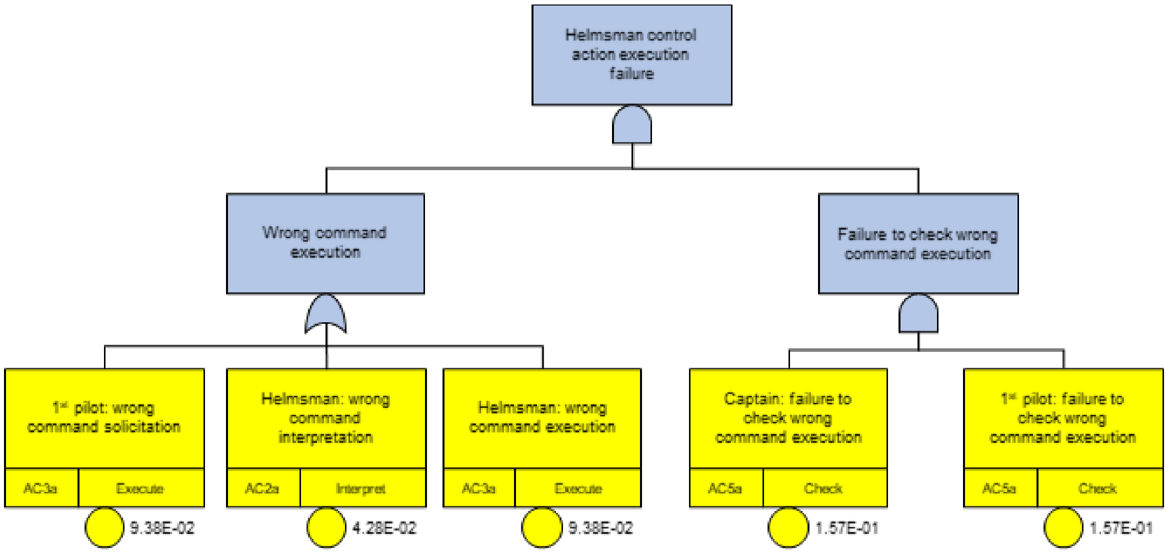


Figure 59 – Recovery action failure (without tugboat support) - one pilot onboard, part 4/4



B.9. Fault tree for the event "Recovery action failure (without tugboat support) - two pilots onboard"

Figure 60 – Fault tree for the event "Recovery action failure (without tugboat support) - two pilots onboard", part 1/5

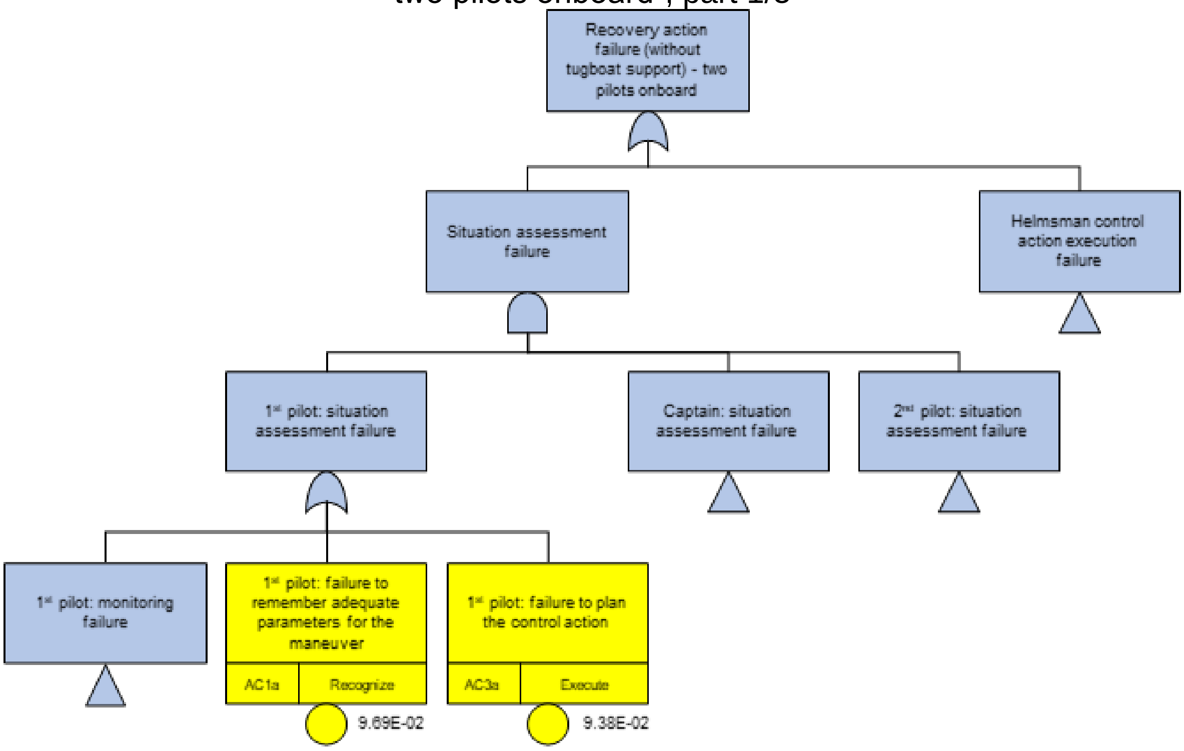


Figure 61 – Fault tree for the event “Recovery action failure (without tugboat support) - two pilots onboard”, part 2/5

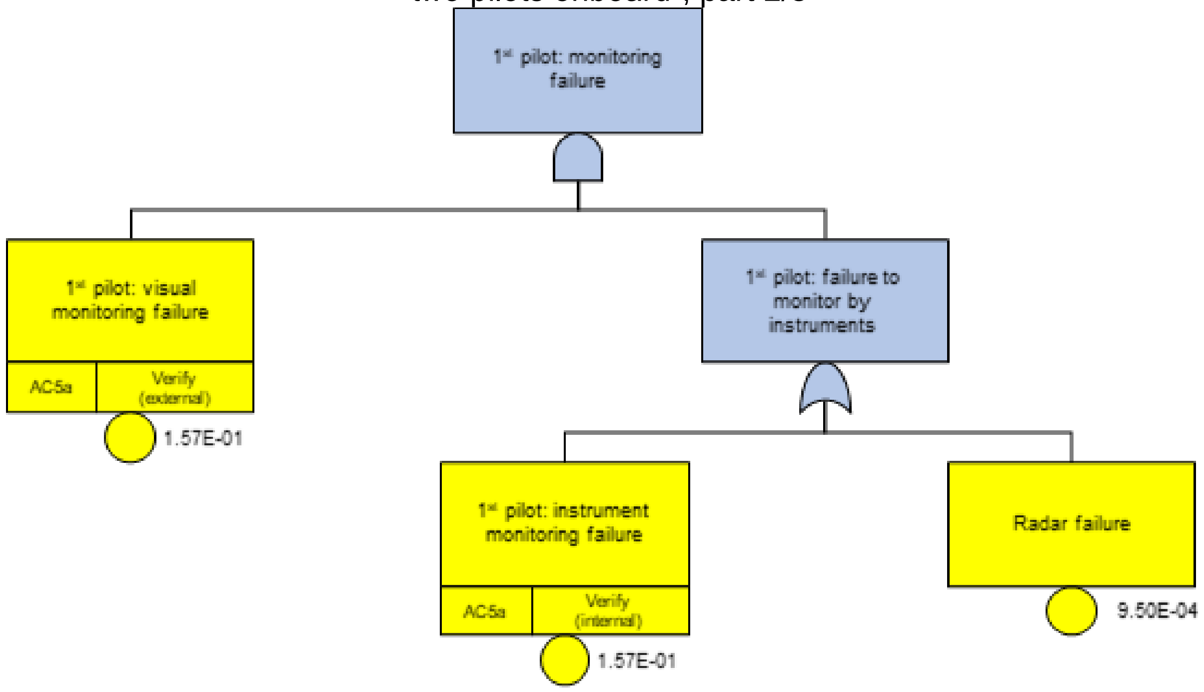


Figure 62 – Fault tree for the event “Recovery action failure (without tugboat support) - two pilots onboard”, part 3/5

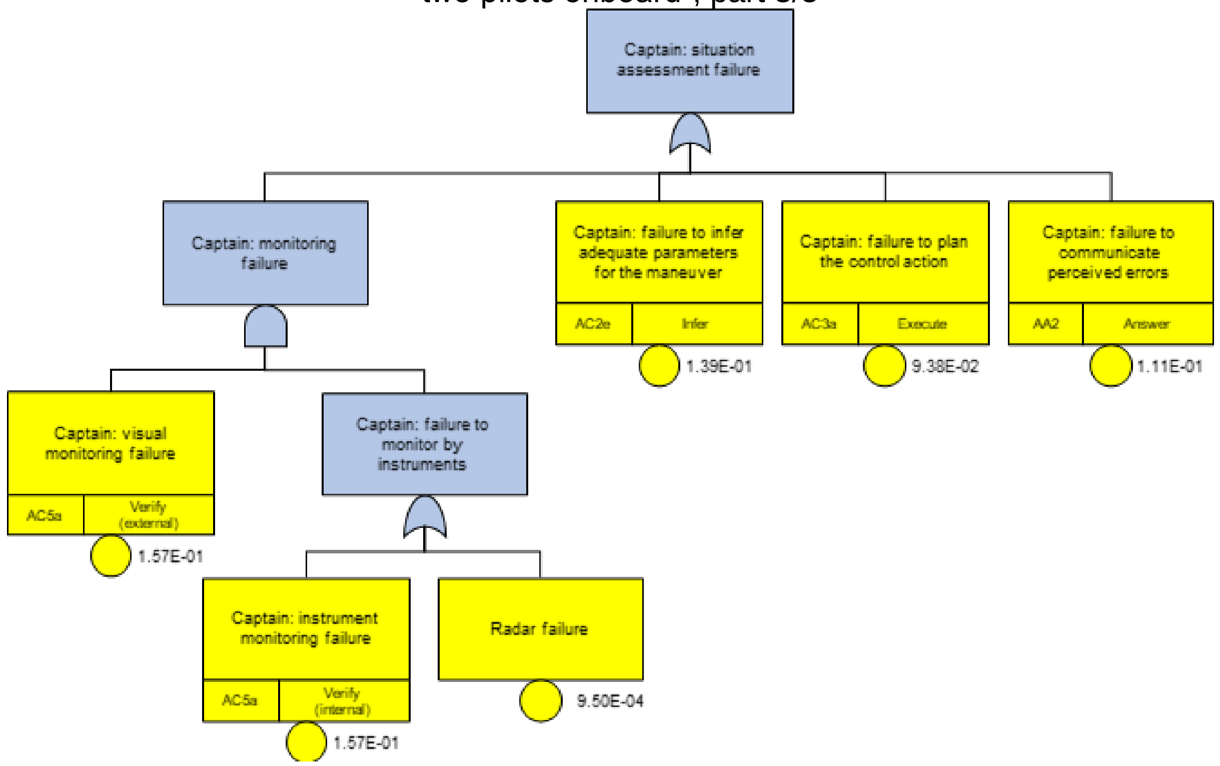


Figure 63 – Fault tree for the event "Recovery action failure (without tugboat support) - two pilots onboard", part 4/5

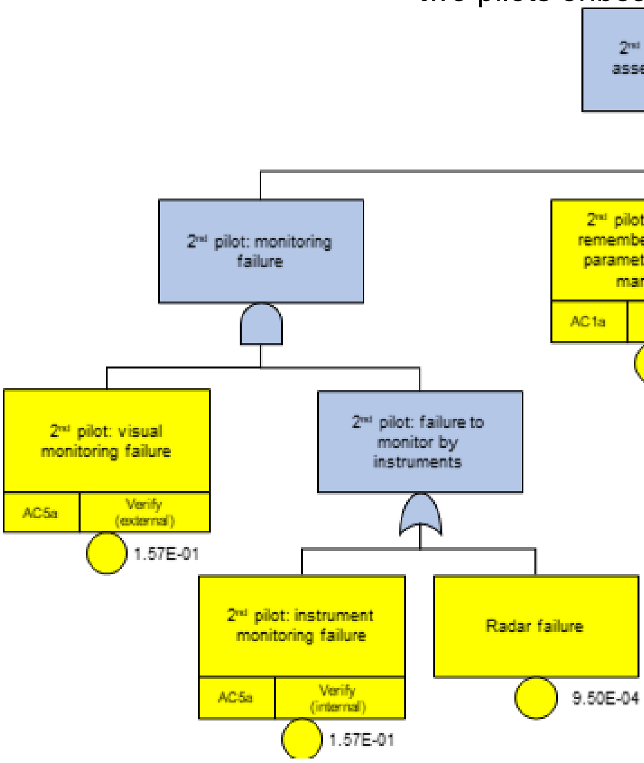
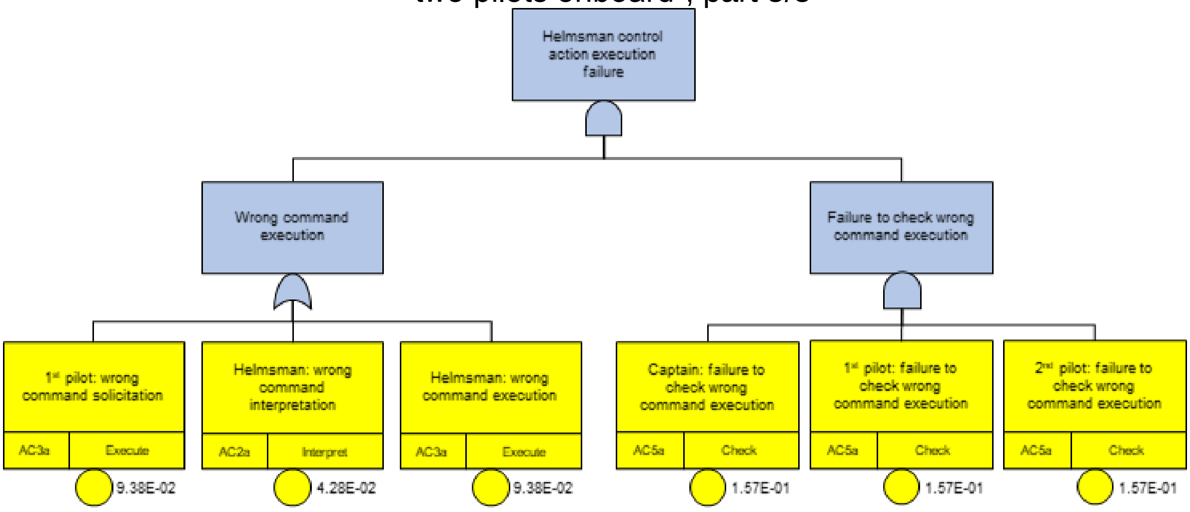


Figure 64 – Fault tree for the event "Recovery action failure (without tugboat support) - two pilots onboard", part 5/5



B.10. Fault tree for the event "Recovery action failure (without tugboat support) – no pilot onboard"

Figure 65 – Fault tree for the event "Recovery action failure (without tugboat support) - two pilots onboard", part 1/4

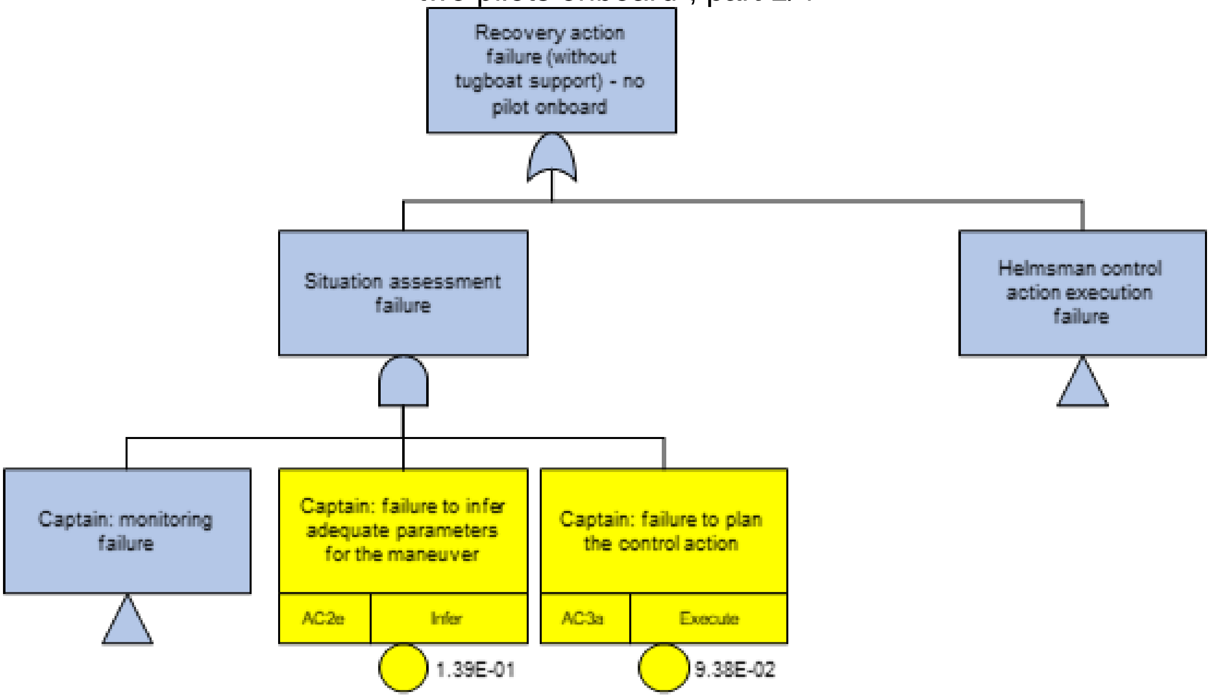


Figure 66 – Fault tree for the event "Recovery action failure (without tugboat support) - two pilots onboard", part 2/4

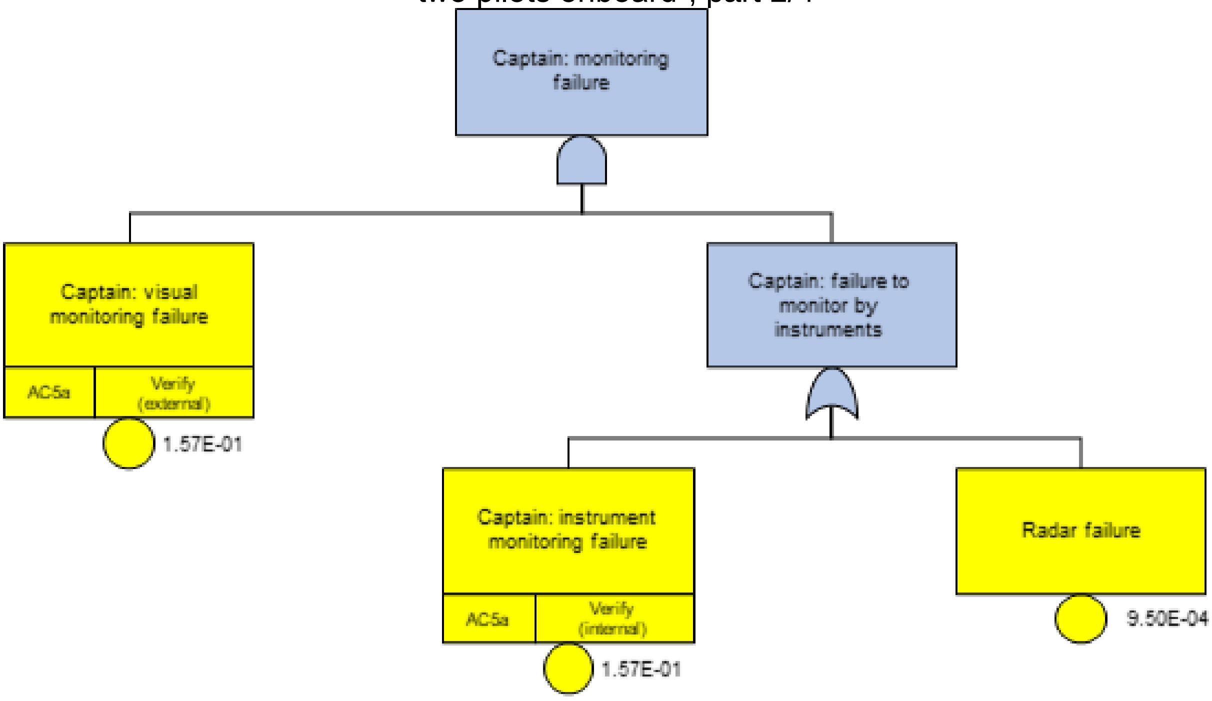


Figure 67 – Fault tree for the event "Recovery action failure (without tugboat support) - two pilots onboard", part 3/4

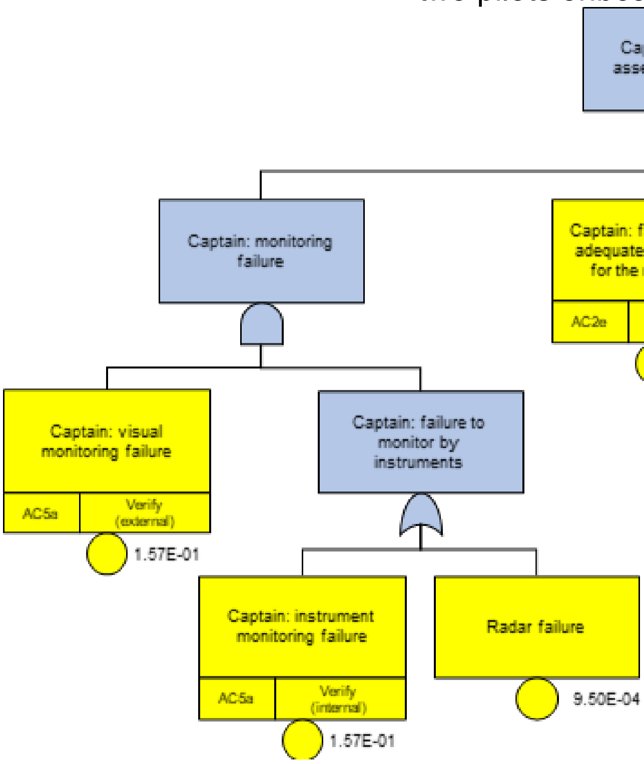
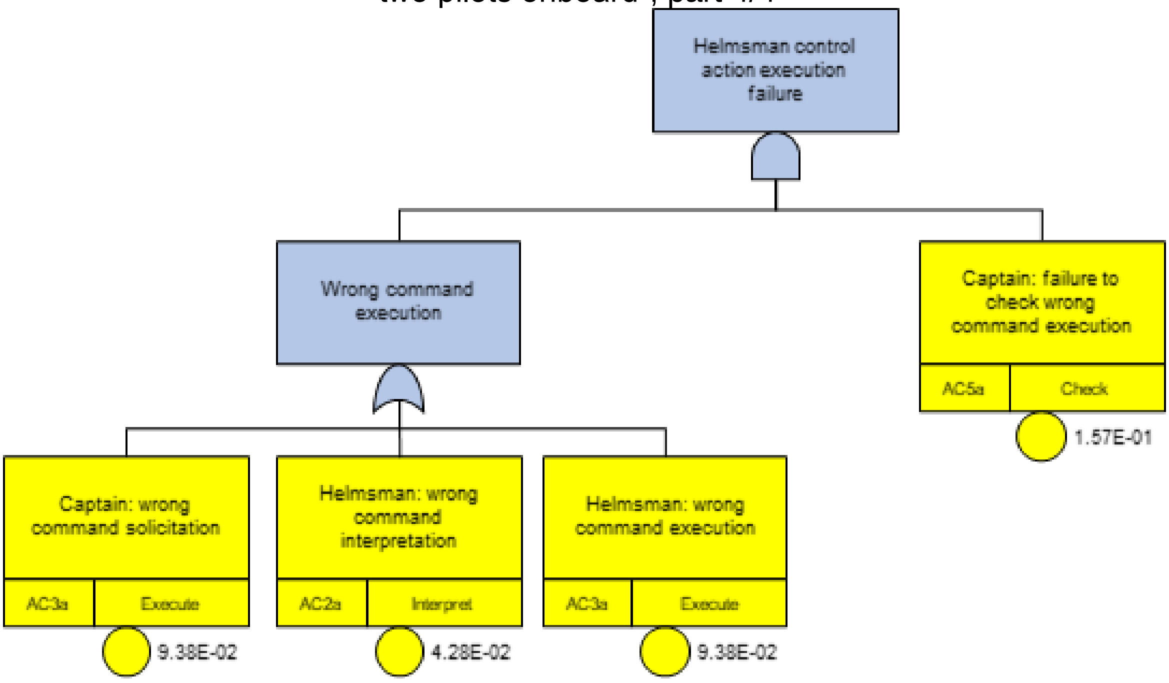


Figure 68 – Fault tree for the event "Recovery action failure (without tugboat support) - two pilots onboard", part 4/4



B.11. Fault tree for the event "Recovery action failure (with tugboat support) - one pilot onboard"

Figure 69 – Fault tree for the event "Recovery action failure (with tugboat support) - one pilot onboard", part 1/5

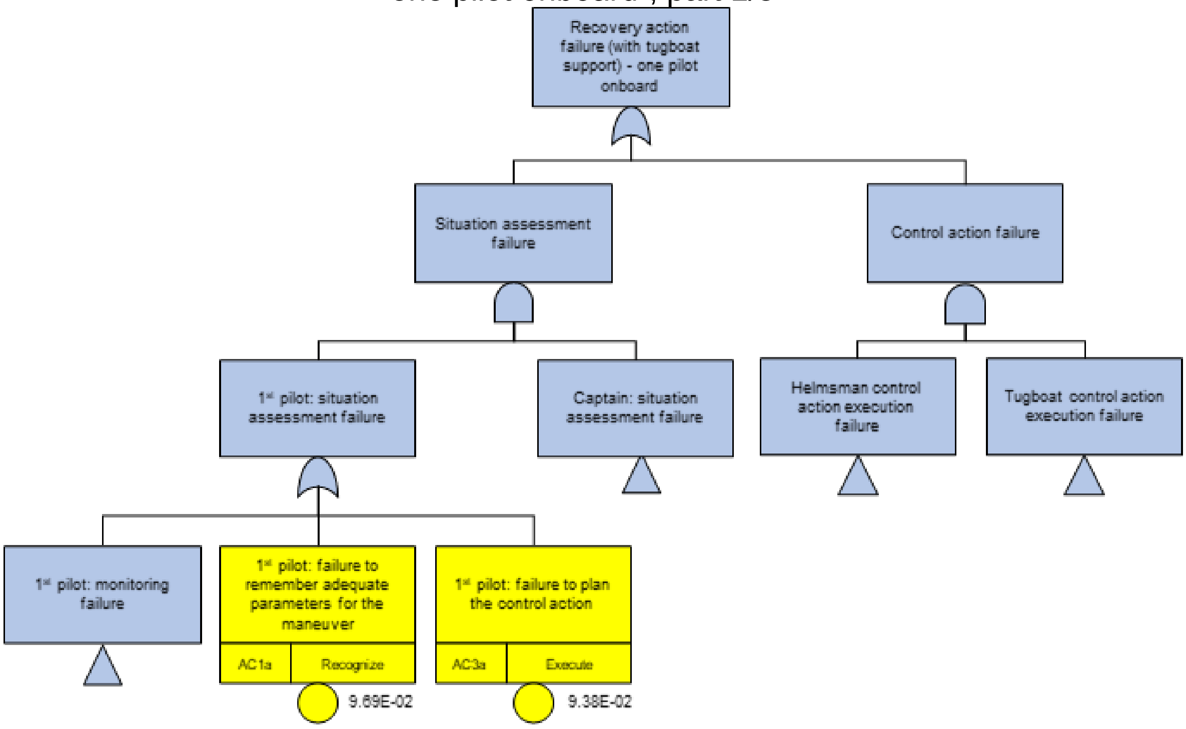


Figure 70 – Fault tree for the event "Recovery action failure (with tugboat support) - one pilot onboard", part 2/5

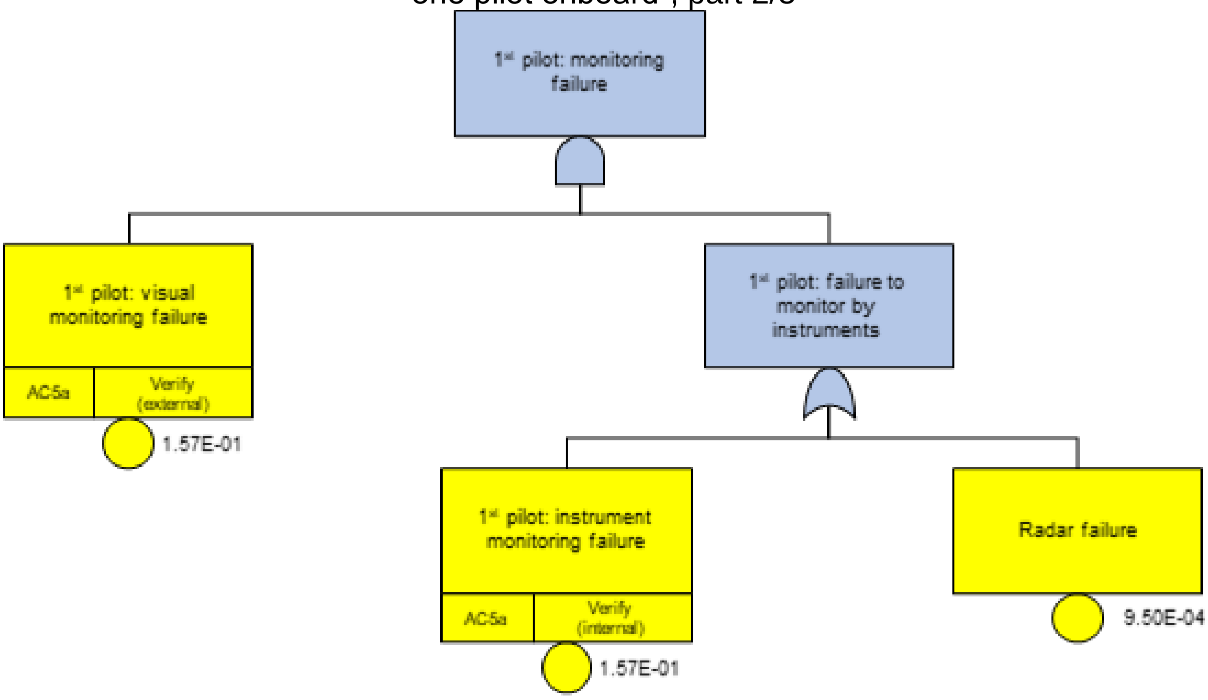


Figure 71 – Fault tree for the event "Recovery action failure (with tugboat support) - one pilot onboard", part 3/5

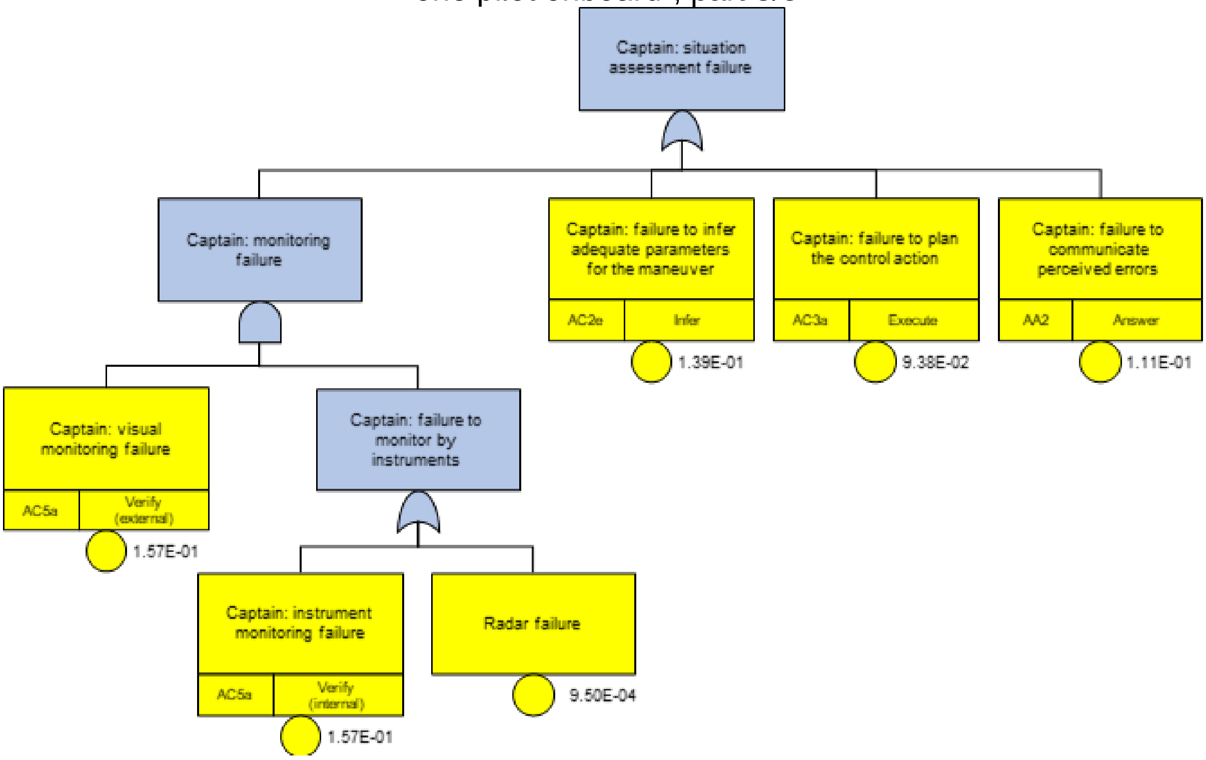


Figure 72 – Fault tree for the event "Recovery action failure (with tugboat support) - one pilot onboard", part 4/5

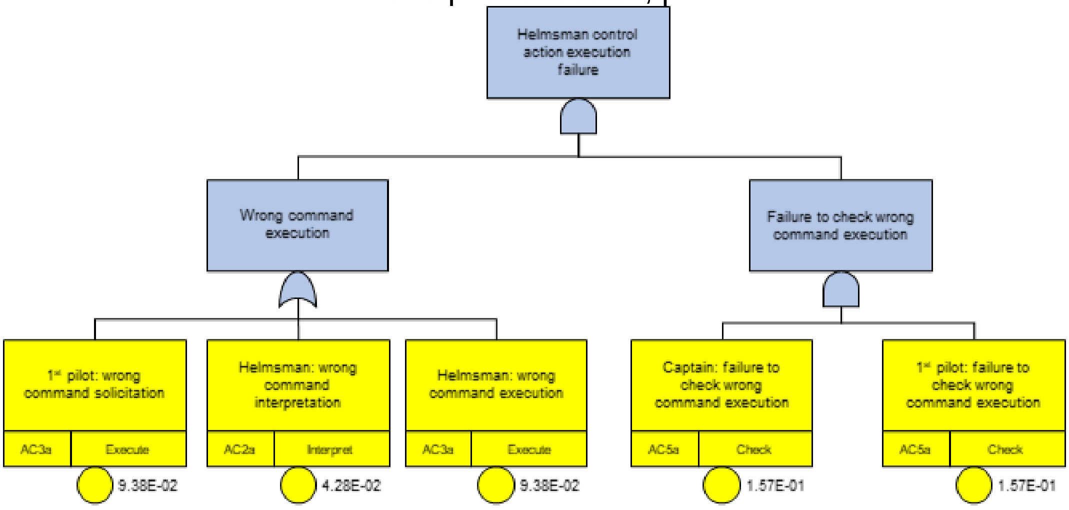
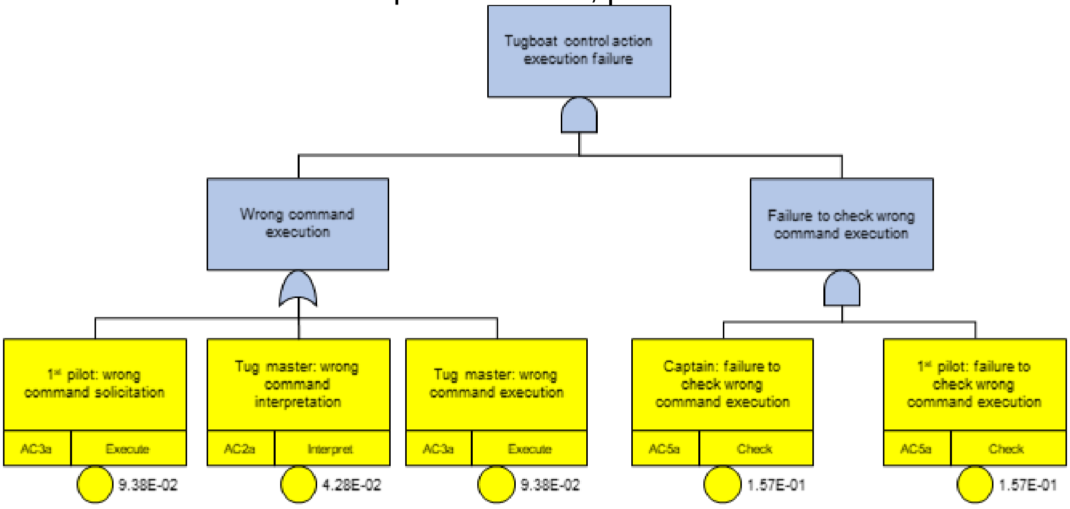


Figure 73 – Fault tree for the event "Recovery action failure (with tugboat support) - one pilot onboard", part 5/5



B.12. Fault tree for the event "Recovery action failure (with tugboat support) - two pilots onboard"

Figure 74 – Fault tree for the event "Recovery action failure (with tugboat support) – two pilots onboard", part 1/6

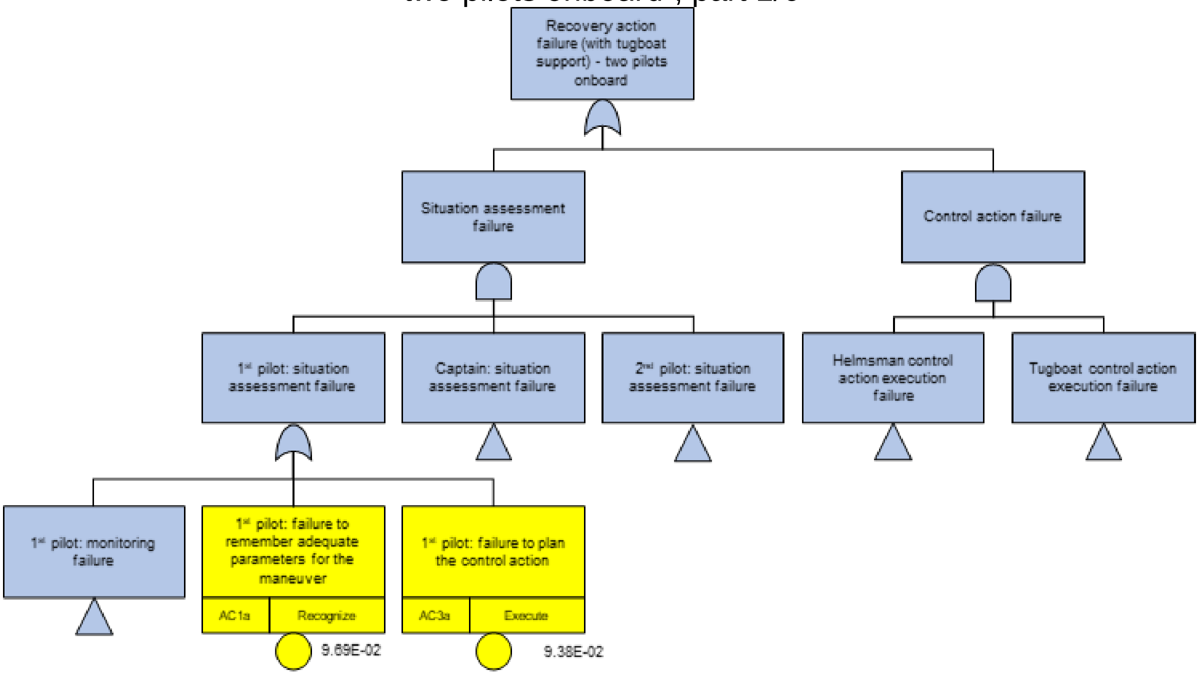


Figure 75 – Fault tree for the event “Recovery action failure (with tugboat support) – two pilots onboard”, part 2/6

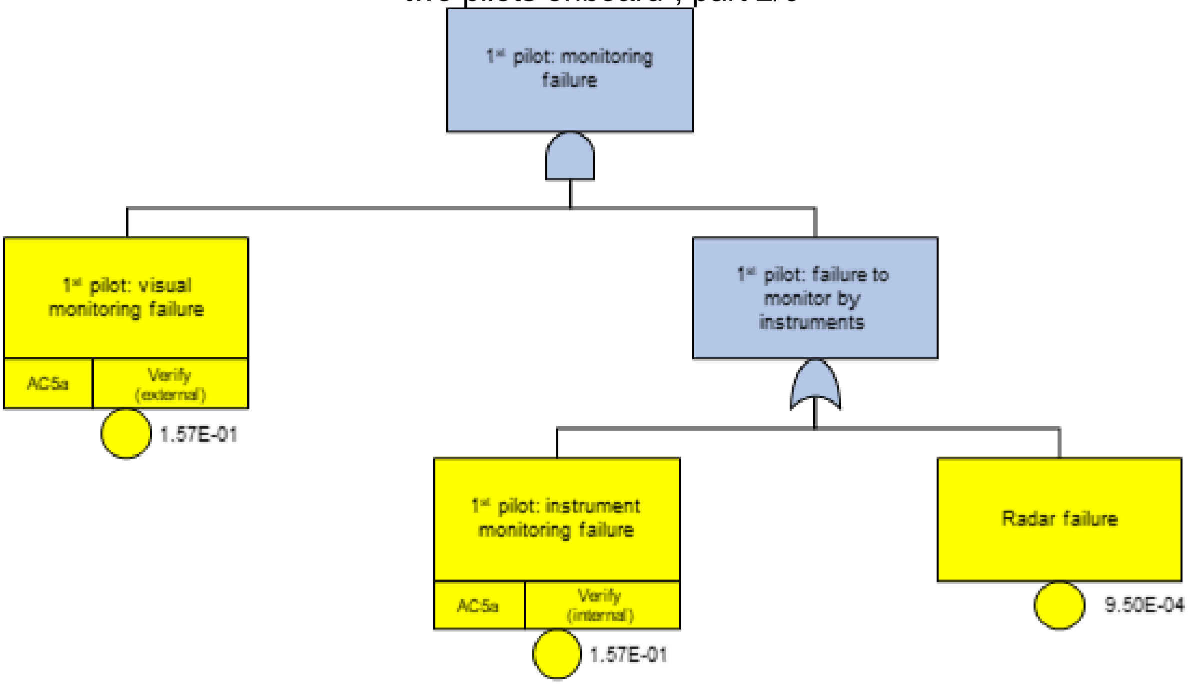


Figure 76 – Fault tree for the event “Recovery action failure (with tugboat support) – two pilots onboard”, part 3/6

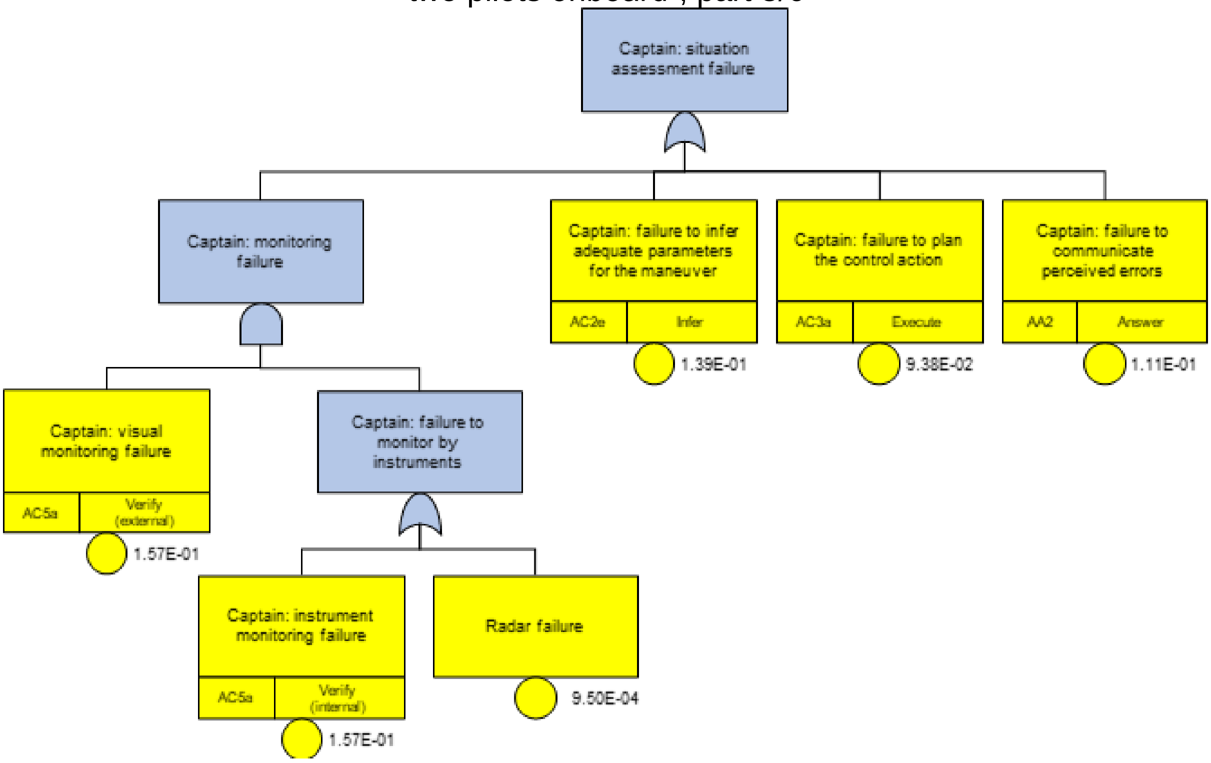


Figure 77 – Fault tree for the event "Recovery action failure (with tugboat support) – two pilots onboard", part 4/6

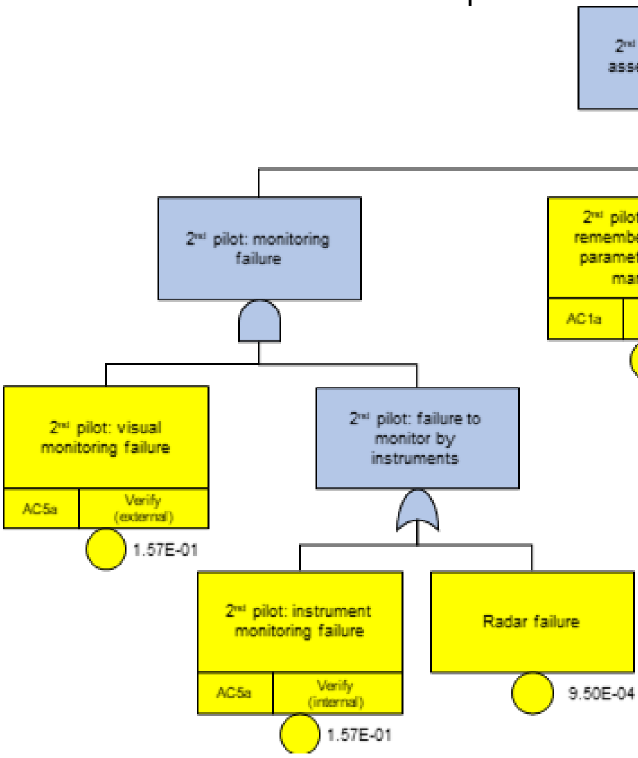


Figure 78 – Fault tree for the event "Recovery action failure (with tugboat support) – two pilots onboard", part 5/6

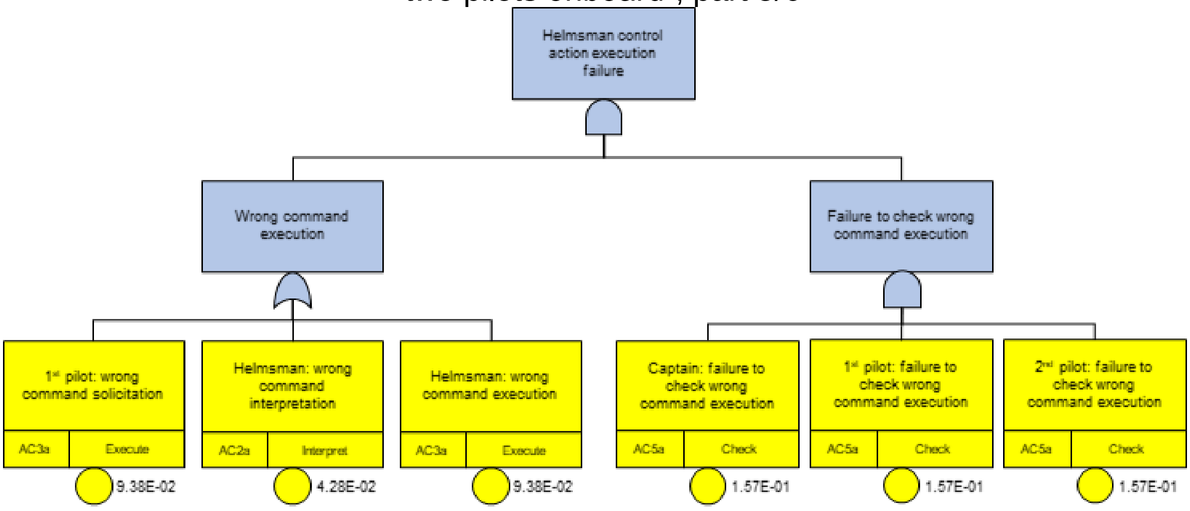
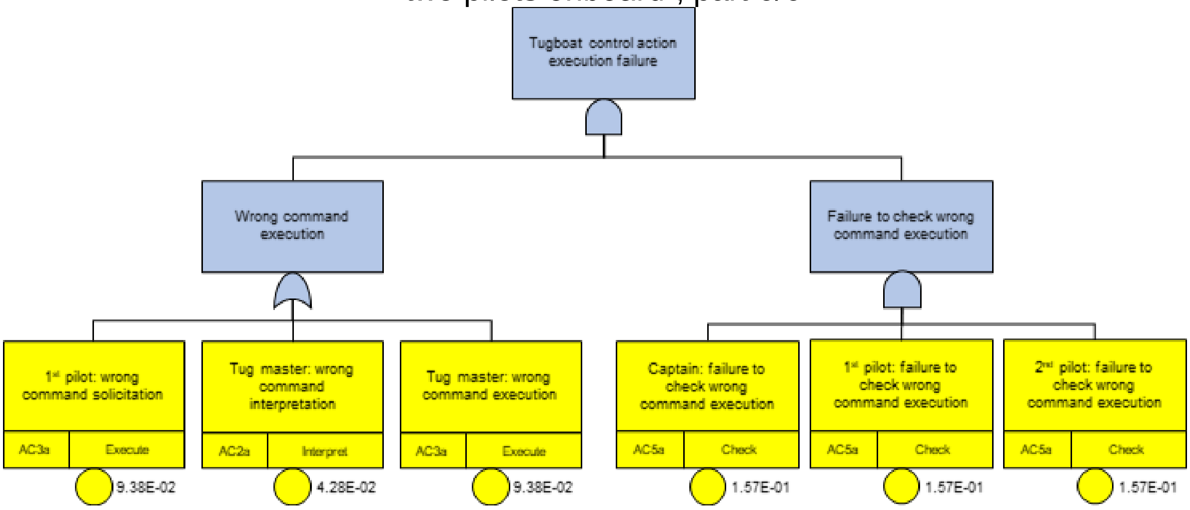


Figure 79 – Fault tree for the event "Recovery action failure (with tugboat support) – two pilots onboard", part 6/6



B.13. Fault tree for the event "Recovery action failure (with tugboat support) - no pilot onboard"

Figure 80 – Fault tree for the event "Recovery action failure (with tugboat support) - no pilot onboard", part 1/4

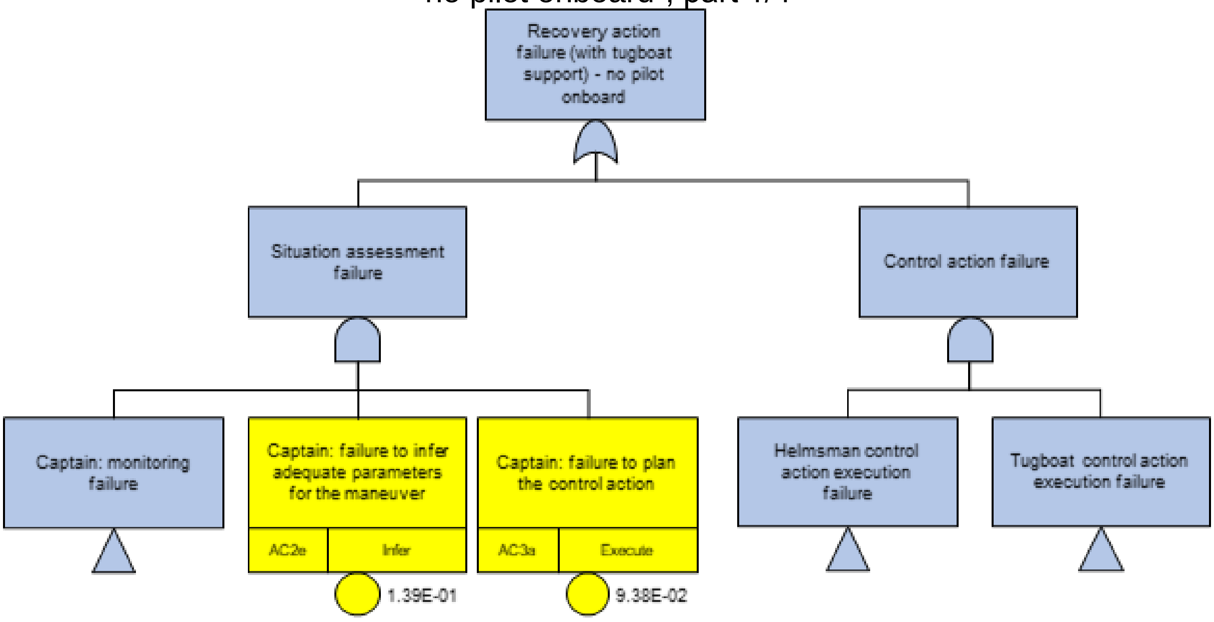


Figure 81 – Fault tree for the event "Recovery action failure (with tugboat support) - no pilot onboard", part 2/4

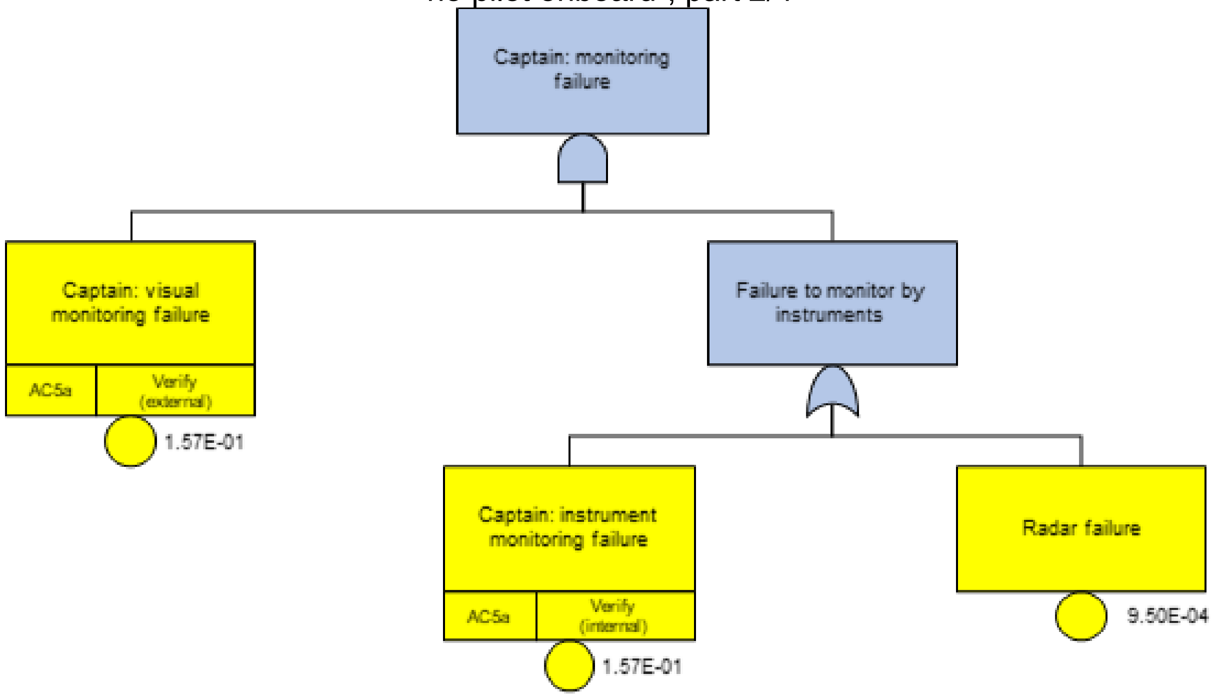


Figure 82 – Fault tree for the event "Recovery action failure (with tugboat support) - no pilot onboard", part 3/4

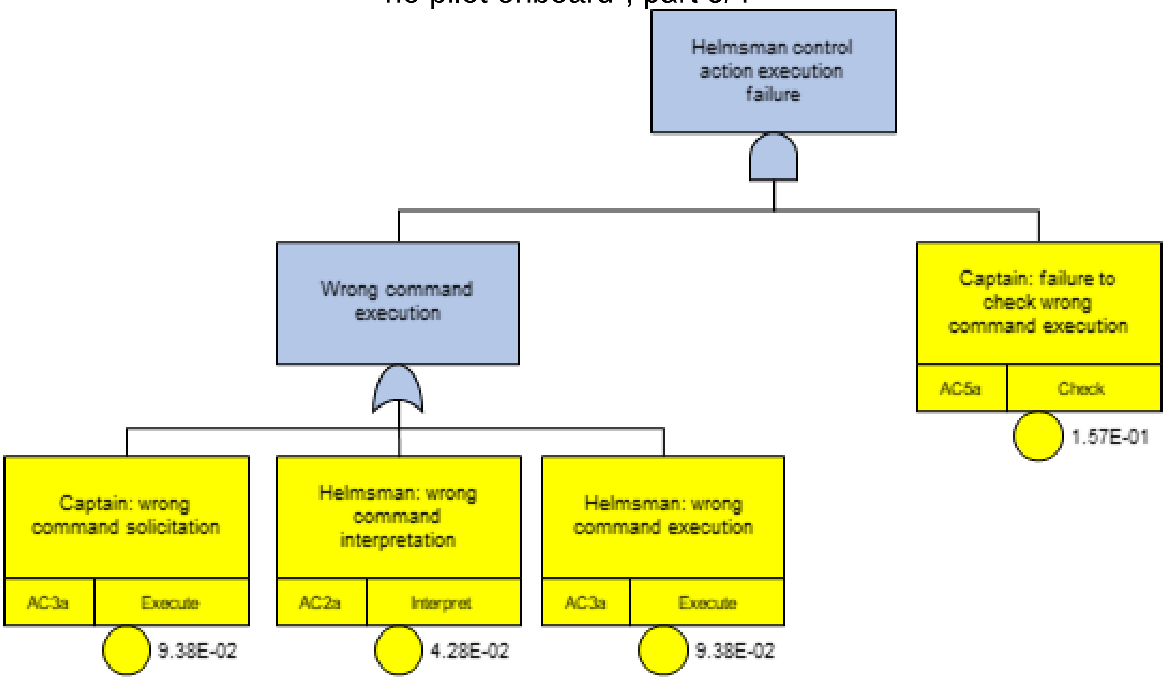
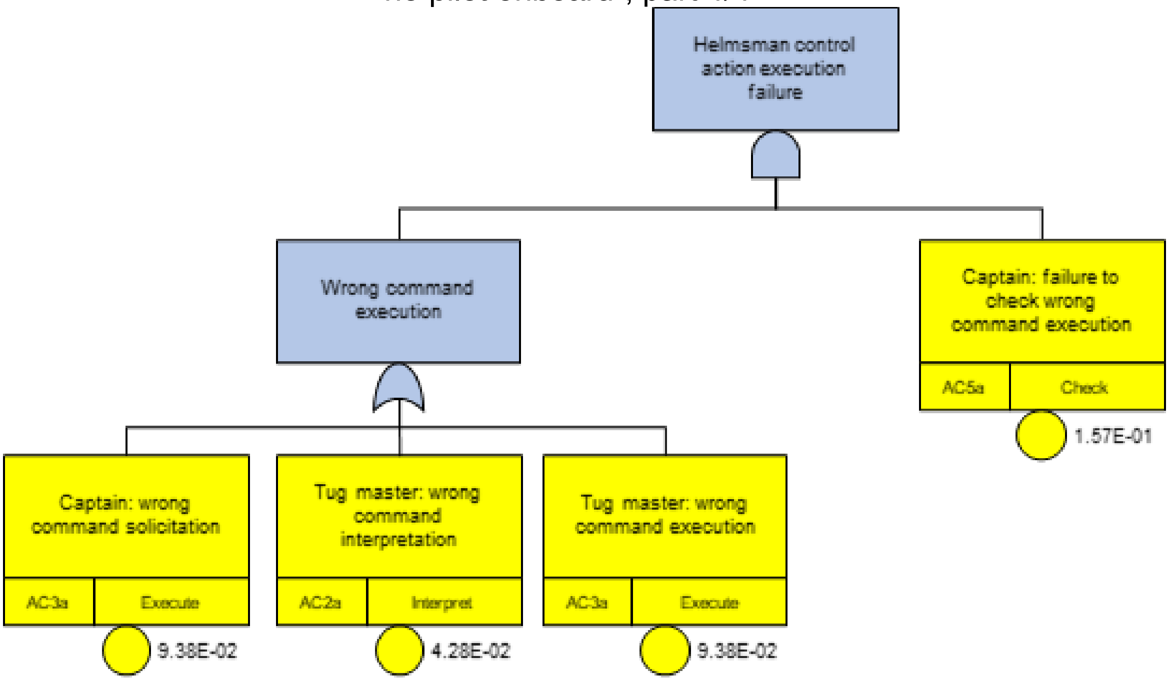
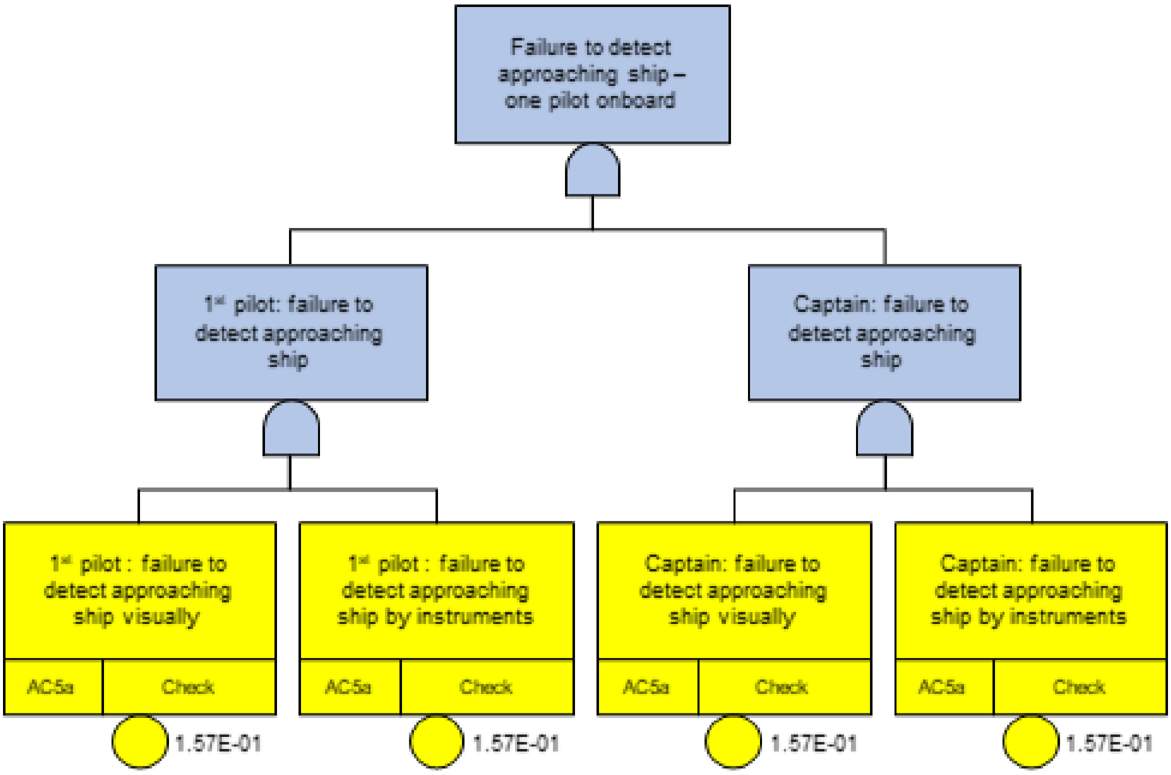


Figure 83 – Fault tree for the event "Recovery action failure (with tugboat support) - no pilot onboard", part 4/4



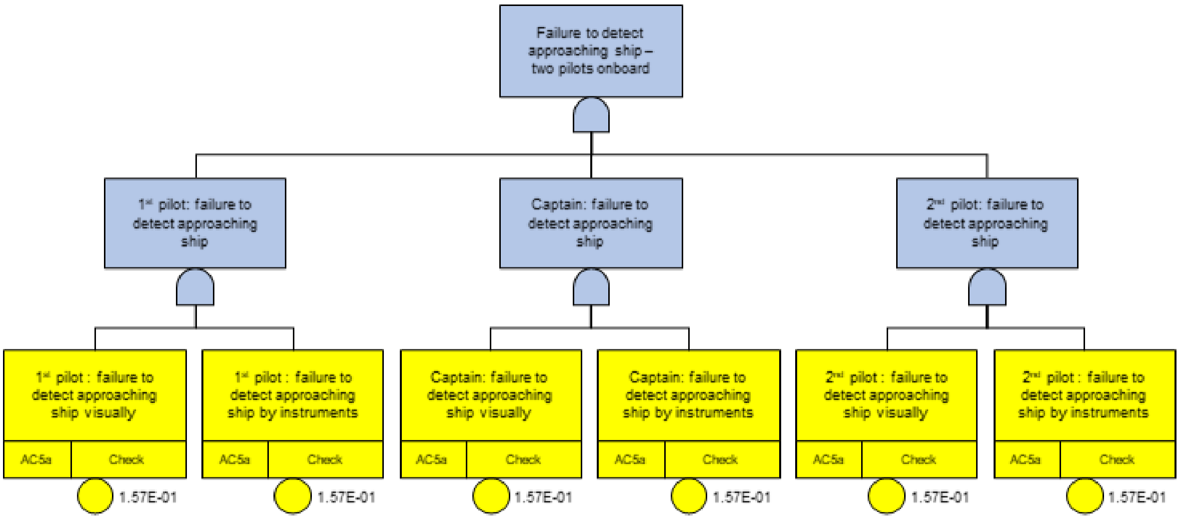
B.14. Fault tree for the event "Failure to detect approaching ship – one pilot onboard"

Figure 84 – Fault tree for the event "Failure to detect approaching ship – one pilot onboard



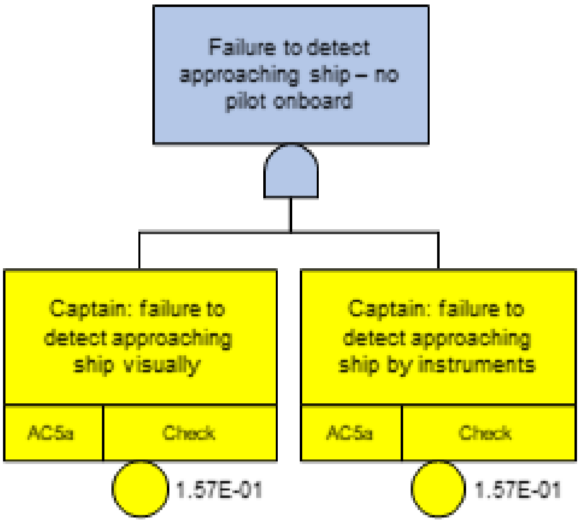
B.15. Fault tree for the event "Failure to detect approaching ship – two pilots onboard"

Figure 85 – Fault tree for the event "Failure to detect approaching ship – two pilots onboard"



B.16. Fault tree for the event "Failure to detect approaching ship – no pilot onboard"

Figure 86 – Fault tree for the event "Failure to detect approaching ship – no pilot onboard"



B.17. Fault tree for the event "Failure to plan maneuver strategy with other ship – one pilot onboard"

Figure 87 – Fault tree for the event "Failure to plan maneuver strategy with other ship – one pilot onboard", part 1/2

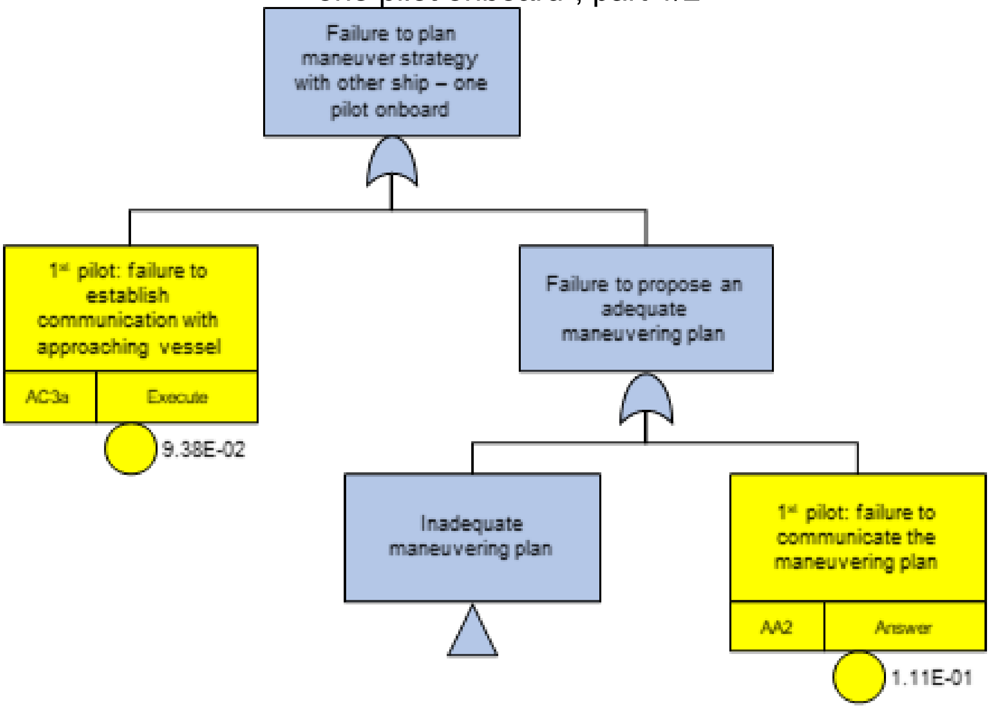
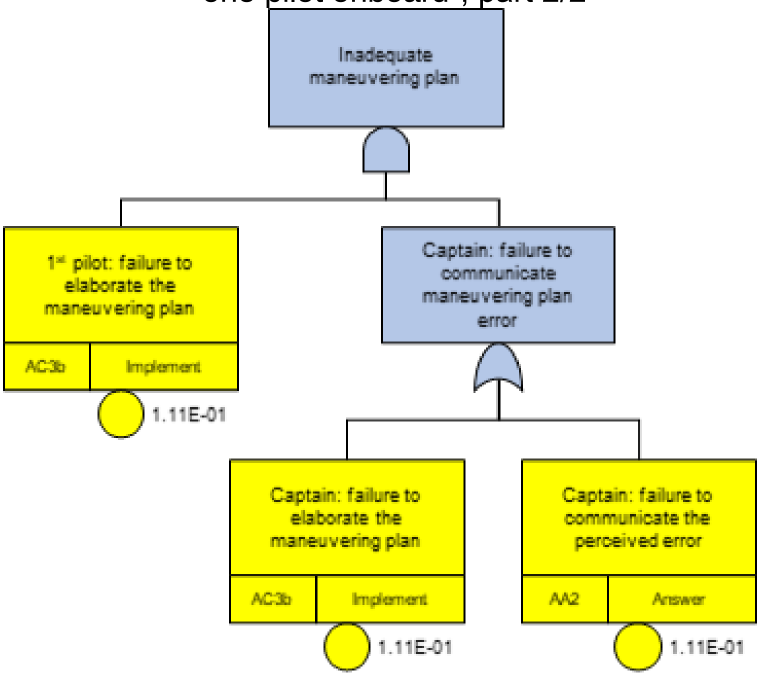


Figure 88 – Fault tree for the event "Failure to plan maneuver strategy with other ship – one pilot onboard", part 2/2



B.18. Fault tree for the event "Failure to plan maneuver strategy with other ship – two pilots onboard"

Figure 89 – Fault tree for the event "Failure to plan maneuver strategy with other ship – two pilots onboard", part 1/2

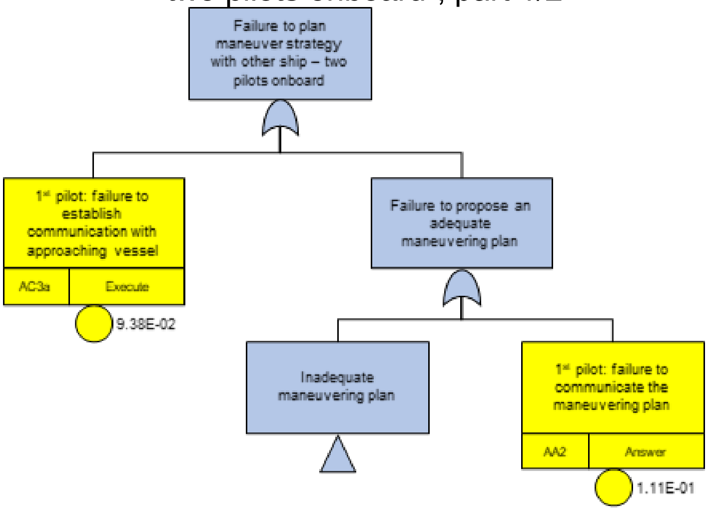
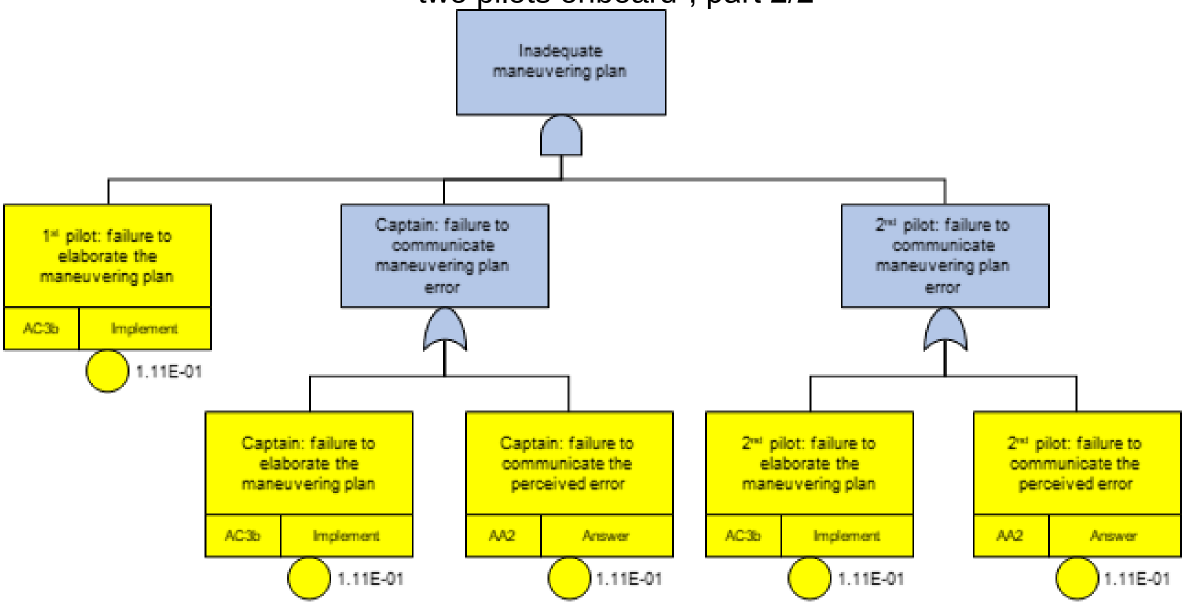


Figure 90 – Fault tree for the event "Failure to plan maneuver strategy with other ship – two pilots onboard", part 2/2



B.19. Fault tree for the event "Failure to plan maneuver strategy with other ship – no pilot onboard"

Figure 91 – Fault tree for the event "Failure to plan maneuver strategy with other ship – no pilot onboard", part 1/2

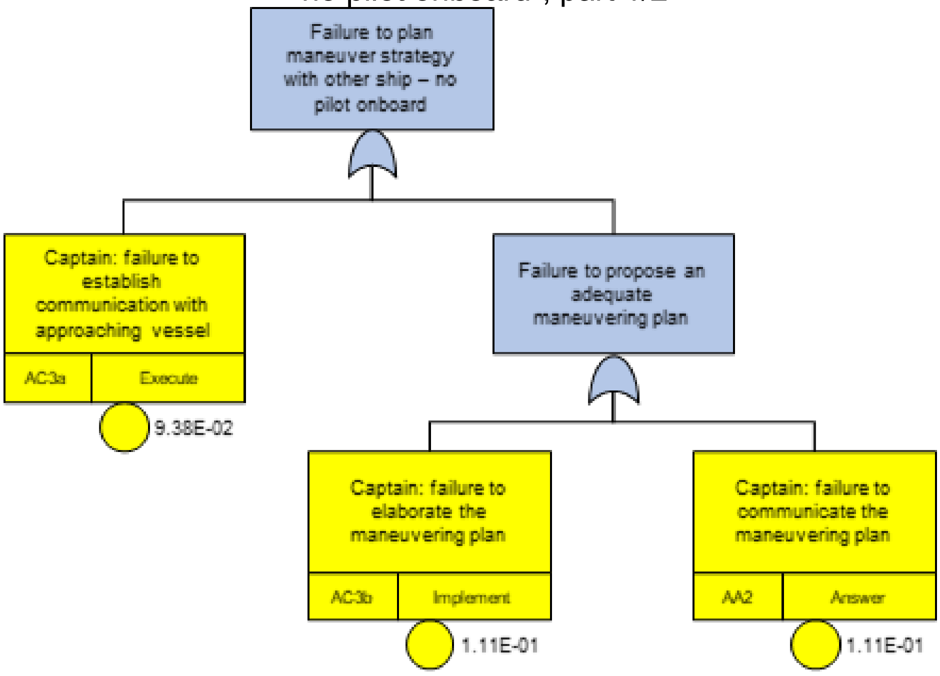
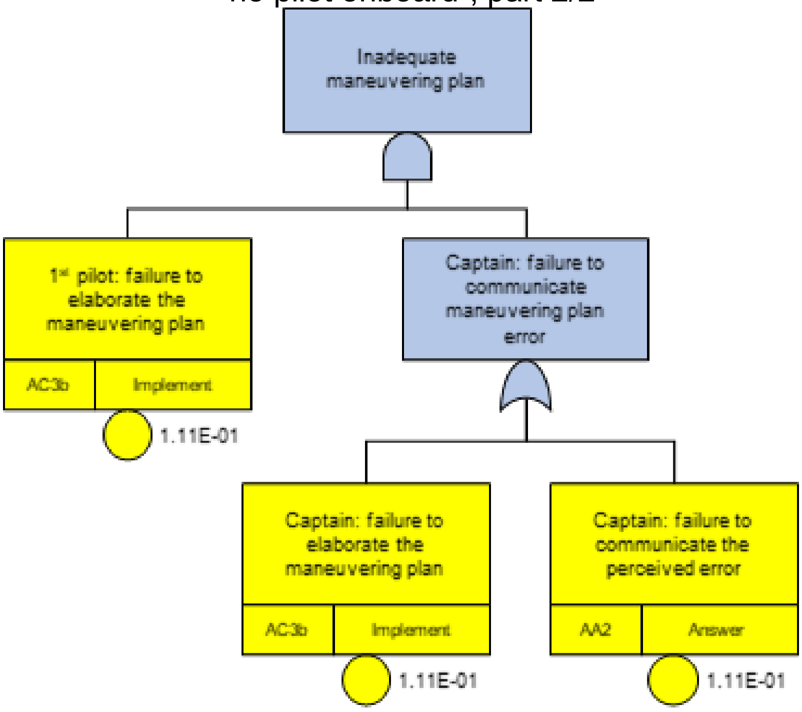
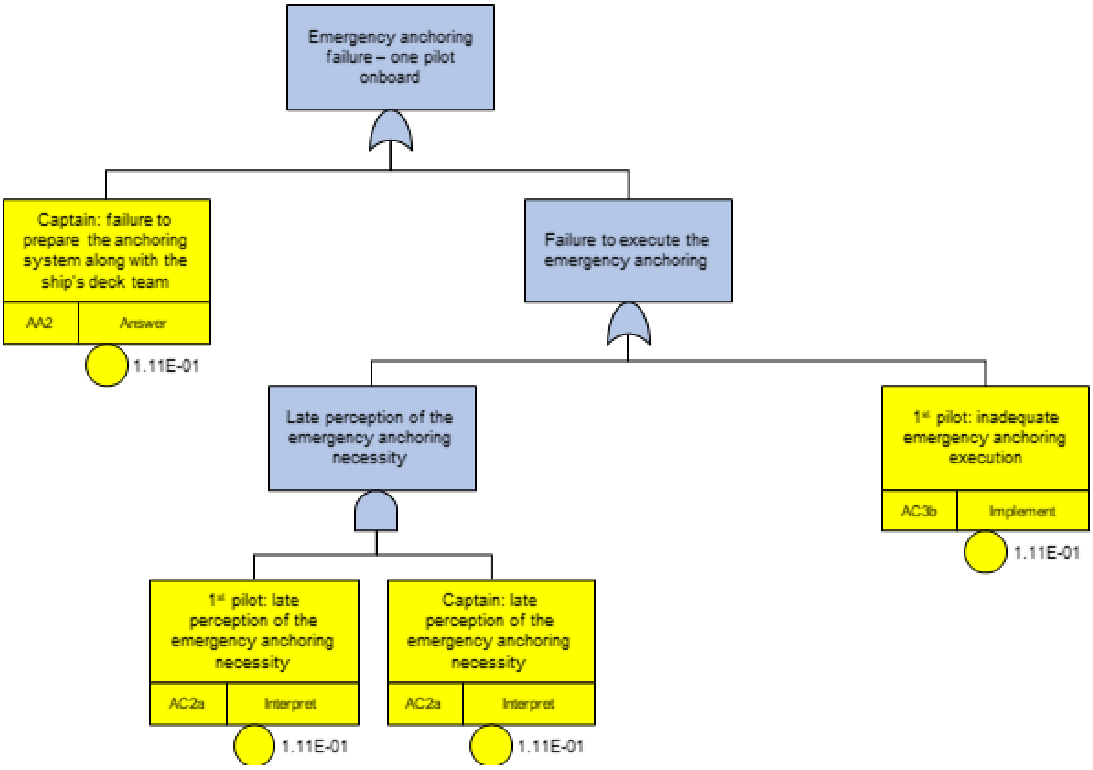


Figure 92 – Fault tree for the event "Failure to plan maneuver strategy with other ship – no pilot onboard", part 2/2



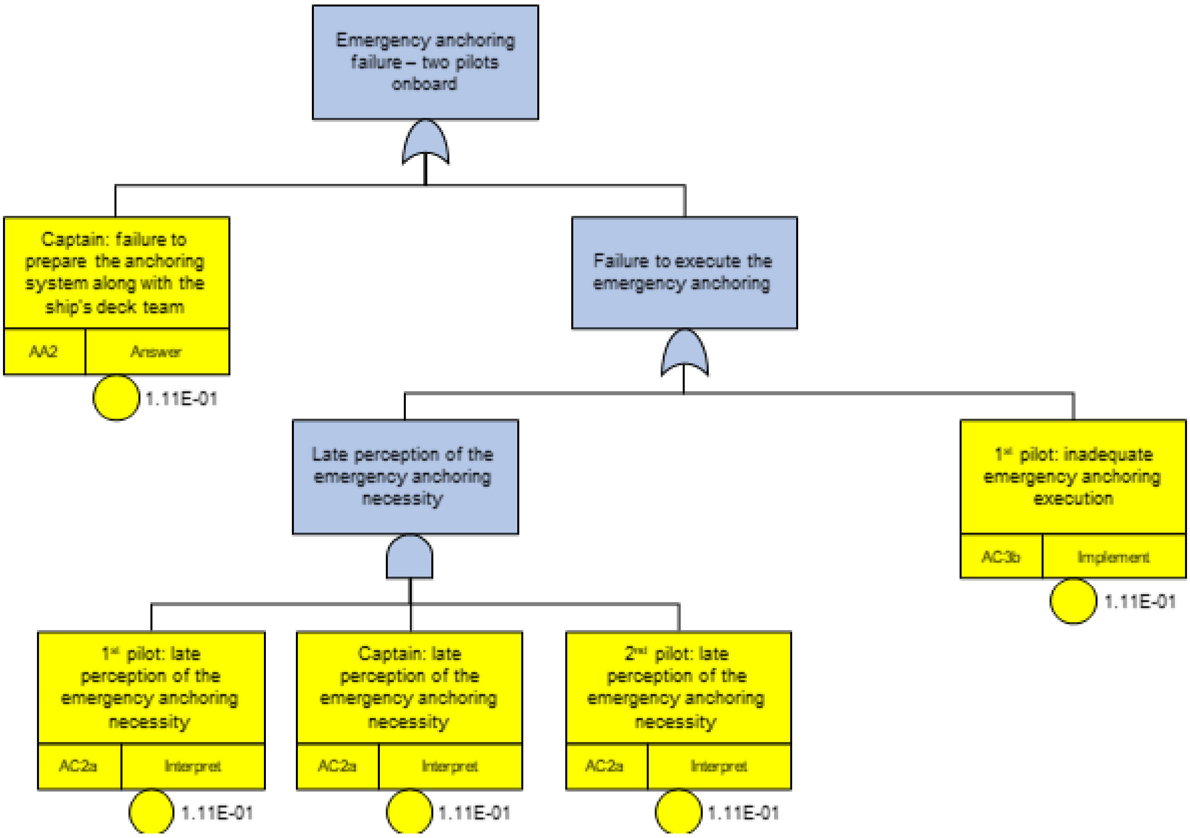
B.20. Fault tree for the event "Emergency anchoring failure – one pilot onboard"

Figure 93 – Fault tree for the event "Emergency anchoring failure – one pilot onboard"



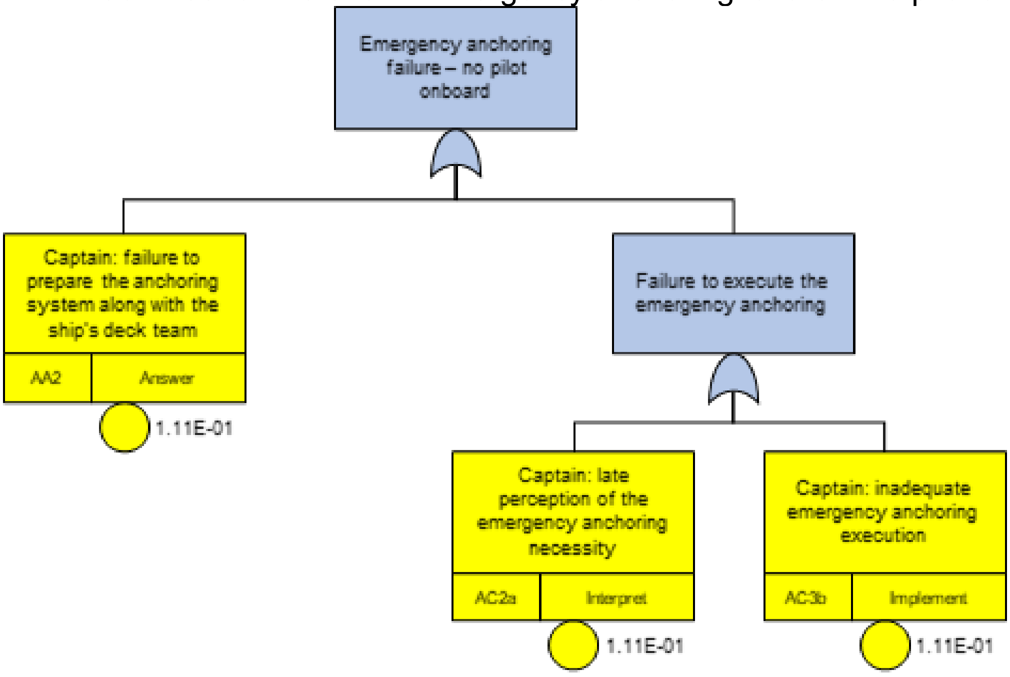
B.21. Fault tree for the event "Emergency anchoring failure – two pilots onboard"

Figure 94 – Fault tree for the event "Emergency anchoring failure – two pilots onboard"



B.22. Fault tree for the event “Emergency anchoring failure – no pilot onboard”

Figure 95 – Fault tree for the event “Emergency anchoring failure – no pilot onboard”



Appendix C. TECHR's taxonomy of human actions

Table 22 – Taxonomy of human actions on the cognitive domain

Category	Category description	Process	Process description	Examples	Code
Remember	Retrieve from long-term memory the relevant information previously learned	Recognize	Find in long-term memory knowledge that is consistent with the material presented.	Discriminate Meet Tag Identify List	AC1a
		Remember	Retrieve relevant knowledge in long-term memory.	Exemplify Describe Remember	AC1b
Understand	Determine the meaning of oral, written or graphic information. Demonstrate understanding of facts by exposing ideas and concepts.	Interpret	Change from one form of representation to another.	Convert Rewrite Report Recognize	AC2a
		Exemplify	Find a specific example or illustration of a concept or principle.	Illustrate Express Describe	AC2b
		Rank	Determine that something belongs in a category.	Categorize Distinguish	AC2c
		To sum up	Summarize a broad theme or larger subject.	Sum up Abstract	AC2d
		Infer	Outline a logical conclusion based on the information presented.	Conclude Extrapolate Interpolate	AC2e
		Compare	Detect matches between two ideas, objects, etc.	Compare Discuss Identify	AC2f
		Explain	Build a cause and effect model of a system.	Model Explain	AC2g

Table 22 – Taxonomy of human actions on the cognitive domain (continuation)

Category	Category description	Process	Process description	Examples	Code
Apply	Perform or use a procedure in a given situation. Use information in situations other than when obtaining knowledge.	Execute	Accomplish a goal or fulfill an order in a known situation.	Schedule Calculate Compute Demonstrate Draw	AC3a
		Implement	Solve problems in new situations by applying knowledge, facts, techniques and rules.	Adapt Modify Build Discover Dramatize Teach	AC3b
Analyze	Separate a matter into its constituent parts and determine how the parts relate to each other and to the whole. Find evidence to support generalizations.	Differentiate	Distinguish relevant and irrelevant parts or important and unimportant parts of presented material.	Tick Centralize Rank Compare Contrast Decompose Discriminate	AC4a
		Organize	Determine how elements work or fit within a structure.	Evaluate Discover Diagram Find consistency	AC4b
		Assign	Determine the point of view, deviations, value or basic purposes of a presented material.	Criticize Debate	AC4c

Table 22 – Taxonomy of human actions on the cognitive domain (continuation)

Category	Category description	Process	Process description	Examples	Code
Evaluate	Make judgment based on criteria and standards (determined by or offered to the individual). Justify a decision or action plan.	Check	Apply an evaluation standard.	Compare Coordinate Describe	AC5a
		Criticize	Evaluate options quantitatively or qualitatively (e.g., opinions, materials, methods) by judging information, idea validity or quality of work based on a set of criteria.	Support Appreciate Argue Evaluate Collaborate Comment Conclude Contrast Criticize Debate Decide	AC5b
Create	Gather elements to form a coherent and functional whole.	Generate	Present alternative hypotheses based on a set of criteria.	Explain Formulate Generate Imagine	AC6a
	Rearrange the elements into a new pattern or structure.	Plan	Elaboration of a procedure for the execution of some task.	Categorize Set up Manage	AC6b
	Generate new ideas or ways of seeing things. Propose alternative solutions	Produce	Invent a product.	Match Compose Create Develop	AC6c

Source: Maturana (2017)

Table 23 – Taxonomy of human actions on the affective domain

Category	Description	Example	Code
Receptivity	Passively following up phenomena of interest or specific stimuli (e.g., oral instructions, texts). Focus attention, including showing openness to new experiences and willingness to listen. Be aware of the occurrence of a phenomenon or the existence of something.	Accept Annotate Watch Focus Discuss	AA1
Answer	Watch and react to a phenomenon. Actively participate in an activity, demonstrating assertiveness, desire and / or satisfaction. Show interest in the results of an action, suggesting ideas and interpretations of the results. Question new ideas, concepts, models in order to fully understand them. Know the safety rules and practice them.	Help Cheer up Present Approve Watch Clarify Agree	AA2
Appreciation	Value objects, phenomena and behaviors, i.e., decide the value and relevance of ideas and experiences. Raise awareness of individual and cultural differences. Show concern for the welfare of all and take responsibility for the functioning of a group. Internalize a set of specific values and express them (express opinions). Accept or commit to a posture or action. Demonstrate ability to resolve conflicts.	Argue Challenge Commit Confront Criticize Debate Deny Differentiate	AA3
Conceptualization of values	Organize values by priority, contrasting different values, resolving conflicts between them and creating a unique value system. Qualify and quantify personal opinions, express opinions, reasons and beliefs. Accept responsibility for one's own behavior. Recognize the need to balance freedom and responsible behavior. Accept standards of professional ethics. Recognize the importance of systematic planning for problem solving.	Join Change Balance Match Compare Complete	AA4
Internalization of values	Form a value system (generalized, consistent, predictable, characteristic and self-sufficient) that controls the behavior. Review judgments and behaviors considering new evidence. Value the "being", not the "opinion".	Cooperate Discriminate Influence Interpret	AA5

Source: Maturana (2017)

Table 24 – Taxonomy of human actions on the psychomotor domain

Category	Description	Examples	Code
Reflective motion	React automatically (involuntarily) to a stimulus. Reflexive movement - segmental, intersegmental and suprasegmental reflexes.	React Respond	AP1
Basic movement	Change position, move, perform a simple action. It includes the basic movements that can compose more complex groups of fundamental movements: locomotor, non-locomotor movement and manipulation.	Get up Walk	AP2
Perceptive ability	Respond to different sensory perceptions. Responding to a kinesthetic, visual, auditory, tactile stimulus or grouping of environmental stimuli that allow the individual to adjust their movements.	Distinguish using the senses	AP3
Physical ability	Activities that require endurance, strength, stamina and agility; that require further development of physical skills (endurance, strength, flexibility and agility).	Support Keep Repeat	AP4
Qualified movement	Perform activities where a good level of efficiency is required. Perform advanced moves. Perform and adapt complex operations and integrated movements.	Steer Build Juggling	AP5
Nonverbal communication	Produce significantly expressive movements. Communicate bodily effectively.	Express feelings	AP6

Source: Maturana (2017).

Appendix D. Sensitivity analysis results

D.1. Sensitivity analysis results for the skills

Figure 96 – Relative sensitivity to the skills for the collision scenario during the waterway navigation considering no pilot onboard

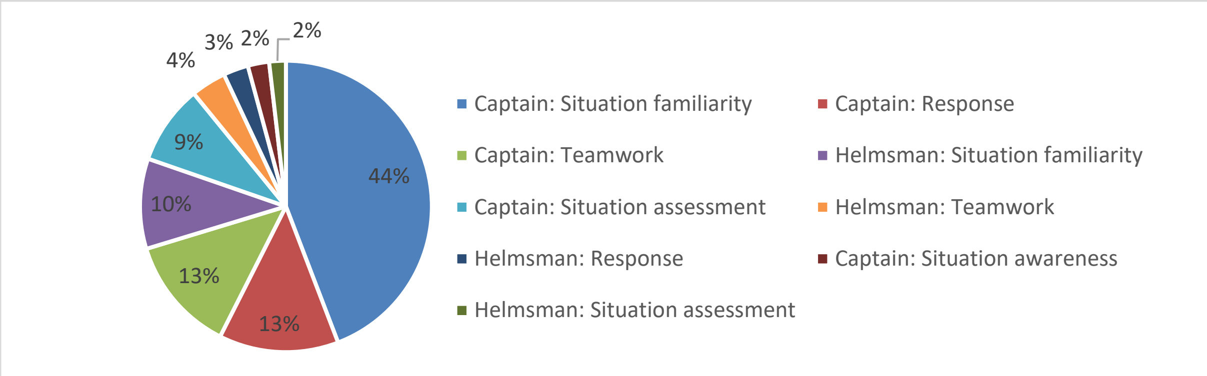


Figure 97 – Relative sensitivity to the skills for the collision scenario during the waterway navigation considering one pilot onboard

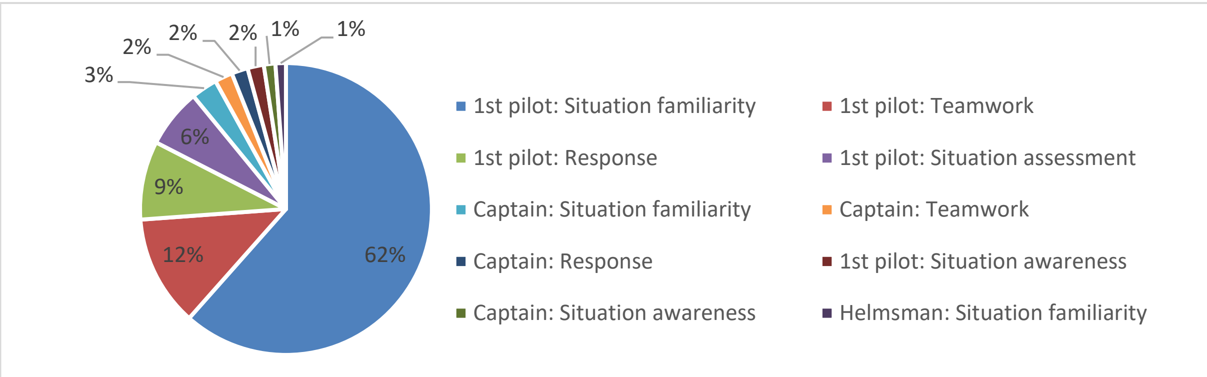


Figure 98 – Relative sensitivity to the skills for the collision scenario during the waterway navigation considering two pilots onboard

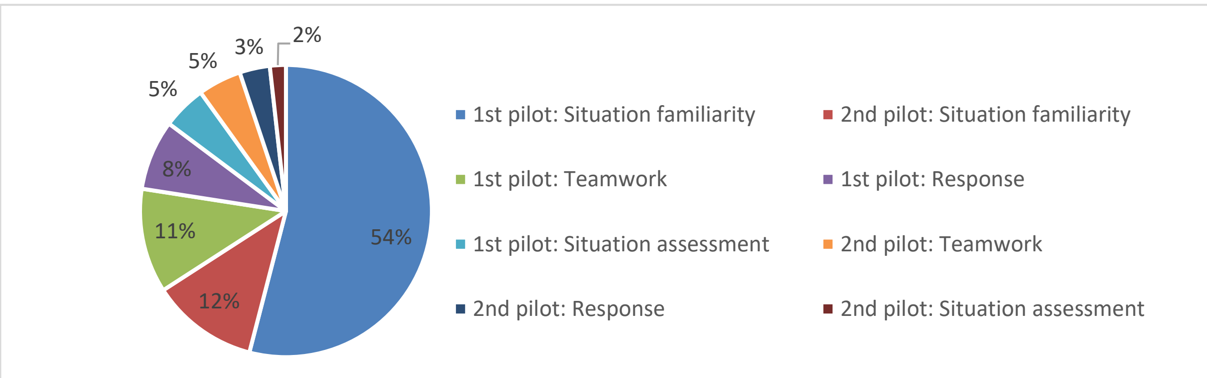


Figure 99 – Relative sensitivity to the skills for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure considering no pilot onboard

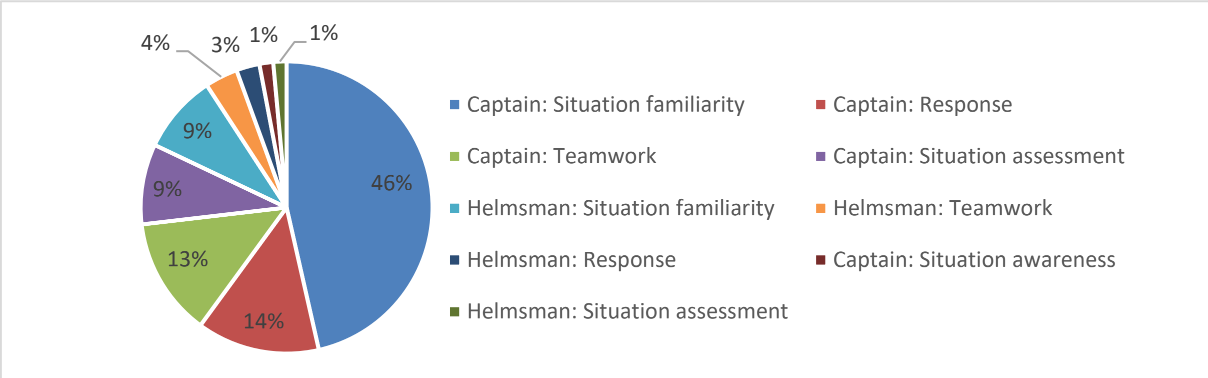


Figure 100 – Relative sensitivity to the skills for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure considering one pilot onboard

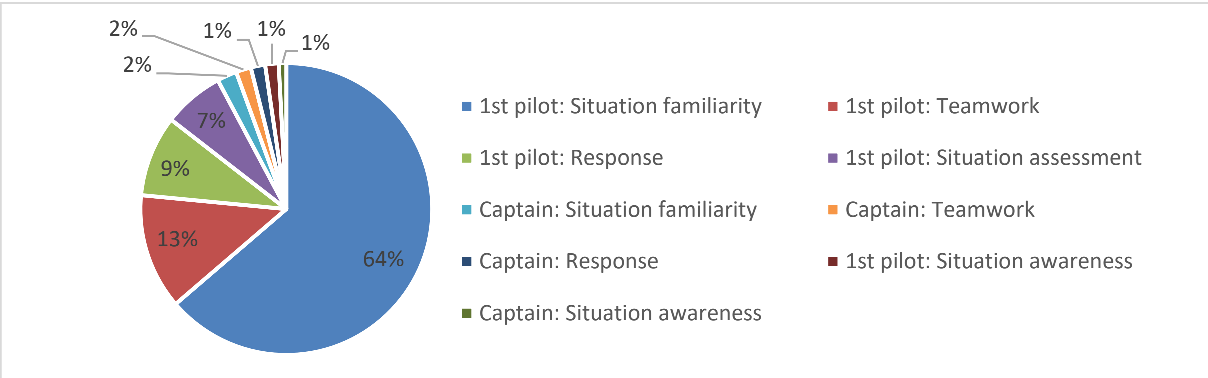


Figure 101 – Relative sensitivity to the skills for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure considering two pilots onboard

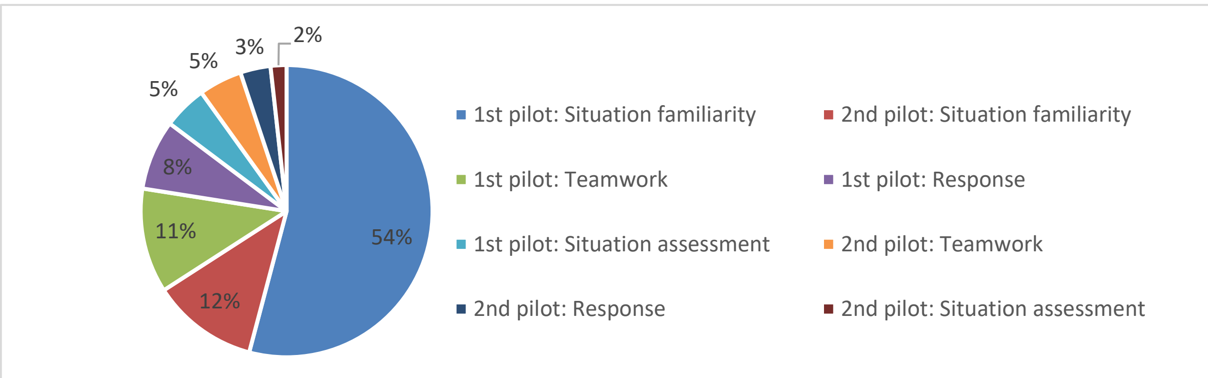


Figure 102 – Relative sensitivity to the skills for the contact/grounding scenario during the waterway navigation considering no pilot onboard

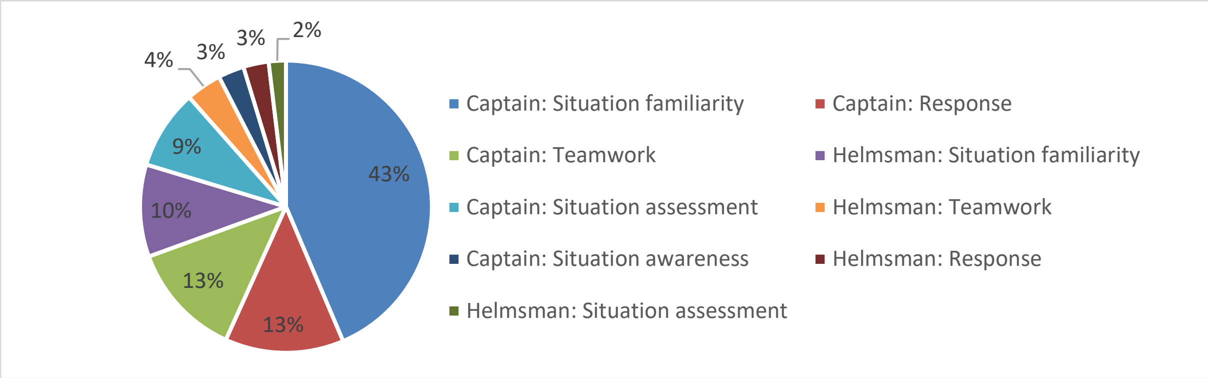


Figure 103 – Relative sensitivity to the skills for the contact/grounding scenario during the waterway navigation considering one pilot onboard

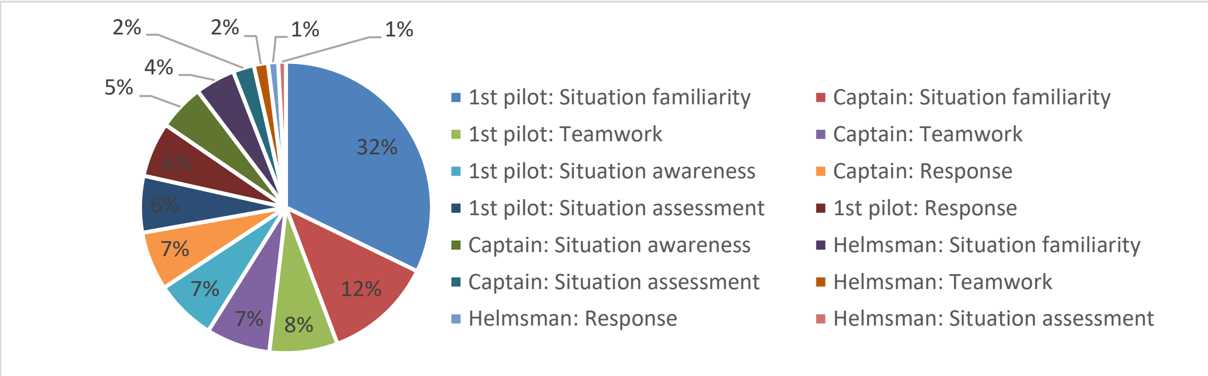


Figure 104 – Relative sensitivity to the skills for the contact/grounding scenario during the waterway navigation considering two pilots onboard

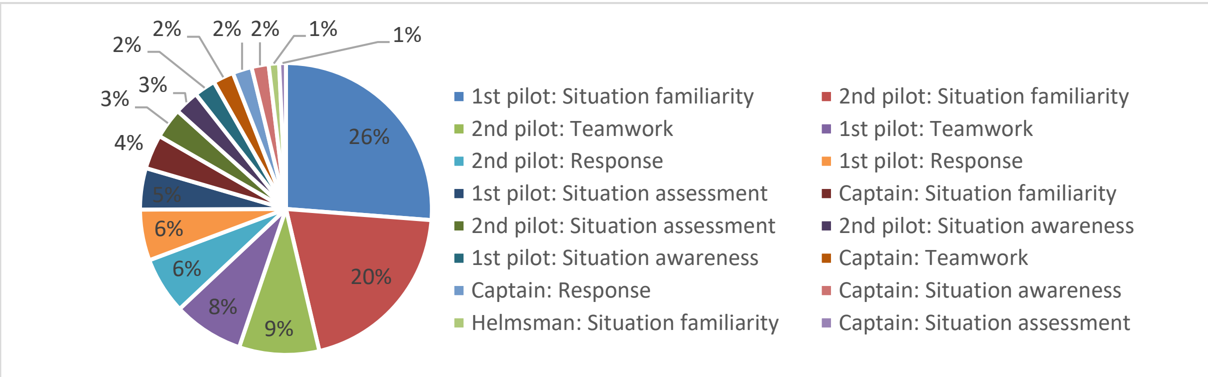


Figure 105 – Relative sensitivity to the skills for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure considering no pilot onboard

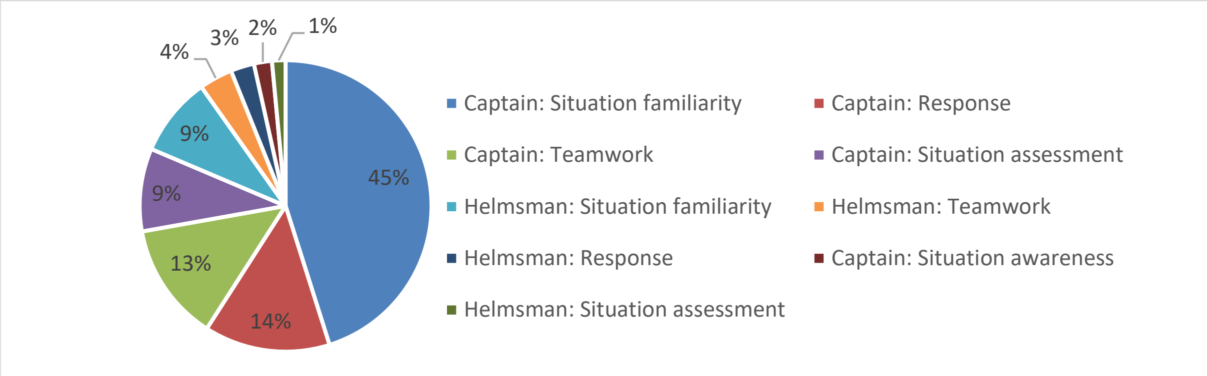


Figure 106 – Relative sensitivity to the skills for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure considering one pilot onboard

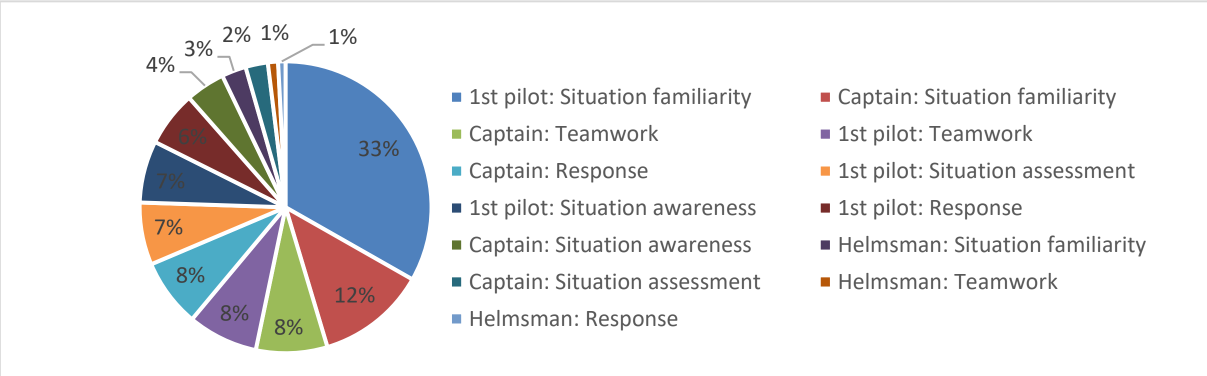
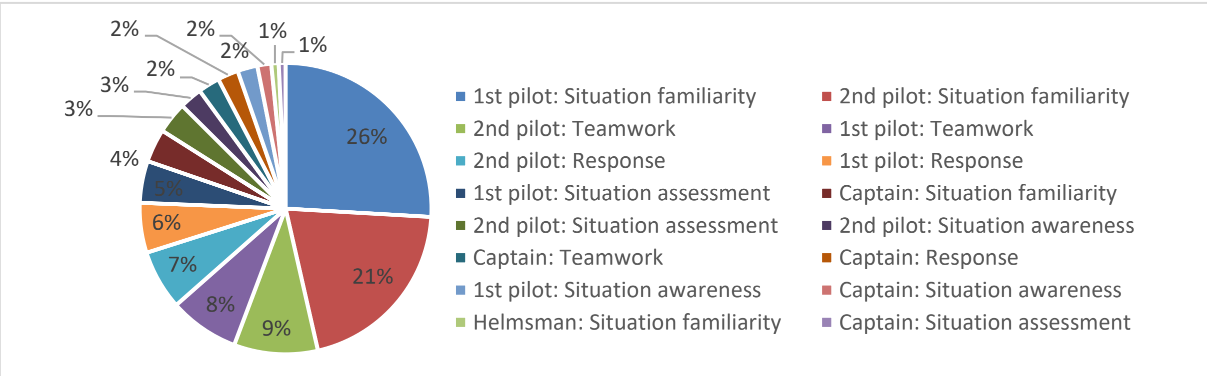


Figure 107 – Relative sensitivity to the skills for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure considering two pilots onboard



D.2. Sensitivity analysis results for the internal factors

Figure 108 – Relative sensitivity to the internal factors for the collision scenario during the waterway navigation considering no pilot onboard

Figure 109 – Relative sensitivity to the internal factors for the collision scenario during the waterway navigation considering one pilot onboard

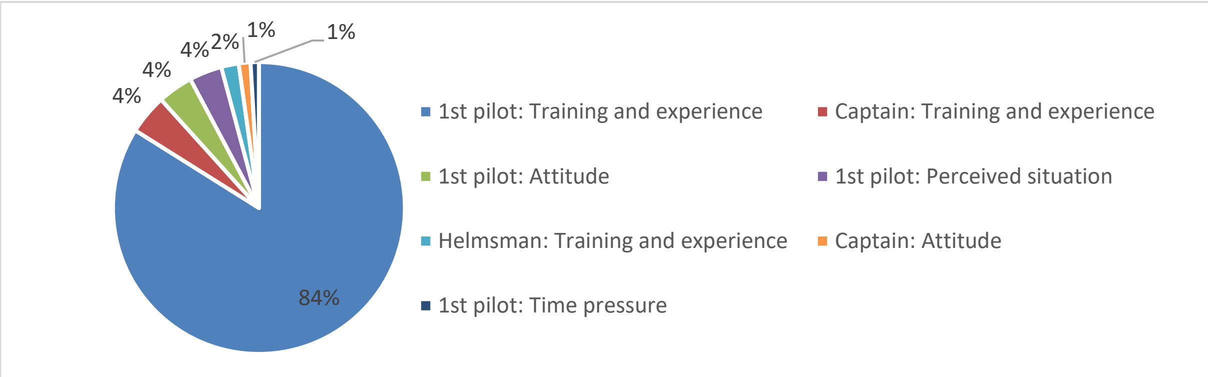


Figure 110 – Relative sensitivity to the internal factors for the collision scenario during the waterway navigation considering two pilots onboard

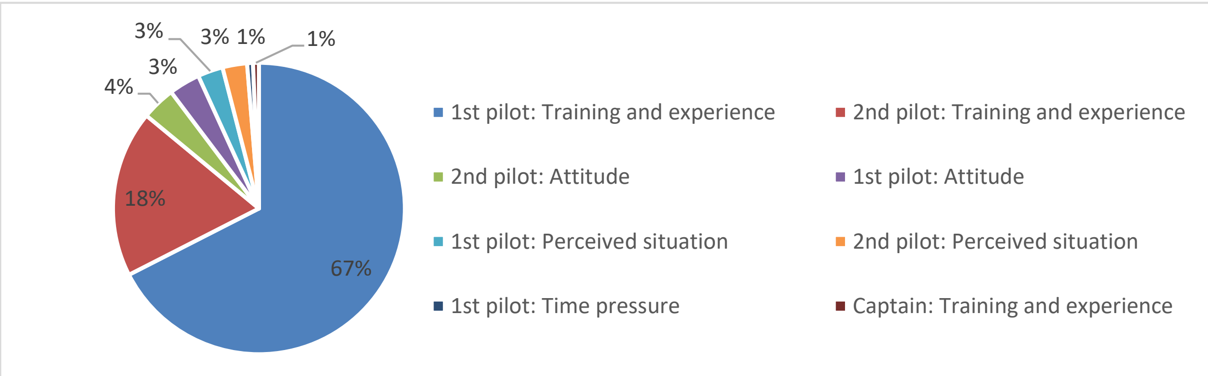


Figure 111 – Relative sensitivity to the internal factors for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure considering no pilot onboard

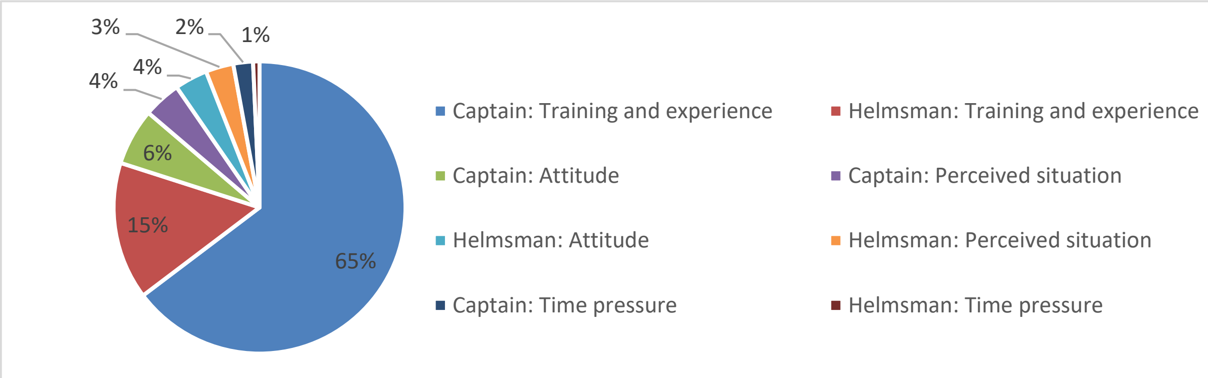


Figure 112 – Relative sensitivity to the internal factors for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure considering one pilot onboard

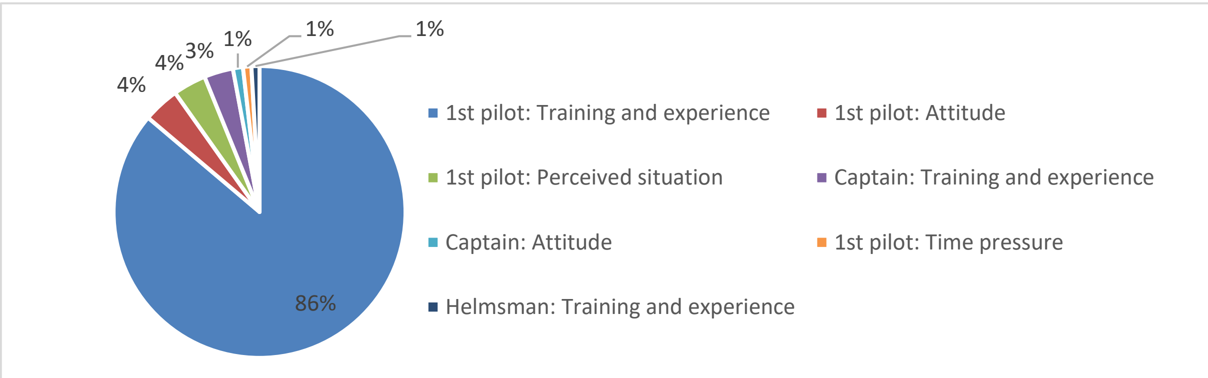


Figure 113 – Relative sensitivity to the internal factors for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure considering two pilots onboard

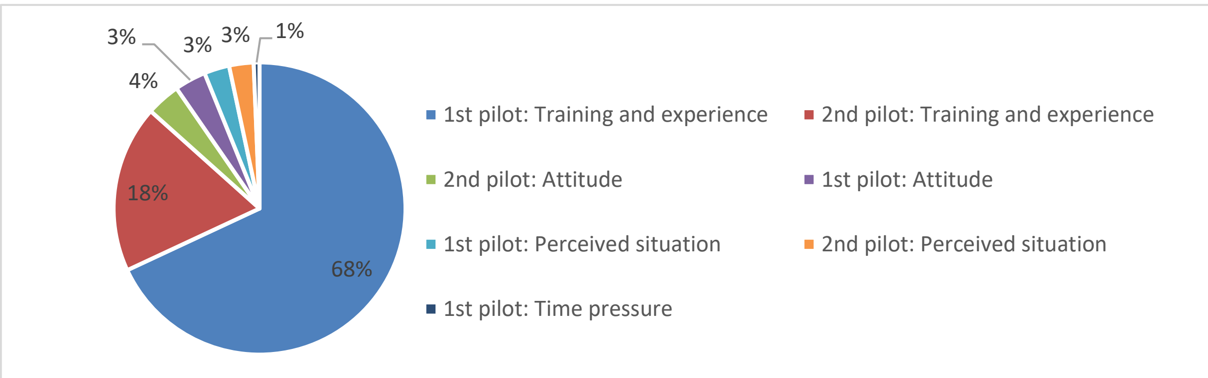


Figure 114 – Relative sensitivity to the internal factors for the contact/grounding scenario during the waterway navigation considering no pilot onboard

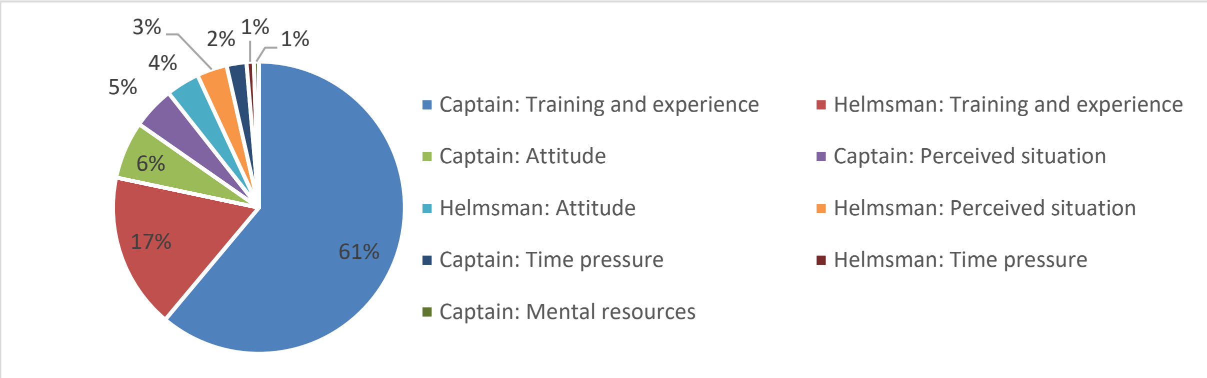


Figure 115 – Relative sensitivity to the internal factors for the contact/grounding scenario during the waterway navigation considering one pilot onboard

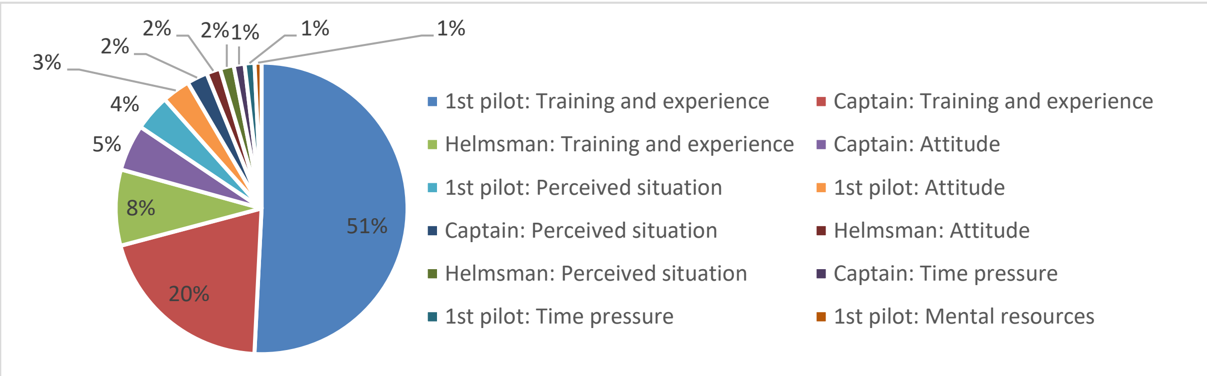


Figure 116 – Relative sensitivity to the internal factors for the contact/grounding scenario during the waterway navigation considering two pilots onboard

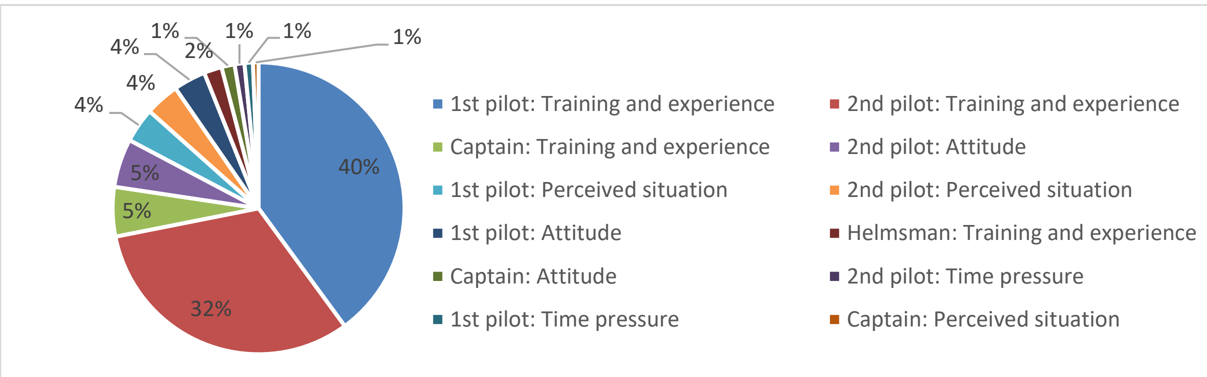


Figure 117 – Relative sensitivity to the internal factors for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure considering no pilot onboard

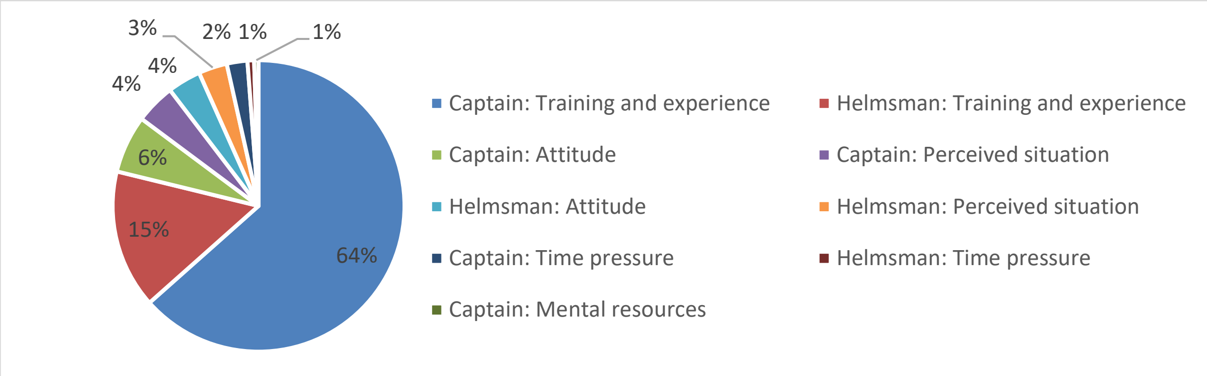


Figure 118 – Relative sensitivity to the internal factors for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure considering one pilot onboard

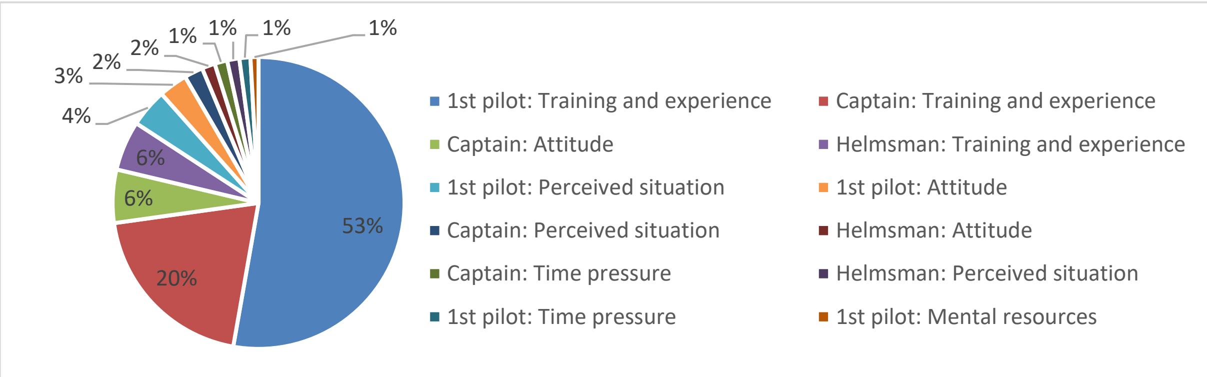
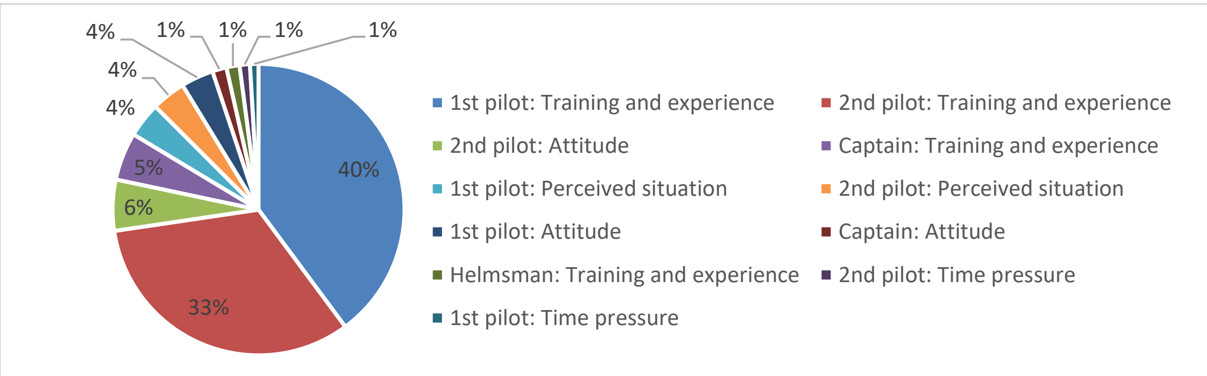


Figure 119 – Relative sensitivity to the internal factors for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure considering two pilots onboard



D.3. Sensitivity analysis to the MOFs

Figure 120 – Relative sensitivity to the MOFs for the collision scenario during the waterway navigation considering no pilot onboard

Figure 121 – Relative sensitivity to the MOFs for the collision scenario during the waterway navigation considering one pilot onboard

Figure 122 – Relative sensitivity to the MOFs for the collision scenario during the waterway navigation considering two pilots onboard

Figure 123 – Relative sensitivity to the MOFs for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure considering no pilot onboard

Figure 124 – Relative sensitivity to the MOFs for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure considering one pilot onboard

Figure 125 – Relative sensitivity to the MOFs for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure considering two pilots onboard

Figure 126 – Relative sensitivity to the MOFs for the contact/grounding scenario during the waterway navigation considering no pilot onboard

Figure 127 – Relative sensitivity to the MOFs for the contact/grounding scenario during the waterway navigation considering one pilot onboard

Figure 128 – Relative sensitivity to the MOFs for the contact/grounding scenario during the waterway navigation considering two pilots onboard

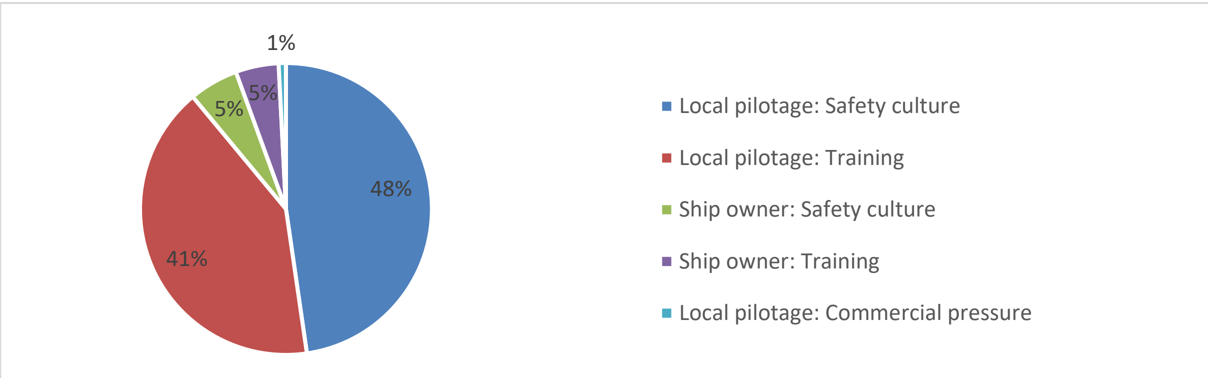


Figure 129 – Relative sensitivity to the MOFs for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure considering no pilot onboard

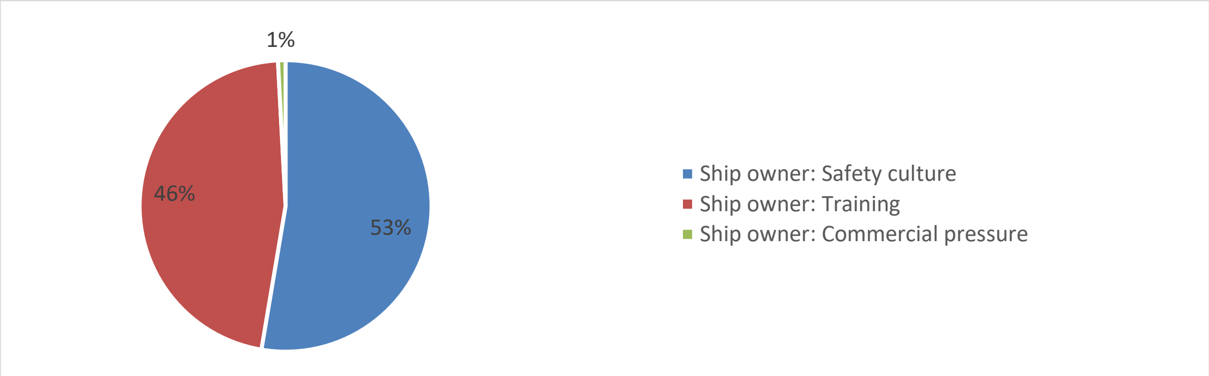


Figure 130 – Relative sensitivity to the MOFs for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure considering one pilot onboard

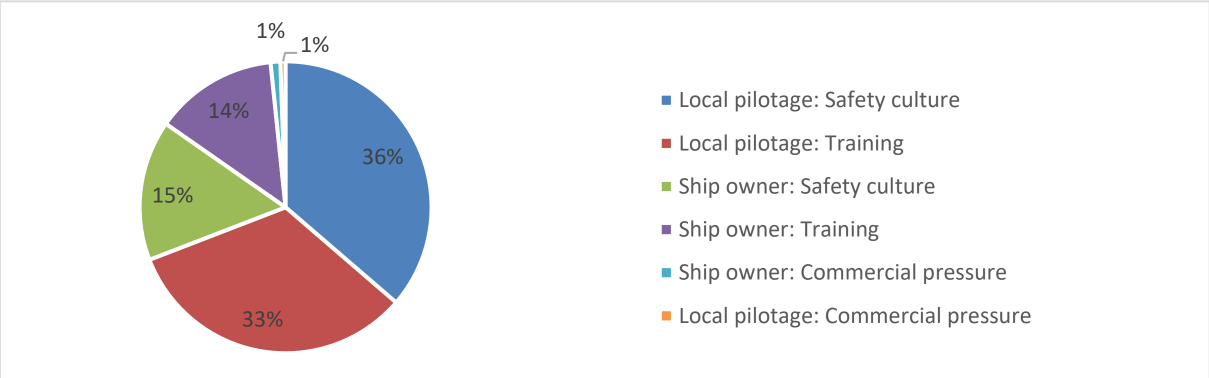
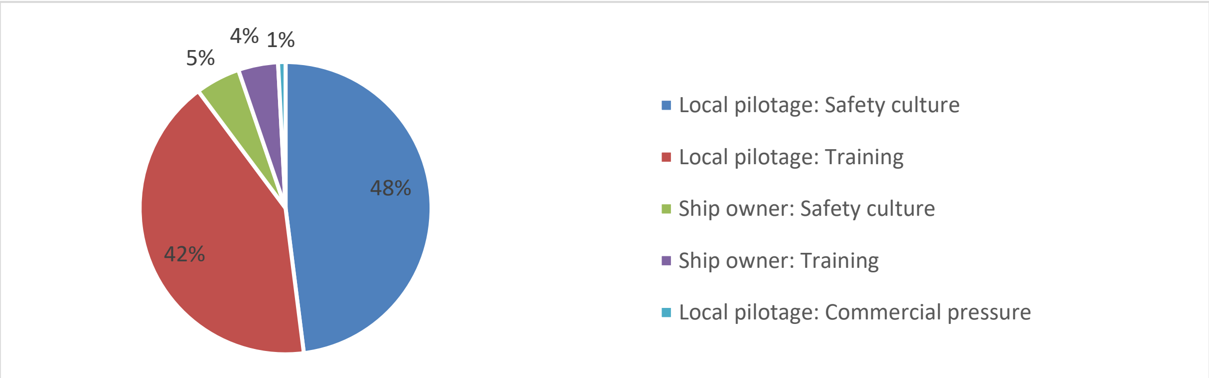


Figure 131 – Relative sensitivity to the MOFs for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure considering two pilot onboard



D.4. Sensitivity analysis to the environmental factors

Figure 132 – Relative sensitivity to the environmental factors for the collision scenario during the waterway navigation considering no pilot onboard

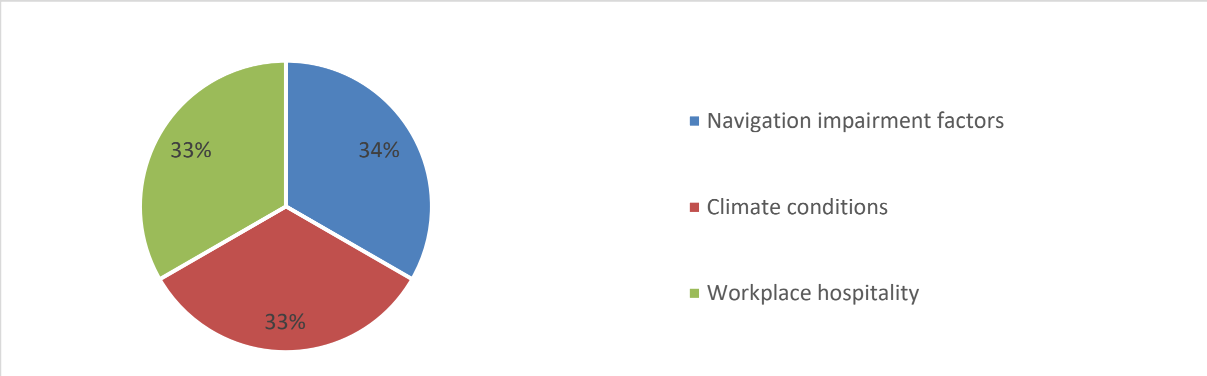


Figure 133 – Relative sensitivity to the environmental factors for the collision scenario during the waterway navigation considering one pilot onboard

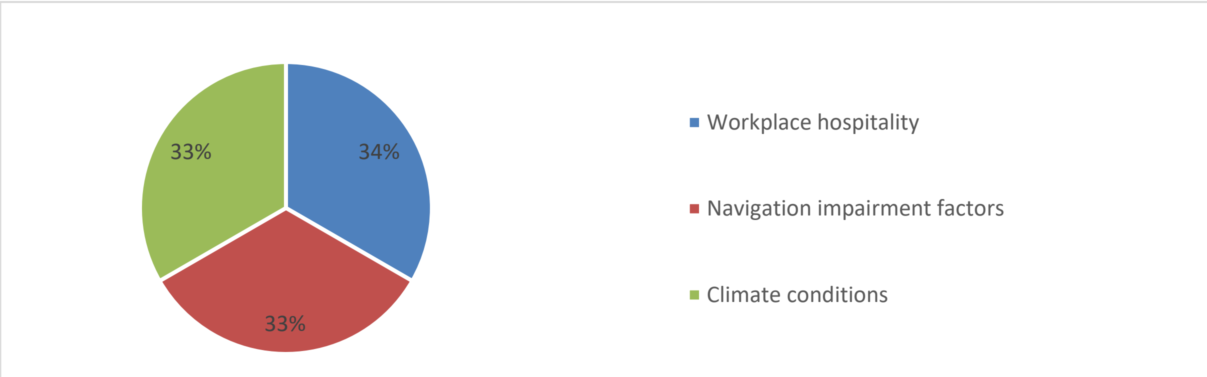


Figure 134 – Relative sensitivity to the environmental factors for the collision scenario during the waterway navigation considering two pilot onboard

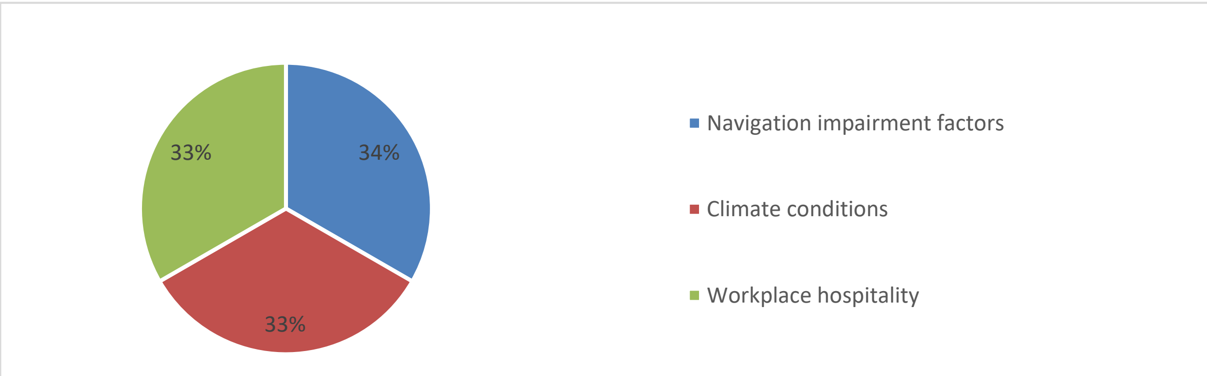


Figure 135 – Relative sensitivity to the environmental factors for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure considering no pilot onboard

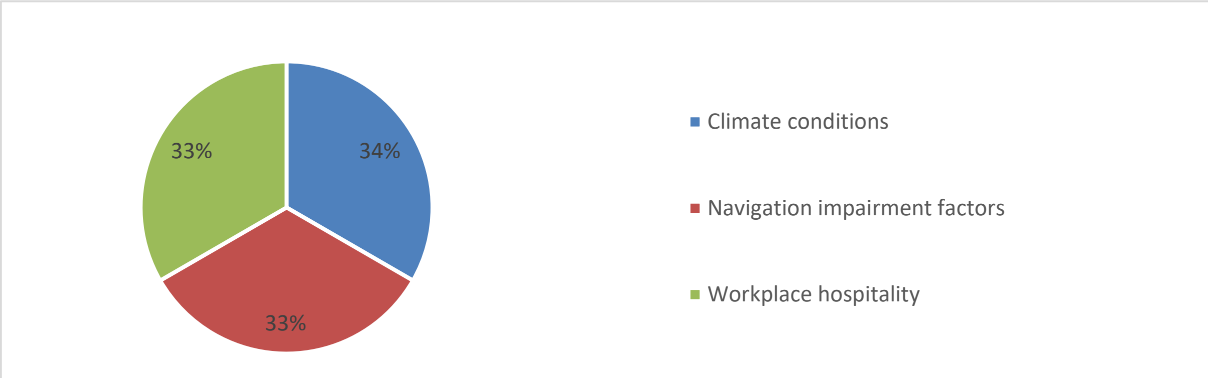


Figure 136 – Relative sensitivity to the environmental factors for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure considering one pilot onboard

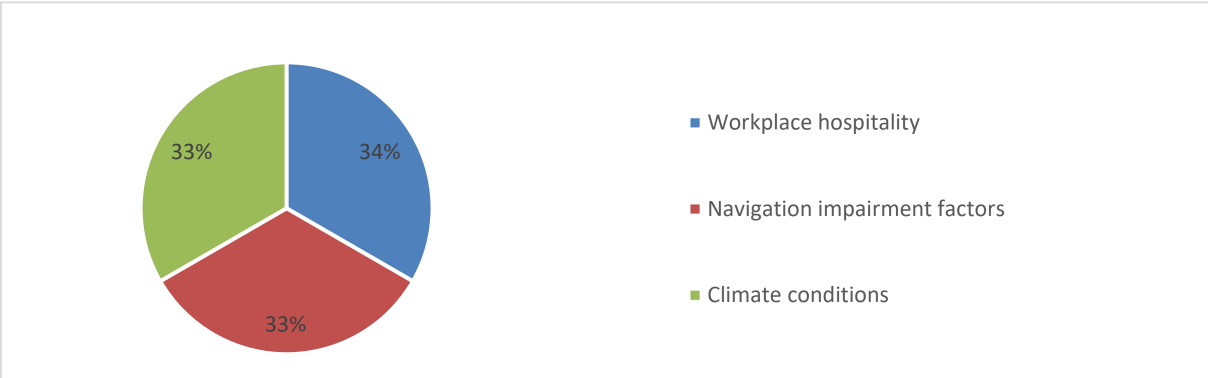


Figure 137 – Relative sensitivity to the environmental factors for the collision scenario during the terminal approaching & berthing/unberthing & terminal departure considering two pilots onboard

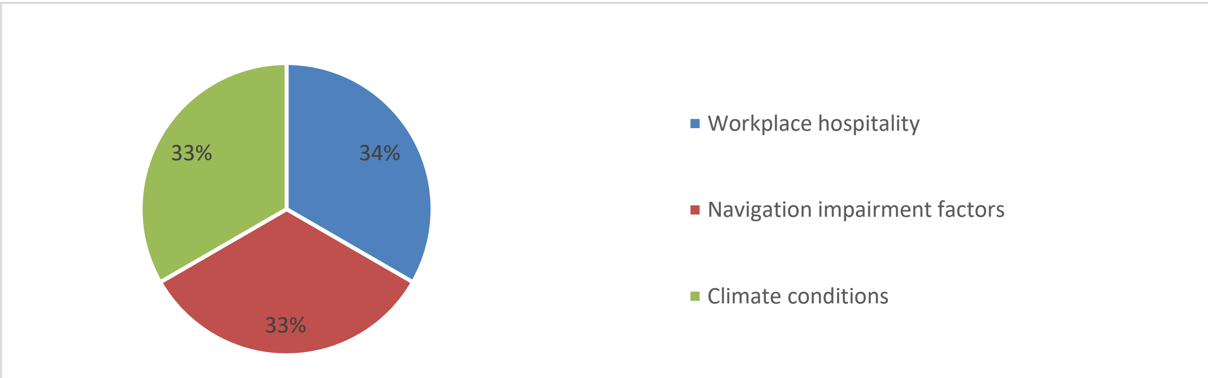


Figure 138 – Relative sensitivity to the environmental factors for the contact/grounding scenario during the waterway navigation considering no pilot onboard

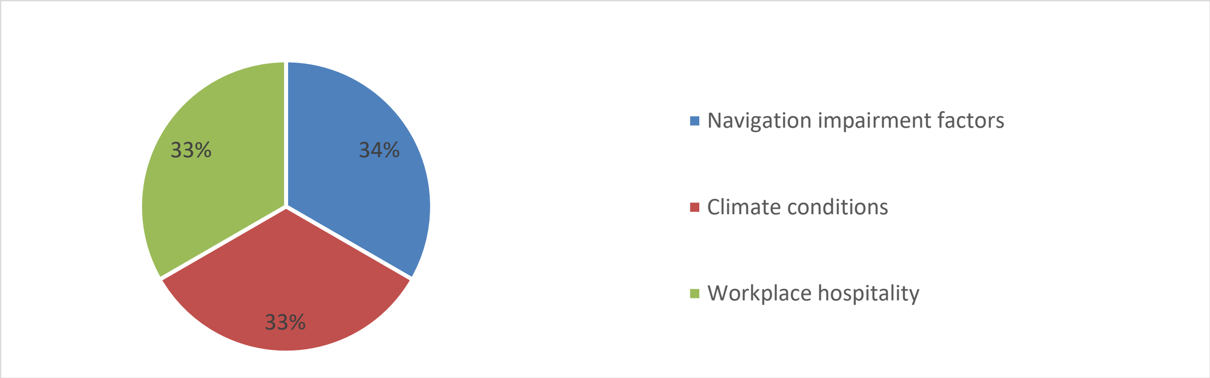


Figure 139 – Relative sensitivity to the environmental factors for the contact/grounding scenario during the waterway navigation considering one pilot onboard

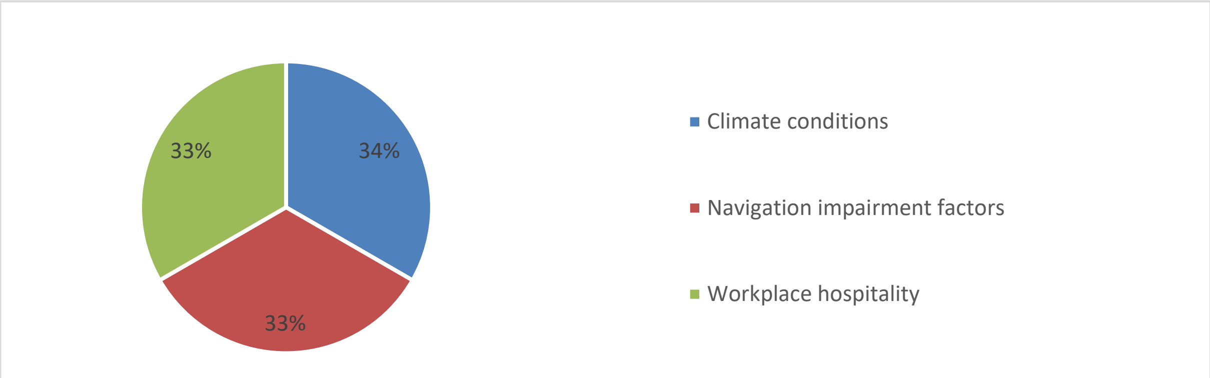


Figure 140 – Relative sensitivity to the environmental factors for the contact/grounding scenario during the waterway navigation considering two pilots onboard

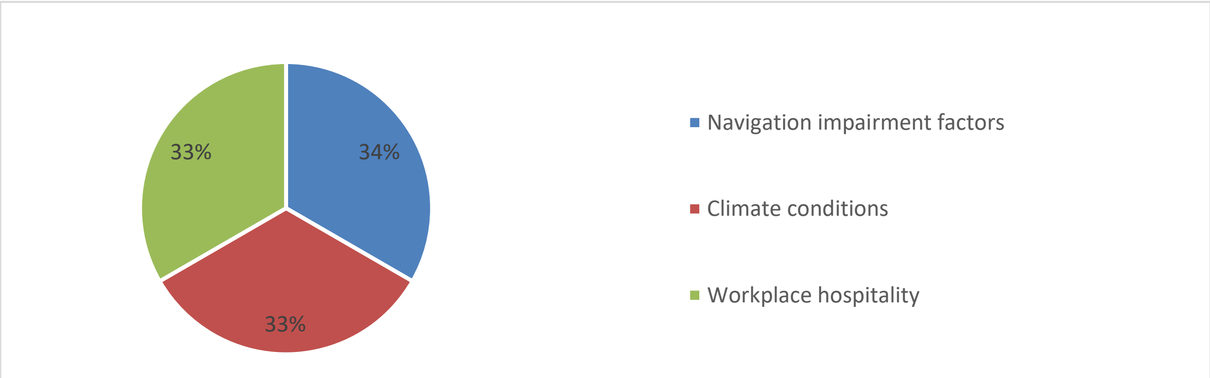


Figure 141 – Relative sensitivity to the environmental factors for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure considering no pilot onboard

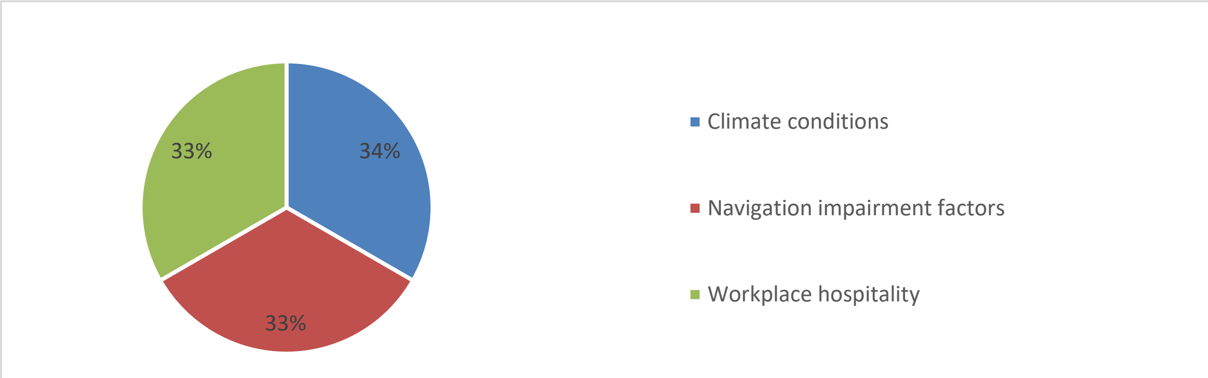


Figure 142 – Relative sensitivity to the environmental factors for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure considering one pilot onboard

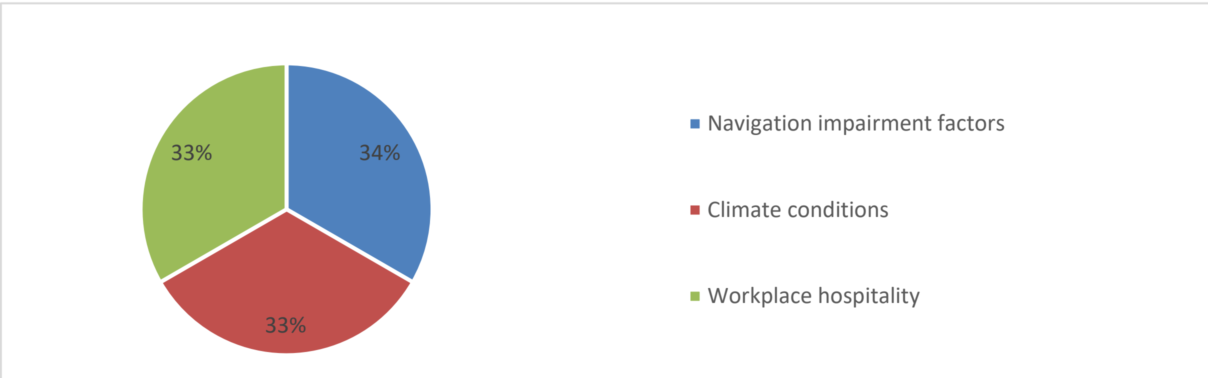


Figure 143 – Relative sensitivity to the environmental factors for the contact/grounding scenario during the terminal approaching & berthing/unberthing & terminal departure considering two pilots onboard