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Analysis of Loss of Position Incidents for Dynamically Operated Vessels

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"*Analysis of Loss of position incidents for dynamically operated vessels*"

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Background

By so called simultaneous operations (SIMOPS) are understood vessels operating near to platforms or other floating units on an offshore field. There is a certain risk for collision due to operator error or systems failure. Typical scenarios are drive-off or drift-off. The International Marine Contractors Association (IMCA) is reporting these accidents or incidents in a systematic manner and format. The data represents a source of information for analysis of dominating accident mechanisms.

The Bayesian Belief Network (BBN) technique has emerged as a promising method for analysis and projection of accidents. The method offers greater flexibility for modelling of accidents compared to traditional methods like FTA and ETA. A number of software packages are available for the application of the method.

The candidate has in his project assignment made a preliminary assessment of the potential of analyzing SIMOPS related accidents by means of the BBN technique.

Objective

The overall aim of the Master thesis assignment is to undertake an analysis of drive-off and drift-off accidents and incidents. Dominating causal factors shall be identified and typical accident mechanisms shall be described by means of BBN.

Tasks

The candidate shall cover following tasks:

1. Give an introductory assessment of the risks related to marine operations close to offshore installations and motivation for the investigation.
2. Develop a systems oriented description of a DP system and the related Class regulations.
3. Choose and present an approach for categorizing and analysis of human error.
4. Give an overview of the IMCA data, define the analysis approach and causal categories applied in the reports.
5. Undertake a frequency analysis of the causal factors.
6. Describe the BBN method: Model elements, conditional probability tables and analysis techniques.
7. Undertake a BBN based analysis of the dominating accident mechanisms in both qualitative and quantitative way by means of the GeNIe software package.
8. Discuss findings and propose plans for further work.

The project work should be reported in accordance with the guidelines given by the Department for MSc Thesis work.

Advisor is Em. Professor Svein Kristiansen.

Trondheim, January 2014.

Ingrid Bouwer Utne

Professor/Responsible Advisor

Abstract

This project sought to identify the causal factors related to loss of position incidents for dynamically positioned vessels, and to explore the possibility of using a Bayesian Belief Network (BBN) to model the identified factors.

The causal factors behind loss of position incidents were iand sorted by the author through a study of the DP (Dynamic Positioning) system, and analysis of loss of position incidents reported to the International Marine Contractors Association (IMCA) register.

One or more of three categories were found to be present in more than 90% of all loss of position incidents; propulsion failures, position reference failures and human factors.

According to IMCA definition, no loss of position actually has to occur for a scenario to be defined as a loss of position incident. This discovery led to the identification of four terminal events (end of the causal chain) of such incidents; drive-off, drift-off, operation abort and time loss. Due to limitations in the available data, about one third of all incidents resulted in an unknown terminal event. Drive-off occurred in 11 % of the incidents and drift-off in 17 %. Consequently, Loss of Position (LOP), as a minimum occurred in 28 % of all incidents reported to IMCA from 2008 to 2010.

Dependencies in causal factors such as system failures, and their resulting terminal events were presented. For modelling of such dependencies a Bayesian Belief Network analysis were utilized. The Bayesian Belief Network was constructed upon the same categories of failure as defined through the data sorting. The process of creating the BBN involved establishing causal flowcharts and use of the GeNIe software package.

The main findings regarding the method of Bayesian Belief Network analysis, is that this method enabled the combination of qualitative knowledge (beliefs), with data frequencies in a systematic way. Additionally a Bayesian Belief Network allows for a graphical and intuitive presentation of modelled systems, with the possibility of quick and easy sensitivity analysis. However the method has some limitations. In order to be understandable for the reader, the network must be limited in the number of connections between nodes, which may lead to loss of information, especially in large networks.

Acknowledgements

First of all, I wish to thank my advisor, Em. Professor Svein Kristiansen.

His patience, “open door policy” and experience has been an invaluable assistance through this project.

Also thank to Professor Ingrid Utne, for her guidance.

I would like to express my thanks to my fellow MSc students at Marine technology for creating a great and social working environment. A special thanks to Anders Bidne for his cooperation and valuable inputs.

My family and girlfriend, Hanne, has supported me, and made my days brighter, thank you!

The final acknowledgements are to the people working at the Oslo office of Global Maritime. Their contributions have made this project possible, and I hope they will find some use in its final contents.

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PART I BACKGROUND

1 Introduction

The oil industry is a relatively new industry in Norway and has gone through many changes since its beginnings in the 1960's. In this time, offshore safety has come a long way. The rapid increase in safety is partly due to our ability to learn from previous accidents. Naturally when the safety level increases, the frequency of accidents will go down. In order for the safety work not to stagnate as the accident frequency mitigates, the methods of risk analyses must be developed to be less dependent on accident data.

1.1 Background/motivation

When studying risk and safety lack of data is always an issue. Therefore, approaches that may utilize qualitative knowledge in a systematic manner is always interesting. A company or institution often possess years of human experience and expert knowledge that can be hard to "transform" into facts and numbers in a risk perspective. Bayesian probability theory, and especially the use of Bayesian Belief Network (BBN), may provide the tools necessary to take advantage of this knowledge in a systematic way, when performing an analysis of a system such as the Dynamic positioning system of a vessel.

Many operations where vessels apply Dynamic Positioning are in near proximity of offshore installations. To lose control of the vessel position in such an operation may endanger the environment, assets and human lives. In spite of this, alarmingly small amount of data exists to analyze the causal factors leading to loss of position (LOP) incidents. My motivation for this report is to analyze these causal factors, based on my available data, but just as much to present some of the possibilities I believe exists in using Bayesian Belief Network as an analysis tool.

If the methods presented in this report is proven useful, they may be applied by analysts with more experience than myself, which I find exciting and motivating.

1.2 Objectives and limitations

This report can be divided into the following parts, derived from the general outline of any risk assessment:

1. The identification of the DP system with key components/equipment
2. The identification causal factors related to LOP incidents, based on incident data and DP system knowledge
3. The evaluation of causal frequencies, in respect to top events of loss of position incidents.
4. The creation and evaluation of Bayesian Belief Network(s) to model loss of position incidents

This report is not a full risk assessment due to focus on probabilities of failures, and lack of consequence study for each particular failure mode. To assess risk, both the probability of an event and the possible outcomes (potential harm) of that event must be estimated.

PART II DP SYSTEM

2 Literature review- DP system

This chapter will present the reader with the knowledge of the Dynamic Positioning (DP) system necessary to analyze Loss of position (LOP) incidents.

2.1 Dynamic Positioning

The dynamic positioning system of a ship includes all the equipment that directly or indirectly affects the ships position keeping ability.

Definition of dynamic positioning:

"A means of holding a vessel in relatively fixed position with respect to the ocean floor, without using anchors accomplished by two or more propulsive devices controlled by inputs from sonic instruments on the sea bottom and on the vessel, by gyrocompass, by satellite navigation or by other means" (Holvik, 1998).

A vessel is subject to various forces. Wind, waves, and currents are the most important. The vessel itself also generates forces through its propulsion system. How the forces affect the position of the vessel are measured by the position reference system. These inputs makes a computer system able to calculate the difference between the actual position of the vessel, and the required position during a small time interval. The system then calculates the thrust force necessary to make the resulting change in position as small as possible. (Holvik, 1998).

2.2 Scenarios for loss of position during DP operations

According to Shi, Phillips, & Martinez, there exist two main scenarios for loss of position during a DP-operation; drift-off, and drive-off.

Drive-off

A drive off is a powered move away from the desired vessel position. A drive off may occur at full power. The drive-off may occur due to false position information or wrong position inputs from the operator (Shi, Phillips, & Martinez, 2005).

Drift-off

A drift-off is a loss of power that causes the vessel to move off location in the direction of the prevailing environment.

The distance that the vessel travels before the drift-off is stopped depends on the forces the vessel is subjected to, and how quickly the situation leading to the drift-off is resolved.

There are three situations that may lead to a drift-off (Shi, Phillips, & Martinez, 2005):

- Total blackout
- Partial blackout resulting in insufficient thrust
- Incorrect thrust commands

2.3 DP system main components and system structure

The DP system comprises three main areas: power, control and references. Power can be sub-divided into generation, distribution, and consumption.
Control refers to a power management system and the position control system. References are essentially sensors giving position, environmental and vessel attitude information (IMCA, 2007).

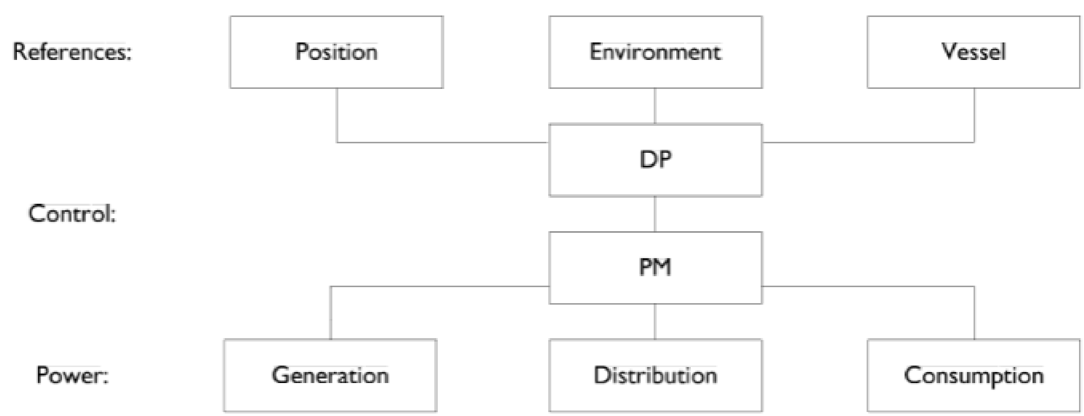


Figure 1 DP system (IMCA, 2007)

Crucial parts of the DP system are those which combines or binds several items of equipment together, these parts must exist in a position keeping system no matter the level of redundancy or type of design. Their importance is due to the fact that the different parts of the system must be coordinated and work together in order to in a precise and effective matter maintain the correct position.

Global Maritime, is a marine engineering consultancy that has contributed to the creation of this report. Based on a study of their FMEA's (Failure Mode and Effect Analysis'), Figure 2 has been created as an outline of the dynamical positioning system. The outline contains only equipment that could have been active in all vessels applying DP, no matter type of vessel or DP class. The figure is greatly simplified to fit the detail level of this report.

The red lines of Figure 2 indicates signals between equipment, while the blue lines indicate transfer of power. The red lines have arrows pointing in both directions to indicate two-way communication. Power always have a single direction indicated and therefore has one-way arrows. The functions of the equipment presented in Figure 2, is further explained in chapter 2.3.1-2.3.6. If no other source of reference is mentioned, the equipment study is based on various FMEA's performed by Global Maritime, that due to the anonymity have no further references.

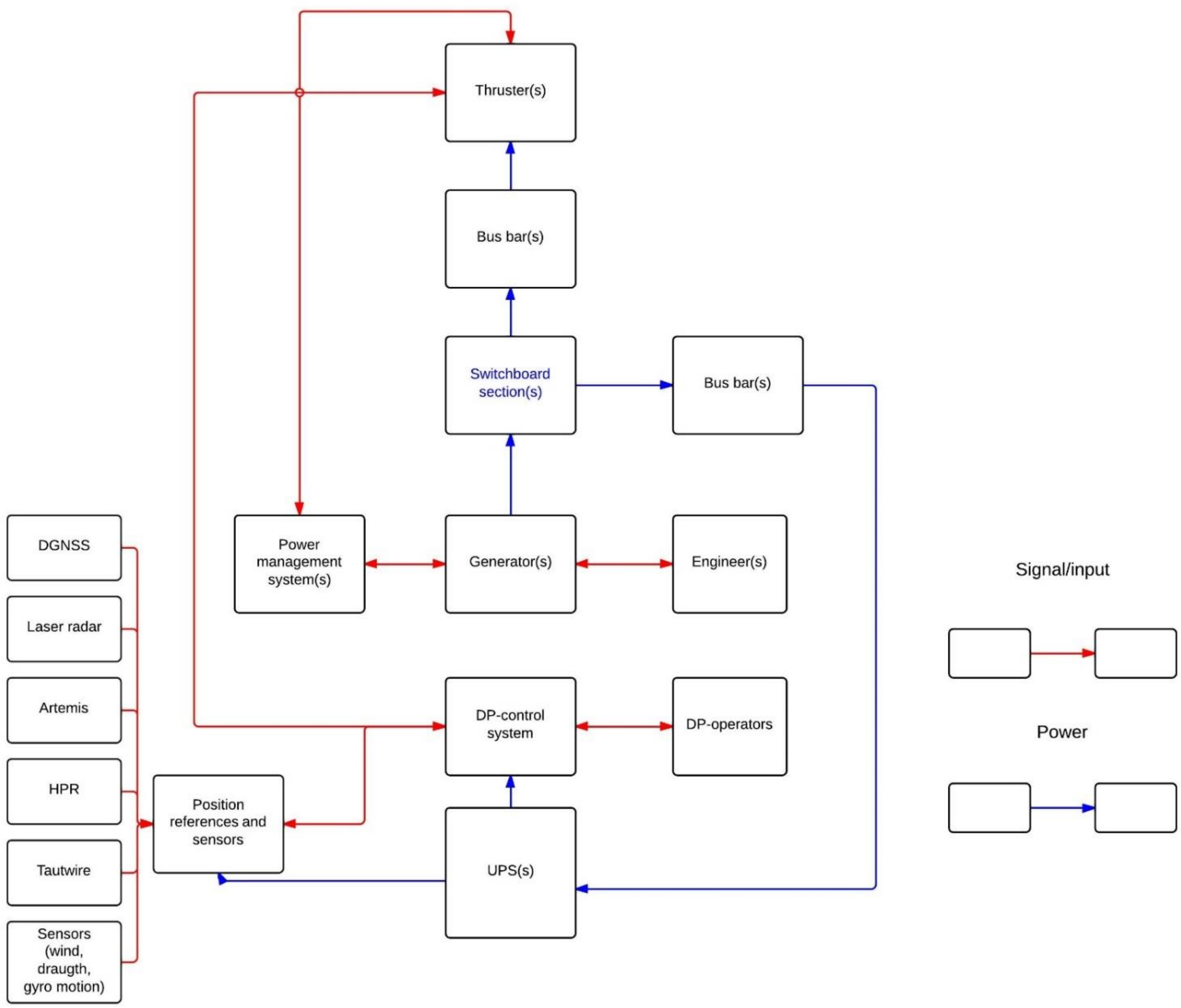


Figure 2 DP system structure based on study of FMEA's (Global Maritime)

2.3.1 Power generation

«Generators and their distribution systems are, as a minimum, to have the capacity to supply sufficient power to the thrusters to maintain vessel's position within the specified operating area in addition to supplying industrial activities and essential ship service loads. When power is shared, power supply to industrial activities and essential ship service loads is not to affect DP operations» (ABS, 2013).

Generators

The generators are to supply the propulsion units with the necessary power to uphold the position in a DP operation. The power is delegated through the switchboard and controlled by the power management system. Typically a ship has several main generators working in parallel to avoid full loss of power in the event of a single generator failure. In addition emergency generator(s) should be on stand-by. However the emergency generators should not be relied on for DP purposes. (IMCA 2007)

Uninterrupted power supply (UPS)

For all DP classes, uninterruptible power supply system (UPS) has to be provided for the DP control system and its reference and sensor system. The UPS' are delegated power from the switchboards. Each UPS is to be capable of supplying power for a minimum of 30 minutes after failure of the main power supply. (Global Maritime)

2.3.2 Power distribution

It is not enough to simply generate power, the generated power has to be distributed in a controlled and consistent manner to the correct consumers at all time. The power distribution system, basically consists of the following equipment.

Switchboards

The switchboards divides the power supply from the generators to the references and propulsion units, (the consumers). An emergency switchboard should exist in the event of a failure. The switchboard is to be arranged for manual and automatic control.

The switchboard is usually divided in at least two separate parts to provide redundancy, but may be run as one system during operation. Even then they should be connected only through bus-tie breakers (bus bars) to separate automatically upon failures. The separation is to avoid common cause failures which could be transferred across systems, including overloading and short-circuits (Global Maritime).

Bus bars

The bus bars are electrical conductors that may carry power at a specific voltage. The bus bars connects different circuits together in the system, and are designed to break the connections in case of, for example, a voltage drop (Global Maritime).

Power management system

The power management system is actually a part of the DP control system but could also be looked at as part of the power distribution system, due to its important task of delegating power between consumption units.

When operating in DP mode, the DP control system continuously monitors the generator power and power to thrusters. If any of the generators reach a level that is defined as too close to the maximum load, typically 90%, the power management system (PMS) will reduce thrust to reduce the risk of overloading the generator(s), which could result in a blackout. The power management system will reduce thrust and hold the thrust as close to limit as possible but never exceed it. When a new generator has been connected, the thrust will be restored to the wanted level (Global Maritime).

Wiring/cables

Wiring/cables is a loosely defined equipment group created due to the immense diversity of electrical delegators in a DP system. In general static equipment that serves to distribute power are included in this equipment group, such as wires and cables that in the event of a failure may create short circuits in the power system.

2.3.3 Propulsion

Beside the shaft propeller, thrusters are the main propulsion units utilize by DP vessels. The motors of the shaft propellers may be directly connected to the shaft which give a simple and robust propulsion suitable for “simple” operations like transit. However for more complex maneuvering, thrusters are commonly used for their increased flexibility (Hackman, Ådnanes, & Sørensen, 1997).

Thrusters

The propulsion system is critical for the overall performance of the vessel, including the vessel's station keeping ability. Electric propulsion is the preferred solution for many DP vessels (Hackman, Ådnanes, & Sørensen, 1997).

Thrusters are the main power consumers in a DP system. Their job is to provide the necessary thrust which enables the DP system to maintain the desired position in a dynamic environment. There exists several types of thrusters, commonly divided into Tunnel thrusters, Azimuth thrusters and Azipods. Tunnel thrusters produce thrust in a fixed direction, while the Azimuth thrusters are rotatable and may produce thrust in any direction, as well as a certain degree of negative thrust to avoid continuous rotation in a DP operation. Finally the Azipods besides being freely rotational like the Azimuth thrusters, have the propeller mounted directly on the motor shaft, the removal of the gear gives the Azipods a higher transmission efficiency than the Azimuth thrusters, at the cost of the flexibility a gear provides (Hackman, Ådnanes, & Sørensen, 1997).

2.3.4 Position references

The position reference system provides the DP control system and the operator with continuous feedback on the vessel position, either by satellites or as relative to nearby objects.

A modern DP vessel has several position references active at the same time, depending on the type of operation. The resulting "weighted" position is based on the accuracy reported positions by all the position reference systems enabled in the DP system. The position reference with the least deviation is given the highest weighting. The purpose of combining several position references, is to give the vessel the most precise and reliable position possible (Global Maritime).

DGNSS/DGPS

Differential Global Navigation Satellite System (DGNSS) and Differential Global Positioning System (DGPS) are relative position signals based on satellite input, and is perhaps the most common position reference system (Global Maritime).

Laser radar

The laser radar system, commonly referred to as “Fanbeam”, as this model is much used, is a positioning system that is used to measure distance and angle by reflecting pulsed laser light. The system measures the vessel position based on relative distances to reflective targets, for example placed at an offshore installation (IMCA, 2007).

HPR

Hydro acoustic position reference systems (HPR) are commonly used in several kind of DP operations. Three primary types of HPR exists: Ultrashort baseline, short baseline and long baseline. No further study into these systems differences is practical for the detail level of this report. The HPR system determines the bearing from a transceiver at the vessel to underwater beacons. Acoustic pollution (underwater noise) may be an issue for this system. (Vickery, 1998).

Artemis

Artemis is a radio system used to measure the position of the vessel. The system operates using a microwave frequency to measure the position and bearing of the vessel relative to a fixed station. The station could for example be installed on an offshore installation (IMCA 2007).

Taut wire

The taut wire is a position reference that utilizes a tensioned wire vertically to the seabed, or horizontally to a fixed object, to measure a vessel’s position (IMCA 2007).

2.3.5 Sensors

Sensors are feeding the DP control system with additional information besides the position of the vessel, necessary to calculate the necessary thrust to uphold the desired position.

Gyrocompass

A gyrocompass is a nonmagnetic compass which bases the geographical direction on the rotation of the earth and is therefore unaffected by the normal deviations of a regular compass. The gyrocompass will therefore always point true north (Global Maritime).

Draught sensors

The draught sensors measures the vessel’s draught continuously. Draught sensors are placed at the hull of the vessel, usually at least at bow and stern (Global Maritime).

Wind sensors

The wind sensors measures the speed and direction of the wind, and will be especially exposed for environmental forces (Global Maritime).

2.3.6 DP control system

The DP control system is the set of computers that combines automatic computation with instructions from operators, enabled through its interfaces. The DP control system allows simple inputs from the operator such as a wanted position. The wanted position is combined with the information provided from the position reference system and sensors. The combined input is continuously evaluated by various software to determine the correct amount, and direction, of thrust power. A simple presentation of the system is shown in Figure 3.

The number of equipment presented in Figure 3, is merely an illustration to indicate redundancy. The actual number of diesel generators (DG), and thrusters (Thr) varies from each vessel.

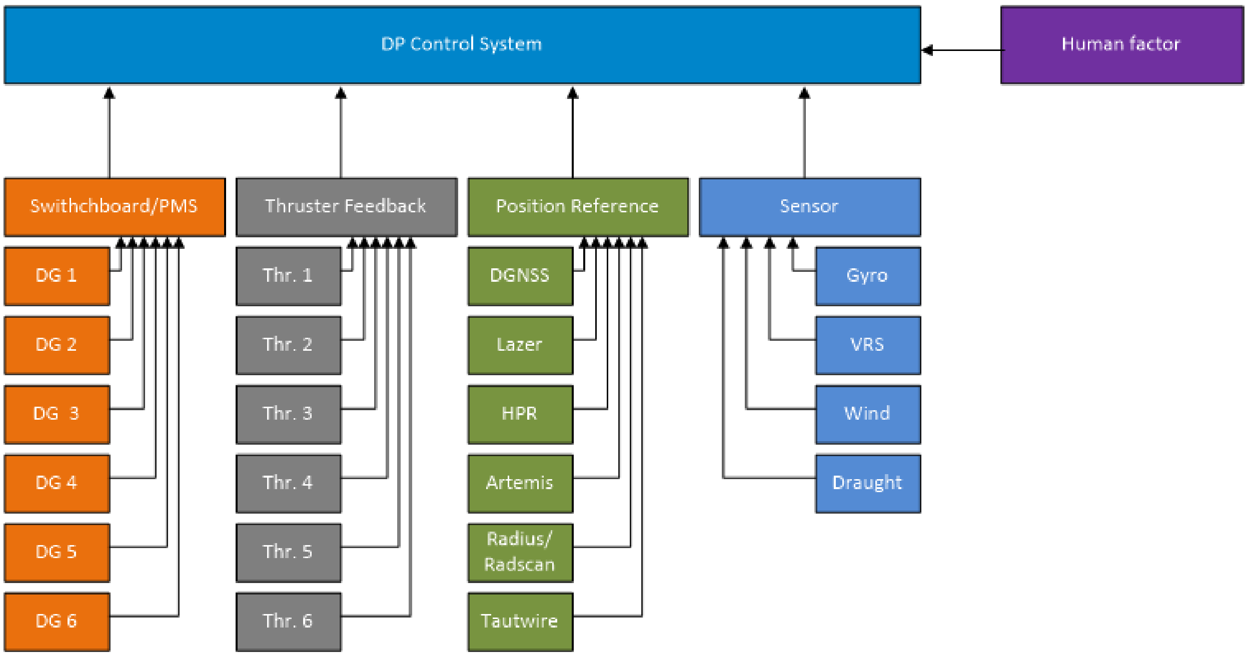


Figure 3 DP control system (Global Maritime).

DP hardware

The DP hardware represents the physical interface that enables operator commands to the computers, such as monitors, keyboards and joysticks (Global Maritime).

DP software

DP software represents software that continuously calculates how the vessel reacts upon the external forces.

"The calculated "vessel model" is a hydrodynamic description, as a result of inputs, and also includes vessel characteristics as mass and drag. The wind, current and thruster forces, as well as the current position speed and heading goes into the vessel model", (Holvik, 1998).

The outputs from the mathematical calculations are thruster commands based upon estimates of the vessel's heading, position and speed estimates, which then again produces new estimates and inputs. The "loop" of information makes the computer able to continuously monitor and adjust the thrusters, to achieve the wanted position given by the controller (Holvik, 1998).

2.4 DP classes

Due to the many different types of DP operations carried out with individual risk for individuals and assets, a set of DP classes has been created. The classes represent different demands to system redundancy, and help vessel owners and operators to achieve the accepted risk criteria no matter their type of operation. The International Maritime organization (IMO), recommends that all vessel built after 1994 are assigned an equipment class.

IMO DP classification

Based on International Maritime Organization publication 645, (IMO, 1994).

DPS-1

"Equipment class 1 has no redundancy. Loss of position may occur in the event of a single fault."

DPS-2

"Equipment class 2 has redundancy so that no single fault in an active system will cause the system to fail. Loss of position should not occur from a single fault of an active component or system such as generators, thruster, and switchboards, but may occur after failure of a static component such as cables, pipes, manual and valves."

DPS-3

"Equipment class 3 also has to withstand fire or flood in any one compartment without the system failing. Loss of position should not occur from any single point failure."

DPS-0

Equipment class 0 allows for manual position control and automatic heading control under specified maximum environmental conditions. DP-0 is considered a description of a vessel state with loss of automatic control, but that still has the necessary propulsion power to manually uphold position by direct operator control.

3 Human Factors

“Human Factors (HF): The work situation is assessed in the light of psychological factors. A key aspect is the relation between the job or task requirements and the human capacity. Factors such as mental capacity to process information, motivation and interaction with colleagues have to be taken into consideration.” (Kristiansen, (2005)

The human factor is an important aspect of the DP system. No matter how advanced an automatic control system is designed, unforeseen situations could always arise where human intervention is necessary to avoid potential harm to assets. Unsafe human acts may also compromise an otherwise functional control system.

The Human Factors Analysis and Classification System (HFACS), is used to identify the human causes of an accident or incident. The HFACS structure is based on the "Swiss Cheese Model” created by James Reason. (Reason, 1990)

The Swiss Cheese Model defines four levels of active errors and latent failures: Unsafe acts, preconditions for unsafe acts, unsafe supervision, and organizational influences. (See Figure 4).

A simplified version of the HFACS classification system is presented in this chapter, based on the detail level of the analyzed data. For a complete presentation of the HFACS framework see appendix A.

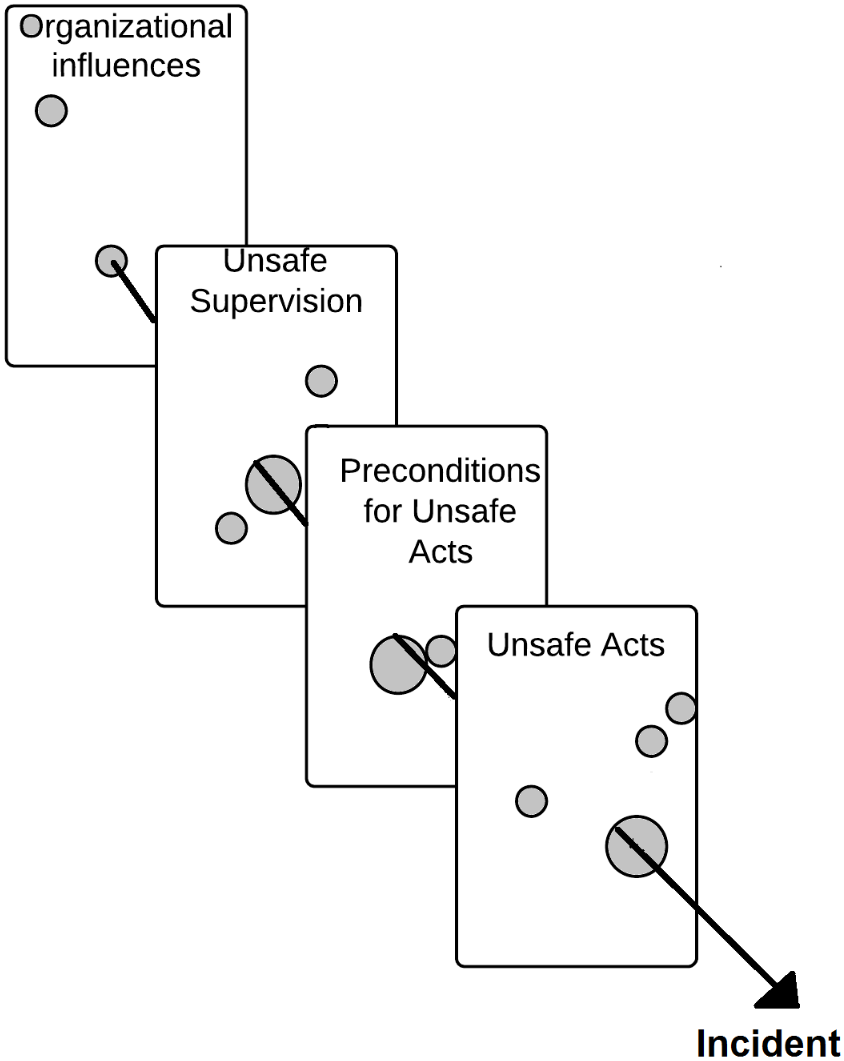


Figure 4 HFACS SWISS CHEESE MODEL (Reason, 1990)

3.1 Unsafe acts

Unsafe acts, (active failures) is the final, or bottom level, of the HFACS and the Swiss Cheese Model presented in Figure 4. Unsafe acts is further categorized into Skill, rule and knowledge-based errors.

“When trying to negate or avoid human errors, it is important to distinguish between the types of which they occur. This will aid us in deciding and implementing effective risk reducing measures” (Reason, 1990)

3.1.1 Skill-based errors; slips/lapses

“At the skill based level, human performance is governed by stored patterns of preprogrammed instructions. Skill based errors are related to unintended actions, or slips and lapses, which may occur at "every- day" actions in familiar surroundings.” (Reason, Human error, 1990)

Two conditions are often present for the occurrence of skill-based errors. The performance of a repetitive or automatic task in a familiar context, and being distracted by something not directly related to the assigned job, for example due to boredom. Skill-based errors are unintended actions, and thereby separates them from rule- and knowledge-based errors which are intended actions where the outcome is unsuccessful (Reason, Human error, 1990).

3.1.2 Rule-based errors

“The rule- based level is applicable to tackling familiar problems in which solutions are governed by stored rules. In this instance errors are typically associated with the misclassification of situations leading to the application of the wrong rule or with the incorrect recall of procedures” (Reason, Human error, 1990).

Rule based errors may arise when the operator bases his actions on his earlier experiences. The human brain is very good at creating patterns, even those that are untrue. If we followed a rule of action at some previous instances with a successful outcome, our natural assumption is that the rule is a good one, even if unknowingly our success was a sheer coincidence. To create such patterns was very useful in our evolution, where we adapted fast to our environment. Unfortunately it is often too simple to apply such logic in the controlling of advanced systems where a lot of factors have to be considered. To blindly assume our previous solutions to a problem will be sufficient in the future may lead to wrong decisions or even wrong training, if the training is based on insufficient data or experience.

3.1.3 Knowledge based error

“The knowledge-based level comes into play in novel situations for which actions must be planned on-line, using conscious analytical processes and stored knowledge. Errors at this level arise from resource limitations and incomplete or incorrect knowledge. (…) With increasing expertise, the focus of control moves from the knowledge-based towards the skill based levels, due to increased familiarity of scenarios. But all three levels can co-exist at the same time" (Reason 1990).

As stated above by Reason, knowledge based errors arise when people must evaluate their course of action without being familiar with the situation. The situation must be analyzed and decisions must be made directly "on the spot" without having any similar experiences or "rules" to support their choice of actions. In order to avoid the need of knowledge based decisions situations, increased expertise on the subject is necessary, this is usually achieved through training.

3.2 Latent failures that may lead to unsafe acts

Latent failures are failures that may lead to unsafe acts, but that do not directly lead to harm themselves. Latent failures are further divided, as shown in Figure 4, into preconditions for unsafe acts, unsafe supervision and organizational influences.

3.2.1 Preconditions for unsafe acts

Preconditions for unsafe acts, represents underlying failures on the operator level that may lead to unsafe acts, and may be subdivided into Crew Resource Mismanagement and Adverse Mental States (Wiegmann, 2001).

Crew Resource Mismanagement:

Crew Resource Mismanagement essentially covers lack of teamwork/cooperation between crewmembers, or insufficient clarification of roles in an operation.

Often times, the practices of operators or crew will lead to unsafe acts. Failure to coordinate the team, or insufficient clearance of roles may lead to confusion and unsafe acts. Also failure of coordination of activities before, during or after an operation is included in this category (Wiegmann, 2001).

Adverse Mental States:

Adverse Mental States refers to an individual's state of mind, more specifically factors that degrade the level of concentration of the crewmember.

"To be prepared mentally is critical in nearly every endeavor. With this in mind, adverse mental states, was created as one of three subcategories of operator condition to account for those mental conditions that adversely affect performance" (Wiegmann, 2001).

Examples:

- Visual illusions (for example due to weather blindness, fog or haze)
- Illness, (seasickness or other)
- Impaired hearing or lack of control due to noise or vibration
- Confusion (for example due to miscommunication, or unclear clarification of roles)

Physical and/or Mental Limitations:

Physical and/or Mental Limitations represents those instances where individuals are unable to retrieve the information necessary to solve a situation. Also scenarios where the information is available, but they do not have the skill or time they need to utilize it is included in this category. In critical situations during a DP operation, the operator may be required to act very fast and correct in order to avoid an emergency (Wiegmann, 2001).

It is important to remember that the resulting limitations of the crewmember, could be due to insufficient knowledge/training, not only as a result of a complicated situation.

Examples:

- Short reaction time during loss of position

3.2.2 Unsafe supervision (middle management)

"Clearly, aircrews are responsible for their actions and, as such, must be held accountable. However, in many instances, they are unwitting inheritors of latent failures attributable to those who supervise them"(Reason 1990).

Reasons' statement is clearly directed towards the crew on an airplane, but could be just as true for a supply ship or other vessel on the sea. To account for these supervision failures, the overarching category of unsafe supervision was created.

Unsafe supervision thus represents failures on the middle management level, sometimes referred to as Bridge resource management when regarding vessels.

Supervision roles exists for a reason. Sometimes it is hard to achieve the full picture of a situation from a limited vantage point. The middle management should in many cases be able to achieve a better overview of a situation and help the acting crewmembers perform their actions sufficiently.

3.2.3 Organizational influences

Organizational influences refers to formal processes, procedures and oversight within the organization. Failures in the upper level management is covered by this category, these types of failures may affect the work environment, every day performance and motivation of those within the organization. (Wiegmann, 2001)

Examples of organization influences:

- Human resource management (selection, training, staffing).
- Organizational Climate (chain of command, delegation of authority)
- Monetary decisions (delegation of resources)

PART III INCIDENT DATA

4 Incident data, relative failure frequencies

The method and results of incident data sorting is presented in this chapter. The sorted data forms the basis for a quantitative analysis of LOP incident causal factors.

4.1 Incident definition

An incident is in general terms defined as "an unplanned and unforeseen event that may or may not result in harm to one more assets" (Rausand, 2011).

For this report only position loss incidents during a DP operation are of concern. These types of incidents are defined by The International Marine Contractors Association (IMCA) as "Loss of automatic DP control, loss of position or any other incident which has resulted or should have resulted in a «red alert status"

Red alert status is further defined as; "Position and/or heading loss have happened or are inevitable" (IMCA, 2007).

The incident definition used by IMCA, states that vessel does not actually have to lose position for an event to be defined as a LOP incident. Consequently, not all incidents analyzed in this report will lead to a drift off or a drive off.

4.2 IMCA register- selecting credible data

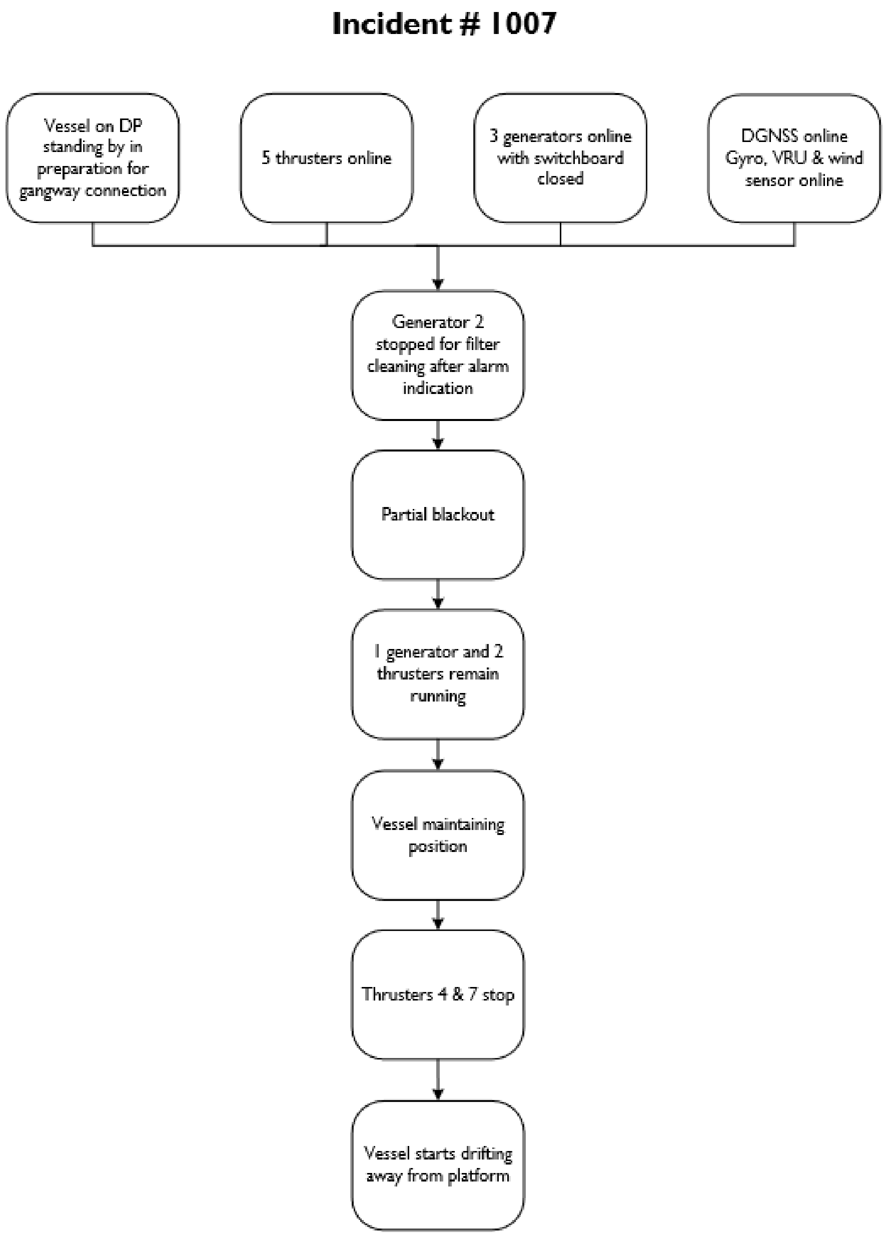
The literature emphasizing operation risk for DP vessels in the oil and maritime industry is mainly focused on the direct collision risk by the study of past collisions. Similarly, most statistics are based on the end result of the incidents, and by that excludes near misses and dangerous incidents with no visible consequence. Much less attention is divided on studying and filing the causes behind every situation that only could have led to an accident, probably due to the several practical challenges of gathering and keeping such records. Unfortunately this makes finding reliable and extensive incident data difficult.

IMCA gathers incident data from DP operations and publish the results for their members every year, however the reports are solely based on voluntary contributions from vessels. The reports are based on predefined reporting schemes available for download on any computer.

IMCA accepts reports from all vessels and make sure the incident cannot be traced back to the vessel reporting it. Global Maritime has access to the IMCA reports presented annually for each year from 1980 to 2010. These reports, which they have shared, represent the best data available for the author today, when studying position loss incidents for vessels applying dynamic positioning.

Historically IMCA has used seven categories when determining the cause for a position loss: Computer, environmental, power generation, operator errors, references, thruster/propulsion and electrical. However the categories have been changed several times over the years, which makes the combination of data more complicated. Some of the categories have only been used a few years which makes the number of incidents under this category few. The incidents are presented individually by flow charts created by IMCA on the basis of their gathered report schemes.

In Figure 5 an IMCA incident flowchart is presented. The failure of a generator resulted in a partial blackout, and eventually the loss of all 5 thrusters.



Comments	This incident appears to have coincided with a generator being taken out of service to clean a filter. Initially vessel was able to hold position on one generator and two thrusters however system stopped two remaining thrusters
Initiating Event	Two generators stopping
Main Cause	Power – Partial blackout

Figure 5 Example of IMCA flowchart (IMCA, 2000-2010)

4.3 Sorting of incidents after IMCA categories

Every incident is given a main cause, and some also a secondary cause by IMCA. The main causes are defined as “a fault that starts or results in a position loss”, while the secondary are “causes which could be attributed to the incident or complicate the position loss recovery” (IMCA 2000-2010).

The IMCA categories of main and secondary causes presented in Figure 6 and Figure 7, have, as earlier mentioned, been changed several times which makes some of the categories overlapping. Based on IMCA definitions, the categories can be explained as follows, (IMCA 2000-2010):

- DP computer - Fault on DP hardware or software
- Reference – Fault on reference system or sensors (in some reports sensors are separated)
- Power generation – fault on generator or PMS
- Thruster/Propulsion – fault on thruster control, mechanical, rudder etc. (Mechanical is separated in some reports)
- Electrical – fault in switchboards, UPS, voltage
- Environmental – excessive wind, wave or current
- Operator error – fault by human (operator electrician etc)
- External forces – other vessel, 3rd party interference
- Procedures – poor maintenance insufficient testing etc. (Closely linked to human error).
- Undetermined/not established – the main or secondary cause was not identified

By combining the available reports from 2000-2010 it is possible to present the mean percentage of causes over this period of time. The incident presented in Figure 5, has been given the main “power” by IMCA, with no secondary cause, as this is not specifically stated.

After sorting the 620 incidents that were presented in the IMCA reports from 2000 to 2010 after IMCA’s own categories, the resulting frequencies are presented in Figure 6 and 7. Only 361 of the incidents had been assigned secondary causes.

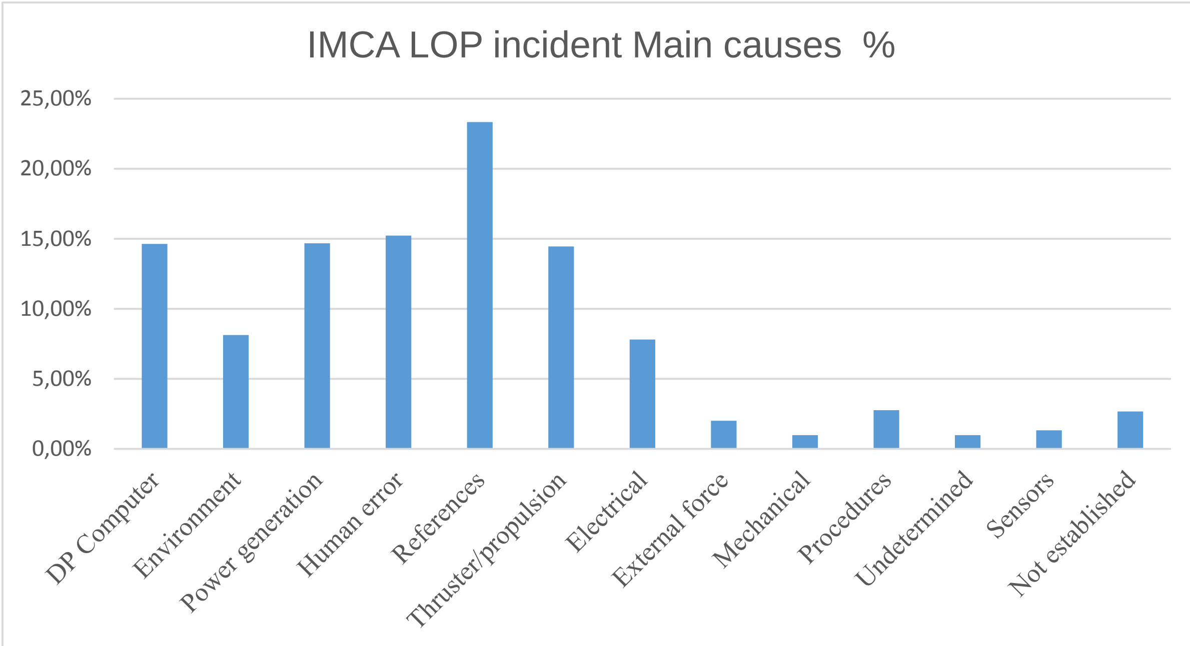


Figure 6 IMCA Main Causes, in percentage of 620 incidents

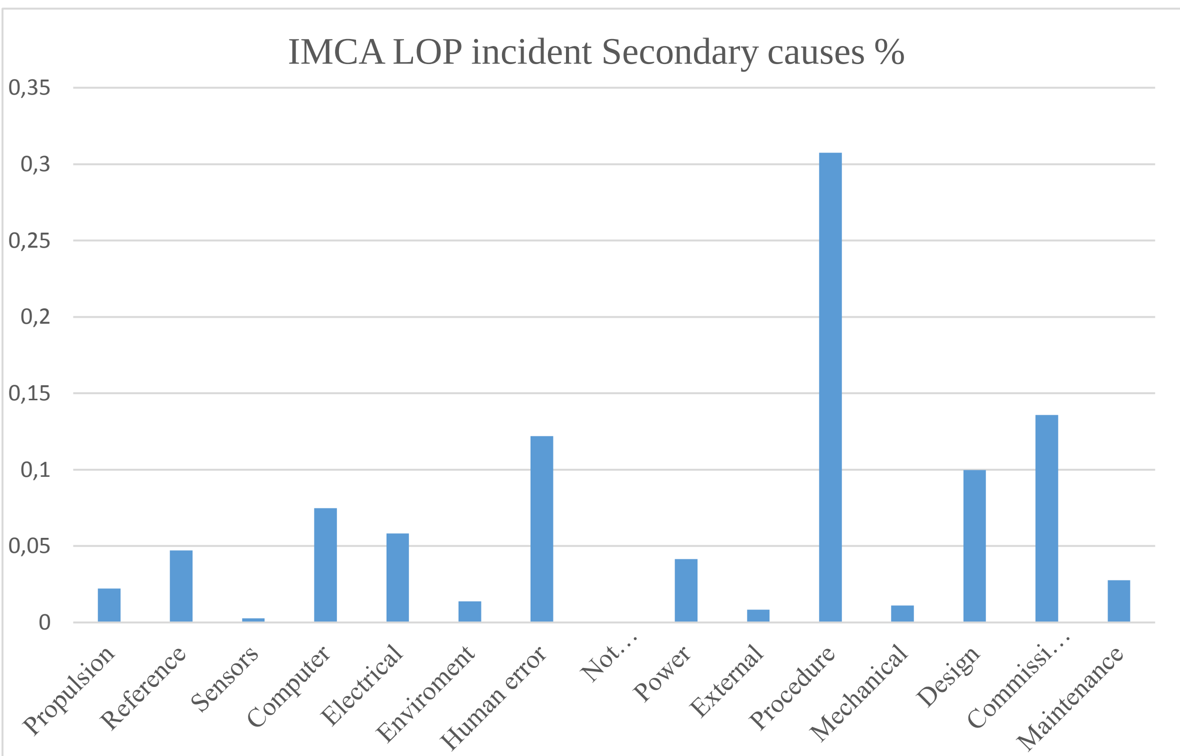


Figure 7 IMCA Secondary causes, in percentage of 361 incidents

According to the IMCA categorization presented in Figure 6, “references” are the most common main cause of LOP, followed by “human error”, “thruster/propulsion”, “DP computer” and “power generation”. As seen in Figure 7, “procedures” are the most common secondary cause by far. Following “procedures”, “commissioning”, “human error” and “design” are highly represented. The sorting of secondary causes show that failure categories typically related to human factors (human error, procedures, commissioning) are contributing to, and complicating, equipment failures such as propulsion and power faults.

The sorting of main and secondary causes, provides some insight into which part of the DP system that are commonly involved in LOP incidents and is a good starting point for further analysis, as they represent a vantage point to important causal categories. The results however provides precious little clarity regarding the causal unfolding of incidents.

In an effort to obtain deeper insight of causal dependencies, a matrix combining main and secondary causes was created. The matrix is presented in Appendix B.

Unfortunately, few clear tendencies of dependencies between main and secondary causes were observed. Due to the lack of cause dependencies the IMCA system provides, a more in depth sorting system based is introduced in chapter 4.4.

4.4 Sorting of data based on IMCA flowcharts

As the IMCA sorting system gave little information regarding dependencies in causal factors, a more detailed sorting is necessary. The IMCA flowcharts, as presented in Figure 5, contains some specific information on causal factors for each incident. The presented information may provide additional clarity if sorted in a systematic manner.

For this more specific data sorting, it was determined to reduce the number of years to the last three years 2008-2010. These three years equals to 234 incidents. The reduction in number of incidents was due to the large amount of work necessary by the author to not just to read and identify causal factors in each incident, but also to identify patterns in their unfolding.

The incident represented by the flowchart in Figure 5, represents factors as generator failure, partial blackout and multiple thrust failures. The author has used Microsoft Excel for this sorting. The system for sorting data can be described as follows. Each row in Excel represents a specific incident, like the one shown in Figure 5. Each column represents a group of causal factors with common properties, for example all kinds of generator failures. The identified groups are based on the system structure and equipment types presented in chapter 2.3, as well as information obtained from the actual reading and sorting of incidents. If the incident includes a specific group, it is marked by filling the cell with the value "0". Factors not identified has the value "1". The information provided by sorting the data in this more detailed way, is an important part of creating causal flowcharts and eventually Bayesian Belief Networks.

A small part of the excel file is shown as an illustration in Figure 8.

fullbo	partialt	multipl	singleth	Thrustf	thruste	wiring	relay	busbar	generat	DPSW	DPHW
1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	0	0	1	0	1	1	1	1	1
1	1	1	1	1	1	0	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	0	1
1	1	1	0	0	1	1	1	1	1	1	1
1	0	0	1	0	1	1	1	1	0	1	1
1	0	0	1	0	1	0	1	0	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	0	0	1	0	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	0	1
1	1	1	1	1	1	1	1	1	1	1	1
1	1	0	1	0	1	0	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	0	1
1	1	0	1	0	1	1	1	1	0	1	1
1	0	0	1	0	1	1	1	1	0	0	1
1	1	1	1	1	1	1	1	1	1	0	1
1	1	1	1	1	1	1	1	1	1	0	1
1	1	1	1	1	1	1	1	1	0	1	1
1	1	1	1	1	0	1	1	1	1	0	1
0	1	0	1	0	1	1	1	1	0	1	1
1	1	1	1	1	0	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	0	1	1	1	1	1	1

Figure 8 Excel sorting of data

The criteria for including an incident in the specific data sorting, is that the incident could have occurred at any vessel operating on DP. This is a necessary limitation since the vessel type in each incident is removed due to the need for anonymity. All incidents that are clearly due to failure of equipment exclusively present on a certain type of vessel, i.e. a pipe-laying vessel, has been excluded from the analysis. The limitation was made in order to generalize position loss incidents across several vessel types. If one were to include incidents with root causes exclusively present in pipe laying equipment, these incidents would have to be separated as an individual category. Since pipe laying incidents naturally not is possible on all of the vessel types analyzed, this would create a false perspective to which degree this certain equipment is the cause of LOP incidents.

Out of the 234 cases, 222 were found applicable for this study. Those removed are either due to a very high degree of uncertainty in the report, or due to equipment failures which cannot be generalized (and normalized) across all vessel types.

A presentation and explanation of the identified groups of causal factors may be found in appendix C.

4.5 Terminal events

Terminal events represent the causal end of an incident and are presented in Table 1. Besides the actual LOP scenarios identified as drift off and drive off in chapter 2.2, two other terminal events were discovered by sorting of data; Operation abort and time loss. These terminal events exist since not all LOP incidents actually leads to LOP. See chapter 4.1 for LOP incident definition.

Unknown terminal event represents those incident where the terminal event could not be defined due to lacking or too uncertain information in the flowcharts.

Table 1 LOP terminal events

Drift off	See chapter 2.2
Drive off	See chapter 2.2
Operation abort	No LOP, but the DP operation was aborted.
Time loss	No LOP, operation not aborted. Includes reduced system redundancy, where time loss is considered highly probable due to the degraded system.
Unknown terminal event	Unable to identify the terminal event of the LOP incident.

4.6 Relative frequencies of LOP incident causal factors

For the creation of flowcharts the causal factors were sorted in three main categories. Propulsion, references/sensors and human error. A single incident may represent causal factors in more than one of the three groups, as shown in Figure 9. Some incidents are rather special, and do not involve a causal factor in any of the three categories. Such an example could be an internal error in the DP control system, with no human factors identified, that did not affect the propulsion or reference system. 18 such incidents has been recorded which is equal to roughly 8% of the 222 incidents.

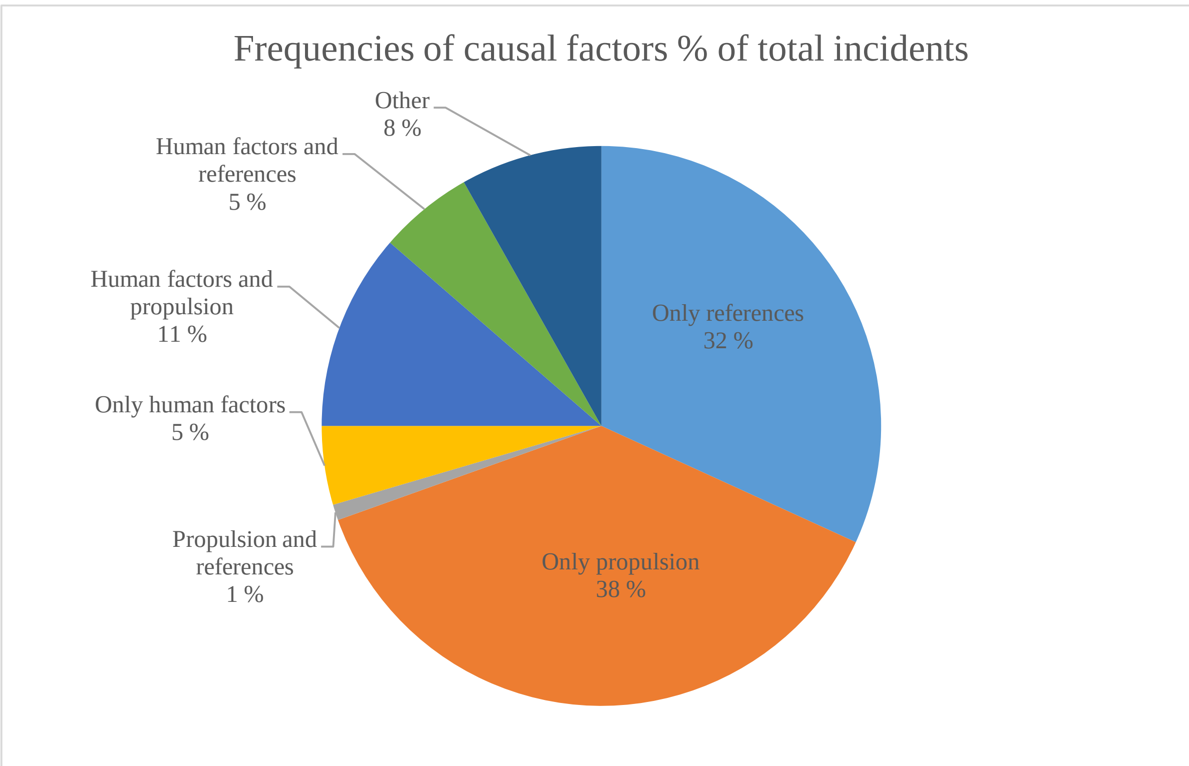


Figure 9 Causal factors percentage of the total 222 incidents,

IMCA has 7 main categories of causes or causal factors, this report has three. These three categories are shown to cover above 90 % of all incidents analyzed. The other categories of IMCA causes are necessarily usually in combination with one of these three, which further supports the statement in chapter 4.3 that to only determine a main and (sometime) secondary cause, may not capture the full causal dependencies of LOP incident causes.

One interesting observation made from the data presented in Figure 9 is that human factors rarely lead to terminal events directly. "Only human factors" represents below five percent of the incidents. Human factors rather lead to other system failures, and then most often to propulsion failures. Additionally we see that the propulsion and position reference systems may be considered close to independent. Only one percent of the analyzed incidents have causal factors from both these systems. However, according to the presented DP system structure, (see Figure 2), an equipment failure in the power generation or distribution system, could potentially have an effect on both references and propulsion. The low percentage of such results may be due to the limited information presented in the IMCA flowcharts.

4.6.1 References/sensors

In 84 of the 222, or roughly 38% of the analyzed incidents, some sort of reference or sensor failure occurred. In total 104 reference equipment failures has been assigned to the 84 incidents due to common cause failures such as DP control equipment and power. In incidents with common cause failures, it is sometime hard to evaluate exactly which equipment(s) that failed. If the flowchart from IMCA says that all position references failed, but no information exists to which reference systems that were active at the time of the incident, this complicates the sorting of failures. The most common reference systems have then been assigned the incidents, but there are few examples of such common failures with lack of information. An example of such an incident is presented in Figure 10.

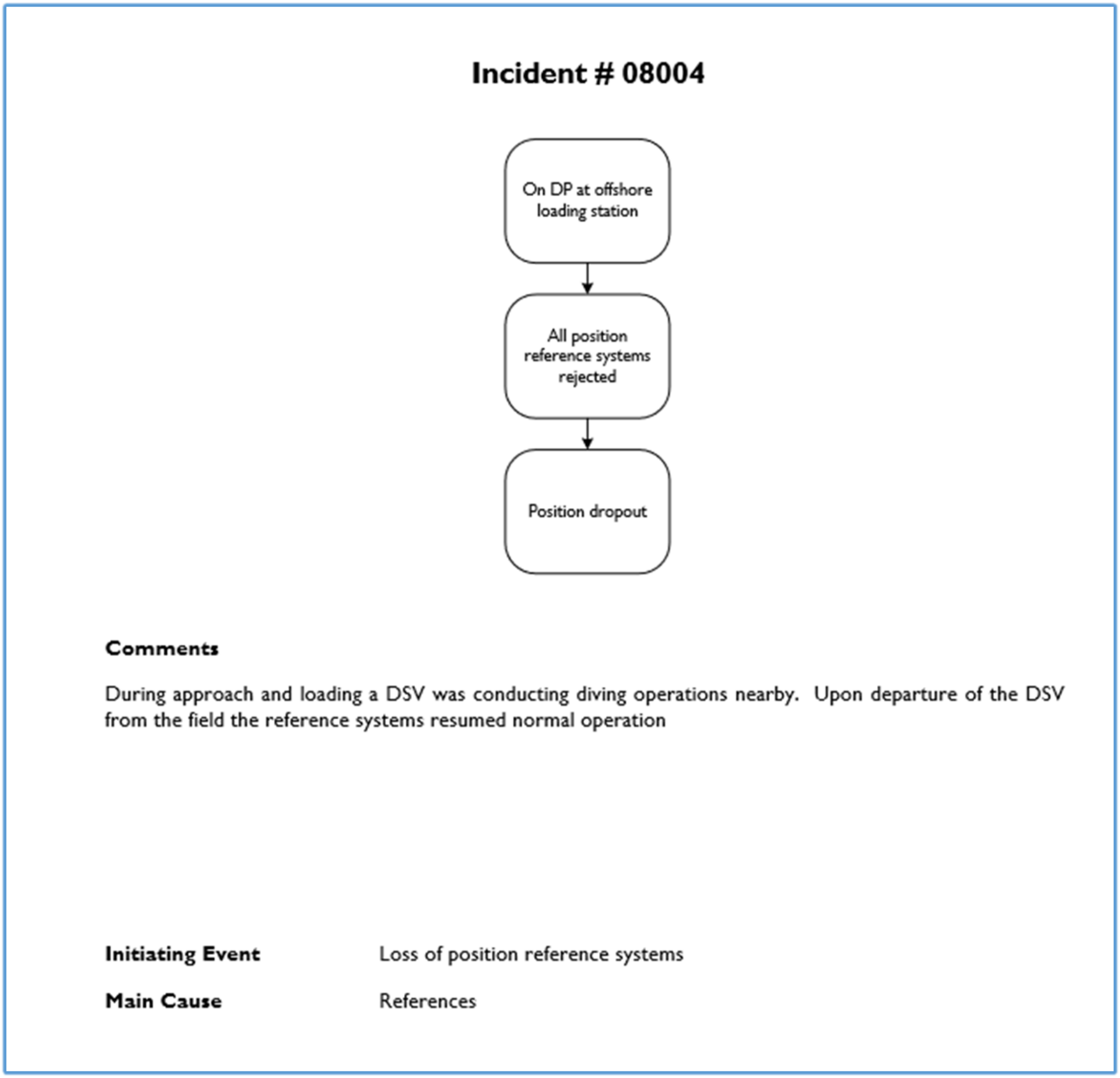


Figure 10 Unclear common cause reference failure (IMCA, 2000-2010)

In Figure 11 the percentages of incidents involving failures of each specific reference/sensor equipment type is shown. The sum of percentages are above 1, due to 104 failures in 84 incidents.

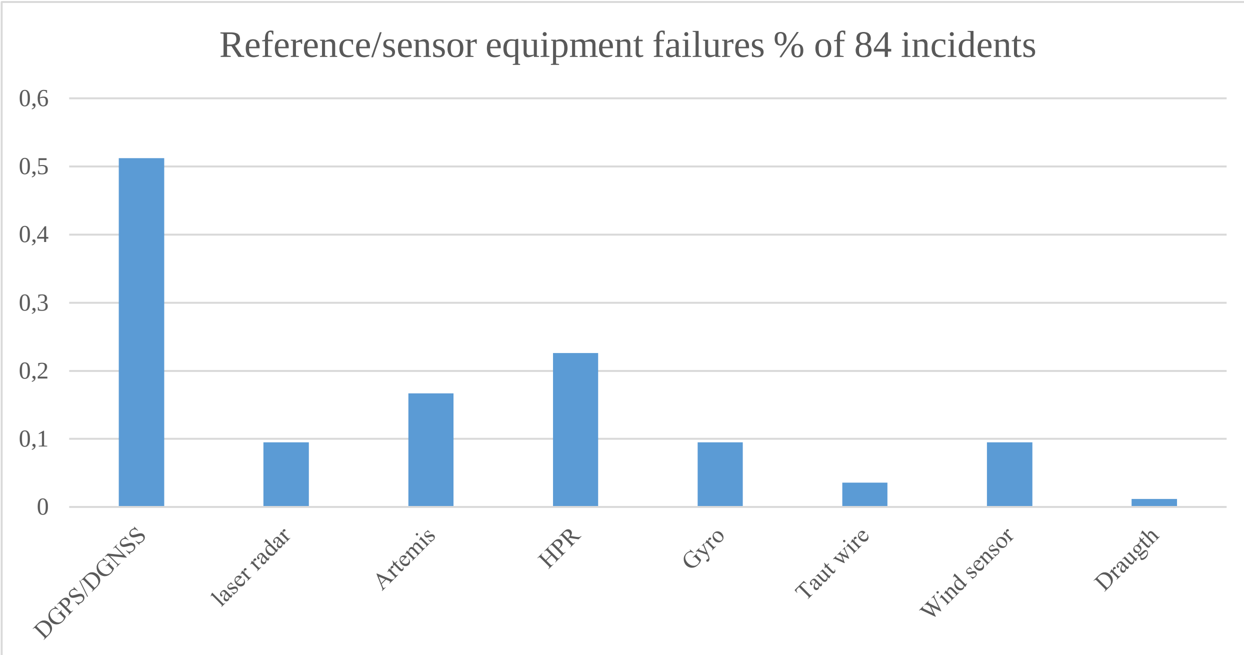


Figure 11 Reference/sensor failures in percentage of incidents, 84 incidents, 104 failures

Figure 11 shows extreme differences in failure frequencies between equipment types. The DGPS/DGNSS fails in above 50 % of all incidents involving a reference or sensor failure. Does the high number of failures mean that this reference system is poorly designed? What is the reason for the high percentage of failures compared to the other systems?

One natural explanation is that not all reference systems are active on each vessel at all times, which leads to a higher failure frequency for commonly active equipment.

To further investigate this theory, the reference equipment failure rates have been adjusted to the number of times the reference were specified to be active on the vessel. In 51 of the 84 incidents, information regarding active systems was given. The other 33 incidents are removed from the data material for this investigation. The adjustment was done by dividing the number of incidents the system failed, to the number of incidents it was specified active on a vessel, as shown in Table 2.

The Draught sensor was never specified active in any incident.

$$Adjusted\ failure\ freq = \frac{Number\ of\ failures}{Number\ of\ incidents\ specified\ active}$$

Table 2 Relative reference failures normalized online, 51 incidents, 67 failures

Reference type	**Failures**	**Original failure frequency**	**Specified active**	**Adjusted failure frequency**
DGPS/DGNSS	33	64.7%	51	64.71%
laser radar	6	11.8%	15	40.00%
Artemis	2	3.9%	5	40.00%
HPR	9	17.6%	18	50.00%
Gyro	6	11.8%	41	14.63%
Taut wire	5	9.8%	13	38.46%
Wind	5	9.8%	41	12.20%
Draught	1	2.0%	0	#DIV/0!

As one can see in Table 2 and Figure 12, the relative differences in failure rates between equipment types are much smaller in the adjusted frequencies, compared to the original failure frequencies. The adjusted frequencies points in the direction of a more equal failure ratio per time unit across reference equipment, even though commonly active equipment types naturally fail more often than those less used. The exceptions are wind sensor and Gyrocompass that have almost unchanged, (still relatively low) failure frequencies.

However, for the creation of a BBN, the original failure data presented in Figure 11 will be applied, as we mainly are interested in which equipment type that contributes most to LOP, regardless of how often they are active.

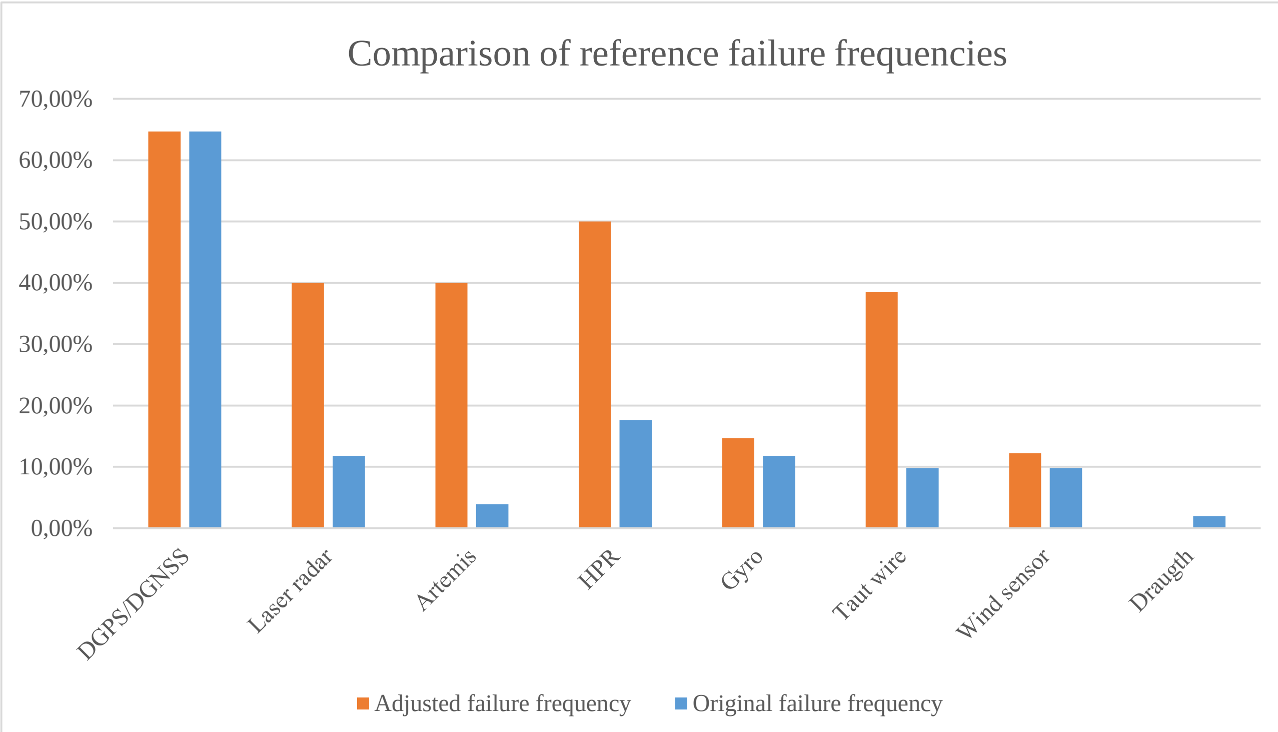


Figure 12 Comparison of reference failure frequencies, 51 incidents, 67 failures

4.6.2 Propulsion

In 111 of the 222, exactly 50% of the analyzed incidents, some sort of propulsion failure occurred. In total 111 propulsion failures has been assigned to the different incidents. The identical number of failures and incidents is due to mutually exclusive failures types. Single and multiple thrust dropout, refers to the complete stop or loss of thruster from the DP-system, thrust error, represents those incidents where no thrusters actually stopped, but where either wrong amount of output were given, or the output was uncontrolled by the operator. The relative propulsion failures are presented below in Figure 13. Due to limited incident information no distinction between thruster types can be made.

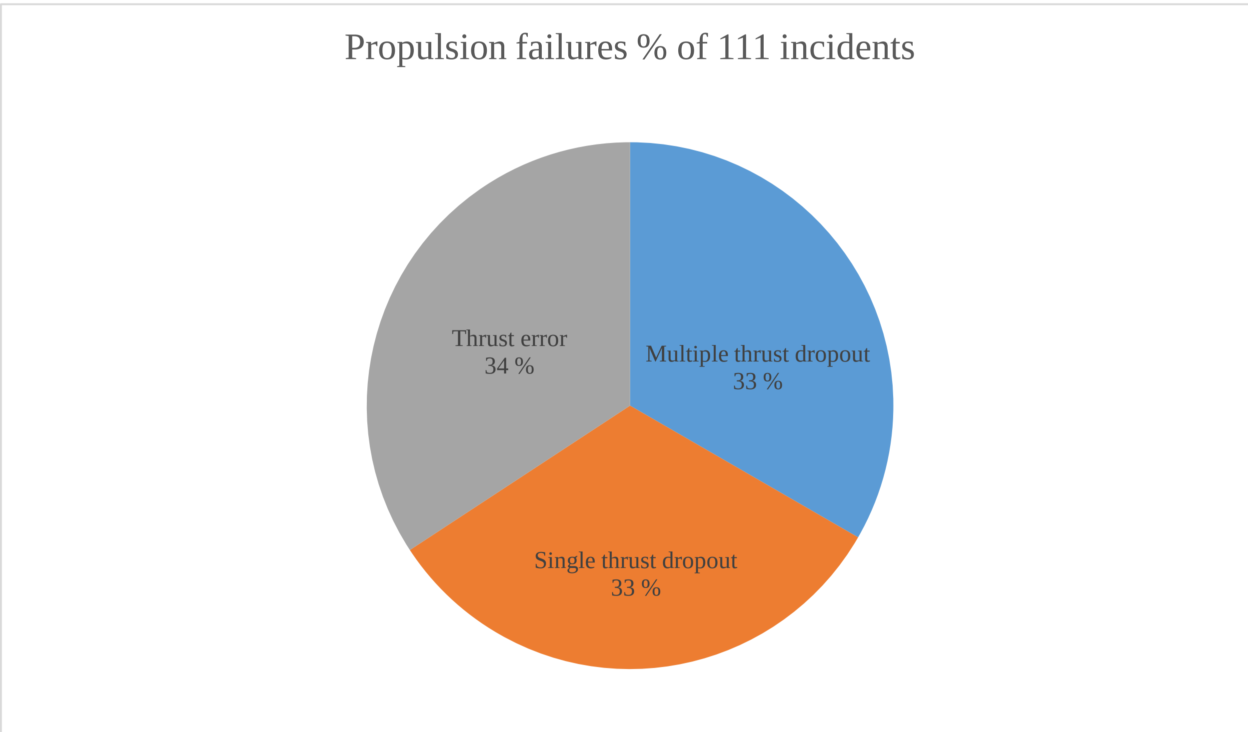


Figure 13 Propulsion failures in percentage of incidents, 111 incidents, 111 failures

4.6.3 Human factors

Human factors have been present in 46 LOP incidents which equals to roughly to 21 % of the analyzed incidents. These 46 incidents have all been assigned an unsafe act. The unsafe act is one of three; slip/lapse, rule based error or knowledge based error, see chapter 3.1

The resulting relative frequencies of unsafe acts are displayed in Figure 14.

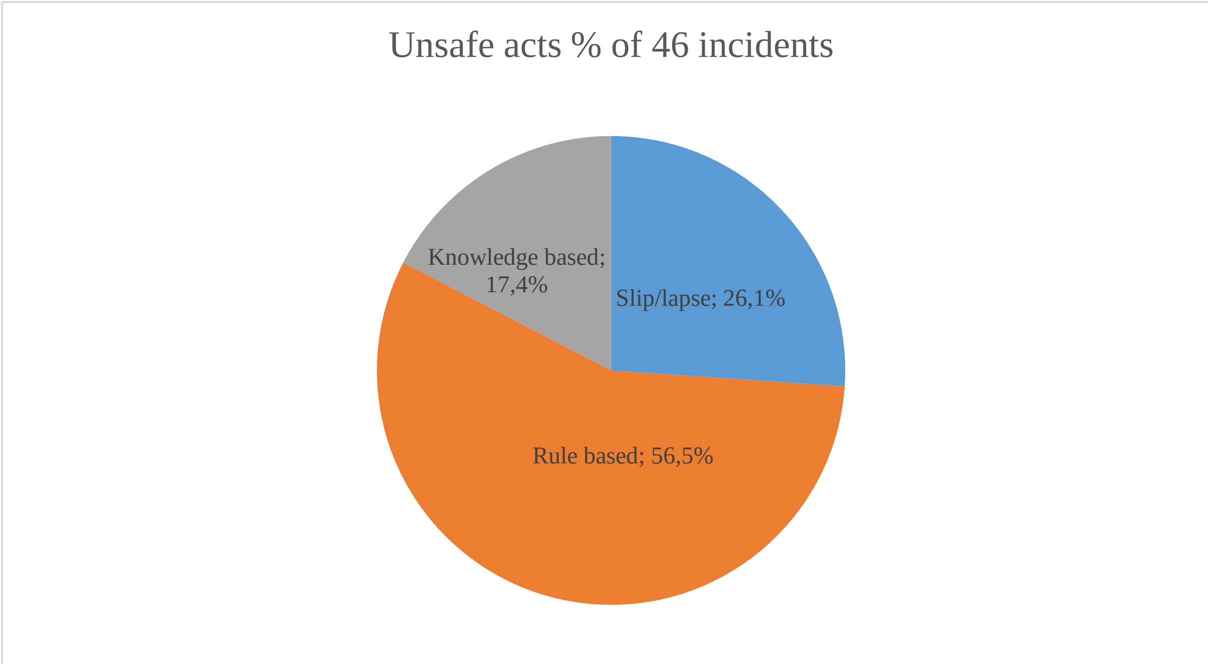


Figure 14 Unsafe acts included in LOP, 46 incidents, 46 unsafe acts

The results presented in Figure 14 show that rule based errors have the highest frequency of unsafe acts, even though one could have expected every day mistakes as slips/lapses represent to be the most frequent.

One explanation for the lower number of slip/lapses, is that less severe incidents caused by slips/lapses may have a higher degree of underreporting in the IMCA. Alternatively, every day mistakes as slips and lapses represent, do not lead to LOP incidents to the same extent as rule based and knowledge based errors. Probably a combination of both statements will be closer to the truth. As expected knowledge based errors have the lowest frequency as they represent the most severe situations.

Some of the incidents containing unsafe acts, have also been assigned latent failures, (see chapter 3.2). The same incident can have more than one latent failure present. The incidents where latent failures were identified, have been sorted by which unsafe acts they contributed to. The result of this sorting is shown in Figure 15.

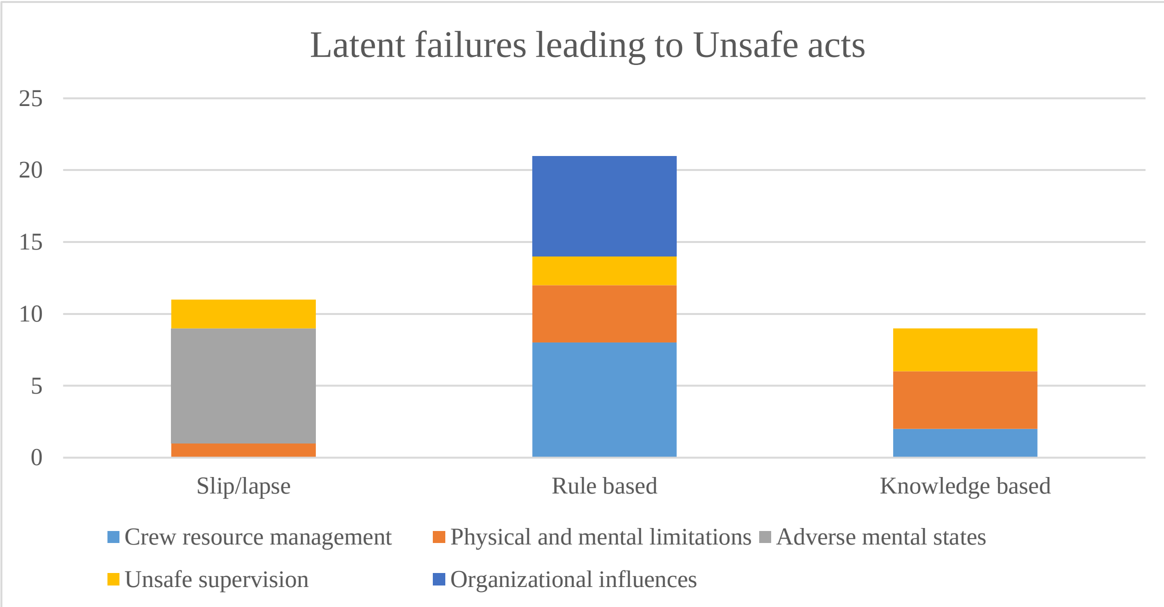


Figure 15 Latent failure leading to Unsafe acts,

According to Figure 15, slips/lapses (skill based errors) are dominated by adverse mental states, rule based errors by organizational influences and crew resource management, while knowledge based errors usually results of physical/mental limitations and unsafe supervision. Is this in accordance with the HFACS system presented in chapter 3?

Firstly, adverse mental states basically represent distraction and it seems logical that this may lead to slips and lapses, based on the definition of skill based errors from chapter 3.1.1.

Crew resource management covers lack of teamwork/cooperation between crewmembers, or insufficient clarification of roles in an operation. Lack of teamwork and unclear roles may be a believable cause for rule based errors as they amongst others represent decisions made on wrong premises.

Organizational influences is a wide term, and should perhaps have been expected to lead to all three unsafe acts, not just ruled based errors. However due to the low detail level of the incident data, organizational factors was the hardest type of latent failures to identify, as they are furthest "removed" from the actual unsafe acts, which could have affected the certainty of the sorting.

According to James Reason, knowledge based errors arise from resource limitations and incomplete or incorrect knowledge. From chapter 3.2.1 we recall that physical/mental limitations represent those times where information is ether unavailable, or if available, individuals simply do not have the skill to utilize it. Based on their definitions, it seems correct that these human factors are related.

According to the presented results, knowledge based errors also arise from unsafe supervision. As mentioned earlier, supervision roles exists for a reason. The middle management should in many cases be able to achieve a better overview of a situation and help the acting crewmembers perform their actions sufficiently. A failure in the middle management could therefore render crewmembers inadequate to solve a potential threat, which may result in a knowledge based error.

The dependencies discovered in the sorting of human factors, seem to be in line with the properties of the HFACS sorting system, and may be therefore be used as a basis for a causal flowchart of human factors.

4.7 Terminal events of LOP incidents

Terminal events marks the end of the causal chain of events in a LOP incident. If an incident has unknown terminal event, this means that there was insufficient information presented by IMCA to determine the end result of the incident.

The relative frequencies of the five terminal events including “unknown” are presented in Figure 16. The results will have a high level of uncertainty due to almost 33% of all incidents have unknown terminal event. Drift-off and drive-off represent those incidents where LOP actually has taken place. Together they sum up to roughly 28% of all incidents. All incidents actually probably includes time loss, however only the most severe terminal event has been assigned each incident. For example even though a drift-off usually includes time loss or operation abort, it is still only sorted as “drift-off”.

One should perhaps expect time loss to be more frequent as this category represents the least severe terminal event. The low percentage may be due to strict procedures regarding aborting an operation in the event of a system malfunction, in combination with lower report rates for the least severe incidents.

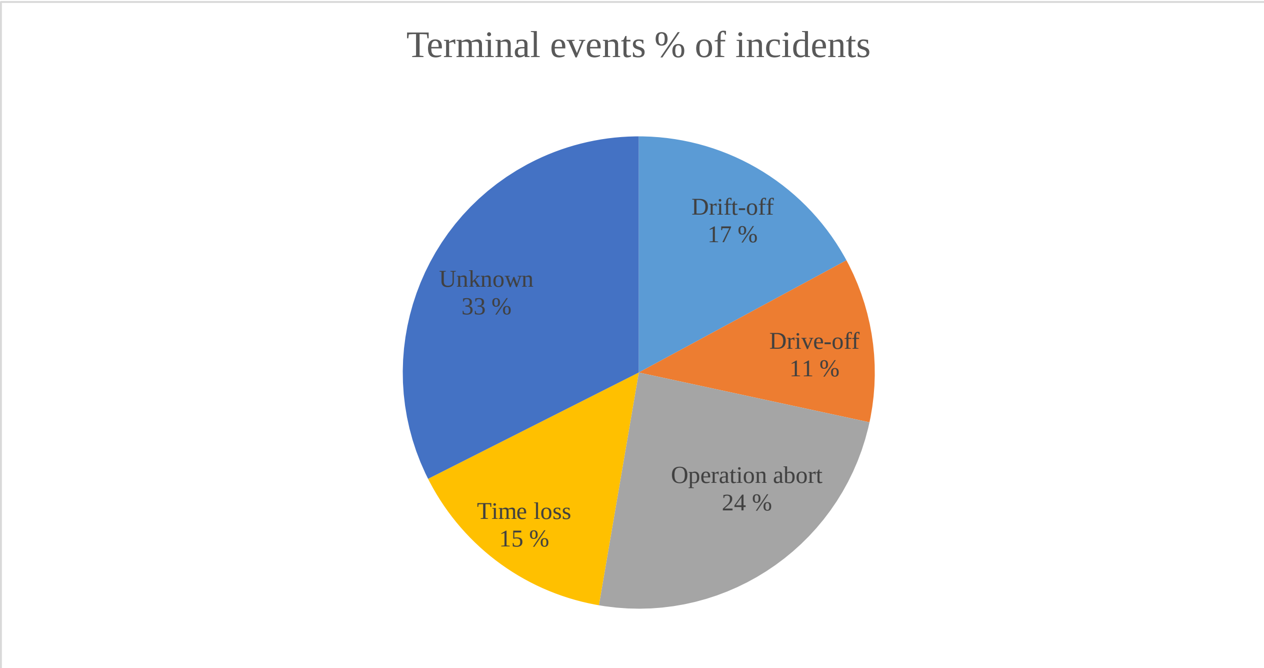


Figure 16 Terminal events present in percentage of incidents

4.7.1 Terminal events in respect to failure type

The distinction between terminal events resulting of the main references and propulsion categories is shown in Figure 17.

Human factors do seldom lead to terminal events directly, and are therefore not presented (See Figure 9).

The incidents with unknown terminal event are removed from the sorting, as an unknown terminal event is due to the detail level of data presented in IMCA flowcharts, rather than the nature of the incident. Therefore any dependencies in failures leading to unknown terminal events, are considered not interesting. The results from this graph is very helpful when creating a BBN, as we see which failure groups that lead to the four different terminal events.

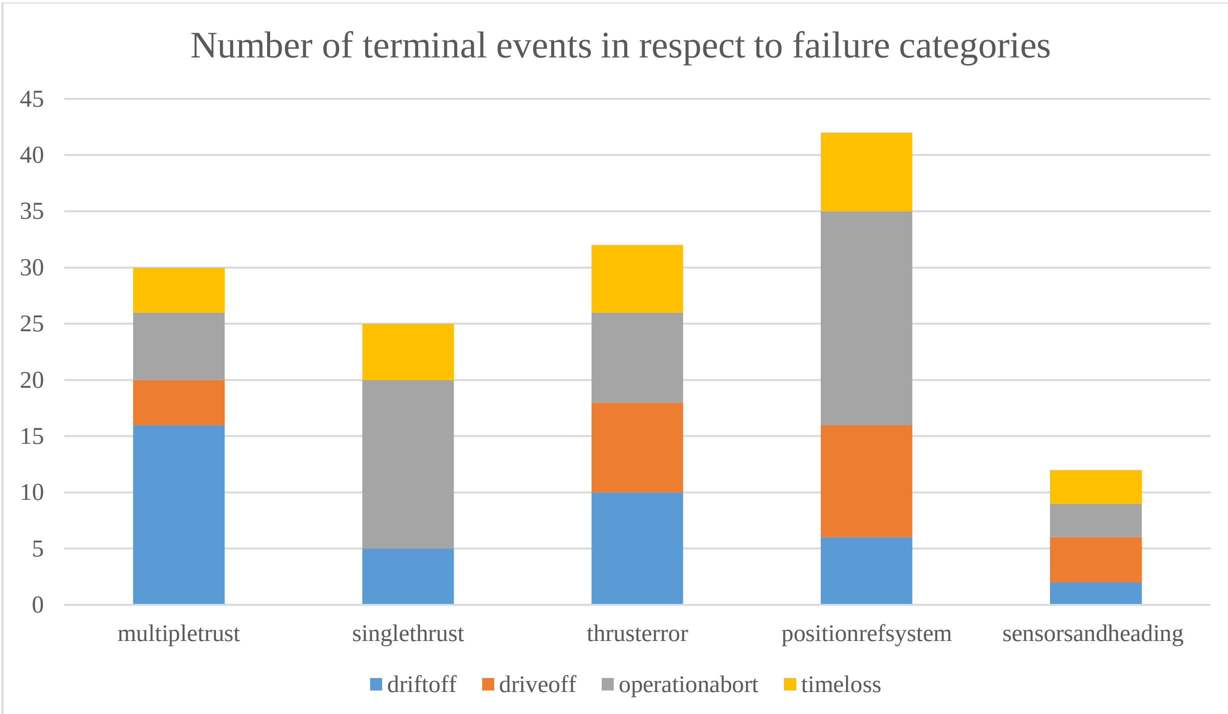


Figure 17 Terminal events in respect to failure type

When multiple thrusters drop out of the DP system, drift-off is the dominating terminal event, when only a single thruster drop out, operation abort is clearly most common. This result is in line with the requirement of redundancy for DP class 2 and 3, where LOP should be avoided in the case of a single point failure. Additionally drive-off is seldom the result of thrust dropouts, which is logical since drive off is defined as; “drive-off is a powered move away from the desired vessel position”. If the thrusters drop out of the system they cannot power the vessel out of position. However in some cases thrust dropout may occur as a result of uncontrolled force sometimes applied in a drive-off, which makes this combination possible.

The failure type, “thrust error”, captures the incidents where thruster(s) do not drop out of the system, but rather deliver incorrect or uncontrolled amount of thrust. Naturally thrust error may lead to a drive off (extensive thrust), or a drift off (insufficient thrust). Operation abort and time loss is also often the result of this failure mode, as the thrust error in some cases does not affect the total thrust output enough to cause a LOP.

Position reference system and sensors both leads to all 4 terminal events. A drift-off can be the result of a stationary position reference, which leads to the vessel “believing” it is in correct position while actually drifting.

A drive-off may on the other hand be the result of the vessel “believing” it is off position due to a false position reference, and applying unnecessary thrust to regain position the “correct position”, thereby performing a powered move off location. Time loss and operation abort is often the result when the incorrect position reference is given low weighting and discarded, (see chapter 2.3.4). In such cases, it may be decided to abort the operation due to degraded system, or time may be lost before “fixing the problem”.

4.8 How DP classes potentially affect LOP frequency

In chapter 4.1 LOP incidents that are analyzed in this report was defined by IMCA as “Loss of automatic DP control, loss of position or any other incident which has resulted or should have resulted in a «red alert status”

Red alert status was in chapter 4.1 defined as; “Position and/or heading loss have happened or are inevitable.”

However the red alert status is dependent on the system redundancy which is given by the DP class of the vessel. The differences in DP classes directly affect which scenarios that fulfill the definition of “red alert status”. No information on DP class is provided for each incident, but if one assume that all vessels have DP-2 or DP-3, this would reduce the numbers of LOP incidents by definition.

The clearest example of such a difference is that many “single thrust failure” would not necessarily count as a LOP incident in a DP2 or DP3 vessel. “Single thrust failures” equals roughly to 16% of all the incidents analyzed. However if the causal factors that lead to a single thrust failure just as likely could have led to for example multiple thrust failures due to the nature of the incident, then the red alert status may still be correct for all DP classes. The actual effect of DP classes on the LOP incident frequency is therefore hard to calculate without comprehensive data regarding each particular incident, and detailed system knowledge for each particular vessel in question.

5 Creation of causal flowcharts

The sorting and frequency analysis of causal factors, in combination with knowledge of the DP system structure and its main components, form the basis to create causal flowcharts. The flowcharts represents the most influential failure patterns that were identified in the data sorting. These dependencies are beliefs of the analyst, and even though these beliefs are based on data, they are still somewhat subjective as limitations and choices must be made in the creation process.

Three flowcharts are created: propulsion, reference/sensors and human factors, these are shown in chapter 5.1-5.3, together with concise explanations of the main findings each flowchart represents. For further information of the causal factors modelled in the flowcharts, see appendix C.

5.1 Flowchart Propulsion

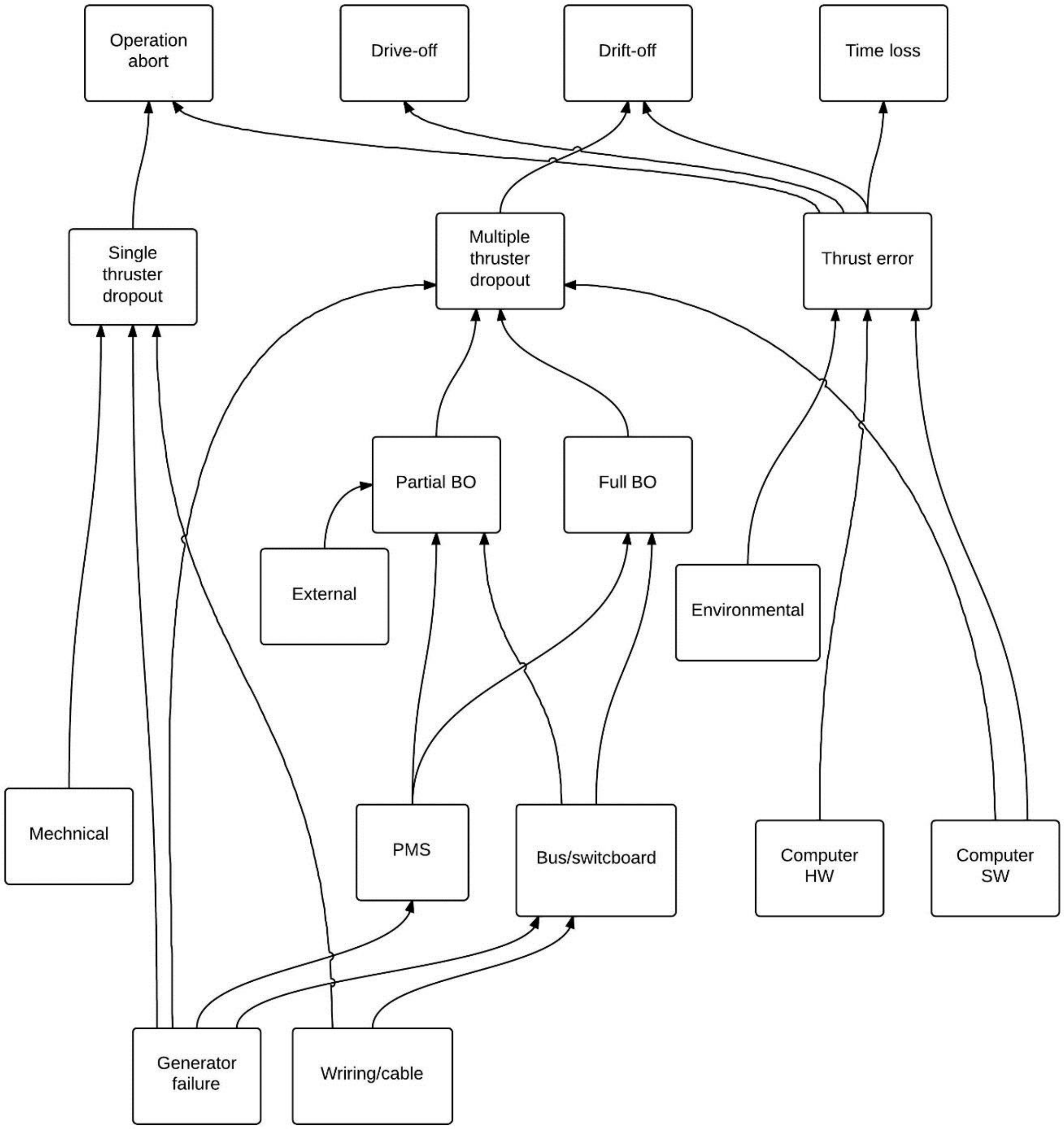


Figure 18 Propulsion flowchart

The connections to the terminal events are based on the sorting of terminal events in respect to failure type presented in Figure 17. A single thruster dropout usually led to operation abort, multiple thruster dropouts led to drift-off, while thrust error just as likely could lead to all 4 terminal events.

Three causal factors strongly related to “Single thruster dropout” were identified: Mechanical wiring/cable and generator failure. Generator and wiring failures could potentially affect several thrusters as well, but usually system redundancy made these failures types limited to affect only one thruster. Mechanical failures in a thruster was found very unlikely to have a direct effect on other equipment beside the actual thruster itself, therefore the causal factor “mechanical” only is connected to single thrust dropouts.

Multiple thrust dropouts are strongly related to common cause failures such as blackouts When the power management system fails or is unable to reduce the thrust output in the event of a generator failure, this leads to insufficient power on the switchboard and blackout, (loss of power). Partial blackouts have also in some incidents been caused by external forces outside of the vessel, which overloads the generators.

Software failures in the DP control system may affect the control of several or all thrusters. Either by direct loss of DP control (thrusters dropped out of system due to for example a bug in the software), or through unwanted changes in DP-control modes that overloads the thrusters.

Thrust error represents those incidents where no thrusters actually stopped or dropped out of the system, but where either wrong amount of output were given, and/or control of thrust output were lost/reduced.

Reduced control of thrust output is usually the result of unwanted inputs from DP software, or due to operator station failures, (DP hardware). Additionally when environmental forces moves the vessel off position, even though all thrusters are active, this is looked upon as a thrust error.

5.2 Flowchart References

“Position reference failure” and “sensor and heading failure” are groups created to limit the number of arcs connected to the terminal events. The drawback of creating such “dummy nodes” is adding a layer between the terminal events and equipment failures. The upside is however easier modelling of common cause failures, such as power supply failures (UPS failures), which otherwise would have arcs connected to all the different reference types. According to Figure 17, drift-off has been removed from the reference flowchart as this terminal event is dominated by propulsion failures.

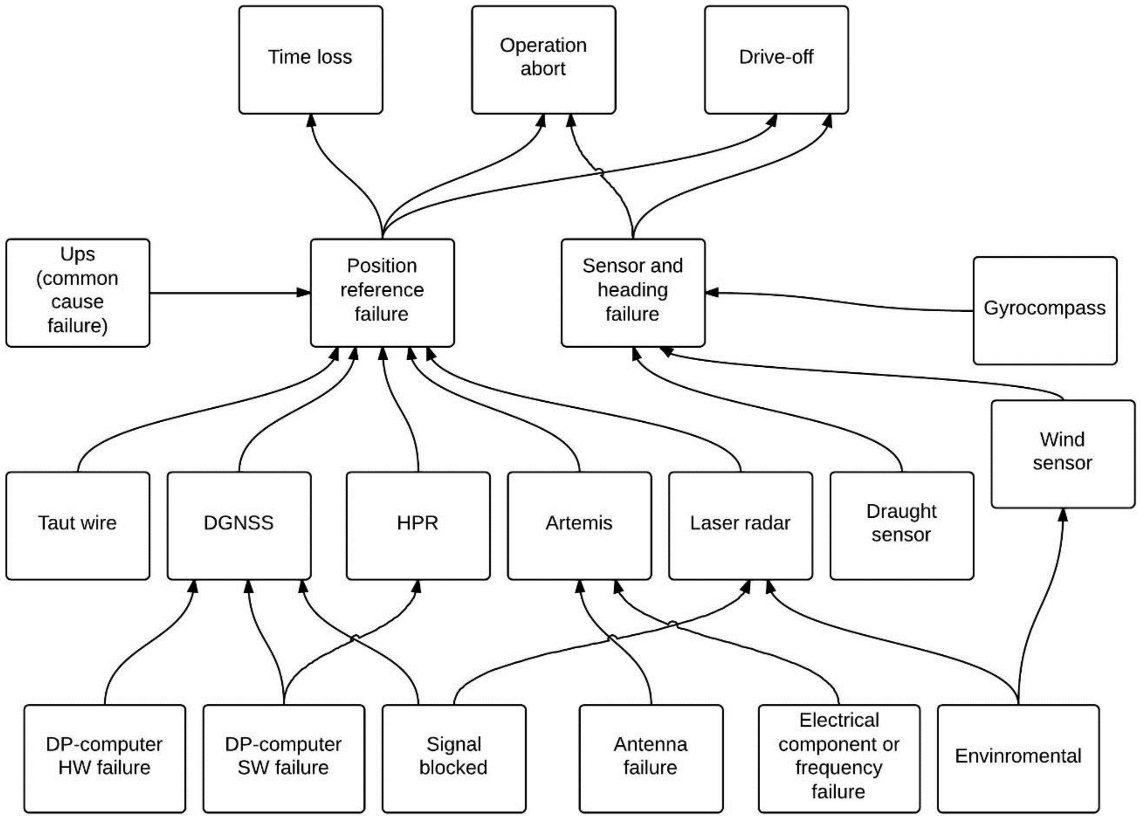


Figure 19 References flowchart

DP software and hardware failures could have been modelled as common cause failures in the same way as UPS, however due to a high percentage leading to DGNSS and HPR these were the only equipment types connected s shown in the flowchart. Probably given more incidents, one would suspect DP control failures to affect all reference equipment based on the study of the system.

The equipment failure cause “Signal blocked” affected, beside the DGNSS, the Laser radar system. The result is not surprising as the Laser radar bases its position on measuring the distance to reflective targets. “Antenna failure”, sums up sources of physical damage to references and affected the Artemis system most. However, this failure cause is rare, and the results therefore more uncertain. “Electrical component/frequency” is presented as a failure cause for the Artemis system, as Artemis uses radio frequencies to transmit signals. “Environmental” is given as failure cause for the Laser radar system when for example waves or rain is the source of the disrupted laser signal. Environmental also affects the wind sensors, as these are placed to measure the strength and direction of wind, and will be especially vulnerable to such forces. No clear dependencies in failure causes were found for the Taut wire, Gyro compass and the Draught sensor. These equipment types are rarely mentioned to fail in the IMCA data, and therefore dependencies in failure causes are harder to determine.

5.3 Flowchart Human factors

The created flowchart is based upon the HFACS system and the data dependencies presented in Figure 15. The flowchart does not show where in the DP system the human factors contribute, rather the effect each type of human factor has on the others. The author has only allowed the three unsafe acts to directly contribute to other parts of the system (Slip/lapse, rule based and knowledge based errors). This limitation was made for a more intuitive BBN, and due to the linearity of Reason's Swiss cheese model which the HFACS system is based on. Any connections made between human error and equipment failure will solely be based on data, (see chapter 6.3 6.4).

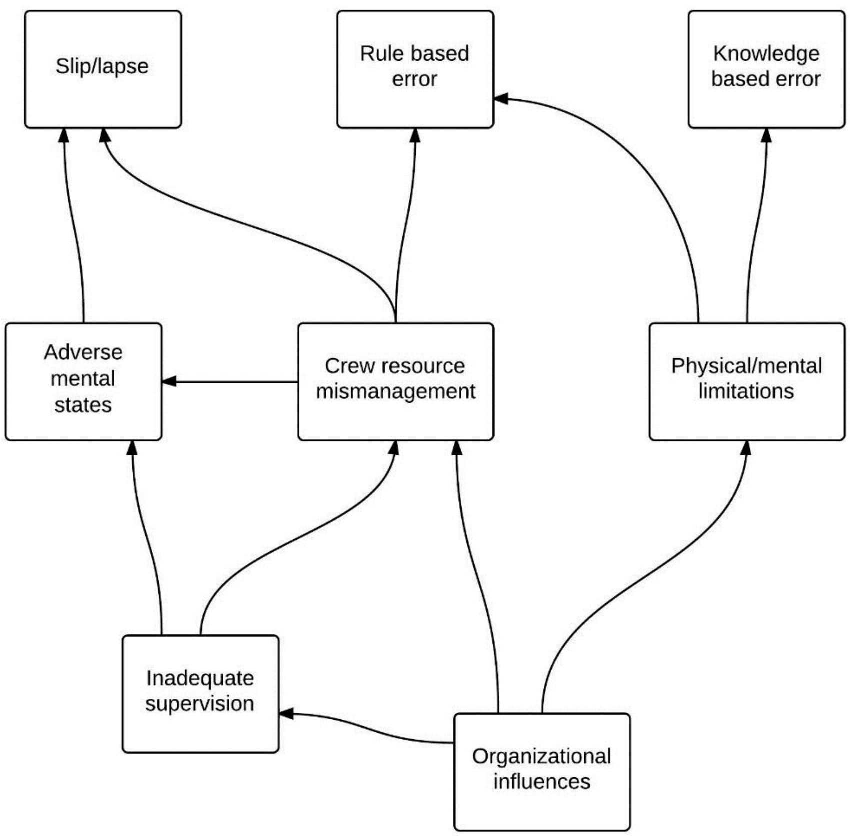


Figure 20 Human factors flowchart

PART IV BAYESIAN BELIEF NETWORKS

6 Creating Bayesian Belief Networks

Chapter 6 will go through the steps of creation and the knowledge necessary to build and understand a Bayesian Belief Network. Additionally the final network will be presented and evaluated. The creation of a BBN will partly be based on the discovered failure frequencies presented in chapter 4, but also try to take into account the "beliefs" of causal dependencies resulting from the discovered system structure. The data dependencies were to some degree modelled in the flowcharts presented in chapter 5, but the creation of a BBN will combine the three flowcharts and enable further verification and evaluation of the results.

6.1 Classical/Bayesian approach to probability

There are two main approaches for calculating probability. The classical, and the Bayesian approach. In order to understand the principles of a Bayesian Belief Network, both these theories of probability should be known to the analyst.

Classical approach

The classical approach to probability is defined by situations or experiments which is limited by a finite number "n" of possible outcomes, each with a set likelihood of occurring. Typical examples that illustrates such scenarios are card/dice games and lotteries. "S" is the sample space (all possible outcomes), and the event "E" is defined as one or more outcomes usually with some common properties. The probability of the event E is then the number of outcomes that belong to E (n_e) divided by the total number of outcomes, n, given a single experiment. If this experiment is repeated many times (under identical conditions), the relative frequency of the event E (the percentage of experiments that results in the event E), will approach the probability of E. (Rausand, 2011)

When certain incidents were excluded from the data material, this was an attempt to establish more identical conditions for LOP incidents. By removing certain incidents with, (for example system failures only possible for pipe-laying vessels), this made it possible to establish frequencies of equipment failures across vessel types, and eventually probabilities. (For data selection, see chapter 4.2)

Bayesian approach

When performing a risk analysis, the criteria's for applying the classical approach to probability are usually never met in full. There are often not a finite number of possible outcomes of an event, and the probability of each outcomes depends on many factors that may rapidly change from one experiment to the next dependent on time. Additionally in many cases the historical data is incomplete or non-existing. Therefore one usually have to make greatly simplified models with severe limitations in order to establish frequencies and risk. The Bayseian approach is less dependent on data compared to a classical frequency study, and does not demand equal contexts for each experiment or event.

The Bayesian approach builds on what is called subjective or conditional probability. That the probability of an event "A" should be modelled as the result of other factors, such as an event "B". The probability and result of "B" is believed to have an effect of the probability "A". (Rausand, 2011)

This is mathematically defined as the Bayes' theorem:

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

Subjective probability: "A numerical value in the interval [0,1] representing an individual's degree of belief about whether or not an event will occur." (Rausand, 2011)

In fact it can be argued that all probabilities to some degree are subjective. The argument for this statement is that there will always be some subjective assumptions in the initial assignments of probabilities, or in other words the probability assigned to an event "A" is always conditional on the context "K". "K" can be the available knowledge and assumptions made on the subject. Even the probability of rolling a specific number on a die, which is the typical frequentist example of probability, is dependent on both the die and the way the die is rolled. If a die is rolled 1000 times, the classical probability for heads on toss no. 1001 is the same as it was for toss no. 1, but the Bayesian probability may have changed if the 1000 observed tosses doesn't correspond to the classical frequency. Our belief of the context of the experiment may have changed.

The key benefit of the Bayesian approach is that it provide a natural way of modelling conditional probabilities and their contexts (Norman Fenton, 2013).

In the Bayesian approach an experiment must not be repeatable or have the same conditions to have its probability determined. Any given situation may be examined through this approach, however if little information is available regarding the context of the experiment, the results will be highly subjective.

The bottom line is that the probability of any event is based upon a well-known philosophical question: what do we really know for sure? At what level of certainty can we stop including contexts to our probabilities? For the purpose of analyzing LOP incidents the answer to this question is simply defined by the level that can be investigated based on the available data and system knowledge. There is no point introducing contexts to our model that we do not know the effect of.

In summary Bayes theorem is adaptive and flexible because it allows to revise and change the predictions in light of new or improved background information, (context "K").

6.2 Introduction to Bayesian Belief Networks

"The use of Bayesian belief networks (BBN) is gaining popularity among risk analysts as they are flexible and well suited to taking the performance of human and organizational factors (HOFs) into consideration, and they provide a more precise quantitative link between the performances of risk influencing factors." (Vinnem, 2013)

Bayesian Belief Networks are based on the Bayesian approach and conditional probability.

Bayesian Belief Networks are directed graphs with no direct cycles, in which nodes represent variables and arcs represent dependencies between them. A Bayesian Belief Network is a graphical illustration of the interactions or effects among the variables that it models. The structure of the directed graph usually represents the causal structure of the modeled data. A causal structure provides useful insight into the interactions among the variables and allows for prediction of external effects on the system. (Pearl, 1988)

An arc from "A to B encodes an assumption that there is a direct causal or influential dependence of A on B. A is then the defined as a *parent* to B. One also have to avoid circular reasoning. If an arc exists from A to B, and from B to C, then naturally one cannot have an arc from C to A, to avoid infinite loops.

The probability distribution of a node is given as a distribution of conditional probabilities based on the state of its parents, called the node probability table (NPT). Figure 21 shows the NPT of a node with two parents; "wiring" and "generator". Two parents that may fail correspond to 8 different scenarios which constitute the probability distribution of this particular node. State 0 equals failure. The NPT can be interpreted as described in Table 3. The same principle can be applied to all nodes in a BBN.

wiring	State0		State1	
generator	State0	State1	State0	State1
State0	0.0002336...	0.36363636	0.16129032	0.0301204...
State1	0.99976632	0.63636364	0.83870968	0.96987952

Figure 21 NPT from GeNIe

Table 3 interpretation of NPT

wiring	State0		State1	
generator	State0	State1	State0	State1
State0	Node fails given wiring and generator has failed.	Node fails, only wiring failure.	Node fails, only generator failure.	Node fails, no failure in generator/wiring.
State1	Node survives, wiring and generator has failed.	Node survives, only wiring failure.	Node survives, only generator failure.	Node survives, no failure in generator/wiring.

For a node without parents, (called root nodes), the node simply represents the probability distribution of one particular scenario or event. (Norman Fenton, 2013)

The most important assumptions one have to make when creating a BBN, is which nodes that are dependent. (The direction and placement of Arcs between nodes). The arcs can be assigned both quantitatively and qualitatively, or maybe the best option, as a combination of both.

If no assumptions is made then the model will be what is called a “complete graph” where all nodes are dependent of each other. To create a complete graph requires vast amount of data due to the increased number of parents for each node that results in huge probability tables. Also if all nodes are connected this undermines the point of creating a graphical illustration of a problem, where one of the main strengths of such a model should be the clarity such an illustration provides.

6.3 GeNIe

In this report, “GeNIe” is used for creating a Bayesian Belief Network. GeNIe is a development software for building graphical decision models developed at the University of Pittsburgh.

In GeNIe, both the structure and the numerical parameters of a Bayesian Belief Network can be manually inserted, typically by consulting experts on the modelled subject. Alternatively they can be learned from a set of data. If this method is applied, the structure and parameters of a Bayesian Belief Network will be formed solely by data independences (and dependencies). The input from analysts possible in this approach is to inform GeNIe of prior knowledge regarding possible dependencies. The analyst may force arcs between nodes, or deny GeNIe to make certain connections. One may also define “tiers” of nodes. A high tier means the node is placed close to the causal end of the incident. Such limitations are typically based on a propensity interpretation. A propensity interpretation means based on the physical properties of the failures that a computer will not be able to recognize.

However, both the structure and the numerical probabilities can be a combination of expert knowledge and data. One way to combine data frequencies with expert knowledge, is to manually draw the network beforehand, and then let GeNIe learn the parameters (probabilities) of the drawn network based on the data file, which is the chosen method in this report. The network drawn solely on data is used as a supplement for additional information.

6.3.1 Important functions of GeNIe

Some of the most important functions used in GenNIe are explained in this chapter.

Data sheet

At any time you can have as many data sheets, imported from for example from Microsoft Excel open. The datasheets are usually used as a quantitative basis for creating a BBN, by identification of dependencies in the data set.

Learn new network

The learn network function, enables GeNIe to learn the network structure solely based on the data sheet. The analyst may force arcs between nodes, or deny GeNIe to make certain connections.

Change node view:

The nodes in the network can be seen as both icons, and bars as shown in Figure 22. The icons are used mainly for visual understanding of dependencies. The bars also includes the parameters (probabilities) of the node. The bar view is used for setting evidence and observing changes in probability.

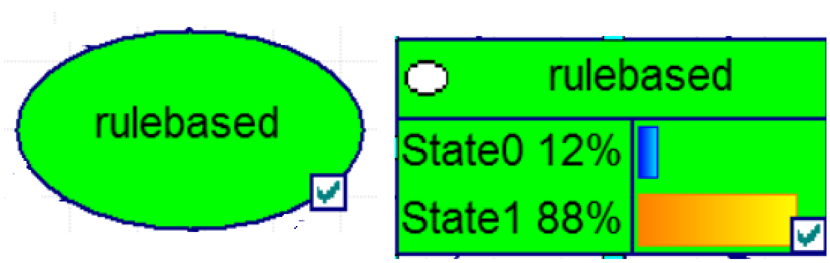


Figure 22 Icon and bar view of nodes GeNIe

Learning parameter function

The learning function demands a predefined (drawn) BBN. The nodes of the drawn BBN must have the exact same names as the colons in the data sheet. In Figure 23 a screenshot of the learning functions show the association between columns and values from excel with nodes in GeNIe. The drawn arcs and nodes are not changed through the learning process, however the nodes are given numerical values as a result of their place in the network and dependencies in the data.

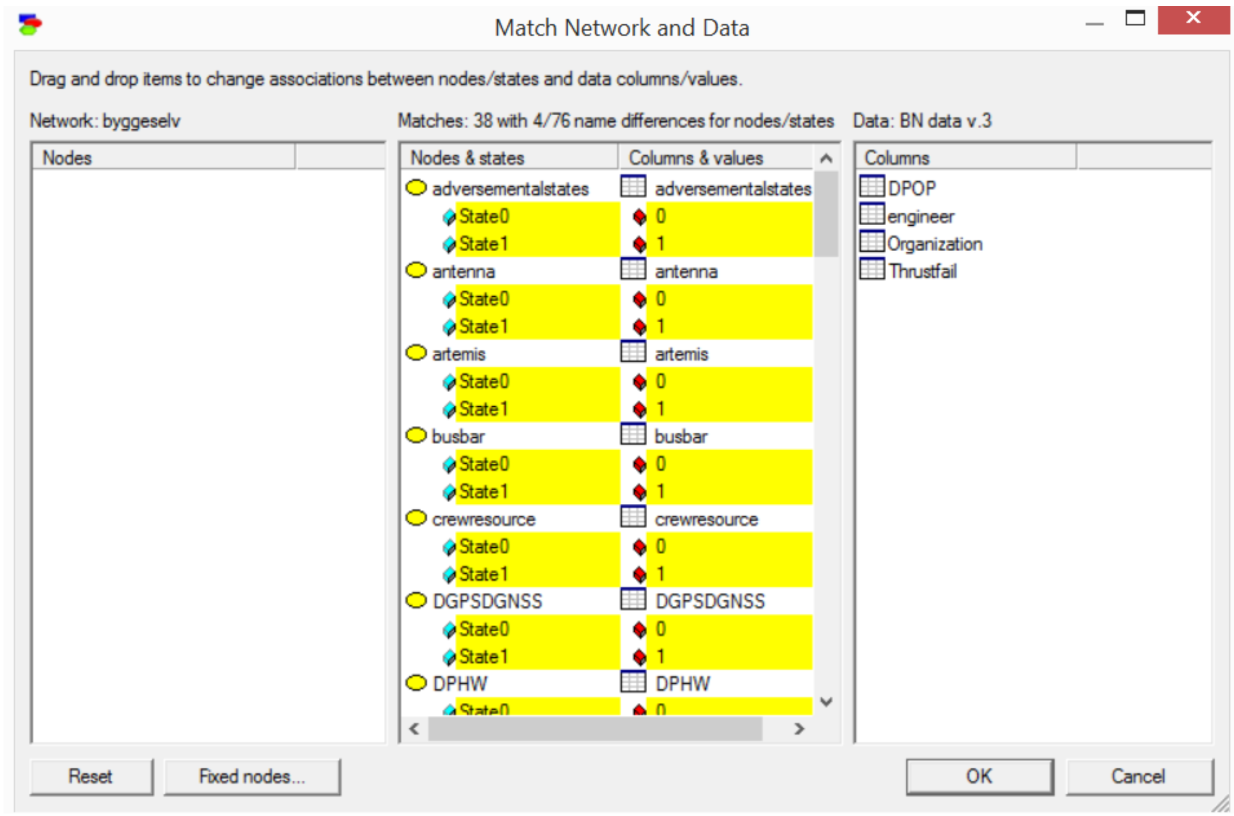


Figure 23 Learning function GeNIe

Set evidence:

By right clicking on each node, and choosing the "set evidence" function, the probabilities of failure for each node may be changed, and the effect of the change may be visually observed through the whole network. This function is applied for the evaluation of BBN in chapter 7.

6.4 Comparison of methods for creating BBN

A qualitative BBN is created based on knowledge of system structure and the causal pathway of the modelled events, in this report referred to as "expert knowledge". A quantitative model will be solely based on available data, where the analyst usually through the use of computer software will identify dependencies in a data set. A comparison of strengths and weaknesses in the different creation methods of a BBN is showed in Table 4.

Table 4 BBN creation methods, strengths/weaknesses

BBN creation method	Strengths	weaknesses
Based on qualitative knowledge	• Utilizes prior knowledge of causal system structure • Most subjective method, prone to misjudgment from analyst	• Will not identify possible data dependencies unknown to the analyst • Time consuming • Demands "expert knowledge"
Based on quantitative analysis of data	• Able to identify possible "unknown" dependencies in the data set • Fast, easy • Little prior system knowledge required	• May identify "false" dependencies due to data variation • Data demanding • Totally dependent on strength of utilized software
Combination of qualitative/quantitative methods (Used in this report)	• May utilize the quantitative method to identify patterns in data, then adjust the result based on physical properties and system structure known to the analyst • May experience contradictions,which identifies weaknesses in data/model	• Most time consuming method

6.5 Stepwise summarized method for creating Bayesian Belief Networks

In this chapter I will stepwise summarize the method chosen in this report for creating the final BBN. This method consists of 7 steps.

System knowledge, chapter 2 and 3

The first step of creating a BBN that represents a physical system is to gain knowledge of the modelled system, in this case the DP system. To gain an overview of the physical properties of the system is strictly necessary in order to be able to sort data into failure modes, and fully understand the description of an incident. Especially when an incident is presented with limited information, the analyst have to utilize his system knowledge to decide “what information is missing”, if any. The system knowledge should as a minimum consist of the main components and structure of the modelled system.

Data sorting, chapter 4

All incidents are sorted in MS Excel as shown in chapter 4.4, when a failure mode is present in the incident, this is indicated through the value “1” while all other cells has the value “0”. If a group of failure modes covers too much deviating information this is typically a sign of the failure group being to large/general. As a result the analyst may have to split this group into several more specific failure groups with fewer failure modes present in each group. In opposite, if the failure group is almost non-existing it may be necessary to combine this group with another group of similar failures. Such decisions require extensive system knowledge and is the hardest and most important part of sorting data.

Causal flowcharts, **chapter 5**

After the data is sorted, the causal flowcharts are created. These flowcharts are based on the system knowledge obtained in chapter 2, in combination with the accumulated knowledge obtained through the data sorting and creation of failure groups.

BBN based on quantitative analysis of data by computer

The excel file is saved as a text file and opened in GeNIe (see chapter 6.3). On the basis of this text file, GeNIe can create a BBN solely based on trends in the data material. As shown in chapter 6.3, the analyst has some tools to help GeNIe understand the system, but this creation method has several limitations as discussed and presented in Table 4. Clear data dependencies are shown here, and observed by the analyst.

Comparison of causal flowcharts with quantitative BBN:

The analyst now compares the results from the quantitative analysis of data with the created flowcharts. When the results coincides no further change is required. However in some cases the data trends may deviate from the qualitative assumptions. When this is the case further study is necessary in order to determine the most corect dependencies. (Direction and placement of arcs in the BBN).

Drawing of BBN:

When all potential deviations of results are evaluated and "solved", the final BBN will be drawn as the resulting combination of expert judgment and data dependencies.

Parameter learning:

The drawn BBN can now be combined with the sorted data to identify the final parameter values of the BBN. In this report the parameter learning is achieved by utilizing the learning function, (see chapter 6.3.1), in GeNIe.

6.6 Final BBN

The final BBN is the result of the 7 steps described in chapter 6.5. The network represents a mixture of the qualitative system understanding that lead to the causal flowcharts, and the quantitative data analysis.

The final BBN is presented in Figure 24. The nodes in the BBN has been sorted by color for a more intuitive understanding, an explanation of node colors is given in Table 5.

Table 5 Explanation of BBN node colors

Node	**Color**
Terminal events	
Failures leading directly to terminal events	
References equipment failures	
Reference equipment failure causes	
Power/propulsion	
Human factors	
DP control	
Environment/external	

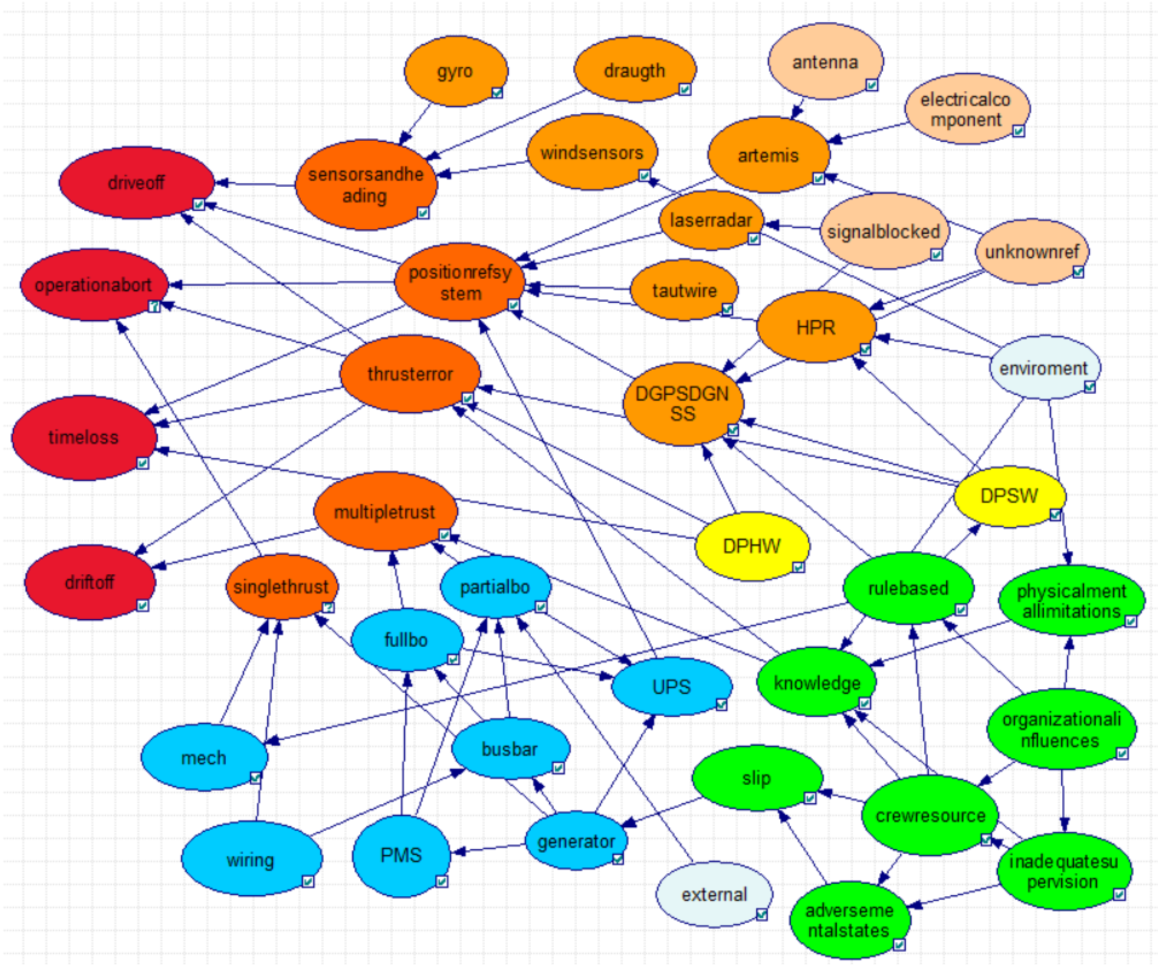


Figure 24 Final BBN from GeNIe graph view

The final BBN presented in Figure 24, is shown as icons, (see chapter 6.3.1), in an effort to highlight dependencies, as the BNN contains more arcs then what is optimal for intuitive understanding. The figure gives a visual presentation of the final network, in which the main lines from the causal flowcharts can still be seen. The human factors, (green nodes), have now been given arcs to equipment failures, based on data dependencies discovered through the quantitative analysis method in GeNIe. Slips/lapses lead to generator failures, (typically through maintenance mistakes). Rule based errors affects DP-software, often seen as breach in procedures related to software updates and testing before an operation. Knowledge based errors are connected to thrust failures, both thrust error and multiple thrust failures. These connections represents the incidents with insufficient control actions by the operator in critical situations resulting in loss of thrusters or thrust control.

7 Discussion- Evaluation of BBN

There are many ways to evaluate the parameters of a Bayesian Belief Network. As mentioned in chapter 6.2, the NPT of each node may be accessed through the GeNIe software, and show probability distributions of nodes. However it is tedious to present each particular NPT for every node in the network, and the information obtained from the NPT's has its own limitations as well. A NPT only show the probability of an event, (state of the targeted node), given the state of its parents. The conditional probabilities are however not the full answer to which parents that are most "important". The probability of failure for each parent should be considered as well, which forces us to combine information from several nodes. Additionally a parent node "A" may indirectly affect the target node "C" trough a second parent "B" as shown in Figure 25. This indirect effect cannot be evaluated through the NPT's.

Chapter 7.1 describes a method that measures which parent that has the highest effect on our target node, in combination with the probability of that particular system failure the parent represents. The described method is developed by the author in cooperation with fellow M.Sc Student Anders Bidne, and we believe the method represents the best way to determine the most critical parents of a node in the BBN. Figure 25 has been created to illustrate the method. Table 6 presents the mathematical terms defined for the illustration of the chosen method.

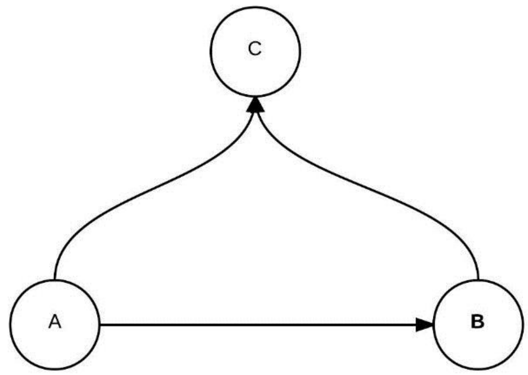


Figure 25 Evaluation of parent criticality in a BBN.

Table 6 Mathematical terms of BBN evaluation

$P(A)_1$	Original probability (of failure) of node A
$P(C)_1$	Probability of node C given original probability of node A and node B
$P(C\|A)$	Probability of node C after probability of node A is set to 100%

7.1 Evaluation method of BBN

The evaluation method begins with setting the probability of failure for the node in question to 100 %, achieved by utilizing the "set evidence function in GeNIe" described in chapter 6.3.1.

In the example case described by Figure 25, the failure probability of parent node A is set to 100 %. As a result of the new evidence in the network, the BBN is updated, which gives us the new probabilities (of failure) for every node affected, directly, or indirectly. In the example case the affected nodes would be both B and C. The effect on the terminal event C, due to the increase of A is easily measured as the difference in failure probability of node C. The resulting effect of B on C will already be included in our evaluation, as the whole network is immediately updated when we change the properties of any of its nodes.

$$Increase\ in\ probability\ of\ C\ due\ to\ increase\ of\ A = \mathrm{P(C|A)} - \mathrm{P(C)}_1$$

The increased probability of node C is an absolute value, a percentage. We want the effect to be measured relative to the original value of the node. This is a more intuitive measure that includes the original state of C in the evaluation. For example a value of “2” means that the definite presence of a failure in node A, led to a 200 % increase in probability of failure for node C. The formula for measuring relative effects is shown below:

$$Relative\ effect\ of A\ on\ C = \frac{\mathrm{P(C|A)} - \mathrm{P(C)}_1}{P(C)_1}$$

However, to only measure the relative effect of node A on C, does not consider the original probability of failure of parent A. To only measure the direct effect of a failure is insufficient, if the probability of the event is not considered.

The wanted adjustment in the formula is easily achieved by multiplying the relative effect of A on C with the original probability of A.

If *the relative effect of A on C* was “2”, and the original failure probability of node A is equal to 0.05, the total *evaluation of A on C* will give us a value of 2x0.05=0.1. This value takes both the effect, and the probability of failure of node A into account. One may argue that this value if a vague form of “risk”, as risk is often referred to as a negative effect, multiplied with the probability of that effect occurring. The most important parent node will be the one with the highest product of effect, and probability of occurring. The final formula is shown below:

$$Evaluation\ of A\ on\ C = \frac{\mathrm{P(C|A)} - \mathrm{P(C)}_1}{P(C)_1}\ x\ P(A)_1$$

A Bayesian Belief Network is a useful tool as the effect of changing the probability of one event can be seen through the whole network. By going through the BBN and individually setting every node to 100% one may measure their resulting effect on all other nodes in the network.

In chapter 7.3-7.6, the results of the evaluation method described in this chapter will be presented, as the most important parents of each of the four terminal events are calculated. The same method could have been applied to determine the most important parents for any node in the network, but in this report it has been limited to the four terminal events.

The values are calculated in MS excel and presented in appendix D.

7.2 Evaluation of BBN- comparison of terminal event frequencies

A comparison of data frequencies of terminal events, to BBN values is presented in Figure 26. The blue bar graph represent the data frequencies, which indicates probability of terminal events according to the frequentist approach. The BBN values are however a combined result of data frequencies and network structure (beliefs of context), and are represented by the blue bars in the red squares, (node bar view).

If the structure of the BN had been causally wrong, this would have led to high deviations in probabilities of terminal events, compared to the data frequencies. “Time loss” and “Operation abort” have the highest deviations, which indicates that some of the context of these terminal events, may not have been properly modelled in the network.

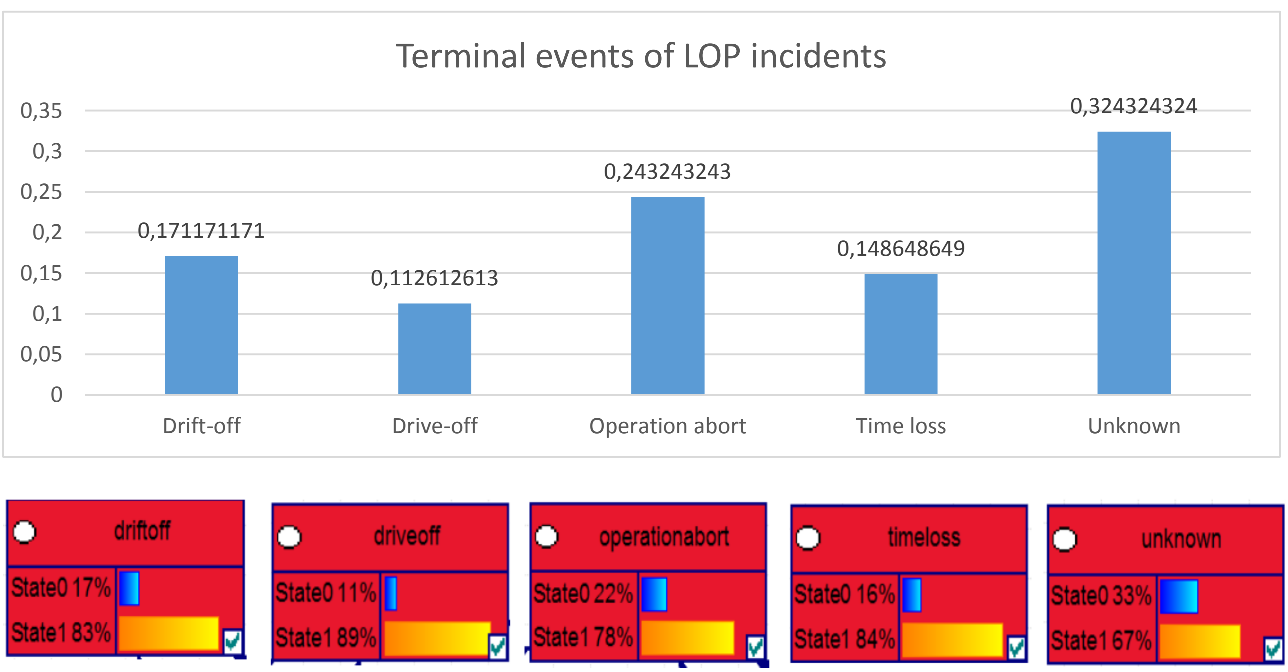


Figure 26 Comparison of data frequencies to BBN parameters

7.3 Evaluation of BBN - Drift-off

All the nodes in the network except, the other terminal events, have been evaluated in respect to drift off. With an original failure probability of 0.15 and a relative effect on drift off equal to 1.59, (see appendix D), multiple thrust failures has been evaluated as the most critical parent. Thrust error, blackouts, busbar failures, DP software failures and generally failures of power supply equipment have strong influences as well.

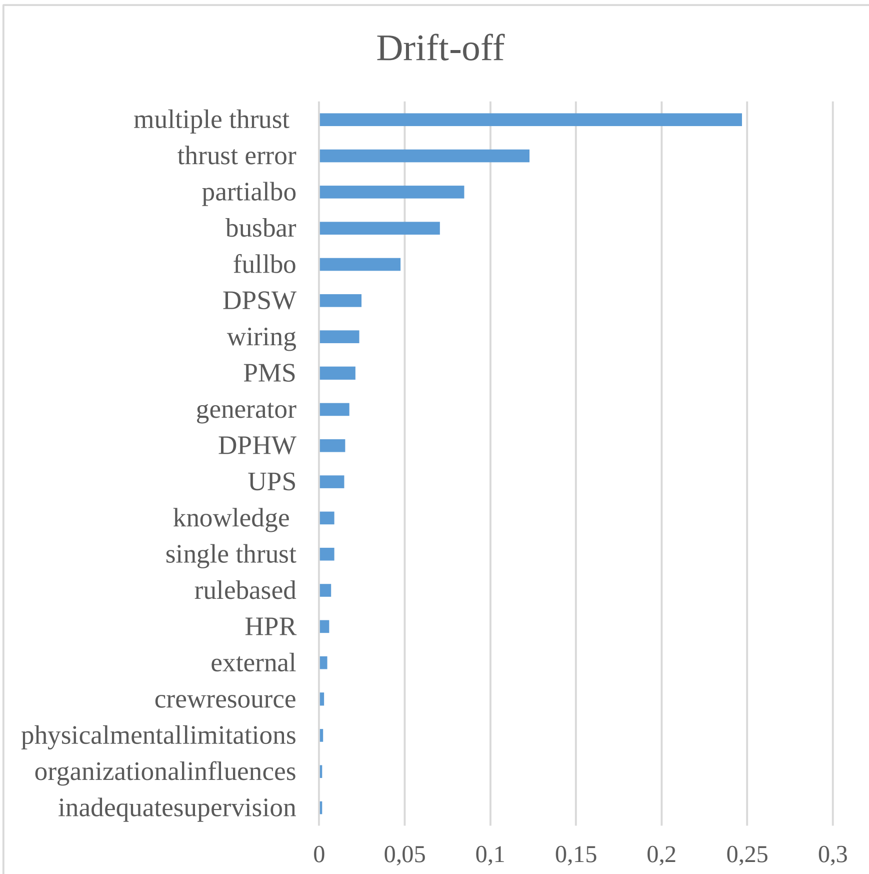


Figure 27 Evaluation of BBN - Drift-off

According to this evaluation, if we want to reduce the frequency of drift-offs we should focus on preventing multiple thrust failures, typically related to common cause failures in the power supply system.

7.4 Evaluation of BBN, drive-off causal factors

In comparison to drift-off, drive-off has a wider "spread" of influencing parents across the BBN. While drift-offs were dominated by parents within propulsion and power supply, drive-off has the most critical parent in thrust-error, followed by a great variety of position reference and DP control equipment. The result is in accordance with the dependencies shown in the causal flowchart of propulsion (chapter 5.1), where thrust errors were connected with failures in the DP control equipment.

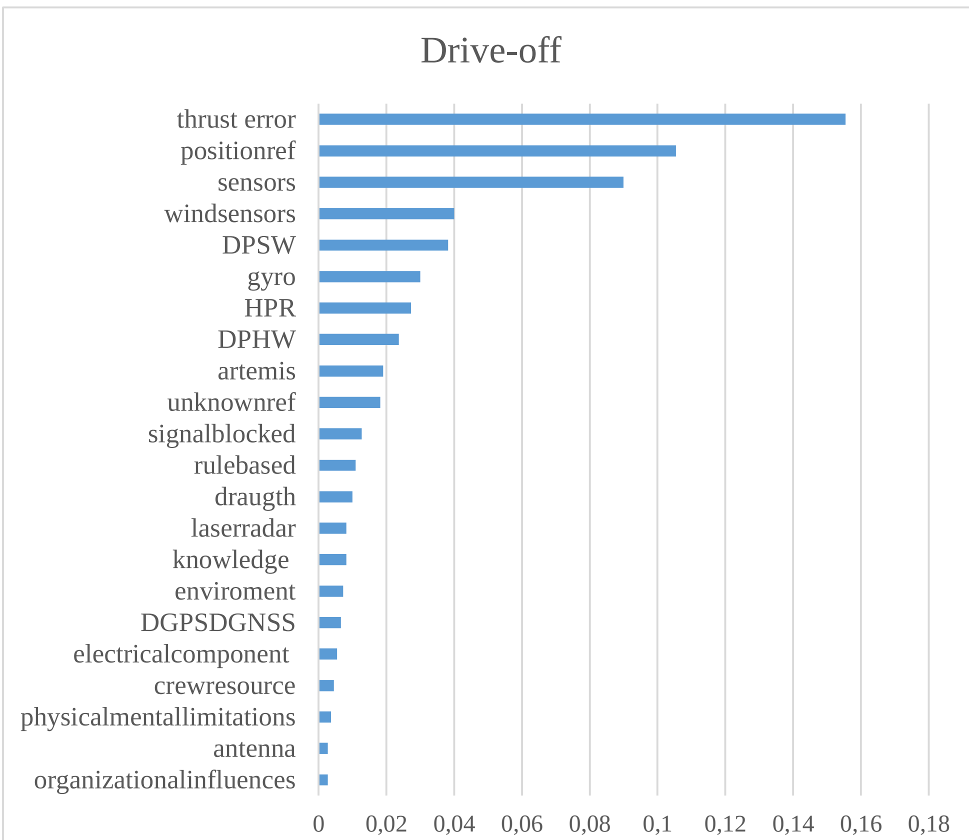


Figure 28 Evaluation of BBN - Drive-off

7.5 Evaluation of BBN, operation abort causal factors

Single thrust failure, typically caused by single point mechanical/wiring failures, (see propulsion flowchart), is the most critical parent of operation aborts. Position reference is the second most critical system, and then especially the HPR system.

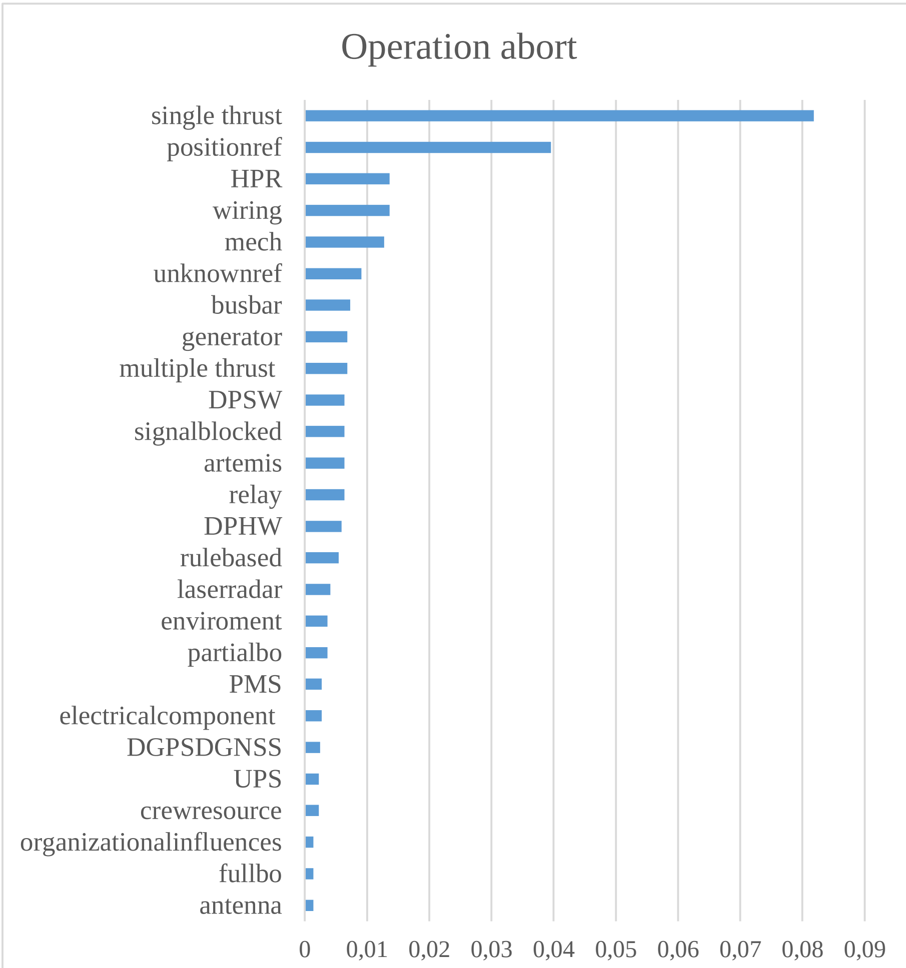


Figure 29 Evaluation of BBN - Operation abort

7.6 Evaluation of BBN, time loss causal factors

Time loss is the least severe terminal event in the created BBN and "suffers" from this in the model structure. The other terminal events, especially drift-off and drive-off but also operation abort requires a certain degree of system degradation to occur. However time-loss could be the result of practically every system failure, and is harder to model due to this.

Many of the severe system failures actually will decrease the probability of time loss. (Since they are much more likely to cause operation abort or LOP). Unfortunately, many of the less severe failures are too "far removed" from the terminal event to cause a visible effect on time-loss. Certain limitations has to be made when drawing the network structure, one of mine was to limit which nodes that directly could lead to a terminal event. This limitation was made in an effort to visibly create and show a clear causal structure, which may have led to loss of some dependencies in the model.

Time loss is dominated by DP hardware, followed by thrust error. DP hardware could be a believable cause of time loss. If for example an operator screen goes black, one will "always" have redundancy in such important DP control equipment, and may decide to continue the operation while correcting the problem, thereby avoiding aborting the operation and/or LOP.

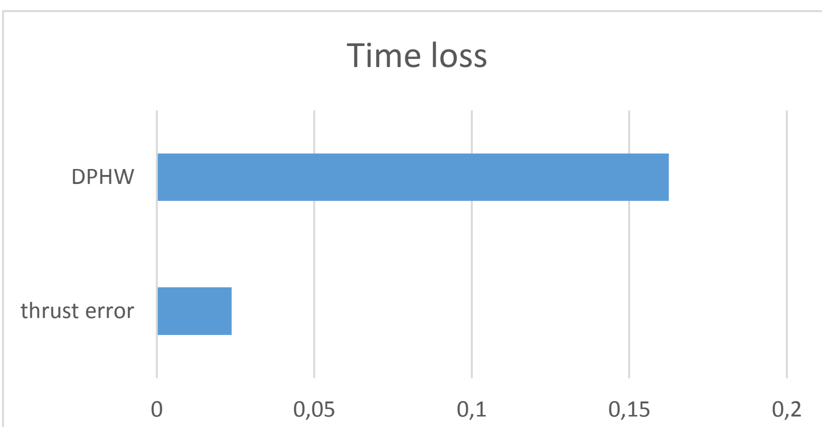


Figure 30 Evaluation of BBN - Time loss

7.7 Weaknesses in the created BBN

As revealed in the evaluation of time-loss in chapter 7.6, the created BBN has some limitations. To avoid a so-called "complete graph" where no assumptions are made, all nodes cannot be connected. To connect all nodes would completely remove the system understanding a visual tool such as a BBN may provide. Additionally the results would be much harder to evaluate and less precise.

Those events that suffers from these limitations are those with a high number of parents, in several "tiers" of the BBN. These will be harder to model with a limited number of arcs. In the evaluation of the BNN, time-loss suffered most from these limitations, as it is the least severe of terminal events, and naturally have a higher number of parents as it "demands" least system degradation to occur. This could have been solved by adding more arcs, also in "weaker" dependencies. Since the presented BBN, already is somewhat complicated, and not as intuitive as it maybe should have been, no more arcs were added.

8 Conclusions

Two main objects were introduced for this report. Firstly through data and system study to identify and perform a frequency analysis of causal factors leading to loss of position incidents. Secondly investigate the possibility of using Bayesian Belief Network to model the identified factors, and evaluate the result of this approach.

One of the greatest challenges was to model the DP system in a concise understandable way. Due to complicity of such a large system, limitations had to be made to a great extent, to match the level of detail in the available incident data. In spite of the limitations in the system modelling, the simple graphic models created for this analysis shows the most important equipment, which is reflected by their presence in the analyzed incidents.

The study of the DP system led to the creation of a sorting system, where three main categories of factors were identified leading to LOP; propulsion failures, reference failures and human factors. At least one of these factors were present in above 90 percent of all incidents analyzed. Limitations were made in the network to which nodes that were allowed to lead to a terminal event accordingly.

The BBN was shown to be a very useful tool for changing the system status, (the context of probabilities), quickly and determine the effect of the changes through the whole network as shown in chapter 7.3-7.4. However, the limitations in number of arcs in the network, led to loss of information when looking at the incidents with less severe terminal events, such as time loss. A single fault "anywhere" in the DP system could potentially lead to this terminal event, which makes its dependencies harder to model sufficiently. However the causal factors related to terminal events that included LOP, (drift-off and drive-off), were identified by the BBN to a high extent.

The overall conclusion regarding the use of BBN for modelling of causal factors in LOP incidents, is a positive one. The method showed flexibility and allowed for a combination of both expert knowledge and available data in a systematic manner. The most useful aspect of this method is its flexibility. Sensitivity analysis regarding data is easily performed by a mouse click, and enable us to see the effect of changes visually and immediately.

The original IMCA sorting system is found to give less information of the causal factors behind a LOP incident, compared to the BBN analysis, and therefore in many ways have less value for interested parties when seeking to avoid these unwanted events. However for a neutral and unbiased presentation of failures, a BBN may not be the best way to present incidents, as an analysis based on Bayesian probability theory always will be dependent on the assumptions of the analyst to a greater extent than a classical frequency study.

8.1 Further work

Suggestions for further work within Bayesian Belief Networks and analysis of loss of position incidents are presented in this chapter.

8.1.1 Build BBN “bottom up”

The potential for a Bayesian Belief Network extends beyond the analysis of data. With extensive knowledge regarding equipment failure frequencies, there is possible to create a BBN that determines loss of position frequency, or any other system failure directly based on root causes.

To do this an expert group could work together and determine the failure frequency per time unit for all involved equipment and other external root causes. Then by knowing which equipment that have common cause failures and dependencies, estimate the frequency of terminal events solely based on root causes, without needing incident data at all. Of course such an estimation would be dependent on the system structure of each particular vessel, and of course type of operation. However, when first established, the BBN could relatively easily be modified to fit each particular scenario.

8.1.2 Determine LOP frequency per time unit

This analysis have been limited to relative frequencies. Not actual frequency for loss of position per time unit has been established. After working with this topic for a longer period of time, it was determined to remove this work from this analysis, as the results were uncertain at best. Three main questions presented themselves in order to establish such a frequency:

- Estimate the degree of underreporting in the analyzed data

- Determine the percentage of each vessel type in the fleet reporting incidents
- Estimate operation time on DP for each vessel type in the fleet

The available data material found by the author could not give sufficient answers to these three central questions.

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APPENDICES

A. HFACS- latent failures

This appendix goes through the complete HFACS classification system of latent failures contributing to unsafe acts.

Preconditions for unsafe acts

Preconditions for unsafe acts, represents underlying failures on the operator level that may lead to unsafe acts. The preconditions for unsafe acts arise from the operator decision process.

Two major subdivisions are described: substandard conditions of operators and the substandard practices they commit. The subdivisions are presented in Figure 31. The categories and sub-categories presented in this appendix are (when not referred to others), derived from Wiegmann and Shappel. (Wiegmann and Shappell 2001). I have included examples relevant for a DP operation in every category.

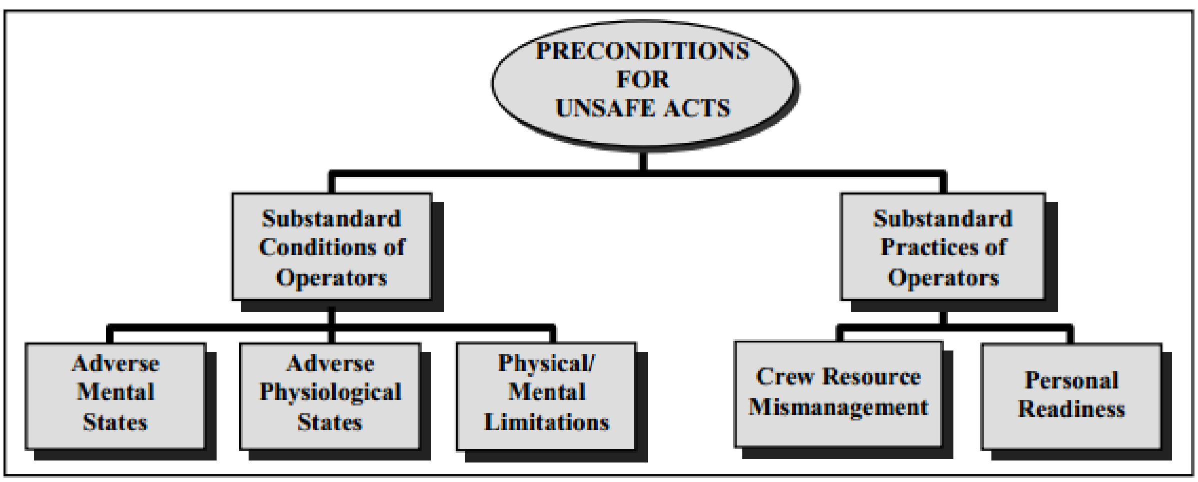

Figure 31 Preconditions for unsafe acts(Wiegmann and Shappell 2001)

Substandard Conditions of Operators

Adverse Mental States:

To be prepared mentally is critical in nearly every activity. With this in mind, adverse mental states, was created as one of three subcategories of operator condition to account for those mental conditions that greatly affect performance.

Examples:

- Visual illusions (for example due to weather blindness, fog or haze)
- Illness (seasickness or other)
- Intoxication
- Impaired hearing or lack of control due to noise or vibration
- Confusion (for example due to miscommunication, or unclear clarification of roles)

Adverse Physiological States:

This category covers different states that preclude the safe conduct of operating a vessel. Examples of this are states that makes the operator fail to rely on his instruments.

Examples:

- Lack of information from visual stimulus and displays
- Lack of skill to process visual stimulus and displays
- Lack of time to safely process information form visual stimulus and displays

Physical and/or Mental Limitations:

The third category of substandard condition includes those instances when necessary information is ether unavailable, or if available, individuals simply do not have the aptitude skill or time to safely deal with it. This is of particular interest in DP operations, where in certain situations, the operator is required to act very fast and correct in order to avoid an emergency.

Examples:

- Short reaction time during loss of position

Substandard Practices of the Operator

Crew Resource Mismanagement

Often times, the substandard practices of operators or crew will lead to unsafe acts. For instance, the failure to ensure that all members of the crew are acting in a coordinated manner can lead to confusion (adverse mental state) and poor decisions. This category also includes those instances when crewmembers do not work as a team, and failure of coordination of activities before, during and after an operation.

Examples:

- Failure of communication internal at bridge and/or external
- Lack of teamwork, or unclear clarification of roles at bridge
- Potential misunderstanding in clarification of roles due to two operators at bridge

Personal Readiness

This category covers individual failures in preparation for an operation. This category also includes behavior that not necessarily is covered by any formal rule or regulation, such as good dietary practices.

Examples:

- rest beforehand
- breach of alcohol restrictions
- may also include behavior that not necessarily violate existing rules, for example over eating before the shift or exercising heavily before shift.

Additional preconditions for unsafe acts arising from DP system design

Due to the design of the DP system I have added this particular section of preconditions arising from the design of the automated DP system. My suggestions are presented below:

- Increased mental strain/lower mental limitation due to opaque system
- Potential overconfidence in system ability to solve situation
- Mental fatigue/misplaced motivation due to inactivity and confidence in system

Unsafe supervision

"Clearly, aircrews are responsible for their actions and, as such, must be held accountable. However, in many instances, they are unwitting inheritors of latent failures attributable to those who supervise them"(Reason 1990).

This statement from Reason is clearly directed towards the crew on an airplane, but could be just as true for a supply ship or other vessel on the sea. To account for these supervision failures, the overarching category of unsafe supervision was created.

Unsafe supervision thus represents failures on the middle management level. This is also referred to as Bridge resource management when regarding vessels. This category is further divided into subcategories as shown in Figure 32.

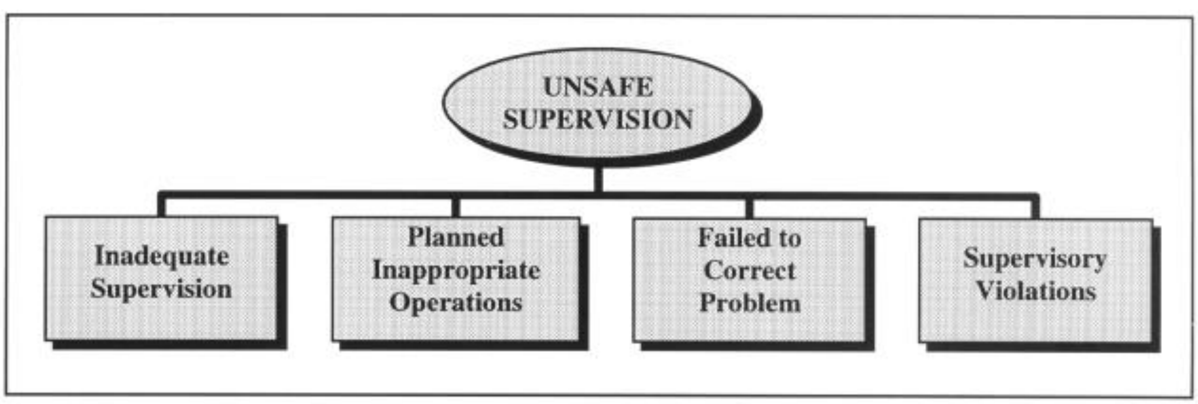

Figure 32 Unsafe Supervision(Wiegmann and Shappell 2001)

Inadequate Supervision

This category refers to failures within the supervisory chain of command, which was a direct result of some supervisory action or inaction. That is at a minimum, supervisors must provide the opportunity for individuals to succeed. It is expected therefore that individuals will receive adequate training, professional guidance, oversight, and operational leadership.

Adequate training also includes correct training based on reliable information.

Planned Inappropriate operations

If the operational tempo and/or schedule are planned such that individuals are put unacceptable at risk, and ultimately performance is adversely affected, this falls under the category, *planned inappropriate operations.* This category was created to account for all aspects of improper or inappropriate crew schedule and operational planning.

Tempo related risks could be very relevant for a DP-operation near an installation. In the oil/gas business delays often equal big financial losses, which could put pressure on the operation schedule. On the other hand there is a high focus on safety in this business, and an acceptance of safety related expenses. I have not pursued this angle further as I have to limit my work.

Failure to Correct Problem

The failure to correct known problems refers to those instances when deficiencies among individuals, equipment, training or other related safety areas are “known” to the supervisor, yet are allowed to continue uncorrected. Contradictory regulations may force a “practical solution” where breach of rules are known and accepted.

Supervisory Violations

This category covers those situations where existing rules or regulations are disregarded in purpose by supervisors.

Organizational influences affecting the DP-operator

This category represents the top level management of the company owning or controlling the DP operated vessel. The top level management may influence policies and especially how the middle management performs their duties (See *Unsafe supervision*, chapter 3.2.2). Unfortunately organizational influences often go unnoticed or unreported by accident investigators. Erroneous decisions of upper level management may affect supervisory practices in a direct way, as well as the conditions and actions of operators. Usually latent organizational failures revolves around three issues, or categories presented in Figure 33.

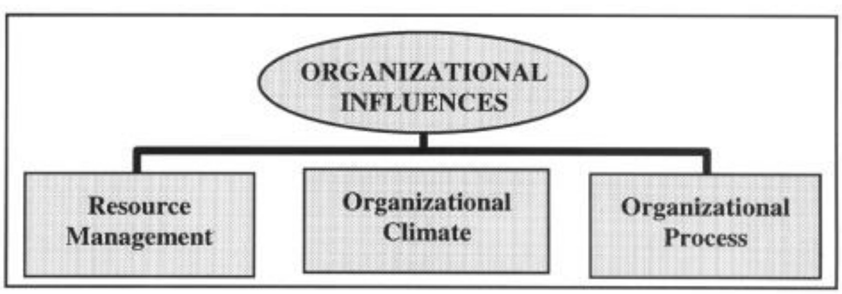

Figure 33 Organizational influences (Wiegmann and Shappell 2001)

Resource Management

Resource management refers to the management of organizational resources. This includes human resource management (selection, training, staffing). Also monetary safety budgets and equipment design is included in this category. Errors in resource management will often be seen when organizations experiences financial difficulties.

Organizational Climate

Organizational Climate refers to a broad class of organizational variables that influence worker performance. One sign of organizational climate it is structure, and is reflected in the chain-of-command, delegation of authority and responsibility, communication channels, and formal accountability for actions.

Operational Process

This subcategory refers to formal processes, procedures and oversight within the organization. Poor upper-level management and decisions concerning each of these organizational factors can have a negative effect on operator performance (Wiegmann and Shappell 2001).

B. IMCA sorting - cause matrix

The 361 incidents given secondary causes, have sorted after their main causes, in an effort to insight into cause dependencies.

		Main causes											
		propulsion	**reference**	**Sensors**	**computer**	**electrical**	**enviroment**	**human error**	**not establishe**	**power**	**external**	**procedure**	**SUM**
Secondary causes	**Propulsion**	0.9 %	0.0 %	0.0 %	0.0 %	0.0 %	0.6 %	0.0 %	0.0 %	0.9 %	0.0 %	0.0 %	**2.3%**
	reference	0.0 %	2.8 %	0.0 %	0.0 %	0.0 %	1.4 %	0.6 %	0.0 %	0.0 %	0.0 %	0.0 %	**4.8%**
	sensors	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.3 %	0.0 %	0.0 %	**0.3%**
	computer	0.6 %	2.6 %	0.0 %	2.3 %	0.3 %	0.3 %	1.1 %	0.0 %	0.0 %	0.6 %	0.0 %	**7.7%**
	electrical	2.0 %	0.9 %	0.0 %	0.0 %	1.7 %	0.0 %	0.0 %	0.0 %	1.4 %	0.0 %	0.0 %	**6.0%**
	enviroment	0.0 %	0.6 %	0.0 %	0.3 %	0.0 %	0.0 %	0.3 %	0.0 %	0.0 %	0.0 %	0.3 %	**1.4%**
	human error	1.4 %	2.0 %	0.0 %	3.1 %	0.0 %	2.0 %	2.0 %	0.0 %	1.7 %	0.0 %	0.3 %	**12.5 %**
	not established	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	**0.0%**
	power	0.6 %	0.3 %	0.0 %	0.0 %	0.3 %	0.6 %	0.6 %	0.0 %	2.0 %	0.0 %	0.0 %	**4.3%**
	external	0.3 %	0.3 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.3 %	0.0 %	**0.9%**
	procedure	3.1 %	7.1 %	0.0 %	0.6 %	0.6 %	4.0 %	11.1 %	0.0 %	4.3 %	0.9 %	0.0 %	**31.6 %**
	mechanical	0.6 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.3 %	0.0 %	0.3 %	**1.1%**
	design	2.3 %	1.4 %	0.0 %	1.4 %	0.6 %	1.1 %	0.9 %	0.0 %	2.6 %	0.0 %	0.0 %	**10.3 %**
	commissioning	2.0 %	2.6 %	0.0 %	6.0 %	0.9 %	0.0 %	1.4 %	0.0 %	1.1 %	0.0 %	0.0 %	**14.0 %**
	maintenance	1.4 %	0.0 %	0.0 %	0.0 %	0.3 %	0.0 %	0.6 %	0.0 %	0.6 %	0.0 %	0.0 %	**2.8%**
	SUM	**15.1 %**	**20.5 %**	**0.0 %**	**13.7 %**	**4.6 %**	**10.0 %**	**18.5 %**	**0.0 %**	**15.1 %**	**1.7 %**	**0.9 %**	**100.0 %**

C. Explanation of causal factors

Table 7 LOP causes

Group of causal factor	**Description**
Failure of wiring/earth/fuse/	A short circuit in the power network should trip switchboard fuses/breakers. A short circuit situation will always result in a momentary voltage drop. If the complete power network is connected together the voltage drop will affect the entire network. If the voltage cannot be maintained by the power management system the voltage drop may lead to consumers tripping. (Dynamic Positioning Conference October 2007)
Switchboard failure	This failure modes covers such situations as when a short circuit in the network or any single equipment failure, leads to loss of all online thrusters/generators due to overload or voltage drop. Any single point failure in the power supply system should with a functioning switchboard lead to a finite/limited numbers of power consumption failures.

Power management system failure	If the PMS delegate wrong amount of power leading to consumers tripping, or situations where he PMS unnecessarily shuts down equipment.
Generator failure	Failure of one or more generators.
Mechanical failure	Mechanical errors, independent of power failures.
Unexplained reference failure	This group was created for when a reference system fails without further information regarding root causes. The majority of incidents in this groups has just system failure as label, while other specified the type of system failure but not the cause. This could be all from wrong position/heading output to erratic signals or loss of reference system to DP.
Reference electrical component failure	Internal electrical components, such as electrical cards.
"Antenna" failure	Generally position reference hardware, physical equipment such as antennas may fail for example due to lack of maintenance.

Reference signal blocked	Signal loss due to shadowing, interference from other sources, false reflection. Excludes reference signals blocked by environmental phenomenon and is therefore independent of “environmental”.
Environmental	When environmental forces are the cause of the equipment failure. For example if a storm destroys sensors, solar flares disrupt the satellite signals, or extreme/sudden changes in current/wind “knocks out” the power supply.
UPS failure	The UPS provides the DP control system and the reference system with power. A failure in the UPS could lead to loss of position references.
External	When external forces results in equipment failure. External forces could be another vessel. Excludes environmental forces.
DP control software failure	Examples are missed updates, virus in the software or missing IP addresses. Usually related to human factors.

DP control hardware failure	Typical examples of this failure type includes monitors going black, computer card failures, or loss of entire operator station. Generally failures of physical control equipment.

Counts and percentages of causal factors:

Factor	**counts**	**percentage**
fullbo	8	3.6%
partialbo	17	7.7%
multipletrust	36	16.2%
singlethrust	36	16.2%
thrusterror	40	18.0%
wiring	23	10.4%
relay	4	1.8%
busbar	18	8.1%
generator	32	14.4%
DPSW	30	13.5%
DPHW	29	13.1%
PMS	14	6.3%
mech	9	4.1%
DPOP	23	10.4%
engineer	18	8.1%
Organization	6	2.7%
h.e	47	21.2%
slip	12	5.4%
rulebased	26	11.7%
knowledge	8	3.6%
crewresource	10	4.5%
physicalmentallimitations	9	4.1%
adversementalstates	8	3.6%
inadequatesupervision	7	3.2%
organizationalinfluences	7	3.2%
DGPSDGNSS	43	19.4%
laserradar	6	2.7%
artemis	15	6.8%
HPR	18	8.1%
gyro	6	2.7%

tautwire	5	2.3%
windsensors	9	4.1%
draugth	2	0.9%
positionrefsystem	75	33.8%
sensorsandheading	18	8.1%
signalblocked	16	7.2%
electricalcomponent	6	2.7%
antenna	2	0.9%
unknownref	22	9.9%
UPS	7	3.2%
external	2	0.9%
enviroment	17	7.7%
driftoff	38	17.1%
driveoff	25	11.3%
operationabort	54	24.3%
timeloss	33	14.9%
unknown	72	32.4%

D. BBN evaluation data

Relative effect of parents on terminal events

	original value	Drift-off	Drive-off	Operation abort	Time loss
original value		**17%**	**11%**	**22%**	**16%**
fullbo	**3%**	1.59	0.00	0.05	0.00
partialbo	**8%**	1.06	0.00	0.05	0.00
multiple thrust	**15%**	1.65	0.00	0.05	0.00
single thrust	**15%**	0.06	0.00	0.55	0.00
thrust error	**19%**	0.65	0.82	0.00	0.13
wiring	**10%**	0.24	0.00	0.14	0.00
relay	**2%**	0.00	0.00	0.32	0.00
busbar	**8%**	0.88	0.00	0.09	0.00
generator	**15%**	0.12	0.00	0.05	0.00
DPSW	**14%**	0.18	0.27	0.05	0.00
DPHW	**13%**	0.12	0.18	0.05	1.25
PMS	**6%**	0.35	0.00	0.05	0.00
mech	**4%**	0.00	0.00	0.32	0.00
slip	**5%**	0.00	0.00	0.00	0.00
rulebased	**12%**	0.06	0.09	0.05	0.00
knowledge	**3%**	0.29	0.27	0.00	0.00
crewresource	**5%**	0.06	0.09	0.05	0.00
physicalmentallimitations	**4%**	0.06	0.09	0.00	0.00
adversementalstates	**4%**	0.00	0.00	0.00	0.00
inadequatesupervision	**3%**	0.06	0.00	0.00	0.00
organizationalinfluences	**3%**	0.06	0.09	0.05	0.00
DGPSDGNSS	**2%**	0.00	0.36	0.14	-0.19
laserradar	**3%**	0.00	0.27	0.14	-0.25
artemis	**7%**	0.00	0.27	0.09	-0.25
HPR	**10%**	0.06	0.27	0.14	-0.31
gyro	**3%**	0.00	1.00	0.00	0.00
tautwire	**2%**	0.00	-0.09	0.00	0.00
windsensors	**4%**	0.00	1.00	0.00	0.00
draugth	**1%**	0.00	1.00	0.00	0.00
positionref	**29%**	0.00	0.36	0.14	-0.31
sensors	**9%**	0.00	1.00	0.00	0.00
signalblocked	**7%**	0.00	0.18	0.09	-0.25
electricalcomponent	**3%**	0.00	0.18	0.09	0.00
antenna	**1%**	0.00	0.27	0.14	-0.31
unknownref	**10%**	0.00	0.18	0.09	-0.19
UPS	**5%**	0.29	0.00	0.05	0.00
external	**1%**	0.47	0.00	0.00	0.00
enviroment	**8%**	0.00	0.09	0.05	-0.06

Evaluation of parents on terminal events

	Drift-off	Drive-off	Operation abort	Time loss
fullbo	0.047647	0	0.001364	0
partialbo	0.084706	0	0.003636	0
multiple thrust	0.247059	0	0.006818	0
single thrust	0.008824	0	0.081818	0
thrust error	0.122941	0.155455	0	0.02375
wiring	0.023529	0	0.013636	0
relay	0	0	0.006364	0
busbar	0.070588	0	0.007273	0
generator	0.017647	0	0.006818	0
DPSW	0.024706	0.038182	0.006364	0
DPHW	0.015294	0.023636	0.005909	0.1625
PMS	0.021176	0	0.002727	0
mech	0	0	0.012727	0
slip	0	0	0	0
rulebased	0.007059	0.010909	0.005455	0
knowledge	0.008824	0.008182	0	0
crewresource	0.002941	0.004545	0.002273	0
physicalmentallimitations	0.002353	0.003636	0	0
adversementalstates	0	0	0	0
inadequatesupervision	0.001765	0	0	0
organizationalinfluences	0.001765	0.002727	0.001364	0
DGPSDGNSS	0	0.006545	0.002455	-0.00338
laserradar	0	0.008182	0.004091	-0.0075
artemis	0	0.019091	0.006364	-0.0175
HPR	0.005882	0.027273	0.013636	-0.03125
gyro	0	0.03	0	0
tautwire	0	-0.00182	0	0
windsensors	0	0.04	0	0
draugth	0	0.01	0	0
positionref	0	0.105455	0.039545	-0.09063
sensors	0	0.09	0	0
signalblocked	0	0.012727	0.006364	-0.0175
electricalcomponent	0	0.005455	0.002727	0
antenna	0	0.002727	0.001364	-0.00313
unknownref	0	0.018182	0.009091	-0.01875
UPS	0.014706	0	0.002273	0
external	0.004706	0	0	0
enviroment	0	0.007273	0.003636	-0.005