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Author: Fredrik Balchen Gundersen	Fredrik B Gundersen (signature of author)
Programme coordinator: Roger Flage Supervisor(s): Frederic Emmanuel Bouder	
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ABSTRACT

Maintenance and modifications for offshore installations are completed on site, on already operating installations. To be able to accommodate the additional personnel responsible for conduction these services, flotels are used. Flotels are floating "hotels" that uses dynamic positioning and/or mooring lines to position themselves in a close proximity to the offshore installation, and utilize gangway bridges or "Walk-2-Work" bridges to allow for transfer of personnel between the floating accommodation vessel and the offshore installation. Crossing the gangway bridge is associated with risks to personnel as elements, such as winds and waves can cause the gangway bridge to exceed its safe operation limit.

In an attempt simplify the workload on the gangway operator, a risk-based decision support model has been developed. This model utilizes algorithms, and the aim of this thesis is to analyze how the use of algorithms to support decision-making impact risk management in the petroleum industry, and how algorithmic risk can be managed in the future.

PREFACE

This Master thesis is the written and submitted as the final part of a MSC in Risk Management with specialization in Offshore Technical Safety at the Faculty of Science and Technology, University of Stavanger, Norway.

The thesis will reflect the two years of academic learning retrieved from attending this university, and is a partial fulfillment of the requirements needed for completing this Master's degree.

I would like to thank Frederic Emmanuel Bouder for great guidance, assistance and inputs towards helping me complete this thesis. I also want to thank my family and friends for all the support and patience displayed throughout this busy period, and for always being by my side.

Fredrik Balchen Gundersen

University of Stavanger, Norway, June 2019.

ABBREVIATIONS

AI	-	Artificial Intelligence
LSOG	-	Location Specific Operational Guideline
ISO	-	International Organization for Standardization
W2W	-	Walk-2-Work
EUT	-	Expected Utility Theory
ALARP	-	As Low as Reasonably Practicable
MCDA	-	Multi-Criteria Decision Analysis
ID3	-	Iterative Dichotomiser 3
AHP	-	Analytic Hierarchy Process
SA	-	Situational Awareness
GPS	-	Global Positioning System
NASA	-	National Aeronautics and Space Administration
ES	-	Expert System
ANN	-	Artificial Neural Networks
MCAS	-	Maneuvering Characteristics Augmentation System
DP	-	Dynamic Positioning
POB	-	Personnel on Board

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1. INTRODUCTION

1.1. Background

Risk management and safety has gone hand in hand throughout history of the offshore industry. The constant pursuit to improve safety together with the zero-vision philosophy has led to giant leaps in risk management and how it`s impacted the industry as we know it today. The development of safety models and methodologies has proven to improve safety standards greatly, and the use of risk acceptance criteria has guided the industry to the right path. Even though the use of risk acceptance criteria today in the "new" risk management theory is under discussion, it has proven so far to be useful as a pin pointer as of which direction risk management should and has taken. However, safety models are built on statistical data in combination with background knowledge, and in some cases with the use of algorithms. The topic for this thesis will revolve around the issue related to the use of an algorithmic decision-support model and its impact on the collective risk and overall risk management for offshore installations.

The model, which is a risk-based decision support model for an offshore gangway bridge mounted at a flotel, is studied.

A flotel is as the word suggests a floating hotel. It has several different purposes, but the most frequent use in the offshore industry is as living accommodations for worker's conducting maintenance- and modification operations on already established offshore installations. The flotel is connected to the offshore installation by the use of a gangway bridge, often referred to as a Walk-to-Work bridge. The bridge retains its position relative to the flotels and the offshore installations movement by the help of multiple systems ranging from Dynamic Position thrusters on the flotel, station keeping performance, gangway stroke and elevation readings, to the weather forecasted/real-time weather.

But under certain circumstances the gangway is unable to remain connected to the offshore installation, and the bridge will enter a disconnect mode. This mode carries with it risks, related to both personnel injury and lost work time. In an attempt to help mitigate/reduce the risks related to an unwanted gangway disconnect Erdogan et.al. (2018) developed a model using a software called DEXi, which is an advanced multi-attribute decision-tool, to help guide the gangway operator into making better calculated decisions on when the gangway bridge enters more critical stages and whether a disconnect is imminent.

The idea of the model sounds promising, but how does the use of algorithm's in decision-making affect risk management? Are computers capable of making sound decisions? How does the human and computational decision-basis interlink? Is the model built up of the best possible algorithmic framework? This is all questions that this thesis seeks to answer.

1.2. Research Question

The research question the thesis will answer is:

> *"How do algorithms incorporated into decision-support tools impact risk management in the oil industry?"*

By studying the paper "Risk-Based Decision Support Model for Offshore Installations", the thesis will create an understanding of how algorithms are incorporated into the mentioned model. It will also answer how algorithmic risk impact field operators in general, and what the future of risk management most likely will look like due to the incorporation of algorithms into every day applications, as a result of the "digital revolution".

1.3. Outline of thesis

The first chapter of the thesis introduces the gangway model, which is the algorithmic decision-support tool used as a basis for analyzing how algorithmic safety models impact risk management for the offshore petroleum industry. Chapter two is a theoretical review of necessary documents for conducting the qualitative research assessment of the model. Chapter three covers the methodology for the thesis. The fourth chapter is a detailed explanation and analysis of the algorithmic decision-support tool for offshore gangway bridges used on flotels, and an assessment of how this algorithmic model impacts risk management. Chapter 5 discusses the results discovered, and chapter 6 is a concluding remark.

1.4. Limitations

- Its beyond of the scope of this thesis to develop a functional machine learning model for guiding computational decisional-support for gangway bridges. Only the theoretic for developing the model will be provided.
- Being a discursive thesis, calculations using numerical data will not be provided. Positive and negative reflections on each topic will be provided instead.

2. THEORETICAL BACKGROUND

2.1. Risk Management

Risk management has two main purposes. Firstly, it is in place to ensure that people, the environment and assets are protected adequately from undesirable consequences of the activities that are being conducted. Secondly, risk management is there to balance different concerns related to e.g. safety and costs. Both measures are covered by risk management in the form of avoiding the occurrence of hazards/potential threats and measures to reduce the potential consequences of these events. In the oil & gas industry, as well as the nuclear industry, risk management used to be based on a prescriptive regulating regime, were design and operation of plants/offshore modules were governed by detailed requirements. Later, this regime has taken a new adaptation towards a more goal-oriented regime, that puts emphasis on what to achieve rather than on the means of doing so (Aven, 2011).

Risk is according to international standards such as ISO defined as *"combination of the probability or an event and its consequences" (ISO 31000:2018).* Other standards define risk as *"A term which combines the chance that a specified hazardous event will occur and the severity of the consequence of the event"*. Risk can be expressed both quantitatively and/or qualitatively by distributions, expected values, single probabilities of a specific consequence, etc. And the operational expression for practical calculation of risk is (Vinnem, 2016):

$$R = \sum_i (P_i \cdot C_i)$$

where:
P = probability of accidents
C = consequence of accidents

PSA (Petroleum Safety Authority Norway) states that risk shall be reduced and the responsible party shall select technical, operational and organizational solutions that reduce the likelihood that harm, errors and hazard/accident situations occur according to their §11 Framework Regulations (PSA, 2018). The framework states that:

"Harm or danger of harm to people, the environment or material assets shall be prevented or limited in accordance with the health, safety and environment legislation, including internal requirements and acceptance criteria that are of significance for complying with requirements in this legislation. In addition, the risk shall be further reduced to the extent possible…" (PSA, 2018)

From ISO31000:2018 it becomes clear that the purpose of risk management is the creation and protection of value. The principles provide guidance on the characteristics of effective and efficient risk management, communicating its value and explain its intention and purpose. The risk management principles in ISO31000:2018 are derived into eight different categories, starting with 1) framework and processes being customized and proportionate, 2) appropriate and timely involvement from stakeholders is necessary, 3) structured and comprehensive approach is required, that 4) risk management is an integral part of all organizational activities, and that 5) risk managements job is to anticipate, detect, acknowledge and respond to change. The first five principles mentioned (there are 8) provide guidance on how risk management should be designed. Principles 6-8 are related to the operation of the risk management initiative. 6) Risk management must consider any limitations of available information, 7) human and cultural factors influence all aspects of risk management, and 8) risk management is continually improved through learning and experience. The 3 last principles should confirm that the best information available is used, that human/cultural factors should be considered, and lastly but most important, that the risk management activities are continually improved. (ISO31000, 2018).

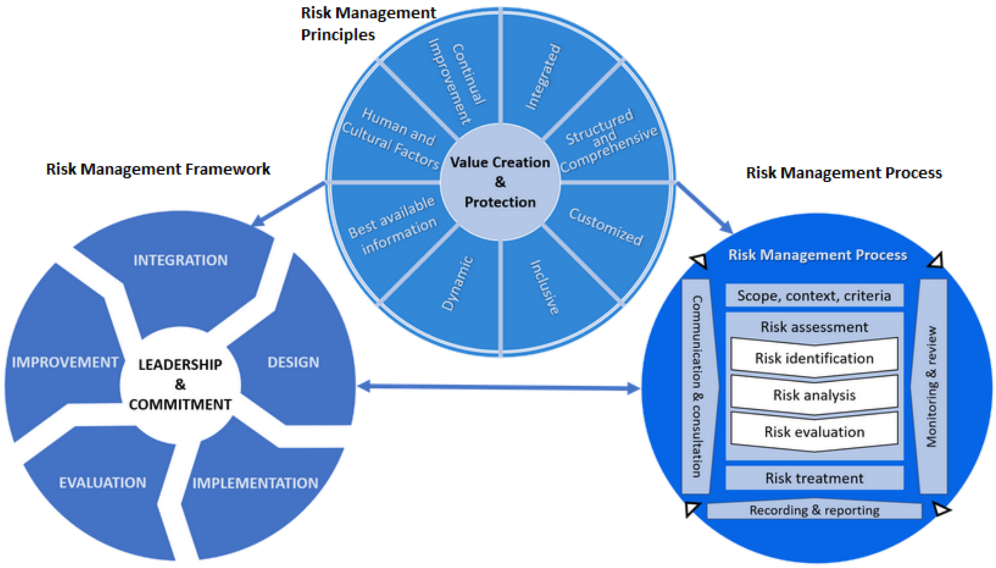

Figure 1 – Principles, framework and risk management process ISO31000:2018 (ISO31000, 2018)

Closely related to the risk management principles lies the risk management framework. The framework guidelines are centered around leadership and commitment, and the effectiveness of risk management will depend on the integration into aspects of the organization, not excluding decision-making support. The other parts of the framework including implementation, design, evaluation and improvement is often referred to the well-known Plan-Do-Check-Act approach. (IRM, 2018)

The risk management process describes risk assessment and risk treatment as being the center of the risk management process. The process comprises of firstly establishing the scope, context and criteria for the assessment to be made, followed by conducting the risk assessment. The risk assessment should include a risk identification process (formally known as hazard identification in ISO31000:2009), risk analysis and a risk evaluation. The resulting risk assessment should be subjected to risk treatment, meaning using the outcome as a basis for the decision-making process to determine how the risk should be treated. Relevant stakeholders should be included throughout the process through recording and reporting, monitoring and reviewing the information, and communicating and consulting on the information provided from the risk assessment.

Risk management involves decision-making in situations involving high risks and large uncertainties, and such decision-making is difficult as the consequences of the decision is hard to predict. For decision-making support there are several tools available including risk and uncertainty analysis, risk acceptance criteria (tolerability limits), cost-benefit analyses and cost effectiveness analyses. But these tools do not always produce a clear answer. They have limitations as they are built up on several assumptions and presumption, are not only made up of scientific knowledge and also rely on value judgements reflecting ethical, strategic and political concerns (Aven & Vinnem, 2007).

The importance of risk management boils down to a few objectives, as proposed by Hopkins, 2012:

Objective	Description
Compliance	The basic objective for any risk management initiative is to ensure compliance with applicable rules and regulations.
Assurance	The board and audit committee of an organization will require assurance that risk management and internal control activates comply with PACED.
Decision making	Risk management activities should ensure that appropriate risk-based information is available to support decision making.
Efficient operations Efficient processes Efficacious strategy	Risk management considerations will assist with efficiency of operations, effectiveness of processes and efficacy of strategy to ensure the best outcome with reduced volatility of results.

Figure 2 - Risk management objectives (Hopkins, 2012)

2.1.1. Expected Utility Theory

The Expected Utility Theory is the ruling paradigm for decision-making under uncertainty, which states that the decision alternative with the highest expected utility is the best alternative. (Abrahamsen, 2010). It can be denoted in mathematical terms as:

$$E[u(i,X)] = u(i,0)P(X=0) + u(i,1)P(X=1)$$

Where **i**, is a function of the consequences and **0,1** represents consequences between one alternative to another. **P** represents the probability of the consequences, and as above, 0,1 represents the belonging probability for different alternatives.

Through the expected utility theory, one can reflect that the negative consequence of an event is disliked so strongly that there are given more weight to these negative consequences than what is justified by the expected value. The decision-maker's attitude towards risk is then risk averse, which is a standard behavioral assumption (Abrahamsen, 2010).

For assessments related to uncertainty of events and its coherency, it is a requirement that one follows the rules of probability. On the other hand, coherency for consequences means adherence to several axioms, including the transitive axiom. This axiom states that if alternative b is preferred to c, which again is preferred to alternative d, then alternative b is preferred to alternative d. This acts as a strong tool for guiding decision-making, as a framework for maximization is utilized. The way the expected utility theory is used in practice for decision-making is based on one assesses the probabilities and a belonging utility function for a set of outcomes, and then use the expected utility to define the preferences between these actions. This is commonly referred to as rational decision-making. (Aven & Vinnem, 2007)

2.1.2. Risk Aversion

Risk aversion is a concept that is used to describe an attitude to risk and uncertainty. The concept`s main theme is that one dislikes negative consequences or outcomes so bad that we give more weight to these negative consequences compared to what a statistical mean value would justify (Stearns, 2000).

The risk aversion concept is a concept that describes rather than determining attitudes. One could argue that the main reason for investing in a safety measure is not risk aversion but rather the fact that one wishes to protect some values, when faced with uncertainty. The thinking behind is then cautionary. The decision to invest in safety is based on attempting to reduce uncertainty and provide assurance if a hazardous situation should occur. If the consequences of an outcome are highly disliked, then one will be wanting to use substantial resources to avoid these outcomes from occurring, even though it cannot be justified in a quantitative way.

Using the term risk aversion indicates that one has to base our risk attitude to the expected utility, and in a safety context were the main focus is on attitudes towards uncertainty and risk one would not always be able to see these relationships compared to the expected value.

2.1.3. The Precautionary Principle

The precautionary principle is defined according to the 1992 Rio Declaration as:

> *"In order to protect the environment, the precautionary approach shall be widely applied by States according to their capabilities. Where there are threats of serious or irreversible damage, lack of full scientific certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental damage."*

Looking beyond the scope of environment, the precautionary principle can be defined as an ethical principal that over rules decisions made when the consequences of an event are subjected to scientific uncertainty. If this is the case, it is better not to go through with the action being made, rather than face the uncertainty and the possible very negative consequences. (Ortwin, 2008)

The main message behind the principle is clear. If there is a lack of scientific certainty for an event and its consequences, the action should not be carried out. But sometimes this principle can be considered counter intuitive, as for some cases at the offshore petroleum industry, so the cautionary principle is applied instead.

2.1.4. The Cautionary Principle

In safety management there is a basic principle referred to as the cautionary principle. It is the idea of when facing uncertainty, caution should be the ruling principle (Aven & Vinnem, 2007). An example of the cautionary principle can be drawn from the Norwegian petroleum industry, where it is a regulatory requirement to have fireproof panels of a certain quality protecting the living quarters on an offshore installation. This is an adaptation of a minimum safety level, established after many years of operation of process plants.

Even though the assigned probability of for example a fire in the living quarter is considered low, there is to our knowledge known that fires on offshore installations happen from time to time. It is simply based on how one judge the risk. One should be prepared even if the likelihood of the event is small, and without reference to cost-benefit analysis. This is the bases of cautionary thinking.

Aven and Vinnem (2007) go on to state that *"during the face of uncertainty related to the possibility of hazardous situations and accidents, we are cautious and adopt principles of safety management"* such as:

- Robust design solutions, such that deviations from normal conditions are not leading to hazardous situations and accidents,
- Design for flexibility, meaning that it is possible to utilize a new situation and adapt to changes in the frame conditions,
- Implementation of safety barriers, to reduce the negative consequences of hazardous situations if they should occur, for example a fire,
- Improvement of the performance of barriers by using redundancy, maintenance/testing, etc.
- Quality control/quality assurance
- The precautionary principle, saying that in the case of lack of scientific certainty on the possible consequences of an activity, we should not carry out the activity,
- The ALARP-principle, saying that risk should be reduced to a level which is as low as reasonably practicable.

2.2. Safety models

Systems that are safety-critical have mechanisms that are both passive and active that help to prevent, detect, or tolerate a system failure. These mechanisms are normally built up by safety models. A system model is normally split into two essential parts: a basic system model and a safety mechanisms model.

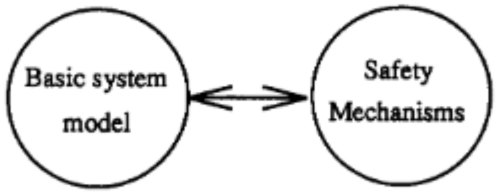

Figure 3 - A Model of a Safety-Critical System (Burns, G., Anderson, S., 2011)

The model's job is then to identify and verify the different property inputs the model receives and then output either an action or a number that can be used both in a physical or a theoretical purpose. An example of a physical purpose would be if a pump offshore fails, a model would detect this failure and shut down the pump before it would reach a safety critical temperature. On the other hand, an example of a theoretical model would be one were historical data and expert opinions would be inputted into a model, and data to help guide a decision-maker would be the output. The latter will be the focus of this thesis with attention to the algorithmic background that is implemented in the model, and how the algorithms process the data input.

The whole reason for implementing safety models is to avoid accidents. Accidents are defined in a broad sense as:

"a short, sudden and unexpected event or occurrence that results in an unwanted and undesirable outcome… and must directly or indirectly be the result of human activity rather than a natural event". (Hollnagel, E., 2004)

For safety management to be considered effective, the aim would be to achieve zero accidents. And on the other hand, if there are accidents, the total safety management seems to be ineffective or absent. This is the reason why it is crucial to understand the fundamentals of how accidents occur, and how one can help to establish preventive measures for preventing accidents from occurring. Through time accident models have been developed and evolved into different phases and variants: 1) Simple linear models, 2) Complex linear models, 3) Complex non-linear models. (Pryor, P., Capra, M., 2012).

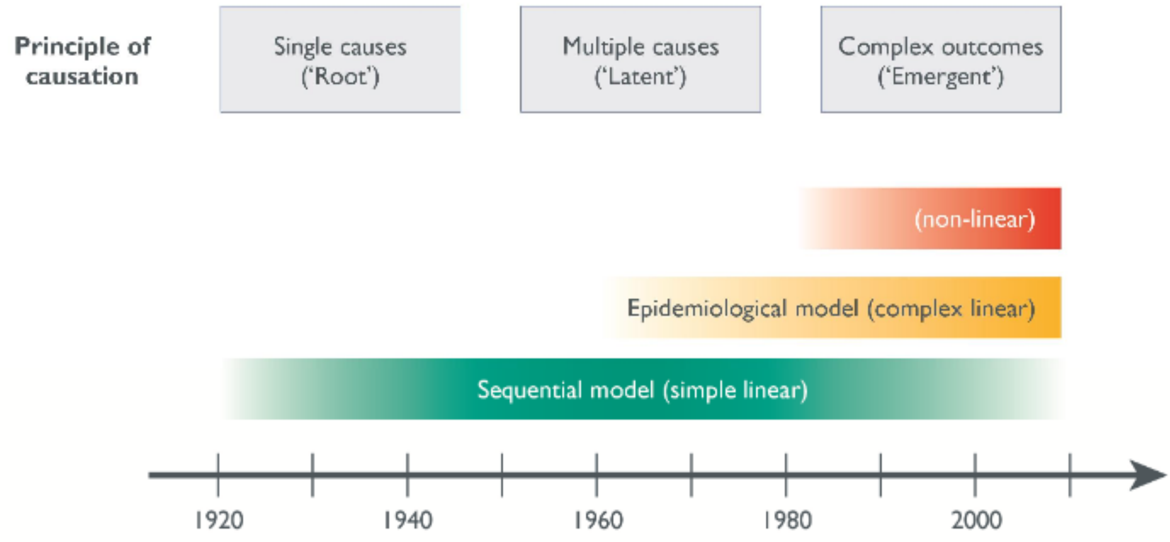

Figure 4 – Summary: the history of accident modelling (Hollnagel, E. 2010)

As Pryor, P. and Capra, M. (2012) mentions, complex non-linear models were developed as a result of technological advances had made systems so complex that that accidents in these systems were considered normal. Tightly coupled systems were almost unmanageable for the operators which resulted in user errors being unavoidable. The complexness of these new systems left a void in safety management and these complex non-linear models were developed in the early 2000s. These models are considered effective in doing what they are made to do, but the process is time consuming, complex and resourceful. As a result of the computational advances that were made in the 2000s, a new tool for developing and improving safety models were considered. Algorithms. Algorithms were implemented into existing and newly developed models and their effectiveness were unparalleled. The analysis of the data with support of algorithms has drastically reduced the time and resources it takes to produce an output for the decision-makers and increased the accuracy.

In the modern area of safety models, algorithms have proven to have a large potential when implemented into a safety models framework.

2.3. Algorithms

An algorithm is a computational procedure which is well-defined ant that takes a set of data as input and produce a set of values (or value) as an output. Algorithms are thus a sequence of computational steps that transform different inputs into outputs. Algorithms can also be viewed as tools for solving well-specified computational problems, where the statement of the problem specifies some terms for the desired input/output relationship. A simple example of an algorithm would be if one wanted to sort a sequence of numbers into decreasing order. The sorting problem would then be defined as follows:

Input: A sequence of n numbers $< a_1, a_2, \dots, a_n >$.

Output: A reordering $< a'_1, a'_2, \dots, a'_n >$ of the input sequence such that $a_{\prime 1} \geq a_2 \geq \cdots, \geq a_n$.

So for example with the number set $< 32, 44, 61, 25, 44, 60 >$, a sorting algorithm would produce an output in the following order: $< 61, 60, 44, 44, 32, 25 >$. This input sequence is commonly known as an instance of the sorting problem, and in general this consists of the input needed to compute a solution to the problem. (Cormon, T. H., Leiserson, C. E., Rivest, R. L., Stein, C., 2001)

But algorithms can be put into use on so many different applications. Its most recent development is the use of AI and machine learning to help problem solving and dealing with large amount of data. This has gone hand in hand with the offshore industry`s shifted focus towards digitalization, and has a promising future for both providing solutions to complicated tasks, but also within the field of risk management.

2.3.1. Machine Learning

To define machine learning it is important to understand its context. It is a part of a bigger concept known as Artificial intelligence which has been around since the 1950s, discovered by AI pioneer called Alan Turing in his paper "Computing Machinery and Intelligence".

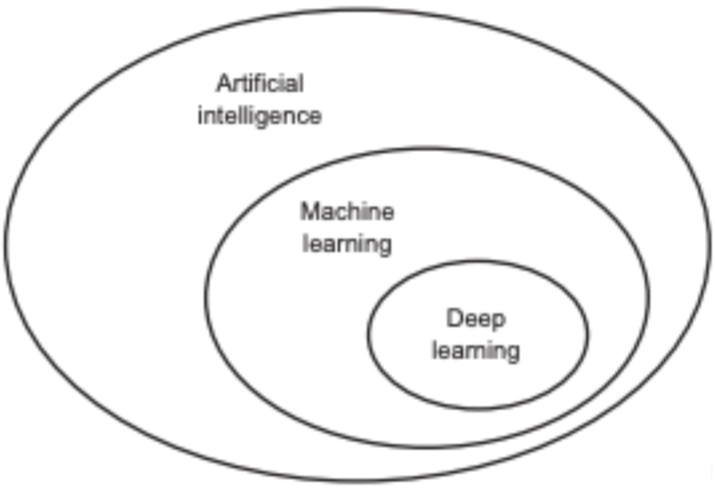

Figure 5 - Correlation between Artificial intelligence, Machine learning and Deep learning (Chollet, F., 2018)

Machine learning can be viewed as a tool used for turning some form of information into useful knowledge. And as the last year's data information has exploded in volume, there seems to be plenty of information available that one is unable to transform into usable knowledge unless one finds a way to analyze the data and find the hidden patterns they contain.

Machine learning is a technique that automatically finds such a pattern by repeating an operation over and over again in a high work rate, thus resulting in it finding the pattern in the highly complex datasets. And as Frances Chollet (2018) states; machine learning can be used to convert this information into patterns that again will provide knowledge about the situation, guiding the end user to predict the future more accurately and support complex decision-making actions.

Software engineers in the common way of using computer power used rules created by humans combined with data to produce an answer to a problem. Machine learning, on the other hand, flips this problem and uses data and answers to discover the rules behind the problem (Chollet, 2018).

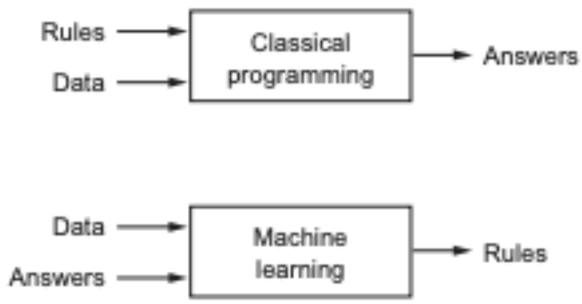

Figure 6 - Classical programming vs. Machine learning (Chollet, F., 2018)

To achieve the purpose of learning a rule that governs a problem, computers that utilize machine learning go through a learning process. In this process the machine runs through many loops with different rules, learning from how well each rule performs for the given task.

Within machine learning there are several forms that it can be split into. The main three are (as indicated in figure 7): Supervised learning, Unsupervised learning and Reinforcement learning. They all have unique approaches of how they tackle the problem at hand, but they follow the same underlying process and theory behind the theory of machine learning, where discovering rules is the main purpose. Supervised and Unsupervised are well established methods that are commonly used.

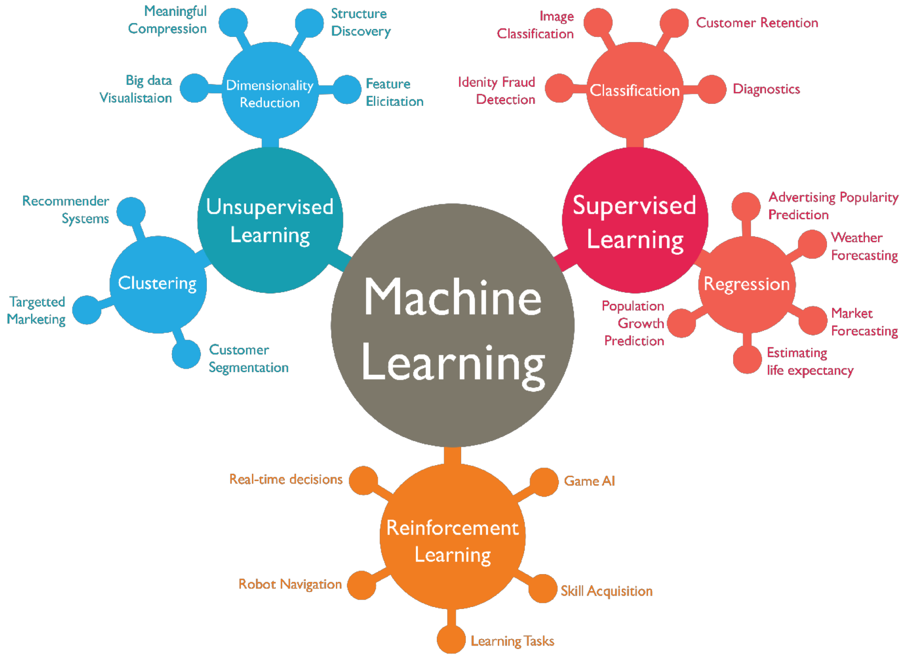

Figure 7 - Machine Learning classification (Wahid, A., 2017)

The process in which machine learning works is displayed in table 1:

Process	**Description**
Data collection	Collect the data that the algorithm will learn from.
Data preparation	Format and engineer the data into the optimal format, extracting important features and performing dimensionality reduction.
Training	Also known as the fitting stage, this is where the Machine learning algorithm actually learns by showing the data that has been collected and prepared.
Evaluation	Test the model to see how well it performs.
Tuning	Fine tune the model to maximize it`s performance.

Table 1 - Machine Learning process (Edwards, G., 2018)

2.3.2. Algorithmic decision-trees

ID3 was developed in 1986 by Quinlan and has become a famous algorithm, and its basic principle is based on decision trees as the development of computers, technology, networks and databases grow so fast that decision trees proved to be the best way of managing this rapid development. The quick growth of information has resulted in database access and query operations no longer meeting the requirements needed, as humans require mining of available information of massive data in a quick and effective methodology. Data mining methods, for the most part, use decision tree classifications to discover rules and patterns within the dataset (Yong & Yunlong, 2012), and the main advantage of utilizing these methods is that they are easily readable by the rules and decision trees they project as an output. The decision tree classification algorithm is an example-based inductive learning algorithm in data mining and looks at different groups, that has no rules, no order and examples that justifies the use of decision tree classification rules. The ID3 algorithm represents a decision set by the use of a tree structure similar to a fault tree diagram to represent a decision set and uses this classification to generate its decision rules. Every attribute test in the three is represented by a non-leaf node and each leaf node represents a category. When constructing a decision tree process, cutting out noise from the dataset and outside influences is crucial, as this improves the reliability of the classification of the unknown data sets. The two most frequently used decision trees in an ID3 algorithm are classification trees and regression trees.

2.3.3. The ID3 algorithm

Information entropy is the basis for the ID3 decision tree classification algorithm. ID3 selects attributes that contain the largest amount of information gain as the test attribute for the node it is currently at, and the core thought of the algorithm is to select properties on the decision tree nodes at all levels. This reduces the amount of information needed by the data classification, and reflects the principle of minimum randomness (Yong & Yunlong, 2012). The main idea behind implementing the ID3 algorithm is to recognize the value of different information assets, thus resulting in valuable identification rules that provide important support for decision making and risk evaluations.

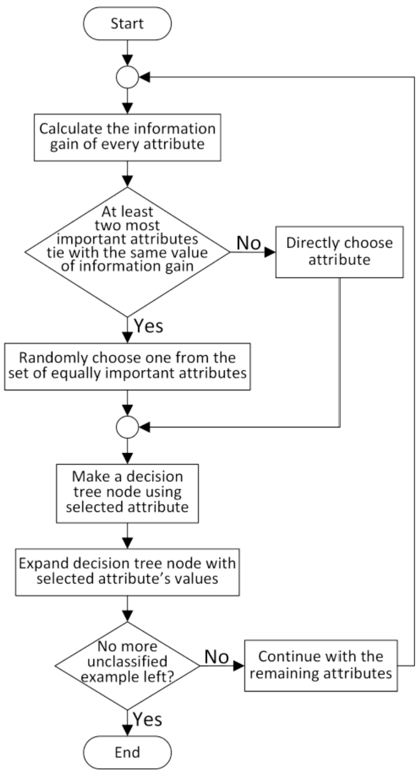

Figure 8 – Flowchart of an ID3 algorithm (Kraidech & Jearanaitanakij, 2017)

2.4. Decision-Making in theory

To be able to analyze whether a computer and belonging algorithms are capable of making decisions (or decision support) that help mitigate and manage risk, one need to first analyze what a decision is and what decisions are based on both in a human and computational perspective.

2.4.1. The Decision-Making process for humans

The decision making process evolves around several different theoretical aspects. Humans have a basic nature on how to take make a decision, and this nature comprises of several strengths and weaknesses. On the other hand, computational decision making has its own theoretical aspects that also carry with them some strengths and weaknesses.

2.4.1.1. The rational approach

Pareto (1927) states that human decision making and its rational has its background on utilitarian theory and the notion of homo economics. The basis is that when humans are opted with a choice, they have two main sources of motivation: either to minimize the cost, or to optimize value.

Utilitarian theory also states that a requirement is that a human decision maker tends to choose the most "attractive" alternative. This is referred to as the "rationality principle", and the approach can be split into four points: (Barthelemy et. al, 2002)

1) The decision maker has to be able to generate possible scenario that is relevant, and the potential outcomes of the situation.
2) The decision maker is able to evaluate the attractiveness of each of the scenarios and available alternatives.
3) The decision maker should be able to aggregate the local evaluations (or partial) into a global perspective.
4) Finally, the decision maker should choose alternatives that are most beneficial in a global perspective.

These four points in the rationality principle are assumed to support the utility theory and its axioms (Von Neumann & Morgenstern, 1944), in the sense that point 1) does not only account for exhaustive descriptions of possible actions, but also the possible likelihood linked to consequences of actions taken. Point 2) involves the axiom that is attached to issues, the notion of utility functions. Probabilities and utilities linked to being able to compute expected utility attached to each perspective is covered in point 3), and finally point 4) emphasizes that the decision maker will choose these actions based on what action will bring with it a maximum expected utility.

The rational principle approach has later been modified to be used in practical tools and as guiding principles for decision-making made on an organizational level. On an organizational level, subjects for analyzation are normally quite complex, involving multiple stakeholders, and involve decisions that are made for a long-term benefit and perspective. A tool that utilizes these aspects and has been converted for real world use is the Analytic Hierarchy Process (AHP) (Saaty, T. L, 2008). Here a technique for making a rational decision is proposed in a systematic manner:

Process steps
1. Define the problem and what kind of knowledge that is needed
2. Make a decision hierarchy, starting with the goal of the decision on top, then state the objectives from a broad perspective at the intermediate levels. Formulate criteria and draw lines representing dependencies to subsequent elements. The lowest level should represent a set of alternatives.
3. Make matrices allowing for pairwise comparison. Upper level elements should be used to compare elements in the level below.
4. Generate priorities from the comparison. Upper level elements should be used to compare elements in the level below.
5. For each element in the level below, apply its weighed value to obtain its global priority. Continue this process of weighting and prioritizing throughout the hierarchy until one reaches the alternative in the bottom most level.

Table 2 - Analytic Hierarchy Process (AHP), rational decision-making technique (Saaty, T. L., 2008)

2.4.1.2. Weaknesses of rational decision making

As early as in 1955, criticism om the rational approach arose. Herbert Simon wrote in his paper (Simon, H. A, 1955) on whether rational decision making was a description of how a decision is made in general or if the approach was simply a guide for how decisions should be made. The main argumentation was related to the human rationality and how this rationality is restricted by the traceability and the limitations this would impose on the decision problem itself. The inherent complexity of making a decision would largely be impacted by the available time to make the decision, as well as limitations in human cognitive capacity.

Humans have proven to cope poorly under time pressure, and the stressful environment around making quick decisions could lead to so called “tunnel vision”, were the bigger picture would be left out by the human brain, resulting in decisions being made without the use of all available information, thus having a bad impact on the risks. The restrictions this imposes result in a subjective and incomplete representation of the context and nature of the problem, in which the decision maker seeks to rationalize (Falk, K et. al, 2018). This principle was named “the principle of bounded rationality”.

As a basis for these limitations humans tend to find a satisfactory choice, and not an optimal one, when it comes to the human decision-making process (Simon, H. A, 1959). Newer research from 1982 build upon the discovery and further reveal that humans tend to seek various biases and heuristics when making a decision. It is here discovered that factors such as availability, representativeness and framing effects all contribute to guide the decision maker into make the choice itself sees fit. In essence this boils down to the human minds capability to process information that is available to him/her and make a judgement call based on this input information, but will struggle to make any rational decision based on this input.

Another example of non-rational aspects of human decision making is linked to The Moving Basis Heuristics, where it is stated that the human brain is subjected to parsimony, reliability and decidability. Parsimony is linked to what has mentioned earlier, that the human brain under stressful situation only is capable of making decisions with partial use of all available information. Reliability in the context of non-rational decision making aims at the fact that the information considered to be sufficiently relevant for the decision maker, is considered the justification background for making that decision. Finally, decidability is an aspect were the information that is to be applied in a decision making context is not static. Information will in theory change depending on the person that is going to make the decision, and also the on the decision to be made itself (Barthelemy, J.P., 1986).

2.4.1.3. Situational Awareness

In complex sociotechnical systems, it has been identified that an important concept that influences the offshore operator’s decision making can be linked to Situational Awareness (SA). In the last two decades, a majority of accidents have occurred in large-scale technological systems that have led to serious consequences, that have been proven to be the result of human error. Human input has (in these accidents) not been identified as the sole reason for the accidents, but have inherited the problems and difficulties they faced during the heat of the moment as a result of having to deal with complex systems designed by engineers. The offshore operator has to deal with several information inputs at the same time, with data that happens in real time. On top of this, the operator has to make the decisions quickly and act on these decisions to allow for the operational units to return back to their normal state, thus preventing an accident. As for situations involving gangway bridges or walk-2-work (W2W) bridges, the operator has to act quickly to prevent an escalation of the problem at hand. Workloads will rise quickly, and mental workloads that are too high for the personnel to handle will increase the rate of error (Naderpour et. al 2014).

Situational awareness is considered one of the most important cognitive human features when it comes to decision-making, and is defined as a perception of the information elements in the dynamic environment, comprehensive of their meaning, and projection of their future status (Endsley, M. R., 1995). The following figure illustrates the three levels of situational awareness that is consistent with the above definition:

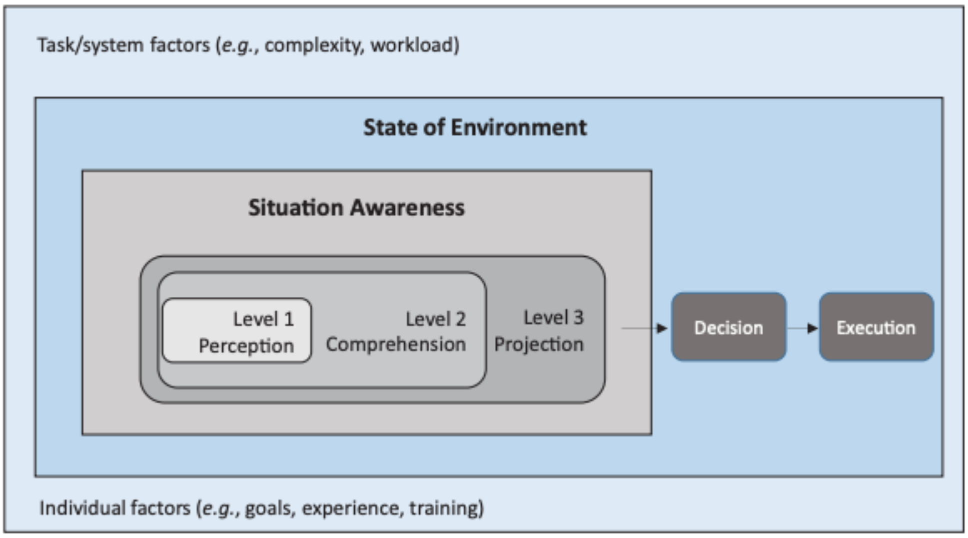

Figure 9 - Endsley`s model of situational awareness (Øvergård et. al., 2015)

Here three levels are mentioned, relating to level 1, level 2 and level 3, that takes into account the different states the human brain enters when making a decision. In the above figure it refers to offshore operators and is suitable for the situation involving offshore gangway bridges. There is an underlying assumption regarding situational awareness that it´s formed by a sequential process progressing from perception to comprehension and finally to projection (Chiappe, Strybel and Vu, 2012).

Stanton et al. (2010) argue that a three-level model is flawed in the sense that it is counter-intuitive. For the operator of a gangway bridge at the flotel the levels mean that first, in level 1 situational awareness, the operator must identify that the gangway bridge is reaching its limits regarding safe operation and that the sway and significant wave height (weather) is above the LSOG limits. Level 2 of Endsley`s situational awareness model implies that the operator has to identify that the forces of the weather conditions causes the flotel to drift off its optimal position. The identification process would typically involve looking at GPS instrumentation and also a visual inspection were the operator would notice a new angle in contradiction to normal relative angle to the stationary offshore installation. What Stanton then questions, is the likelihood that elements of the evolving situation will be properly analyzed and corrective action taken to achieve this appropriate situational awareness.

The situational awareness of the operator is the basis for how the operator will act in the given moment and the also the decision-making process the operator runs through. Whether or not the gangway should be disconnected form the offshore installation is according to the situational awareness principle will not only boil down to the LSOG or computer system and its warning outputs, but also relies heavily on the operator's ability to operate the dynamic position system, seamanship, experience, training and attention. A theory on the above mentioned point is related to mental models and experience. The more experience an individual has, the more evolved the mental models he or she possesses will be, thus resulting in an easier generated situational awareness, which again will change the levels for when one sees fit to disconnect the gangway.

2.4.2. The decision-making process for computers

The human brain compared to computational power is quite different. Where the human brain has a slow evolution, computer`s processing power, memory, storage and data transfer has skyrocketed in a short period of two decades.

During the NASA moon landing project, the computational power in the Apollo 11 equates to a performance less than 1300 times lower than the power that exist in an iPhone 5s from 2013. All that in a period of roughly 50 years. In later years the advancement of artificial intelligence (AI) and machine learning has proven to be a successful technological marvel. Especially in the field of decision making.

The modern computer has proven to be a valuable asset when it comes to advising humans in making decisions. Computers or more specifically computer programs designed to support decision making is normally referred to as expert systems (ES), and are able to receive input from humans (their expertise) in terms of task-specific knowledge and provide the decision maker with valuable information.

2.4.2.1. Expert systems

Expert systems (ES) were developed during the mid-1960s as a branch of applied artificial intelligence (AI). The idea of an ES is simple and involves converting human expertise, which is considered to be the main body behind task-specific knowledge, over to computers. The knowledge would then be saved on a computer and for example an offshore operator could summon upon the computer processed information when advice was needed (Liao, S., 2005).

The computer acts like any human consultant by providing information and belonging explanations based of the conclusions it would draw from its input (Turban & Aronson, 2001). Problems that are considered hard to deal with for humans has a major advantage from utilizing expert systems. There are several forms of expert systems that are developed such as Rule-based systems, Knowledge-based systems, Neural networks, Fuzzy expert systems, Object-oriented methodology, Case-based reasoning, System architecture, Intelligent agents and Ontology.

2.4.2.1.1. Rule-based systems

Rule-based expert systems are systems that contain information that has been collected from experts. It presents the gathered information in form of rules, similar to many computer programs, such as IF-THAN or AND-OR. The rules help guide the computer software to perform operations on a dataset to inference in order to reach a conclusion judged suitable. Inferences is in theory a computer program that provides a reasoning through the use of a structured methodology about the existing information in the rule base or knowledge base.

2.4.2.1.2. Knowledge-based systems

Knowledge-based systems are centered around humans but have their roots in the field of artificial intelligence. They are an attempt at understanding and initiating human knowledge or expertise into computer systems (Wiig, 1993) and consist of four main components:

1) A knowledge base as a starting point, normally from a group of experts or historical data.
2) An inference engine
3) A knowledge engineer tool
4) And finally, a specific user interface.

This type of expert system is normally utilized on an organizational level, where information technology applications help manage the knowledge assets of a business, through the use of expert systems like rule-based systems, groupware and database management systems, but can be used for more detailed levels as well, with less accuracy.

2.4.2.1.3. Neural networks

When one mentions neural networks the first thing to come to mind is the human brain. And one would be correct to assume this, as artificial neural networks (ANN) are models that emulate the biological neural network. Software simulations are implemented into a concept that involves processing several different elements that are interconnected in a network-like architecture (Chollet, 2018).

Artificial neurons receive data input from sensors similar to how the electrochemical impulses in the brain react to pain, if one is to for example touch a hot stove. Here, the fingers act as sensors, and the nervous system carried the data input to the neural network, or the brain. Artificial neural networks that are developed today use a concept were a system is trained without any use of human data or human supervision, but only learning from self-repetition from totally random actions (Edwards, 2018)

The artificial neural networks are of course “guided” towards a purpose, and parent nodes that seem promising are selected out of thousands of samples to produce the next generation of data models. This process is repeated until (and hopefully) a successful model have been constructed.

2.4.2.1.4. Fuzzy expert systems

Fuzzy expert systems follow its name. They use fuzzy logic, meaning they deal with uncertainty. The technique follows a mathematical theory about fuzzy sets, that simulate the process of how humans reason by allowing the computer to behave less accurate and logically than conventional computer software’s. The process is used in the real world solely because decision-making is not always straight forward, true or false, as there are several grey areas in the subject of decision-making. Creative decision-making processes can be characterized as unstructured, playful, contentious, and rambling (Jamshidi et. al., 1997).

2.4.2.2. Negative aspects with computers as decision makers

Artificial intelligence has a promising future, as proven by the Alpha Go Zero project, but it is a known fact from previous research that computers have their issues when it comes to acting as decision makers. With the old technology that the gangway model is based, it has proven to be a potential for many safety related issues when automation is involved. Examples of this date back to the 1980s and 1990s with the airline industry and the many crashes that occurred at that time. Computer systems that were designed to keep the airplane flying did the opposite.

A modern example of the same issue is related to the Boeing 737-8/9 Max airplanes. The preliminary (yet not official) cause for the crash of Indonesian Airlines and Ethiopian Airlines was related to a computer program relying on sensory information to act on behalf of the pilot if it noticed an abnormal speed vs. pitch attitude. An un-healthy relationship with low airspeed and a high nose pitch of the airplane would result in a stall, and a system called MCAS was introduces in the planes to help pitch the nose of the plain forward (thus eliminating the stall situation) if the sensors noticed this undesired relationship. What happened instead with the above mentioned incidents were that the sensor data was wrong, and the computer acted on its automation to trim the nose of the plain down, so far that it resulted in a situation where the pilots no longer could control the plain and a crash was inevitable.

Similar cases are possible when computers act as decision making support tools, like with the gangway model, were sensory data might be corrupted and an auto-disconnect of the gangway bridge might occur. With the misleading information from the computational decision support system, the operator might also act on behalf of the system before the auto-disconnect engages, believing that the actions taken were the right ones because it was supported by the computer. This claim is supported by the above mentioned functionality of how humans make decisions during stressful environments. The overall result of computer misinformation would be severe consequences for personnel on the gangway bridge during the misinterpreted gangway bridge disconnect. It is important that these aspects are properly taken into account when managing the risk of walk-2-work operations.

In addition, there are five different phenomena that reduce the quality of computer-based decision-making, summarized by Falk, K. et. al (2018):

Phenomenon	Description
Brittleness	*Modern socio-technical systems may be so complex that it is almost impossible to define all relevant functions and alternatives, as well as the scope of system limits and relevant interfaces with other systems.*
Opacity	*Technology systems have limited capability to express and explain what it is doing, and what it is planning to do next, to the human operator.*
Literalism	*Automata stick to the rules and instructions given by their programmers or operators (the process), even if they may lead to obviously undesired outcomes (lack of goal orientation).*
Clumsiness	*The system has little understanding of the work situation of the operator, and thus does not aid when needed or call for attention when operator workload is very high.*
Data overload	*Producing large amounts of information, of which only a small part is useful for the operator. The situation may also be opposite: that the system does not produce information that obviously would be helpful from the perspective of the operator.*

Table 3 - Challenges with computers as decision-makers (Onken & Schulte, 2010)

Onken and Schulte (2010) elaborate further on four of the phenomena:

Brittleness describes the flaws of conventional use of automation and computational decision-support as a result of it being close too impossible to verify that everything is working in an acceptable manner in all possibly encountered situations during the development process of highly complex functions. In other words, brittleness refers to conventional automation and decision-support in regards to its characteristics and its ability to work well; according to set specifications and operational limits. These limitations of proper operation will normally not be known for the human operator, as there always will be situations where "n+1" will be hard to predict.

Opacity is the surprising element to the operator when the outcome or action of the computer differs to what is expected i.e. when there are no obvious errors available, but there is still an error message displayed. The human operator simply cannot know all about the complex functions he is trying to use, and has little to no chance of understanding what is going on. Typical questions the operator might ask him/her-self during a stressful situation in relation to opacity would be; *"What is it doing?", "Why is it doing that?"* and *"What's it going to do next?"* (Weiner, 1989). Even though these questions are directed towards more automated systems rather than decision-support systems, they are still relevant and can be translated into *"What is the information its providing?", "Why is it telling me this?"* and "*What will it inform of next?".*

Literalism relates to the programming of computers, and that they normally do what they simply are made to do. They do not deviate from their programmed purpose, and do as the operator and programmer have told it to do. In other words, literalism states that computer programs follow their given instructions strictly no matter if what the program does is right or wrong. Conventional automation and computational decision-support tools do not question or check control operations concerning their ability to make sense in the given context.

Clumsiness, the final challenge in computational decision-making relates to the issue of the computer software producing too much information were very few parts of the information is useful. The overall result of this issue is related to the operator becoming confused and having to de-bug/decipher all the information and come to a conclusion as to which information is the one to act upon. This is very time consuming and not fortunate, especially in situations where time is scarce.

3. METHODOLOGY

3.1. Research method

Research methodology has two approaches that are normally used. A quantitative or qualitative approach. Quantitative research utilizes numerical data or data that can be transformed into statistics and uses measurable data to formulate facts and uncover data patterns. Qualitative research on the other hand is a type of scientific research that attempts to seek answers to a question, systematically predefine a set of procedures to answer the question, collects evidence and produces findings that are not determined in advance (Kothari, 2004).

The thesis studies the use of an algorithmic decision-support model and how the use of such a model impacts risk management in the offshore petroleum sector. Qualitative research was preferred over quantitative as the information available from the model analyzed were only theoretical with no numerical data available, and because qualitative research is quite effective at obtaining information about behavior of humans, and decision-making in general.

Further focusing on the qualitative method, it was chosen to use a case study approach to answer the problem statement. A case study approach should be considered when: a) the focus of the study is to answer "how" and "why" questions; b) you cannot manipulate the behavior of those involved in the study; c) you want to cover contextual conditions because you believe they are relevant to the phenomenon under study; or d) the boundaries are not clear between the phenomenon and the context (Yin, 2003). For the problem statement in this thesis the goal is to answer how the analyzed algorithmic model impacts risk management and how the use of algorithms impact risk management in general, thus supporting claim a). Also point c), stating that contextual conditions relevant to the phenomenon under study, proves to be appropriate as the contextual condition in this case is based on the identification and analysis of the model at hand.

3.2. Data collection

Data collection start when the outline of the thesis and its research question is defined. To be able to take a deep dive into the selected model and answer the research question adequate information is necessary to be able to arrive at results that can be backed up by proven scientific research and theory. As the model studied has not till this date been implemented for use at an offshore installation questionnaires and interviews are not considered necessary for answering the problem statement, but it is justified that only focusing on content analysis that utilizes deep studying of the subject matter will be sufficient.

3.2.1. Content analysis

Content analysis is a method that consist of analyzing the content of documents such as books, magazines, newspapers and scientific paper (Kothari, 2004). Data collection was done using existing data, specifically aiming at the paper “Risk-Based Decision Support Model for Offshore Installations”. This data was collected as the paper was the most promising considering the thesis` set criteria for containing a safety system using algorithms as its foundation, was applicable in a real world scenario, was within the date range (2016-2018), was risk-based, and was utilized in the offshore petroleum sector.

Additional data collected were theoretical reviews of existing information including topics regarding risk, human/computational decision-making, algorithms, machine learning and safety models. The paper that forms the main research analysis was produced in 2018 in collaboration with SINTEF, Statoil (now Equinor) and Oilfield Technology Group and the aim was to develop a decision-support tool using algorithms to guide decision-making for a gangway bridge installed on a flotel.

4. RESULTS

The model that will be evaluated is a computerized model that supports decisions to be made based on operational safety risk on an offshore installation. The model is based on, and developed using the software DEXi and its main task is to automatically provide a decision advice based on 28 different input parameters (Erdogan, G et. al. 2017).

4.1. An Algorithm to Support Risk-Based Decisions for Offshore Installations

The focus of the model is related to major offshore maintenance projects where flotels are used to accommodate the workers. Flotels are vessels that provide sleeping and recreational quarters for the workers and is the work flotel is derived from its purpose, namely a floating hotel. The main problem with adopting a flotel as main quarters for the personnel is related to the flotel needing to be in a close and limited area to the installation that maintenance work is being conducted on. It maintains this close and limited position using several thrusters mounted on the bottom of the vessel that is supported by a Dynamic Positioning system (DP), thruster assisted mooring or more simple mooring systems.

Dynamic Positioning implies using a computer-controlled system that keeps the flotel`s position automatically by using the above-mentioned thrusters. However, maintaining this safe position in rough conditions as one could encounter in the North Sea is proven to be highly challenging. The risks related to the use of the gangway are weather associated as unfavorable conditions provides a decision alternative for the offshore operatives on whether one should lift (disconnect) the gangway from the offshore installation or not. If the gangway remains connected during these weather conditions, there is a risk that an uncontrolled disconnect occurs as the integrated maximum safety level is exceeded as a result of too strong winds and/or too high significant wave height makes it physically impossible to stay connected. This uncontrolled lift can cause harm to personnel and important equipment on the offshore installation, gangway or flotel.

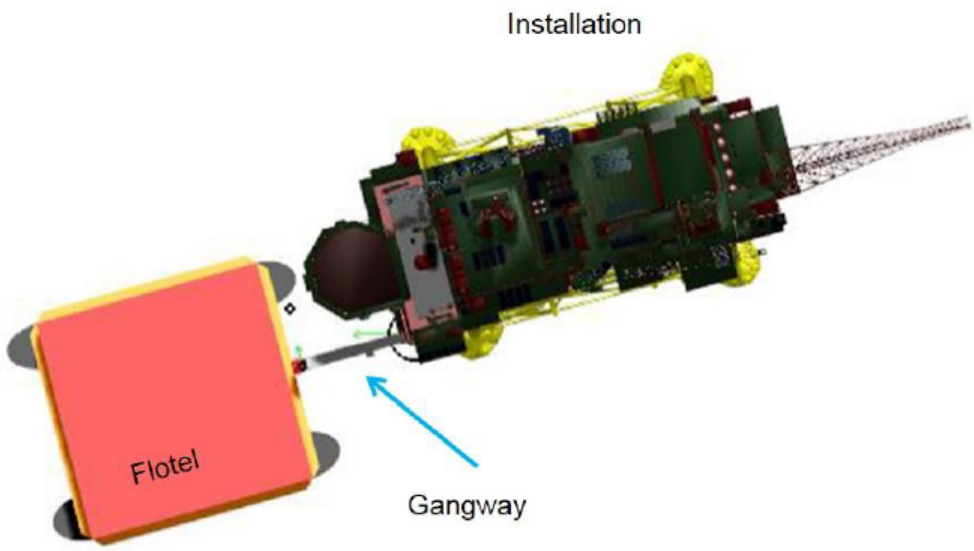

Figure 10 - Gangway connection from flotel to installation (Erdogan, G et. al, 2018)

The decision to disconnect can be difficult to make as there are several factors that affect the risk. In particular there are enormous costs related to lifting the gangway during operation as the workers will be prevented from performing their assigned tasks, impacting both schedule and budget. The decision to lift the gangway is prior to the model based upon paper-based Location Specific Operational Guidelines (LSOG) and other sources of information such as the prevailing weather conditions that the offshore operator's cross reference the current weather conditions with. As this decision carries such a heavy burden on the offshore operators, an algorithmic computer assisted model that acts as a decision-support tool is provided, in an attempt to minimize the risk exposure by releasing the offshore operators from taking decisions that they normally would refrain from doing (Erdogan, G et. al., 2017).

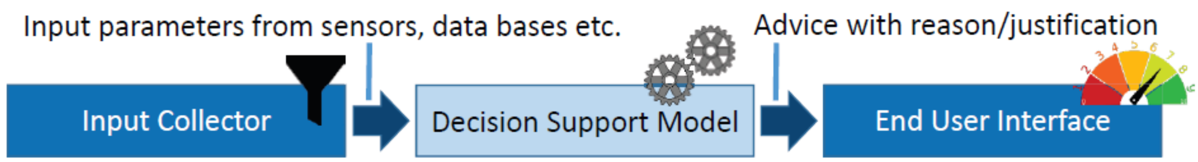

Figure 11 - Vision for overall decision support solution (Erdogan, G et. al 2017)

Figure 11 displays the solution for how the tool supports decision making for the offshore operator. The data (such as weather forecasts) for the input parameters are collected in the Input Collector phase, and the Decision Support Model sorts these data to make a computational aided advice. The advice gets portrayed for the offshore operator in the End User Interface and is tailored for the specific needs the operator might have. The model is according to Erdogan et. al. built up of four success criteria:

C1: *The model should provide advice that correspond with expert expectations.*

C2: *The model should capture all aspects that are important for the assessment.*

C3: *The model should be comprehensible for domain experts.*

C4: *The expected benefit should justify the effort required to develop the model.*

4.2. DEXi

DEXi is a qualitative decision support methodology software for the evaluation and analysis of decision alternatives. The methodology used in DEXi was conceived more than 30 years ago and has a long history of scientific, technical and practical contributions for the real world. It uses an approach of combining "classical" numerical multi-criteria decision modeling with rule-based expert systems, that lead to the development of new algorithms and techniques for acquiring and representing decision knowledge and evaluating/analyzing decision alternatives. DEXi is still very much alive today despite its age and is actively used in international projects. (Bohanec, M., Znidarsic, M., 2013)

4.2.1. Principles of DEXi

DEXi and its basic principles are intentionally kept simple by the developer. The analyst is asked to define a qualitative multi-attribute model with belonging decision alternatives that are evaluated and analyzed. The model, in principle, represents a decomposition of decision problems into smaller and less complicated sub-problems and is represented by a hierarchy of attributes. The DEXi model contains:

- *Attributes:* variables that represent basic features and assessed values of decision alternatives.
- *Scales of attributes:* these are qualitative and consist of a set of words, such as "excellent", "acceptable", "inappropriate", etc. Usually, scales are ordered preferentially, i.e., from bad to good values.
- *Hierarchy of attributes:* represents the decomposition of the decision problem and relations between attributes; higher-level attributes depend on lower-level ones.
- *Decision rules:* tabular representation of a mapping from lower-level attributes to higher-level ones. In principle, a table should specify a value of the higher-level attribute for all combinations of values of its lower-level attributes.

  (Bohanec, M., Znidarsic, M, 2013)

Bohanec 2013 illustrates these above points in a model for evaluating cars.

Attribute	Car1	Car2	Car3
CAR	exc	good	unacc; good; exc
├PRICE	low	medium	low
│├BUY.PRICE	medium	medium	low
│└MAINT.PRICE	low	medium	low
└TECH.CHAR.	exc	good	bad; acc; good
├COMFORT	high	high	medium
│├#PERS	more	more	3-4
│├#DOORS	4	4	3
│└LUGGAGE	big	big	medium
└SAFETY	high	medium	*

Figure 12 - DEXi model example for evaluating cars (Bohanec, 2013)

	PRICE	TECH.CHAR.	CAR
1	high	bad	unacc
2	high	acc	unacc
3	high	good	unacc
4	high	exc	unacc
5	medium	bad	unacc
6	medium	acc	acc
7	medium	good	good
8	medium	exc	exc
9	low	bad	unacc
10	low	acc	good
11	low	good	exc
12	low	exc	exc

Figure 13 - Decision rules for an evaluating function (Bohanec, 2013)

Attribute	Scale
CAR	unacc; acc; good; exc
├PRICE	high; medium; low
│├BUY.PRICE	high; medium; low
│└MAINT.PRICE	high; medium; low
└TECH.CHAR.	bad; acc; good; exc
├COMFORT	small; medium; high
│├#PERS	to_2; 3-4; more
│├#DOORS	2; 3; 4; more
│└LUGGAGE	small; medium; big
└SAFETY	small; medium; high

Figure 14 - Evaluation of three cars (Bohanec, 2013)

The final stage of the DEXi model typically involves using various alternatives for analysis. Such analysis might be structured “what-if” analysis and sensitivity analyses. A normal analysis used with a combination of the DEXi model is a “plus-minus-1” analysis, that investigates the effects of change that results from altering each input variable by one step down (-1) or one step up (+1) in the attribute scale. From figure 15 we can see that even a small step up or down in the given example results in changes from outputs that have previously been rated as “good” to something that is either considered “excellent” or “unacceptable”. This gives a better weight to the decision-support information as it also considers worse/best case as used in cost-benefit analyses.

Attribute	-1	Car2	+1
CAR		good	
├BUY.PRICE	unacc	medium	*exc*
└MAINT.PRICE	unacc	medium	*exc*
├#PERS		*more*	]
├#DOORS		4	
└LUGGAGE		*big*	]
└SAFETY	unacc	medium	*exc*

Figure 15 - DEXi Plus-minus-1 analysis (Bohanec, 2013)

4.2.2. Important concepts

DEXi is in theory a combination of 2 approaches: Expert systems and multi-criteria decision analysis (MCDA). DEXi borrows the idea of evaluating and analyzing decision alternatives using hierarchically structured models but departs from using numerical variables and weight-based utility functions, by introducing concepts from expert systems: qualitative (symbolic, linguistic) variables, if-then rules, dealing with uncertainty, high emphasis on transparency of models and explanation of evaluation results (Figueira et al., 2005).

The most important concepts and principles adopted by the DEXi model are:

Acquisition of decision rules: Direct definitions of tables is tedious and error-prone, and computer-based assistance is vital in particular when there are large rule sets. DEXi has adapted these rules by implementing certain simple, predetermined definitions: "direct", "use scale orders", and "use weights" (Bohanec et. Al., 2013).

Validating rules: DEXi rules are simple and restricted by the scales of the corresponding attributes, compared with common expert systems. This makes them suitable for validation of completeness and consistency. This is said to help improve the overall quality of the models it produces.

"The user is always right" principle: DEXi gives precedence to information provided by the user, rather than looking for errors. Thus, any decision rule is taken literally and is never modified by the software, and instead the software only provides an error label.

Dynamic aspects of model creation: The model provided as an example above in fig 12 is considered static. But in reality, the model is constantly changing and improving. Parts of the model are created, extended, moved or deleted. These operations must be supported by appropriate algorithms so that the information already contained in the model is retained as much as possible and handled within the decision rules.

Bridging the gap between qualitative and quantitative MCDA: Traditional MCDA relies heavily on weights to define the importance of attributes. There are no weights in decision rules, however it turns out that it is practically important to deal with weights, so these are included into the DEXi model as well. Partial transformation is possible to achieve in two ways: 1) weights are estimated from defined rules by linear approximation, and 2) the values of undefined decision rules are determined on the basis of already defined rules and user-specified weights.

Handling uncertainty in alternatives and rules: An expert system must, by definition, be able to deal with incomplete and uncertain knowledge. This is done by using probabilistic distribution rules in decision-making as supported by the work of Znidarsic et al. (2008).

Transparency and explanation: It is essential that DEXi models appear transparent and comprehensible to the user. DEXi provides mechanisms for presenting decision rules from a ID3-based decision tree learning algorithm.

Analyses of alternatives: As mentioned in chapter 4.2, evaluation of alternatives is an important part of DEXi. The decision support methodology has to provide advanced tools for the analysis of alternatives, including methods like "what-if" analysis, "plus-minus-1" analysis and "selective explanation" (Bohanec, M et al, 2012).

4.3. The Gangway Decision Support Model

Figure 16 is extracted from Erdogan et. Al`s (2018) DEXi tool and presents the layout and attributes that are included in the algorithmic model. Each attribute is assigned a name, with respective sub attributes. The main model that receives all the input data is called "Gangway operational risk" and is feed by 4 attribute categories:

1) Flotel criticality state
2) Gangway criticality state
3) Weather
4) Installation criticality state

The above main categories receive different input from several sub attributes included in the categories, that feed information to the hierarchy category (the model). The totality of the information received is then processed and the model gives four different scales for which state the gangway should be in.

Value	Description
3. Abandon operation	There are very strong reasons for disconnecting the gangway; an auto lift or other incidents are likely.
2. Prepare to abandon operation	There are strong reasons for disconnecting the gangway. Preparations for disconnection should be considered.
1. Advisory state	If already disconnected, the gangway should remain so. If it is currently connected, it may remain connected.
0. Normal state	The gangway may safely be (or remain) connected.

Table 4 - Scale for top attribute Gangway operational risk (Erdogan et. al. 2018)

The four values in table 4 represent all the possible advice states that the model can produce. Risk is presented in decreasing order meaning that "Abandon operation" is the least desirable state, while "Normal state" is the best possible scenario for the gangway operation.

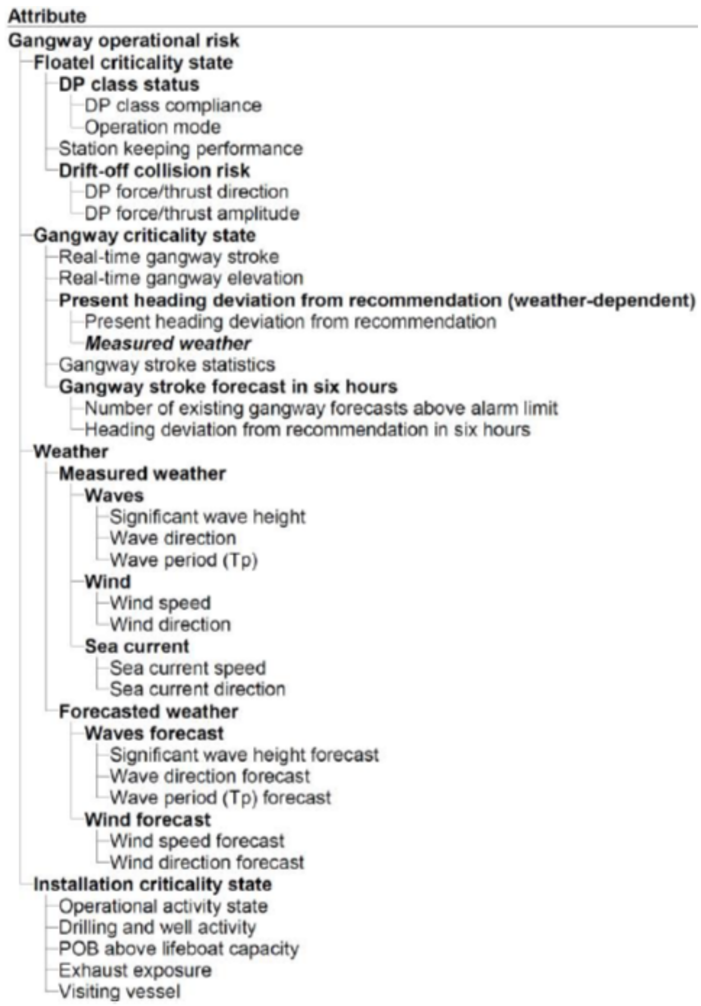

Figure 16 - DEXi model structure (Erdogan G, et. al, 2018)

The first main category is *"Flotel criticality state"* which solely capture the factors that influence the flotel. DP class status refers to the dynamic positioning system and is dependent of *DP class compliance* and *Operation mode*. *DP class compliance* is an attribute that logs the degree to which the redundancy of sensors, actuators and controllers follow the necessary requirements. A loss of redundancy will lead to a higher risk of not being able to control the flotel`s position thus increasing the probability of a collision or collapse of the gangway bridge.

The attribute referred to as Operation mode records whether the flotel is kept in position using only the DP system, thruster assisted mooring (which is a combination of the DP system and standard mooring) or only mooring lines. The *DP class status* attribute ranks over the attributes *DP class compliance* and *Operation mode* as the importance of fulfilling the DP system redundancy requirements depends on to which degree the DP system is currently used to keep the flotel in position.

The sub attribute *Station keeping performance* gathers its input data from the position the flotel is in in real time, and its ability to remain within the preferred/safe position and heading in relation to the offshore installation. Finally, the last input for the *Flotel criticality state* we find the *Drift-off collision risk* sub attribute. This attribute represents the risk imposed by the flotel drifting too far out from its desired position, resulting in a collision with the offshore installation. The risk is dependent on the thrusters and their ability to withstand the forces exerted on them from any given direction, meaning that the thrusters should be able to counteract the forces that waves, winds, etc. produce. The DP system then records these force inputs and adjusts for this in the *DP force/thrust direction* and *DP force/thrust amplitude* sub attributes.

"Gangway criticality state" is the second main category and captures factors that are relative between the flotel and the offshore installation. Stroke and elevation of the gangway bridge are essential features that need to be recorded by sensors. These numbers need to stay within the fixed limits that are considered safe, or it could result in a catastrophic failure and loss of the gangway.

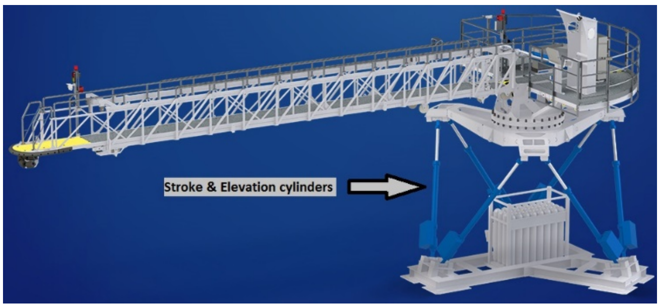

Figure 17 - Stroke & Elevation cylinders for gangway bride (Ampelmann, 2019)

These factors are recorded in the sub attribute categories *Real-time gangway stroke* and *Real-time gangway elevation. Present heading deviation from recommended heading (weather dependent)* relates to the flotel remaining in a heading (degrees) relative to the offshore installation that is within safe limits. It also must be emphasized that these heading limits are weather dependent, meaning the recommended limits are dynamic. The number of times the stroke of the gangway has exceeded its fixed limit during a 10-minute period is captured in the *Gangway stroke statistics* sub attribute and is a crucial indicator for situations that could lead to an involuntary gangway disconnect. The last attribute is *Gangway stroke forecast in six hours* which gets its data from a stroke prediction system used to forecast the expected deviation from the recommended heading in the next six hours.

The third main category is *Weather*. This is again spilt into two sub attributes; *Measured Weather* and *Forecasted Weather.* Measured weather records and measures the real-time weather at the location, with appropriate sensors and measuring equipment (wind, waves, etc.) and feeds the model and operation room this data. Forecasted weather captures data from several forecasts (as there are deviations in the accuracy of predicting future weather) in the immediate future. These two sub attributes are used as a form of elementary redundancy for each other. By looking at forecasted weather one can estimate when there is a safe time space to performing the work tasks as demanded.

The final main category is *"Installation criticality state"*. This category involves aspects that affect the offshore installation as it is connected to the flotel via the gangway bridge. This category is split into 5 sub attributes that focus on operational, safety and managerial input data. *Operational activity state* records input data from what type of activity or operation that is being conducted at the offshore installation. The activity could range from maintenance work to production, which each carry with them different levels of risk depending of what activity is currently ongoing. *Drilling and well activity* carry with it the same as for *Operational activity state*, with the fact that the risk picture is alternating depending on what activity/sub-activity that is being carried out.

POB (Personnel on Board) focuses on the demand for lifeboats when there are more maintenance crew from the flotel on the offshore installation than what the installation is designed for, regarding lifeboats. If there are more personnel onboard than there are available lifeboats the gangway has to either remain down to ensure a safe evacuation, or the personnel has to be retracted back to the flotel in good time before the tolerable limits are close to being succeeded. *Exhaust exposure* is an attribute which looks at the issue regarding exhaust produced by the offshore installation that exceeds the safe level, causing personnel to vacate the installation. Finally, *Visiting vessel* is taken into the equation, to factor for those cases where for example a supply vessel is in the vicinity and could cause an increased collision risk.

4.4. The algorithmic framework of the model

The model is designed as an expert system that uses rule-based algorithms supported by the ID3 decision tree. As the model is built up on rule-based algorithms for decision-making using expert knowledge, there has been identified advantages and disadvantages related to utilizing this method for developing a model for making risk-based decisions to aid as decision-support.

4.4.1. Natural knowledge representation

Rule-based expert systems like the gangway model, are good tools for representing natural human knowledge that experts might have obtained throughout years of experience, were the goal is to guide the model by giving strict commands to the algorithm based on IF-THEN statements.

An example would be for the "Installation criticality state" where an expert would state that in a situation where: are there personnel onboard the offshore installation exceeding the lifeboat capacity? This would be the IF in a rule-based expert system. The output of this IF rule would then either be "Yes" or "No" depending on the LSOG data the experts have chosen as their acceptable figure. This is where THEN in the rule-based system would occur, telling the system to either do one action dependent on the state of the personnel onboard versus the number of available lifeboats present, and the knowledge is all determined by the expert in advance, and programmed into the computational ID3 algorithm that the software DEXi is built upon.

Natural knowledge representation is evaluated to be one of the main advantages of using a rule-based expert system for decision-making, as it is a uniform structure. Each rule is represented as an independent piece of knowledge that can be self-documented, meaning that the produced rules have a uniform IF-THEN structure that it is easy to categorize, identify and follow up.

4.4.2. Knowledge separation

In expert systems, and especially rule-based ones, knowledge is separated from the processing. What this essentially means is that the interference engine, the DEXi software, and the knowledge base that forms the underlying input information from the experts are split up into separate structures. This is very different from conventional computer software were knowledge and control structures are mixed together.

Knowledge separation allows for easy manipulation and alteration of the built model, as one simply can add new rules to the model that directly impacts the knowledge without having to redesign the model based on new knowledge input.

4.4.3. Managing incomplete and uncertain knowledge

Rule-based expert system algorithms are in general quite capable of dealing with incomplete and uncertain knowledge. This is considered as a positive attribute for the gangway model, as there have been identified scenarios were the data is incomplete, outdated or irrelevant, so the need to being able to handle this incomplete data is crucial for the integrity of the model and the application in risk management. This is explained in more detail in chapter 4.5.1.1 Input Data.

4.4.4. Inability to learn

Being able to learn is a crucial success factor from any task in general. And when one considers risk management, the ability to learn has proven even more crucial towards the path to success. This is where the model struggles the most by utilizing a rule-based algorithm as part of its framework, as it is incapable of learning by itself, but is rather dependent on being programmed every time there is a change in experience and knowledge.

Human experts when faced with change in knowledge know how and when to break the given "rules" for the situation they are dealing with. Rule-based algorithms on the other hand are incapable of automatically modifying its knowledge base, or adjusting existing rules as well as adding new rules.

4.5. Impact on Risk Management

After analyzing decision-making principles, the gangway decision-support model, expert systems in general and the use of an algorithmic framework for supporting gangway bridge decisions, the use of a rule-based algorithm as a theoretical backbone will be analyzed in regards to the broad topic of risk management. Several factors such as risk aversion, the expected utility theory, the sociotechnical perspective and the cautionary principle all play a vital role in factors that fall under the category referred to as algorithmic risk in models.

4.5.1. Algorithmic risks

Algorithmic risk is a phenomenon that arises when one uses cognitive technology-based algorithms in software and in data analytics for semi-automated decision-making scenarios. (Deloitte, 2019). "Risk-Based Decision Support Model for Offshore Installations" is a model that fits that description perfectly as it aims at guiding a decision-maker (the operator) into making a decision that minimizes risk with the use of an algorithmic framework.

With the use of algorithms in the context of decision-making several factors are vulnerable to algorithmic risk, as illustrated by figure 17:

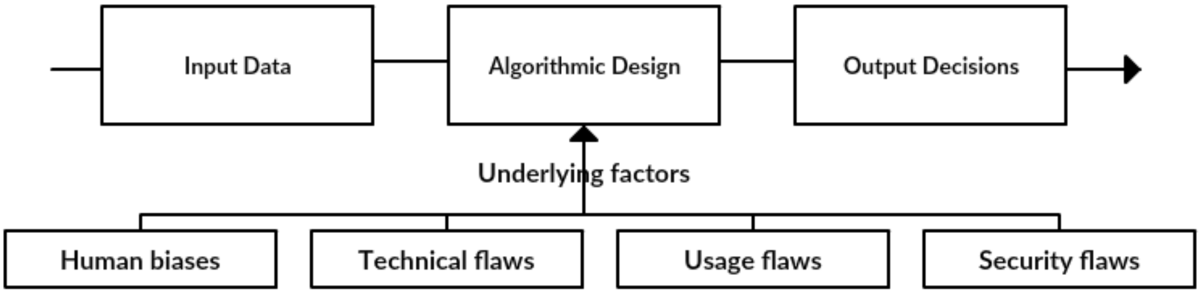

Figure 18 - Framework for understanding algorithmic risk, adopted from (Deloitte, 2019)

4.5.1.1. Input data

Input data is the information that gets fed into the model. The data comes from multiple sources, a total of 28 sub nodes, that uses both predicted and real time measurements. Risks related to data inputs are discovered to be incomplete, outdated and/or irrelevant data, and mismatching between data used and actual data input. There are several risks related to these nodes and their belonging data:

- The Weather attribute could suffer from irrelevant, incomplete and outdated data:
  - **Incomplete**: Some factors to the forecasted weather might not be available for a given date.
  - **Outdated**: The forecasted weather might have changed dramatically due to some weather phenomenon, resulting in data inputs that are way off relative to what was the data basis to start off with as an input
  - **Irrelevant**: Wind direction forecast, Sea current direction, Wind direction and Wave period are all examples of input data that has been included in the model, but are found to have no impact on the actual output decision, and is only included for completeness. This could lead to the risk of data clutter and confusion while implementing the model.
- Installation criticality state attribute suffers from:
  - **Mismatch between data used and actual data input**: Exhaust exposure is a sub-attribute that uses a subjective opinion on whether there is a too high

exposure of exhaust on the offshore installation and is an attribute that does not work well with the model quantifiably.

In addition to the above identified input data risks, insufficiently large and/or diverse sample sizes; and inappropriate data collection techniques are other input data risk factors that have not been identified in the model, but are weaknesses worth pointing out with regards to algorithmic risk.

4.5.1.2. Algorithmic design

Algorithmic design is for the gangway model the framework on which the model is based on. Risks related to algorithmic design are normally linked to biased logic, misguided assumptions or judgements, and inappropriate modeling techniques.

Inappropriate modeling techniques is a risk that is quite present in the gangway model. Utilizing a rule-based algorithm for use in applications such as decision-support has proven un-fruitful or even not beneficial as stated by Tiwari et. al. 2017 and further elaborated on in chapter 4.4. There are 5 additional challenges with using a rule-based algorithm for decision-support and it is connected to the following aspects: brittleness, opacity, literalism, clumsiness and data overload, which are denoted as challenges related to using computers as decision-making tools.

A rule-based algorithm struggles to verify that every sensory data input it receives are functional in an acceptable manner, thus suffers from brittleness. The consequence of this issue is that the computational support tool is unable to provide verification to the gangway operator at the flotel on whether the tool is producing decision-support outputs that are made on false or missing sensory data inputs. If for example the gangway elevation attribute and its sensory data is corrupt, the decision-support tool will simply ignore the whole attribute, rendering it as a state 0 or “normal operation” state. The implications of this is severe, as the gangway bridge has maximum and minimum elevation limitations between -16 to 24 degrees (Erdogan et. al. 2018). If this elevation is exceeded the gangway bridge will disconnect, but the operator would have no output from the computer recommending or warning about the imminent disconnect situation, which again could result in undesirable events and potential injury. If this factor is ignored when the tool is implemented from a risk management perspective, it could result in a miss-informative risk management process (Onken and Schulte, 2010).

Opacity, one challenge related to computers as decision makers, states that rule-based algorithms have limited capabilities for expressing and explain what it is doing, and what it is planning to do next, to the human operator. Linking this to the utilitarian theory, the theory that human decision-makers tend to choose the most "attractive" alternative, it becomes clear that opacity and this theory is contradicting each other. It becomes hard to pick the most promising alternative when the outputted information from the model is confusing, and hard to interpret.

Computational decision-support tools with a rule-based algorithm as its backbone do not question nor check control operations concerning their ability to make sense in a given context, and is referred to as literalism. The algorithm does not deviate from its programmed purpose, simply following what it is programmed to do. The most prominent disadvantage related to this issue in terms of decision-support is that out of the 28 nodes that form the decision-support model, several of them have the potential to learn and adapt from the data input it receives. An example is the forecasted weather attribute were forecasted weather does not always directly relate to measured weather at the specific location. This is discussed further in appendix A, where a machine learning approach to the model is proposed.

Clumsiness is the issue of the model producing too much information, where several sources of information is considered useless. The overall effect is that the gangway operator would have to de-bug/decipher all the incoming information and determine which piece of information he/she should make the decision-basis on. This is not necessarily identified as a problem with the current model, as it is not clear how the authors plan to portray the information to the operator. It is included as a point however, as the potential for computational clumsiness is present when one deals with data from 28 independent source nodes.

4.5.1.3. Output decisions

Output decisions is the final attribute for understanding the framework behind algorithmic risk that effects the gangway bridge decision-support model. Risks related to the output decisions are: incorrect interpretation of the output, inappropriate use of the output, and disregard of the underlying assumptions.

4.5.1.4. Underlying factors

Risks mentioned above can be caused by multiple underlying factors, as shown by figure 17. There has not been identified any underlying factors that directly influence the model and its associated risks, but they are worth mentioning (Deloitte, 2019):

- Human biases:
  - Cognitive biases of model developers or users can result in flawed output. Also, lack of governance and misalignment between the organization's value and individual employee's behavior can yield unintended outcomes

- Technical flaws:
    - Technical rigor or conceptual soundness missing in the development of the algorithm, failures in testing, training and validation of the algorithm, that could potentially lead to incorrect data output.
- Usage flaws:
    - When the algorithms get implemented into either a model, or a model containing algorithms gets implemented into a system, there could be faults in the process. Also, the how the end user uses the output could be inappropriate in regards to decision-making
- Security flaws:
    - The potential for internal or external threat is there. Acts of misuse or manipulation is a possibility, that could potentially harm the decision outputted from the algorithm. Also, developers could deliberately introduce flawed outcomes.

4.5.2. Expected Utility

The gangway model analyzed does not capture any uncertainty for its attributes (Erdogan et. al. 2018). When one studies what data input it bases its decision on, it is clear that there definitely is uncertainty present in the parameters it makes its decision on. The most obvious example is for forecasted weather, and it is stated by Erdogan et. al. that there is an assessment of the uncertainty for this attribute but that it is ignored by the model. It is argued that incorporating uncertainty in the model will be to complex and that LSOG data does not include uncertainty in its guidelines.

However, as it is a fact that there is uncertainty present in the attributes contributing to the outputted computational advice, it should be incorporated into the model (Onken & Schulte, 2010). This would also allow the model to avoid one of the most common pitfalls for decision-support systems; confusing likelihood with importance. Importance is derived from the expected utility theory and maximizing this expected utility. Combining the utility theory with the available probabilities pave ways for the decision-support system to make rational decision advice based on both what the system believes and what it wants. This will make sure the model stays in line with the basic principle of decision theory, the maximization of expected utility.

The problem, however, with using EUT for a rule-based (algorithmic) decision support tool like the gangway model is that for several attributes, it is difficult to assign a probability that it can compare its utility to. In other words, when the system has to handle attributes that involve uncertainty, it becomes difficult to give weight to the EUT and more weight has to be given to the cautionary principle. From an operational/personnel perspective, EUT will not be considered beneficial, as the personnel value decisions that are motivated by safety over decisions that are motivated by economic gain.

4.5.3. The Cautionary Principle

Previously it has been elaborated that the gangway bridge model does not incorporate uncertainty for any of its attributes. But as explained in chapter 4.5.2 about the expected utility theory, the uncertainty is certainly present. Also, determining the probability for several of the attributes in the model has proven to be difficult, as their nature is based on arbitrary values.

As a result, the cautionary principle has to be implemented as there is at the current time no way for handling the uncertainty. The cautionary principle states that in face of uncertainty, caution should be the ruling principle (Aven & Vinnem, 2007). This means for the sake of implementing the model that the determined risk picture should be viewed as risk averse. Even though the likelihood of the model producing recommendations that are wrong as a result of uncertainty values that are not incorporated, one should still evaluate the recommendation output with caution and thus not follow the information blindly.

To elaborate, caution could be used in this context with relation to situational awareness (Chiappe, Strybel & Vu, 2012). Situational awareness is, when handling complex systems, viewed as a contributor for accidents occurring (Naderpour, 2014). This is because the operator has to deal with several problems and difficulties when faced with making a decision in the heat of the moment for these complex systems. What the model has provided, however, is a way for simplifying the rather complex system involved in making a decision on whether to maintain the gangway in a connected state or if it should be disconnected. Now the operator has input from the algorithmic model, that should be viewed according to the cautionary principle, on which decision that is recommended based on all attributes which again removes a lot of stress and information input for the operator, resulting in improved situational awareness. And as situational awareness is considered one of the most important cognitive human features when it comes to decision-making, the collaboration of the implemented model, cautionary principle, and human situational awareness, could help improve the overall risk picture related to gangway bridge operability and help streamline risk management for the period uncertainty is not properly incorporated into the model.

To conclude, as the cautionary principle is recommended for managing the uncertainty until improvements to the model is made, risk aversion should be the ruling view for how to manage risk related to implementation of the model.

4.5.4. The Sociotechnical Perspective

One of the issues of using computational and algorithmic models to govern the decisions to be made on an offshore installation is related to the sociotechnical perspective. Aven (2018) clarifies that for regular risk assessments the main objective is to use linear models (like event trees and fault trees) to provide a system understanding. After this understanding has been met, one then wants to quantify the risk and compare it do criteria that are predetermined and use this to guide the decision-maker in the decision-making process.

When one studies the sociotechnical perspective, that argues that complex systems like nuclear power plants and offshore installations are complex systems where safety is not properly taken into account when using the linear risk assessment models, an issue arises. When dealing with complex systems it can be argued that when predicting system performance and estimating the risk, it cannot be done accurately. When one regards the knowledge and expertise that is applied to a model, one can be certain that there will always be surprises and unexpected events that go along with it (Black swans). The definition of a sociotechnical system is:

"The concept of sociotechnical system was established to stress the reciprocal interrelationship between humans and machines and to foster the program of shaping both the technical and social conditions of work, in such a way that efficiency and humanity would not contradict each other" (Ropohl, G., 1999, Kleiner, BM et al., 2015).

Kleiner, BM et al (2015) go on to say that sociotechnical perspectives include 5 dimensions: 1) two or more persons, interaction with some form of 2) technology, 3) and internal work environment (both physical and cultural), 4) external environment (can include political and cultural, economic, educational and cultural sub-environments), 5) an organizational design and management subsystems. Meaning that sociotechnical thinking involves micro-, meso- and macro elements and that they have interconnections. In other word, the sociotechnical perspective captures the interconnection between society and technology and how interlinked the complexity of human and technological interaction really is.

Looking at the gangway model it can be argued that in a sociotechnical perspective, the model does not capture nor implement the very complexity of the system itself and the interactions it has with the personnel handling the information output from the model. The model is built up of several sensory data inputs that are quite complex, and in a risk management perspective it becomes clear according to the sociotechnical perspective that the prediction of system performance might be considered too far towards the safer side than what it is in reality. A suggestion would be to conduct a robustness- and resilience analysis of the model and all its aspects before it gets concluded whether or not risk is increased or decreased by applying the model to an operational gangway bridge

4.5.5. Risk and Decisions

Risk and decisions in relation to algorithms prove to a complex issue in regards to risk management. When making the decision to either maintain the gangway bridge connected or disconnect without the support of a decision support tool, there are three stakeholders involved: The decision-maker, the risk-taker and the benefit receiver (Holmgren & Thedéen, 2010).

These three stakeholders share a common interest in the decision being made, and all have an impact and/or a risk perception of this decision. The decision-maker for a gangway bridge would be the gangway operator; the person sitting in the control room. The risk-taker can be either the personnel walking over the gangway bridge, or the field operator, depending on which perspective one views the risk from. The personnel would be directly exposed to the risk as the potential of a disconnect could result in personal injury. For the field operator this would boil down to the fact that an un-wanted disconnect could result in increased costs and schedule, loss of personnel and equipment, and reduced reputation. The benefit receiver would be the field operator and the personnel, if the risk is managed well, as the operator would maintain schedule and budget, and the personnel would be able to continue working. The decision being made therefore should have a potential benefit for all three stakeholders involved, and is a common practice when viewing risk in relation to shareholders in regards to decision-making.

When the introduction of an algorithmic decision-support model is introduced, however, the risk picture and its belonging stakeholders change. A proposed 4th stakeholder dimension emerges when risk and decisions are involved, show in figure 18. A major stakeholder when an algorithmic decision-support model is introduced is in fact the computational decision-support model itself(Yong & Yunlong, 2012).

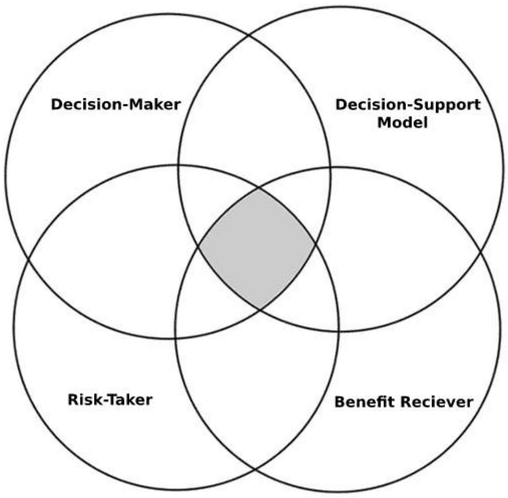

Figure 19 - Proposed framework for involved stakeholders in making a decision when guided by a computational decision-support tool (Author`s work)

As the model shows, each stakeholder can either be independent or overlapping. This implies that the risk that emerges from the decision the operator makes has a unity with all other stakeholders, and that the decision-support model has an equally large stake in the decision being made. Therefore, it becomes crucial to manage the algorithmic risk that is present within the decision-support model on the same level as risk is managed through more traditional stakeholders that regard risks and decisions when conducting a risk analysis of an entire system. Risk management related to the decision-maker, risk-taker and the benefit receiver are areas that have a strong theoretical background within risk management, and thus deviates greatly compared to the theoretical background of managing algorithmic risk.

4.5.6. Managing algorithmic risk

Managing algorithmic risks for the offshore petroleum industry does have many similarities to traditional risk management. What differentiates traditional risk management from algorithmic risk management however, boils down to two main points:

- Algorithms are possessive:
  - Proprietary data, models and techniques are normally what algorithms are based on. Many developed algorithms are trade secrets that are protected from insight due to competitive advantages by having the most effective algorithms. This could result in offshore operators utilizing algorithms that they have little to no

knowledge about and make it difficult for regulatory agencies, let alone the risk management team, to manage and monitor the risks that accompany their use.

- Algorithms are unpredictable, complex and difficult to explain:
    - The inherent complexity of algorithms is a problem, even if the developer of an algorithms chooses to share detailed information about it (Deloitte, 2019). Experts are needed to decipher the true meaning and how the algorithm actually works. In addition, the future of algorithms is based on machine learning, making it even more complex than more traditional algorithms like ID3 and rule-based ones (Chollet, 2018). And to make matters worse, machine learning algorithms have tendencies to produce their own language (especially for unsupervised machine learning), resulting in algorithmic communication between each other, that is close too impossible to decode by humans. This communication could lead to unknown risks (Deloitte, 2019).

This implies that when managing safety models containing algorithms, more weight has to be given to actual framework of the safety model, and the algorithms they are made up of in particular. Failure to get an understanding of the elemental building blocks of any model can lead to a misinformed risk management process (Burns & Anderson, 2011). So the overall impact that algorithms have on risk management for the offshore petroleum industry boils down to:

- The operator of any specific field that wishes to utilize an algorithm incorporated into its safety model should ensure that access to insight information about the algorithm is granted. This will allow for better understanding of the model itself, and thus result in a more accurate risk management process.
- Ensure that the inherent complexity of an algorithm does not justify excluding the belonging uncertainty of the safety model. Relying solely on the precautionary/cautionary principle is not a long term solution when it comes to safety models and algorithms.
- Field operators that is willing to utilize algorithms should be aware that it exists several types of technological algorithms. As an example from the gangway model, a rule-based algorithmic approach is not considered the best for a decision-support model. Research has to be done in advance to ensure that the most suitable algorithm is chosen and incorporated into the safety models, so that it suits its demand. This simple step alone will increase the

likelihood of a positive impact on risk management when utilizing algorithms in safety models.

5. DISCUSSION AND FUTURE RESEARCH

5.1. Discussion

The reviewed model had four success criteria that the model should meet to be successful, according to Erdogan et.al (2018) and as mentioned in chapter 4.1. Only three of them can be reviewed in terms of risk management, as **C4** relates to the expected benefits and how they should justify the effort in developing the decision support model, which is beyond the scope of this thesis.

With regards to **C1**, the model does provide advice that correspond with expert expectations from a gangway operational point of view. Here, the model provides advice for the gangway operator based on a total of 144 attributes that collectively form the basis for the decision-support (Erdogan et. al. 2018). And as the attributes are built up of expert knowledge and the LSOG data, the output can be considered useful in a strictly operational point of view (Turban & Aronson, 2001). There should however be made a strength of knowledge assessment of the data attributes, to further back up the claim.

C2 however, stating that "The decision support model should capture all aspects that are important for the assessment", have issues when it comes to uncertainty, especially in terms of risk management. As stated in chapter 4.5.2 Expected Utility, there is no way for the model to incorporate the expected utility of the decision being made, resulting in the decision being made only on the premises it is programmed to do, and having to rely heavily on the cautionary principle and by being risk averse (Abrahamsen, 2010). In chapter 4.5.6, it is made clear that the complexity of the algorithmic framework should not be a pillar that stands in the way for incorporating uncertainty into the decision-making process, but rather be a pillar that forms the foundation of the model (Chollet, 2018). Incorporating the uncertainty into the algorithm itself could prove to give a better basis for the decision-making process and potentially highlight unknown scenarios for the gangway operator.

C3 (The decision support model should be comprehensible for domain experts) is a success criterion that is to a certain extent not met. The basis for the output of the model is the DEXi software (Erdogan et. al. 2018). It is made clear that the output it produces is comprehensible for the gangway operators, as they have an understanding of what state it recommends and have knowledge of the attributes that are incorporated in the decision-making framework of the model. However, the backbone of the model, which is a rule-based algorithm, there is little knowledge about. Chapter 4.4 elaborate on the issues of using a rule-based algorithm as a framework for a decision-support tool, and this rises doubt on whether all aspects of the decision support model are comprehensible for domain experts. Rather on relying on a rule-based algorithm, a supervised machine learning algorithm that incorporates the underlying uncertainty is recommended for this specific task (Chollet, 2018). This will in turn provide a better and more comprehensible risk management process.

The use of algorithms in a context of risk management has potential. But it is worth noting that using algorithms carry with them risks themselves. As explained in chapter 4, algorithmic risk is a phenomenon that arises when one uses cognitive technology-based algorithms in software and in data analytics for decision-making scenarios (Deloitte, 2019). There were four algorithmic risks identified in the model related to input data: Incomplete data in the forecasted weather attribute, relating to weather data not being available when needed or not available at all. Also for the forecasted weather, the risk of the input data being outdated was identified (Erdogan et. al. 2018). Here, forecasted weather acting as input data could change dramatically due to some weather phenomenon's, resulting in the data coming into the model being misguiding relative to the actual forecasted weather. The model also incorporated input data that was considered irrelevant. Irrelevant data could lead to a model that is too complex, and lead to risks related to wrongful development. For the attribute Installation criticality state, the risk of mismatching between data used and actual data input was discovered. This could potentially lead to risk of data clutters and confusion while developing and implementing the model.

As the use of algorithms most probably will grow exponentially throughout the next couple of years, as the digital revolution is here, the need for risk management of algorithms is becoming urgent. Algorithms are complex, and often combined with advanced systems that make them difficult to analyze, let alone understand. It is therefore important to note that conventional risk management approaches may not be effective for dealing with the current issue.

The risk management community need to rethink and reengineer some of the existing risk management frameworks to be able to cope with algorithms effectively, due to the inherent nature of algorithms and how they are used within safety and decision-making processes in the offshore industry. For instance, algorithms operate and are develop in such a high pace that just monitoring the algorithms could prove to be an issue, and the only way to manage risks related to algorithms might only be possible though the use of other algorithms. This leaves us with a paradox.

5.2. Future research

As the thesis has indicated, using human expertise under a rule-based algorithm as a basis for decision-making support has proven to carry with it some difficulties. The most prominent problem is the fact that the model is unable to learn. As discussed in chapter 4.4.4, the ability to learn has proven crucial towards the search of a successful decision, and the framework of a rule-based algorithm simply does not allow for learning to be incorporated. A suggested approach would be to use the existing attributes and the key idea of the gangway model, but utilizing a machine learning algorithm instead. Using a supervised classification algorithm in collaboration with an artificial neural network will potentially allow for the model to improve on its category orientation and learn. The most promising attributes in the model when it comes to learning is judged to be: forecasted weather vs. measured weather. Here, the neural network could be able to produce rules where the forecasted weather functions as an input, and the measured weather as an output. The advantage with this approach is concluded to be the fact that forecasted weather has the ability to give a better decision-support basis, with a timeline factored into the decision-support provided to the gangway operator. This, in combination with neural networks implemented into the attributes *Flotel criticality state* and *Gangway criticality state* will eliminate the need for solely relying on expert knowledge and LSOG guidelines.

Finally, more work has to be done with incorporating uncertainty into the model. This is the only way an algorithmic decision-support model can be considered useful in a risk management perspective, unless one applies the cautionary principle. While keeping the new perspective on risk in mind, leaving out the uncertainty can be considered to be a too weak of a model, not suitable for implementation in regards to risk management.

6. CONCLUSION

Algorithms and their use will grow in the future. The amount of data being produced today is so vast that the only way to manage them is by utilizing algorithms. However, the correct algorithms have to be applied in different situations, as using the wrong algorithmic framework can lead to misguiding results. In the context of safety model in the offshore petroleum industry the use has large potential. Using machine learning algorithms to promote self-learning by the models could lead to a basis for improved safety levels and reduced accident frequencies.

It is important to manage these algorithms in the right way, especially in terms of risk management. Incorporating uncertainty into the algorithmic framework is crucial to get an output from the models that is in line with the new risk perspective. The gangway model does not utilize the uncertainties for each of its attributes, and therefore has to rely heavily on the cautionary principle to give a sound basis for risk management. Without having uncertainty to guide the model and risk management in general, one cannot get aid from the expected utility theory and the decision-support tool has to be viewed in a risk averse context.

Understanding and getting access to the often protected detailed information of the algorithm to be used within an offshore safety model is crucial for the integrity of the risk management process, and will allow for better handling of all aspects within this subject. Also, it can be argued that the future of managing risks related to the use of algorithms, will require specific risk managerial algorithms themselves.

Thus, further research and comprehensive studies have to be conducted to ensure that a sound risk management framework is in place, and that the risks related to the use of algorithms are properly accounted for.

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