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Prediction of plant-specific failure rates

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MASTER THESIS

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(Prediksjon av applikasjons-spesifikke sviktintensiteter)

When developing technical systems comprising unproven equipment, the designer is often required to come up with an initial reliability prediction for the new equipment as a basis for design decision (e.g., on configuration and redundanc). In most cases, the reliability prediction is given in terms of a constant failure rate. Since the equipment is new, the experience data is usually very scarce, if not non-existing. A reliability prediction procedure is therefore required. For electronic components, the reliability prediction is often based on the procedure in MIL-HDBK-217F. This procedure has been further developed and refined in other data sources, such as FIDES. For mechanical equipment, some similar ideas are presented in MechRel.

It is also possible to use a more physical approach and study the factors that influence the reliability and compare these with similar factors in a known application of similar equipment (if relevant). Procedures have been suggested by Brissaud et al (2011) for transmitters and by Rahimi and Rausand (2014) for subsea pumps.

Reliability prediction of new equipment is a hot topic in the subsea industry, where a lot of unproven process equipment currently has to be installed. Most of the equipment is based on similar topside items and the industry refers to the new application as "marinization" of the topside technology.

An objective of this master thesis is to perform and document a survey of existing reliability prediction approaches and discuss the pros and cons of each approach. Further, to suggest a suitable approach for failure rate prediction of new subsea process equipment that can be considered as "marinized" from topside equipment, for which ample data are available in OREDA.

Questions to be addresses and discussed as part of this master's project are:

1. What do we mean by reliability prediction?
2. What standards and guidelines are available for reliability prediction?

3. Which models and methods have been published related to reliability prediction?
4. What are the pros and cons of each of these models and methods?
5. What do we mean by “marinization” of topside equipment?
6. How can we use information in OREDA for topside equipment to predict the reliability of similar subsea equipment?
7. Can you suggest a detailed procedure for reliability prediction of new subsea equipment based on information from similar topside equipment?
8. Can this procedure be realistically implemented?

Following agreement with the supervisor(s), the questions may be given different weights.

The assignment solution must be based on any standards and practical guidelines that already exist and are recommended. This should be done in close cooperation with supervisors and any other responsibilities involved in the assignment. In addition it has to be an active interaction between all parties.

Within three weeks after the date of the task handout, a pre-study report shall be prepared. The report shall cover the following:

- An analysis of the work task’s content with specific emphasis of the areas where new knowledge has to be gained.
- A description of the work packages that shall be performed. This description shall lead to a clear definition of the scope and extent of the total task to be performed.
- A time schedule for the project. The plan shall comprise a Gantt diagram with specification of the individual work packages, their scheduled start and end dates and a specification of project milestones.

The pre-study report is a part of the total task reporting. It shall be included in the final report. Progress reports made during the project period shall also be included in the final report.

The report should be edited as a research report with a summary, table of contents, conclusion, list of reference, list of literature etc. The text should be clear and concise, and include the necessary references to figures, tables, and diagrams. It is also important that exact references are given to any external source used in the text.

Equipment and software developed during the project is a part of the fulfilment of the task. Unless outside parties have exclusive property rights or the equipment is physically non-moveable, it should be handed in along with the final report. Suitable documentation for the correct use of such material is also required as part of the final report.

The student must cover travel expenses, telecommunication, and copying unless otherwise agreed.

If the candidate encounters unforeseen difficulties in the work, and if these difficulties warrant a reformation of the task, these problems should immediately be addressed to the Department.

The assignment text shall be enclosed and be placed immediately after the title page.

Deadline: 10 June 2014.

Two bound copies of the final report and one electronic (pdf-format) version are required according to the routines given in DAIM. Please see http://www.ntnu.edu/ivt/master-s-thesis-regulations regarding master thesis regulations and practical information, inclusive how to use DAIM.

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Preface

This thesis has been for the course TPK4900-Production and Quality Engineering, Master's Thesis at Norwegian University of Science and Technology (NTNU) spring 2014. The master thesis is written within the Department of Production and Quality Engineering. It is a further research of subsea equipment reliability based on the specification project, Reliability Assessment of Safety Instrumented Systems.

When developing technical systems comprising unproven equipment, the designer is often required to come up with an initial reliability prediction for the new equipment as a basis for design decision (e.g., configuration and redundancy). In most cases, the reliability prediction is given in terms of a constant failure rate. Since the equipment is new, the experience data is usually very scarce, if not non-existing. Although several reliability prediction procedures have been proposed, none of the approaches mentioned above can be used directly to predict the failure rate of a new subsea systems. Therefore, the objective of this master thesis is to suggest a suitable approach for failure rate prediction of new subsea process equipment that can be considered as "marinized" from topside equipment.

Intended audiences are those with basic knowledge of reliability theory.

Trondheim, 24th of June 2014

Shanshan Huo

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Finally I would like to thank my family who always believe in me and support me with whatever decisions I have made. With your love and supporting, I never feel lonely when I am actually alone thousand miles away from home.

SS. H.

Executive Summary

Reliability prediction plays a critical role in the reliability engineering process. It describes the process used to estimate the constant failure rate during the useful life of the system. For electronic components, the reliability prediction is often based on the procedure in MIL-HDBK-217F; besides, several methods and models for reliability prediction have been well established. However, for mechanical and electro-mechanical equipment, there is no generally accepted method for reliability prediction.

Therefore, a literature review of available standards, guidelines, and handbooks, which provide procedures and field data for reliability prediction, is presented first. Based on these literatures, the methodologies widely used are classified into three main categories (i.e., bottom-up statistical methods, top-down similarity analysis methods, and bottom-up physics-of-failure methods).

Further, some commonly used approaches (e.g., the BORA approach, failure rate prediction with influencing factors) mostly based on the proportional hazards (PH) model developed for specific industry areas are presented. Afterwards demonstrate the principle of these approaches by giving simple examples. The discussion of the pros and cons for each approach is followed. In spite of some limitations and inaccurate of predictions, the general principles of these approaches have been used to develop new failure rate prediction methods.

On the basis of these approaches, a detailed procedure that is suitable for reliability prediction of new subsea process equipment, which aiming to overcome some of the shortcomings of the existing approaches, is suggested. The new approach makes it possible to perform a relatively complete consideration of RIFs, includes modelling of interactions between RIFs and mentioned the common cause effects among all failure modes listed.

Finally, test the applicability of proposed procedure using a simple case study on a multistage pump and compare the procedure with the approaches introduced.

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Chapter 1 Introduction

1.1 Background

In the real world, all products and systems are unreliable because they degrade with age and/or usage and ultimately fail, which have serious consequences for both the producer and user of such products. The reliability of a product depends on a complex interaction of the laws of physics, engineering design, manufacturing processes, management decisions, random events, and usage. Therefore, improving the reliability of a product is also often a complex process, involving many activities, including redesign, upgrading of materials and process improvements, as well as additional elements such as handling, storage, and shipping. All in all, it is very important for both producer and user to get to know the reliability issues (e.g. assessment, prediction, improvement, and so forth) at each stage in a product life cycle.

When developing technical systems comprising unproven equipment, the designer is often required to come up with an initial reliability prediction for the new equipment as a basis for design decision (e.g., configuration and redundancy). Reliability prediction often takes place or should take place in the early phase in a life cycle thereafter, resulting in updated predictions. This would be the case, for example, in analysis of systems where: *(i) The product is complex, often involving new technology; (ii) Reliability is critical, with lack of reliability being very costly and possibly resulting in loss of life; (iii) Overdesign is highly undesirable*, as it results in increased weight and hence highly inflated operating costs (Blischke and Murthy, 2011).

In most cases, the reliability prediction is given in terms of a constant failure rate. Since the equipment is new, the experience data is usually very scarce, if not non-existing. A reliability prediction procedure is therefore required. For electronic components, the reliability prediction is often based on the procedure in (MIL-HDBK-217F, 1991). This procedure has been further developed and refined in other data sources, such as FIDES. For mechanical equipment, some similar notions are presented in MechRel (NSWC-11, 2011).

1.2 Motivation

Reliability prediction is important for both hardware and software. When a complex system involves both, prediction of total system reliability becomes more important and difficult. This is certainly the case in analysis of any subsea equipment. Reliability prediction of new equipment is a hot topic in the subsea industry, where a lot of unproven process equipment currently has to be installed. Most of the equipment is based on similar topside systems and the industry refers to the new application as "marinization" of the topside technology.

In the subsea oil and gas industry, new systems and new technologies are often met with skepticism, since the operators' fear that they may fail and lead to production loss, costly repair interventions, and hydrocarbon leakages to the sea. Before a new system is accepted, the producer has to convince the operator that it is fit for use and has a high reliability. This is often done through a technology qualification program. An important part of the technology qualification program is to predict the system failure rate at an early stage in the system development process owing to the high cost of design modifications later in the development process (Rahimi and Rausand, 2013).

Except for those procedures in several data sources, it is also possible to use physical approaches, study the factors that influence the reliability and compare these with similar factors in a known application of similar equipment/technology (if relevant). So the situation of no clear nor agreed procedure existing, large potential economic benefits, few realistic feedback data for newly designed subsea process equipment has driven both the oil and gas companies' and mine attention to establishing a feasible and effective approach to predicting the plant-specific failure rates for which ample data are available in (OREDA, 2009).

1.3 Objective

The main objective of this master thesis is to perform and document a survey of existing reliability prediction approaches and then discuss the pros and cons of each approach. Furthermore, suggest a suitable approach for failure rate prediction of new subsea process equipment that can be considered as "marinization" from similar topside equipment.

These challenges are addressed explicitly and the main objectives are achieved through meeting the sub-goals of the thesis:

- Present existing definitions of reliability prediction and discuss the importance and difficulties of executing the prediction.
- Review some commonly used standards and guidelines for reliability prediction and discuss their scopes of application as well as limitation.
- Perform a literature review to study different methods and models that have been published related to reliability prediction and give a general classification for these methodologies. Furthermore, discuss the pros and cons of these methods and models.
- Develop a detailed procedure for reliability prediction of new subsea equipment that can be considered as the "marinization" of topside equipment based on the information of similar topside equipment and explain the improvements of this approach comparing to existing approaches afterwards discuss the limitation and difficulties during implementing.
- Demonstrate the new approach through a case study involving the information from OREDA for topside equipment to predict the reliability of the subsea equipment.

1.4 Assumptions and Limitation

Failure rate predictions are based on the following assumptions:

- The prediction model uses a simple system with all components in series.
- Component failure rates are assumed to be constant for the time period considered.
- All failure modes listed in the following approaches are considered to be independent.
- No distinction is made between complete failures and drift failures.
- Process weaknesses have been eliminated.
- The control of probability of failure on demand (PFD) can be achieved through the control of changes in RIFs

Due to the limited time and knowledge, many relevant issues are not included in this master thesis. Some of them do not influence the estimate of system failure rate a lot, others are very difficult to analysis owing to the lack of new system design or else. The issues that are not considered in the thesis are:

- Results are dependent on the trustworthiness of data input.
- Only a few critical failure modes and failure causes are considered in the case studies. Therefore, it is not possible to obtain an accurate estimate for the plant-specific equipment.

- The interactions between RIFs are mentioned and a practical analysis model is presented. However, due to the high workload, we do not include the interaction effects into failure rate calculation.
- A comprehensive and thorough reliability influence factors (RIF) consideration is very important for getting a realistic estimate. Therefore, the RIF model should contain factors of technical, operational, human, as well as organizational aspects. Due to the difficulty of measuring human and organizational factors, we choose only two RIFs relating to human error for simplification.
- We assume the design and materials difference between topside and subsea equipment could be ignored since there is no available information and data.
- In some approaches, they followed standards and guidelines that are established for electronic devices rather than mechanical equipment.
- Common cause effect is mentioned but not analyzed quantitatively.
- In general, redundancies cannot be modelled.

1.5 Structure of the Report

This master thesis is structured as follows:

- Chapter 1: A literature review was undertaken to identify the problem, objectives, limitations and structure of the thesis.
- Chapter 2: Present the necessary background information and concepts to readers. Introduce and discuss existing methods and models used for reliability prediction presented in several standards e.g.,(MIL-HDBK-217F, 1991), give a general classification for these methodologies. Furthermore, discuss the pros and cons of these methods and models.
- Chapter 3: Elaborate some approaches developed for specific industries or issues. Demonstrate the principle of these approaches by giving simple examples.
- Chapter 4: Suggest a detailed procedure that is suitable for reliability prediction of new subsea equipment. Test the applicability of proposed procedure using a simple case and compare the result with the approaches introduced in chapter 3.
- Chapter 5: Present the summary and conclusions for this thesis, and then propose recommendations for further work.

Chapter 2 Reliability prediction

This thesis aims at dealing with various aspects related to failures of equipment or systems that are “marinization” from topside technology. The study of these topics requires that we begin with a good and clear conceptual understanding and have a framework that allows us to integrate the various issues involved in an effective manner. In this chapter, we discuss the basic concepts needed and define the scope of methodologies, guidelines, methods and models that we are going through.

2.1 Concepts of Reliability Prediction

In this thesis, we deal with some of the key engineering, analytical, and statistical tools used in reliability prediction indicating their roles in the reliability prediction process. Reliability predictions are made in many contexts. To set the scene, in this section, various definitions of reliability prediction with respect to a product life cycle are introduced.

Reliability prediction describes the process used to estimate the constant failure rate during the useful life of a product. This however is not possible because predictions assume that (EPMSA, 2005):

- The design is perfect, the stresses known; everything is within ratings at all times, so that only random failures occur.
- Every failure of every part will cause the equipment to fail.
- The database is valid.

These assumptions are sometimes wrong. The design can be less than perfect, not every failure of every part will cause the equipment to fail, and the database is likely to be at least 15 years out-of-date. However, none of this matters much, if the predictions are used to compare different approaches rather than to establish an absolute figure for reliability. This is what predictions were originally designed for.

Some prediction manuals allow the substitution of use of vendor reliability data where such data is known instead of the recommended database data. Such data is very dependent on the environment under which it was measured and so, predictions based on such data could no longer be depended on for comparison purposes.

As noted previously, there are many instances where prediction and/or assessment of product reliability are desired or even may be essential. These may occur in the various stages of product design, development, and testing, production, and operations, and continue nearly until product worn out. Reliability prediction could be used for many objectives (Sinnadurai et al., 1998) (Pechta et al., 2002) including:

- Determining if the generic requirements for materials, parts, components, and so forth are achievable;
- Performing trade-off studies;
- Setting plans for developmental testing;
- Planning for design improvements;
- Providing a basis for evaluation of reliability growth;
- Helping to achieve a reliable manufacturing process;
- Setting of factory standards for accept/reject decisions;
- Cost analysis, including life cycle cost studies;
- Identifying and ranking potential reliability problems;
- Aiding in business decisions (e.g., warranty planning, spare provisioning, budget allocation, and scheduling) and regulatory and certificatory concerns);
- Establishing baseline for logistic support requirements (e.g. maintenance, spares, and upgrades)

Therefore, to be meaningful, reliability prediction must be done in the context of specified goals. Thus target values for reliability must be set up, used as benchmarks, and modified as necessary as further information is developed, cost factors are analyzed, and realistic, achievable goals evolve. In the following section (section 2.2), several methodologies and models used in the industry are presented and furthermore, how they fulfill the aforementioned objectives are discussed.

Reliability prediction has many roles in the reliability engineering process. The predictions can be used for assessment of whether reliability goals e.g. MTTF (mean time to failure) can be reached, evaluation of alternative designs and life cycle costs, the provision of data for system reliability and availability analysis, logistic support strategy planning and to establish objectives for reliability tests.

The impact of proposed design changes on reliability is determined by comparing the reliability predictions of existing and proposed designs. A reliability prediction can also assist in evaluating the significance of reported failures. For the most cases, reliability predictions are made in the early stages of the design and development of an item (i.e., prior to its actual operation). And then the products are ordinarily modified and refined in later stages of its life cycle, and, as testing is done and other information is obtained, prediction progresses to assessment of actual reliability. Therefore, it is necessary to undertake a careful analysis of potential failures and their underlying causes. Failure modes and effects analysis (FMECA) and fault tree (FT) analysis are two of the principal tools used for this purpose.

Typical tasks in reliability predictions are:

- Prediction of the reliability of a system for a given design and selected set of components;
- Prediction of the reliability of a system in a different environment form those for which data are available;
- Prediction of the reliability of the system at the end of the development program.

In summary, reliability prediction deals with evaluation of a design prior to actual construction of the system. It is an attempt to evaluate the consequences of decisions made before the system is built and/or put into industry. It deals with analysis using models rather than actual systems and provides a basis for testing planning, manufacturing, and evaluation of reliability growth, maintenance, and other management activities.

2.2 General reliability prediction methodologies

The method used for reliability prediction is often a matter of contention. It is understood that the benefits of a reliability prediction are dependent on the accuracy and completeness of the information used to perform the prediction and on the other methods used to conduct the prediction (Pechta et al., 2002). The correct way to know the reliability of a product is the collection of field returns, the analysis of the data and then failure analysis of the failed parts.

A wide range of reliability prediction methodologies is available today for electronic systems. According to (Foucher et al., 2002) the commonly used reliability prediction methodologies can be classified into some categories easy for understanding. The most common reliability prediction methods and their latest update are listed in Table 1.

These methods listed above have been grouped into three types:

- Bottom-up statistical methods (BS);
- Top-down similarity analysis methods based on external failure database (TD);
- Bottom-up physics-of-failure methods (BP).

The first two types use statistical analysis of failure data while the last one refers to the use of physics-of-failure (PoF) models. There had been several articles on the merits and demerits of the statistical methods of reliability prediction. Detailed introduction to these three types of methods will be discussed in the following sub-sections. The different instances for applications are also clarified.

Table 1 Non-exhaustive list of assessed reliability prediction methods and their updates

BS	SAE[a] reliability prediction method	1987
	Mil-Hdbk-217	1995
	Telcordia SR-332	1997
	CNET[b] RDF-93 Corrected 1999	1993
	CNET RDF-2000	2000
	British Telecom HRD-5	1995
	Siemens SN29500	1999
	NTT[c] procedure	1985
	Reliability Analysis Center PRISM	2000
TD	Honeywell In-Service Reliability Assessment Program (HIRAP) similarity analysis method	1999
	REMM Reliability Enhancement Methodology and Modelling	2001
	DERA[d] Transport Reliability Assessment and Calculation System (TRACS)	1999
BP	Airbus-Giat use of manufacturer testing results	1999
	CADMP, calcePWA, calceFAST (CALCE EPSC[e], University of Maryland) software	2001

[a] Society of Automotive Engineers (USA)

[b] Centre National d'Etude des Télécommunications (France)

[c] Nippon Telephone & Telegraph (Japan)

[d] Defence Evaluation and Research Agency (UK Ministry of Defence)

[e] Computer Aided Life Cycle Engineering (CALCE) Electronic Products and System Center (USA)

2.2.1 Bottom-up statistical methods

BS methods use prediction models developed from statistical curve fitting of component failure data, which may have been collected in the field, in laboratory or from manufacturers. These models are dependent of the component manufacture and incorrectly assume that the failure rate of each electronic component is constant over time, the system or equipment failure causes are inherently linked to components whose failure are independent of each other, and the failure rate for a complete product could be determined by adding together the failure rates of all components. As the causes of failure in the field are rarely determined, tradeoffs between competing technologies a baseline for reliability assessment, or the extension of these models to new products or to new applications are inadequate (Pecht and Dasgupta, 1995).

The methods used in BS methods are mainly based on two types:

- Failure rate prediction at reference conditions (parts count method)
- Failure rate prediction at operating conditions (part stress method)

As shown in Table 2, "parts count analysis" models assume that the component operators under typical operating conditions, whereas "part stress analysis" models require an input of parameters that are included in the models of the component failure rate, λ. Although the parts count methodology is available for use, the focus is on the part stress methodology for most accurate results. The explanations to these equations can be founded in (Foucher et al., 2002).

Table 2 Examples of models used in BS methods for microcircuits

Parts count	$\lambda = \lambda_G \prod_Q \prod_L$ (Mil-Hdbk-217)	(1)
	$\lambda = \lambda_a \prod_Q$ (CNET)	(2)
Parts stress	$\lambda = (C_1 \prod_T + C_2 \prod_E) \prod_Q \prod_L$ (Mil-Hdbk-217F)	(3)
	$\lambda = (C_1 \prod_t \prod_T \prod_V + C_2 \prod_B \prod_E \prod_s) \prod_Q \prod_L$ (CNET)	(4)

The models may be detailed as in the last project of CNET, known as RDF2000 (IEC62380, 2004), see (Telecommunications, 1993), where models have been defined for boards and hybrid circuits as well (UTEC80810, 2000).

2.2.2 Top-down similarity analysis methods

Top-down similarity analysis methods based on proprietary databases (TD) use similarity analysis between previous system or sub-systems with a known level of reliability and newly designed systems. This is the very useful for predicting the failure rate of new subsea equipment and will be used in the case study in chapter 4. All failure causes, not only component failure rates are considered and therefore, failure cause analysis is of the utmost importance.

A typical TD approach is summarized by the following steps:

- Collection of failure data from the field;
- Assessment of field data (particularly equipment/board failure causes, calculation of the associated reliability);
- Determination of failure rates at the circuit card assembly (CCA) level, based on the number of unique CCAs per equipment;
- Determination of the failure rates at the piece part and interconnect levels based on the number of piece parts and interconnects per CCA;
- Determination of the failure rates for equipment/board failure causes not related to piece parts and interconnects;
- Creation of the in-service failure rate database with all previous pieces of information according to the following physical model categories: passive (low/high complexity), interconnections, semiconductor (low/high complexity), manufacturing process, design process, other failure causes;
- Comparison of existing to proposed designs or similarity process with the following steps:
    i. Review products for which field data is available;
    ii. Identify characteristic differences (e.g., design, manufacturing, and so on)
    iii. Quantify the impact of the characteristic differences on each physical model category;
    iv. Incorporate field data (percent of each physical model category, overall end item or assembly failure rates);

v. Compute the new item (board, CCA or equipment) failure rate according to:

$$\lambda = \lambda_p \sum_{a=1}^{n} (D_a \times F_a d) \quad (1)$$

Where λ_p is the field failure rate for the predecessor item, D_a is the distribution percentage for physical model category a, F_a is the difference factor between the new and previous items for category a, and n is the total number of physical model categories.

2.2.3 Bottom-up physical-of-failure methods

Due to the unrealistic assumptions used in BS and TD methods, reliability predictions are usually far from accurate. Manufactures begin to use physics-of-failure methodology, which incorporates reliability into the design process, in an effort to prevent parts from failing in service. A new criterion for judging failure models, their applicability, utility and design implications were established and constant definitions of failure, failure mechanism, failure modes and production confidence were developed and used.

Therefore, BP methods requires comprehensive knowledge of the thermal, mechanical, electrical and chemical life cycle environment as well as processed leading to failures in the field in order to apply appropriate failure models. This type of prediction method has been used quite successfully in the design of mechanical, civil, and aerospace structures. It is almost mandatory for buildings and bridges, because the sample size is usually on, affording little opportunity for testing the completed product, or for reliability growth. However, electronics packaging and interconnection community is lagging behind in adopting physics-of-failure methods.

The first BP method listed in Table **1** uses the manufacturer’s reliability data test results (highly accelerated stress test, temperature humidity bias, and temperature cycling …) at the component level. These data are computed with the help of statistical laws with confidence levels generally set at 60%. The ways to get accelerate factors (AF) can be found in the detailed acceleration models proposed by (Charpenel and P, 1997). The component failure rate is the sum of all the failure rates (thermal, humidity, voltage, thermal cycling). The board failure rate is the sum of all the failure rates of the components.

The highest level of BP methods (CALCE software) predicts the time to failure of board or component by targeting the most common failure mechanisms at various sites of the component assembly. Required information includes material characteristics, geometry, environmental, and operation loads. Detailed description can be found in (McCluskey, 2001). The reliability of a system is the reliability of the weakest point in the system with the associated failure site, mode, and mechanism identified.

2.2.4 Discussion of applicability of these methods

The discussion focuses on the following areas: the sources of the data, the inputs, the sensitivity of the models and the outputs.

Generally, the more generic the sources of data and environment they come from the better. However, each method considers the environment differently: BS methods use environmental and load fitted factors (for operating mode with or without storage) based on failure modes (not causes) whereas BP methods use load profiles. This is because that the environment for the BS methods derives from the failure databases that may be hampered by the following issues:

- A large amount of experimental data is required to set up representative fittings;
- These fittings become pessimistic over time because of data aging and component reliability improvement;
- New technologies are conservatively dealt with, although PRISM (Denson, 1999) and CNET(Telecommunications, 1993) latest issues then to address this problem;
- Extrinsic and intrinsic failures are mixed and are used to get aggregate failure without mathematical or physical justification.

Similarly, TD methods need a regular updating of their failure in-service databases, which depends on the companies policies and investments. Eventually, all removals need to be analyzed, failures tracked down and failure rates stored for each cause of failures at each level. The inputs to the methods are summarized in Table 3.

In most cases with BS methods, the result reflects the reliability of the components, which are no longer the main contributors to the system reliability due to quality improvement and system increased complexity (system level failures are overlooked). Results with TD methods could be refined by a large use of tests and field data. BP methods like CALCE software need a detailed knowledge of information, which might be considered as proprietary by manufacturers. These methods also require significant time resources. A prior knowledge of failure mechanisms of failed products is also need to choose models geared to actual failure mechanisms.

Table 3 Inputs to the different reliability prediction methods

Method	Inputs
BS	Part types, count and quality level Application environment System configuration
TD	Failure rates of several similar items Characteristic differences
BP	Material properties Design characteristics Assembly techniques Usage environment Functional loads

The elements that measure the sensitivity of the models differ among these methods. In BS methods, the sensitivity to operational and environmental parameters varies and the predictions are optimistic or pessimistic depending on the application. However, the models account for a great deal of components and their implementation is easy to use. This is halfway from TD methods, which models account for internal design and manufacturing failures at a high level. When considering BP methods, a difference shall be made between Airbus-Giat and CALCE methods.

The outputs of the methods are quite different. BS methods provide the users with an average failure rate of the average production. Failures are considered to occur randomly and failure rate is therefore considered as constant. TD methods output a failure rate, which is monitored over time. This failure rate is an average of a given production. Failure causes are identified but no confidence level is provided. The outputs from BP methods differ. Some deliver an average failure rate of a given production, while some deliver a time to failure for the component.

Based on the discussions above, Table 4 rates subjectively the characteristics of these methods in view of a set of criteria deemed appropriate. As can been seen no single method addresses all criteria comprehensively: tradeoffs need to be made between the models usability and the required amount of detailed information.

Table 4 Comparison criteria for use

Comparison criteria	BS	TD	BP
Accuracy	Relative	Absolute	Absolute
Ease of data exchange	Easy	Difficult	Easy
Amount of devoted resources	Small	Important	Extensive[a]
Time to obtain reliability estimate	Short	Short	Long
Ease of customization	No	Yes	Yes
Traceability	Difficult	Easy	Easy
Repeatability	High	Medium	Low
Ability for evaluation	Difficult	Yes	Yes

[a] If no material, part, or board library is available

Not all these criteria bear the same significance. Accuracy, amount of devoted resources, ease of customization and ability for evaluation seem to be more important to be achieved. Detailed description can be found in.

There is another way to weigh up the different methods. Table 5 rates BS, TD, and BP methods compared to the satisfaction of the objectives stated in the introduction. This is a subjective evaluation of the methods and their ability to contribute to the overall reliability availability maintainability safety assessment process. However, it shows that BP methods are fit for design trade-off, board qualification, and manufacturing improvements.

BP methods are fit for design trade-off, quantification, and manufacturing improvements. BS empirical data-based methods are appropriate for delivering an average reliability figure for an average production, which may be appropriate for the following stages: selection and management of components figure of merit comparison, warranty, maintenance planning, and contract negotiation.

At the current level of availability of tools, TD methods offer a very good trade-off and satisfy most of the objectives, but one should remember that they cannot be standardized as most data are proprietary. PRISM (Denson, 1999) could lead the way to TD method standardization. Nevertheless, some methodologies of PRISM, which can be considered as a mix between BS and TD, may avoid the need for large internal failure data collection.

Table 5 Comparison criteria as management of objectives

Objectives	BS	TD	BP
Determine if a reliability requirement is achievable	Low[b]	Yes	Yes
Help to achieve a reliable design	No	No	Yes
- By tracking down overstressed parts	No	No	Yes
- By performing a failure root-cause analysis	No	Yes	Yes
- By comparing design trade-off studies	Yes	Yes	Yes
Help to achieve a reliable manufacturing process	No	No	Yes
- Assess potential warranty risks	Low[b]	Yes	No
- Provide inputs to safety analysis	Low[b]	Yes	No
- Establish baseline for logistic support requirements	Low[b]	Yes	No

[b] Use of external databases makes the reliability figure relative and therefore brings little confidence to subsequent steps of the process.

Both empirical and PoF-based reliability prediction methods present advantages as well as shortcomings. On the one hand, PoF methods can successfully be used for qualification and quality assurance in order to improve design and manufacturing robustness. On the other hand, statistical methods, based on and enriched by thorough failure cause analysis, external or internal database and similarity analysis, are fit for rapid assessment and may supply helpful figures for further steps including safety analysis, warranty risk management, and field support.

2.3 Standards for reliability prediction

Reliability specification and demonstration is an activity between customers and suppliers. In the absence of proper procedure, this activity may not meet the requirements and product needs. The methods used for reliability prediction is often a matter of contention. It is understood that the benefits of a reliability prediction are dependent on the accuracy and completeness of the information used to perform the prediction and on the methods used to conduct the prediction (Pechta et al., 2002).

Therefore, several standards, for example (IEEE1332, 1998) and (IEEE1413, 1998) have been established to streamline the process of developing a reliability program that is value added and suits the needs of both customers and supplier, and to understand the risks associated.

For complex electronic systems, reliability prediction is often carried out in parallel with the product design, prototyping, and volume shipment. During the early design phase, reliability prediction provides preliminary knowledge about the lifetime of the new product. MIL-HDBK-217 and SR-332 have been widely used as the guidelines in the industries to forecast the new product reliability (Jin et al., 2010).

These approaches need relevant resources and a large amount of field hours. The economic constraints allow this approach to be used only by large companies. Small companies usually want to obtain a reliability figure, which can be obtained with limited effort; therefore, the use of "reliability handbook" is necessary (Cassanelli et al., 2005).

IEEE 1332

It was developed for the development and production of electronics systems and equipment. The aim was to ensure that every activity during the development of the product adds value and that the customer's requirements and products needs are met, which is achieving by satisfy the following three objectives.

- The supplier shall work with the customer, to determine and understand the customer's rudiments and product needs;
- The supplier shall structure and follow a series of engineering activities to meet those requirements and needs;
- The supplier shall include activities that assure the product need have been satisfied.

The standard guides suppliers in planning a reliability program that suits their design philosophy, the product concept, and the resources at their disposal. It has found wide acceptance in many industries.

IEEE 1413

The IEEE reliability prediction standard 1413 was developed to identify the key required elements for an understandable and credible reliability prediction, and to provide its users with sufficient information to select a prediction methodology and to effectively use the results. A prediction complying with this standard includes sufficient information regarding the inputs, assumptions, and uncertainties associated with the methodology used to make the prediction, enabling the risk associated with the methodology to be understood.

According to IEEE1413, the item for which prediction is performed must be clearly identified. This identification should be performed using the following:

- A description of the product, electronic system, or equipment;
- Product function, architecture, geometries, and materials;
- Possible redundancy;
- Hardware and software relationship and human factors;
- System level block diagram.

Since the reasons for performing a reliability prediction vary, a clear statement of the intended use of prediction results obtained from an IEEE 1413-comliant method is required to be included with final report. Besides, it should also identify the approach, rationale, and references to where the method is documented. Thus, an IEEE 1413-compliant reliability prediction report must include:

- Reasons why the reliability predictions were performed;
- The intended use of the reliability prediction results;
- Information on how the reliability prediction results much not be used;
- Where precautions are necessary;
- Definition of failures and failure criteria (i.e., failure modes and failure mechanisms)
- Description of the process to develop the prediction (i.e., assumptions made in the assessment, methods and models, and source of data)
- Required prediction format (i.e., prediction metrics and confidence level)

As specified in IEEE1413, the inputs includes, but not limited to, usage, environment, lifetime, temperature, shock and vibration, airborne contaminants, humidity, voltage, radiation, power, packaging, handling, transportation, storage, manufacturing, duty cycles, maintenance, prediction metrics, confidence levels, design criteria, and system design parameters. Besides prediction outputs, the prediction results section should also contain conclusions and recommendations.

The IEEE1413 is not a reliability prediction method and it does not replace or supplement any available prediction method. A prediction made according to IEEE 1413 ensures that the benefits and limitations of a prediction method is considered and evaluated by the engineers preparing the prediction and that the users of the prediction are aware of the same.

A guidebook for IEEE 1413

The purpose of this glide is to assist in the selection and use of reliability prediction methodology satisfying IEEE 1413, and thus making informed decisions regarding the compliance of carious methodologies to IEEE standard 1413. The guide is limited to the hardware reliability prediction methodologies and specifically excludes software reliability, availability, maintainability and human reliability. It does not discuss the company specific proprietary prediction methodologies either.

All the methods described in the guidebook are then evaluated as per the requirements established in IEEE 1413 as described in last section. The criteria used for the evaluation of these methods consist of a list of questions based on IEEE 1413 concerning the inputs, assumptions, and uncertainties associated with each methodology, enabling the risk associated with the methodologies to be identified. The assessment criteria are shown in Table 6 and their results are shown in Appendix B.

The guide reviews the engineering information assessment that is critical for developing an IEEE 1413-compliant reliability prediction and describes the reliability prediction methods such as handbooks based on historic data (MIL-HDBK-217, RAC's PRISM, SAE's reliability prediction method, Telcordia SR-332 (SR-332, 2001), the CNET reliability prediction model), predictions using field data and test data, and the stress and damage model approach. Examples of use are provided for each method.

Table 6 Assessment Criteria of Reliability Prediction Methodologies

	IEEE 1413 Assessment Criteria
1	Does the methodology identify the sources used to develop the prediction methodology and describe the extent to which the source is known?
2	Are assumptions used to conduct the prediction according to the methodology identified, including those used for the unknown data?
3	Are sources of uncertainty in the prediction results identified?
4	Are limitations of the prediction results identified?
5	Are failure modes identified?
6	Are failure mechanisms identified?
7	Are confidence levels for prediction results identified?
8	Does the methodology account for life cycle environmental conditions, including those encountered during a) product usage (including power and voltage conditions), b)packaging, c)handling, d) storage, e) transportation, and f) maintenance conditions?
9	Does the Methodology account for material, geometry, and architectures that comprise the parts?
10	Does the methodology account for part quality?
11	Does methodology allow incorporation of reliability data and experience?

IEC61709

The standard (IEC61709, 2004) "Electronic components – Reliability, Reference conditions for failure rates and stress models for conversion" allows developing a database of failure rates and extrapolating the same for other operating conditions using stress models provided.

The standard IEC 61709:

- Gives guidance on obtaining accurate failure rate data for components used on electronic equipment, so that we can precisely predict reliability of systems.
- Specifies reference conditions for obtaining failure rate data, so that data from different sources can be compared on a consistent basis.
- Describes stress models as a basis for conversion of the failure rate data from reference conditions to the actual operating conditions.

Benefits of using IEC 61709:

- The adopted reference conditions are typical for the majority of applications of components in equipment; this allows realistic reliability predictions in the early design phase (parts count)
- The stress models are generic for the different component types; they represent a good fit of observed data for the component types; this simplifies the prediction approach.
- Will lead to harmonization of different data sources; this supports communication between parties.

If failure rate data are given in accordance with this standard then no additional information on specified conditions is required. The stated stress models contain constants that were defined according to the state of the art. These are averages of typical component values taken from tests or specified by various manufacturers.

A factor for the effect of environmental application conditions is basically not used in IEC 61709 because the influence of the environmental application conditions on the component depends essentially on the design of equipment. Thus, such an effect may be considered within the reliability prediction of equipment using an overall environmental application factor.

Figure 1 provides as an example for the use of IEC61709 for developing a failure rate database and for carrying out failure rate predictions.

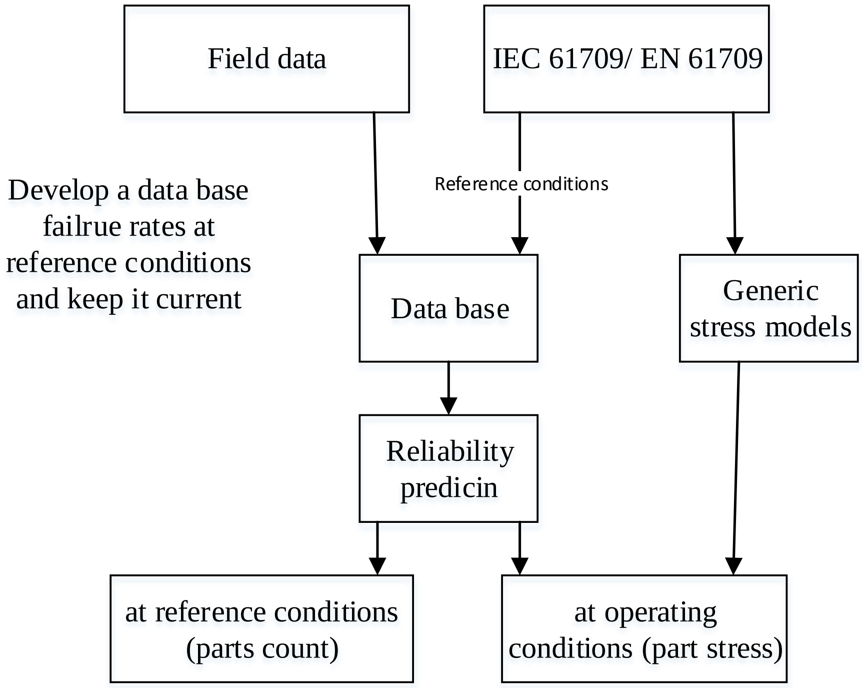

Figure 1 Prediction method

FIDES Guide 2004

The reliability methodology FIDES Guide 2004 is created by FIDES Group-a consortium of leading French companies. It is declared to be based on the physics of failures supported by the analysis of test data, field returns and existing modelling.

FIDES (FIDES, 2004) is a new reliability assessment methodology for electronic systems using COTS (commercial off the shelf), as well as electronic parts developed by boards or sub-assemblies. It is an alternative for the unsuitability of MIL-HDBK 217, lack for harsh environments of RDF 2000 and weakness in models and mission profile definition of PRISM methodology. Moreover, FIDES focused all elemental operations of the life cycle that influence the reliability through a list of reliability related recommendations allowing building the reliability of electronic systems using COTS.

The methodology for reliability assessment in electronics has two parts:

- Component reliability prediction guide,
- Reliability process control and audit guide.

It takes into account the three major contributors of the COTS reliability, which are its technology, process and use. FIDES key points are listed below:

- Accurate modelization for COTS components, electronic boards and subassemblies like hard disks or screens, allowing distinguish many suppliers;
- Identification and qualification of process contributors through the whole life cycle;
- Identification and taking into account all technological and physical factors acting on reliability for harsh environments;
- Modelization of overstresses (electrical, mechanical and thermal);
- Accurate description of any mission profiles.

The generic model consists in the product of two terms, the first one being a sum of terms of physical stress factors and the second one being the product of cycle life process contributions. On another way, the model can be written as:

$$\lambda = \lambda_{Phy} \cdot \pi_{Part\_manufacturing} \cdot \pi_{Process} \tag{2}$$

where, λ is the predicted failure rate of the COTS, λ_{Phy} is the physical contribution, $\pi_{Part\_manufacturing}$ is a factor representing the quality and the manufacturing technical control of the COTS, and $\pi_{Process}$ is a factor representing the quality and the technical control of the design process, the manufacturing and the use of the product holding the COTS. The influence of the process on the reliability is quantified from an audit of the process. A detailed example of implementation can be found in (Charpenel et al., 2003).

RIAC 217Plus

The model in this handbook has been developed by the reliability information analysis center (RIAC) chartered by UD DoD (department of defense) as an official successor of the MIL-HDBK-217F and PRISM methodology. It is based on principles of physics-of-failure endorsed by statistical analysis of empirical reliability data from many different industries and a widespread field of applications and environmental and operational profiles (RIAC-HDBK-217Plus, 2006).

The goal for developing the RIAC 217Plus was to provide prediction models that allow estimation of failure rate of various component types according to the primary failure mechanism adequately sensitive to operating scenarios and stresses with an acceptable accuracy.

- Component reliability prediction model

The component models are the mathematical sum of over the failure rate for each generic class of failure mechanisms. These include operating failures, failures caused by thermal cycling, failures associated with solder joints and induced failures.

Depending on component type, the following application dependent parameters are considered: component characteristics (e.g., capacity of capacitors), electrical stress ratio, and component internal temperature rise.

- System level model

The system level model is an optional term of the reliability prediction to account for the process applied during the product life cycle. The model is express by:

$$\lambda = \lambda_{euqipment}(\prod p + \prod d + \prod m + \prod s + \prod i + \prod n + \prod w) + \lambda_{software} \quad (3)$$

where, $\lambda_{euqipment}$is the total failure rate of the equipment, $\prod p$ is part process factor, $\prod d$ is design process factor, $\prod m$ is manufacturing process factor, $\prod s$ is system management process factor, $\prod i$ is induced process factor, $\prod n$ is no-defect process factor, $\prod w$ is wear out process factor, $\lambda_{software}$ is software failure rate prediction.

Each factor will decrease if "better than average" processes are applied and vice versa.

A comparison between FIEDS and RIAC 217Plus with field data is presented in (Held and Fritz, 2009)

The different methods have various applications, merits and limitations and some of these are listed in the following, see Table 7.

Table 7 Comparison of features of reliability prediction methods

Reliability prediction model	Application	Limitations
MIL-HDBK-217F	It provides failure rate and stress models for parts count and part stress predictions. It provides models for many component and assembly type and fourteen environments ranging from ground benign to canon launch. It is well known for international military and commercial applications and has been widely accepted. It provides predictions for ambient of 0ºC to 125ºC.	The component database omits newer commercial components and has not been updated since 1995 and there are apparently no plans for further updates. It penalizes non-military components, and predicts failure rates of some components as worse than actual performance.
Telcordia SR332/ Bellcore TR332	Updated to SR332 in May 2001. It provides three prediction methods incorporating parts count, lab test data and field failure tracking. It provides models for many component and assembly types and five environments applicable to telecommunications applications.	Predictions are limited to ambient of 30 ºC to 65 ºC.
Siemens SN29500 (derived from IEC61709)	SN 29500 provides frequently updated failure rate data at reference conditions and stress models necessary for parts count and parts stress predictions. The reference conditions adopted are typical for the majority of applications of components in equipment. Under these circumstances parts count analysis should result in realistic predictions. The stress models described in this standard are used as a basis for conversion of the failure rate data at reference conditions to the actual operating conditions in the case that operating conditions differ significant from reference conditions.	Field failure rate data are determined from components used in Siemens products while also taking test results from external sources into account. Page

Chapter 3 Methods for Predicting Plant-specific Failure Rates

As shown in section 2.2, for electronic equipment, several models and methods for reliability prediction have been well established and is often based on the parts count technique and the part stress technique in (MIL-HDBK-217F, 1991) and similar approaches such as (IEC61709, 2004), Telcordia SR 332, Siemens SN 29500, FIDES, and RIAC-handbook-217Plus.. However, for mechanical and electro-mechanical equipment, there is no generally accepted method for reliability prediction.

This may be owing to the higher number of, and more complex failure mechanisms. Several studies have shown that the reliability of mechanical equipment is sensitive to loading, operating mode, and utilization rate. Meanwhile, reliability prediction plays a really critical role in the oil and gas industry, which is moving more and more of the traditional topside fluid processing systems to the seabed. This strategy has the potential to give increased production from low-energy reservoirs and may also lead to significant cost save. A prerequisite is, however, the failures requiring subsea repair interventions will not occur.

Before an operator accepts to install a new subsea system, he must be convinced that the new system has a sufficiently high reliability. The time to the first planned intervention may be five years, and even longer, and it is important that the installed system is able to survive this period without any failure.

The operator will usually specify strict reliability requirements for the new subsea system and require the supplier to follow an agreed technology qualification program (TQP) during every phases of a lifecycle including design, development, and manufacturing phases. These reliability requirements may be stated according to (IEC61300-3-4, 2008) and should be based on (1) the application of the system; (2) the failure criteria, i.e. what constitutes a failure of the system with the intended application; (3) the operating conditions; and (4) the environmental conditions.

System reliability requirements are usually required to be expressed in terms of several different quantitative measures, such as the failure rate, the survivor probability, MTTF and so forth. Due to the critical role of reliability performance for subsea systems, dependability criteria such as PFD therefore have to be evaluated. To perform such analyses, the relevance of existing models (e.g., RBD, FT analysis, Markov process) strongly depends on the quality of input data such as failure rates, maintenance characteristics, and common cause parameters. (Brissaud et al., 2010). Since OREDA only provides constant failure rates, we assume that the subsea systems also have constant failure rates, and denote this by $\lambda^{(s)}$. The corresponding survivor function is $R_{(S)}(t) = \exp(-\lambda^{(s)}t)$ and the mean time to failure is $MTTF = {}^{1}\!/_{\lambda^{(S)}}$.

The rationale for the use of constant failure rate (i.e., exponential distribution) model as a description of the useful life of some component is reconstructed as follow (Pecht and Nash, 1994)

- Data acquired several decades ago were "tainted by equipment acidents, repair blunders, inadequate failure reporting of mixed age equipment, defective records of equipment operating times, mixed operational environmental..." (Wong, 1991) the combination of these effects produce an approximately constant failure rate.
- For a component during infant and wear out phase, there may be high failure rate mechanisms. However, what we deal with are systems during service life where the failure rate can be considered constant according to the "bath tub curve" (Rausand and Høyland, 2004).
- The addition of decreasing (infant mortality) failure rate curve with an increasing (wear out) failure rate curve can give a crudely constant rate for some period of time, even in the absence of external temporally random failure producing events (Holcomb and North, 1985).

Therefore, to obtain application-specific failure rate estimates, various models have been suggested, such as the proportional hazards (PH) model and the accelerated failure time where the RIFs are included as covariates. The BORA approach and the approach suggested by (Brissaud et al., 2011) are both based on a PH model. The BORA project is concerned with reliability assessment of safety barriers on offshore oil and gas installations, and is based on a set of generic RIFs related to human and organizational factors. The approach by (Brissaud et al., 2011) is based on a set of RIFs that are classified according to life cycle phases. The estimation of the application-specific failure rate is comparable with the approach in MIL-HDBK-217F, but the determination of the multiplicative factors is done in another way by a scoring and weighing procedure.

However, none of the approaches mentioned above can be used directly to predict the failure rate of a new subsea system. Using the PH-model requires extensive data for determining covariate values and related parameters. The approach by Brissaud has difficulties in finding the influencing functions for the indicators of each influencing factor. The BORA project mainly focuses on human and organizational factors that influence the risk of hydrocarbon releases. To use the available field data from topside systems, this approach needs some extension in different levels, such as scoring and failure analysis. The general principles of these approaches, however, have been used to develop a new failure rate prediction method, aiming to overcome some of the shortcomings of the existing approaches.

Therefore, the objective of this chapter is to present several existing methods and models for predicting the failure rates of new subsea systems that has been adapted (i.e. "marinized") from known topside systems. Furthermore, compare these approaches with respect to input data, accuracy of estimates, amount of devoted sources, and then list the different usage of each approach.

3.1 Failure Rate Prediction with Influencing Factors

Since new products are often employed under conditions that are also new and many items are intended for uses different from typical applications, it is common in many applications to modify predicted failure rates by application of environmental and factors. The intent is to account for different conditions such as temperature, voltage stress, humidity and so forth. The adjustment is done by multiplication of the predicted failure rate by appropriate constants. A difficulty encountered in practice is that the resources may not agree on the constants or on how to apply them.

For electronic components, the failure rates are given by analytical functions which directly depend on some parameters such as temperature, voltage or electrical intensity. The baseline values correspond to reference conditions. The failure rate of a system is usually obtained by adding the failure rates of all its components (i.e. parts count analysis).

This method for failure rate prediction with influencing factors involves both a quantitative part allowing integrating potential available data from feedback and a qualitative analysis dealing with influencing factors such design, environment, and use to provide more coherent and argued results. The main idea behind this method is to use some criteria to fix the failure rate within a prior interval, according to the influencing coefficient. To this end, the system is broken up into main component groups. When a component group is susceptible to an influencing factor, its baseline failure rate is multiplied by the relevant influencing coefficient. The method therefore aims at meeting the following properties:

- Global enough to be usable for a large number of SIS and influencing factors;
- A quantitative part has to integrate feedback data when available;
- A qualitative part has to compensate for a potential lack of feedback data through the use of organized expert judgment;
- Should provide argued results which logically depend on influencing factors;
- The prospect is for risk analyses to allow more efficient risk managements by acting both on systems and influencing factors.

Although this method has been developed especially for reliability prediction of safety instrumented systems (SISs), it may be more generally applied to any system. And the prospect is for more efficient risk management by acting both on systems and influencing factors. The basic idea is presented in the following section. It is based on the predictive models (i.e. parts count analysis and part stress analysis); a quantitative part may integrate feedback data to set baseline values; and a qualitative part is inspired by human and organization factors frameworks for quantitative risk analysis (QRA) in order to deal with the influencing factors.

Some tools have been developed for the quantitative step, especially for model definition and factor selection. For example, a conceptual tree is proposed in (RIAC-HDBK-217Plus, 2006), and a reliability influence diagram (RID) in BORA (Aven et al., 2006). Then, in order to set the current factors' state, expert judgment is often used. The BORA approach proposes a scale from A (i.e., the best standard in industry) to F (i.e., the worst practice).

A reliability influencing factor may be defined as an aspect of a system or an activity that affects the reliability performance of this system (Øien, 2001). A RIF is, in principle, a theoretical variable, it may or may not be specified how to measure this variable.

One hypothesis is that the control of probability of failure on demand can be through the control of changes in RIFs. Conditions for this hypothesis are that (Vinnem et al., 2012):

- All relevant RIFs are identified;
- The RIFs are "measurable";
- The relationship between the RIFs and reliability is known.

3.1.1 Presentation of the principle

Only the general steps for this method are briefly introduced, to study it further a detailed presentation with several examples can be found in (Brissaud et al., 2010)

As for the predictive models, the system is divided into several main component groups, and the system failure rate is obtained by the sum of the main component groups' failure rates (i.e. as a series system). If the system does not verify serial properties (e.g. redundant systems), the approach may be individually applied to each series subsystem, and the obtained failure rates are then combined into reliability functions according to the proper system architecture, through the system structure function. Notice that having an a priori idea of the whole system failure rate is usually more realistic than getting accurate values for all of the components. Each component (i.e. main component group) baseline failure rate is therefore expressed as a percentage of the whole system baseline failure rate. The effects of the influencing factors are included by influencing coefficients. Each coefficient corresponds to one factor and vice-versa. If a component is susceptible to an influencing factor, its baseline failure rate is multiplied by the corresponding influencing coefficient. The coefficient values are defined according to the states of the influencing factors:

i. If the influencing factor is supposed to be in a medium state according to the reliability, the corresponding influencing coefficient is equal to one;
ii. If the influencing factor is supposed to be in a more suitable state (resp. a less suitable state), the corresponding influencing coefficient is smaller than one (resp. greater than one).

These properties can be summed up by the following equations:

$$\lambda_s = \sum_{i=1}^{N} \lambda_i = \sum_{i=1}^{N} [\lambda_{i,mean} \cdot \prod\nolimits_{j \in J_i} c_j^* \tag{4}$$

$$\lambda_{i,mean} = c_i \cdot \lambda_{s,mean} \text{ with } \sum_{i=1}^{N} c_i = 1 \tag{5}$$

where λ_s and λ_i are respectively the system's and the components' failure rates, according to the current states of the influencing factors; $\lambda_{s,mean}$ and $\lambda_{i,mean}$ are the system's and components' baseline failure rates; C_i is the contribution (in percentage) of component i in the whole system's baseline failure rate; N is the number of components which make up the system; C_j^* is the influencing coefficient which corresponds to the influencing factor j; and J_i is the set of indices of influencing factors which have an effect on component i. In order to have coherent results with a presupposed failure rate scale, a prior interval [$\lambda_{s,\min}, \lambda_{s,\max}$] is set.

The model is based on the following assumptions which are summed up in Figure 2:

- The system baseline failure rate $\lambda_{s,mean}$ is reached when all of the influencing factors are, on average, in a medium state;
- The lower value $\lambda_{s,\min}$ (resp. the upper value $\lambda_{s,\max}$) of the prior interval is reached when all of the influencing factors are, on average, in a defined proportion J of the most suitable states (resp. the least suitable states).

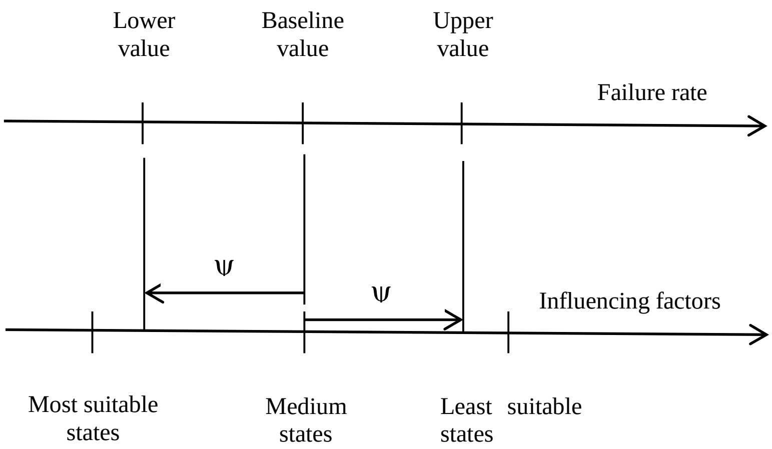

Figure 2 Functional assumption

3.1.2 Stepwise procedure

Step 1: functional analysis and input data

First of all, it is advisable to delimit the scope of the study. The failure rate has to be precisely defined. For example, only the dangerous and undetected failures can be relevant for the study, and the unit can be ‘‘per hour’’ or ‘‘per solicitation’’.

Using available feedback data, reliability data handbooks and, if required, expert judgment, a system baseline failure rate, $\lambda_{s.mean}$, has to be set. As much as possible, it must fit the medium conditions, according to the reliability, in which the system can be. This baseline value is surrounded by an interval, [$\lambda_{s,\min}, \lambda_{s,\max}$]. It corresponds to the extreme failure rates which it is possible to observe for this type of system, according to the worst and the most suitable influencing factor states.

FMECA is recommended in order to identify the components of the system which are susceptible to different influencing factors. Using the FMECA and, if available, some reliability data, the contribution of each component in the system baseline failure rate, C_i with $i = 1, ..., N$, has to be evaluated.

Step 2: model definition and influencing factors selection

A reliability influencing diagram is proposed for model definition and the selection of the relevant influencing factors. Four levels are represented from the right to the left, see (Brissaud et al., 2010).

Table 8 provides a sample checklist for influencing factors selection according to the system life phases. Human and organizational factors can be added, for example according to the taxonomy proposed by (Kim and Jung, 2003). The choice of influencing factors must follow some criteria:

- It is possible to measure or evaluate the states;
- The state measurements or evaluations must allow differentiation between the studies systems;
- The selected factors are exhaustive enough to explain the observable reliability differences.

An influencing matrix $F_{N,M}$ is defined on $N \cdot M$ as follows:

$F_{N,M}(i, j) = 1$ if the component i is susceptible to the influencing factor j , $F_{N,M}(i, j) = 0$ otherwise.

Table 8 Sample of checklist for the influencing factor selection

Category		Influencing factors
Design		System type Work principle Dimensions (sizes, length, volume, weight) Materials Component quality (quality requirements, controls) Special characteristics (supply)
Manufacture		Manufacturer Manufacture process (procedures, controls)
Installation		Location (access facilities) Assembly/activation (procedures, controls)
Use	EUC	Equipment under control (EUC) type Special characteristics
	Solicitation	Type of load (cycling, random) Frequency of use Loading charge/Activation threshold Electrical load (voltage, intensity)
	Environment	Mechanical constraints (vibration, friction, shocks) Temperature Corrosion/ Humidity Pollution (dust, impurities) Other stresses (electromagnetism, climate)
	Requirements	Performance requirements Failure modes
Maintenance		Frequency of preventive maintenance Quality of preventive maintenance Quality of corrective maintenance

Step 3: indicators selection and graduation

An indicator is the means to observe the state of an influencing factor. (Øien, 2001) proposes some criteria for indicator selection in terms of the amount of data, available sources, and relationships with observed factors, validity, and repeatability. For the proposed model, the indicators have to be set on a numerical scale. Moreover, the effects of factors (positive or negative) will be assumed continuous and monotonous according to the indicator values. For qualitative indicators (e.g. manufacturer, type of material), a scale from 0 (i.e., very not suitable for the reliability) to 5 (i.e., very suitable for the reliability) is proposed. For quantitative indicators (e.g. pressure, voltage, and temperature) the obtained values can be directly used if they account for the previous conditions. Otherwise, a multiple level scale has to be defined as for the qualitative indicators.

Using technical reports, operational data, feedback knowledge, measures, and investigation with key staff and so on, three particular levels must be set for each indicator: one which represents the medium influencing factor state, two which represent the extreme observable values (the least and most suitable values for reliability). The scale for the indicator I_j of the influencing factor j is denoted $[I_{j,lower}, I_{j,upper}]$, and the three particular levels are $I_{j,mean}$ for the medium value, $I_{j,worst}$ and $I_{j,best}$ for the least and the most suitable values which are observable, respectively.

Step 4: influencing factors rating

A weight is given to each selected influencing factor. Normalized weight w_j for each influencing factor j :

$$w_j = \frac{\sum_{i=1}^{N} c_i \cdot F_{N,M}(i,j) \cdot W_j}{\sum_{i=1}^{N} \sum_{k=1}^{M} c_i F_{N,M}(i,j) \cdot W_k} \text{ for } j = 1,\dots,M \tag{6}$$

It represents the relative potential effect on the susceptible component failure rates, according to a change from the least to the most suitable value of the corresponding indicator.

A rating from 1 to 5 or from 1 to 10 is usually suitable for the proposed model. Feedback knowledge, graduating processes, comparisons by pair, tests or expert judgment can be used to set weights. The weight of the influencing factor j is denoted by W_j, and it is normalized using Equation 4.

Step 5: indicator functions

In order to deal with uncertainties, especially when expert judgment is required, indicator functions aim to represent the current indicator values not as fixed points, but by probability density functions. In fact, the indicator values are seldom known precisely and are sometimes subject to changes during the system life phases (e.g., temperature, humidity, and load). Three types of density function are proposed:

- Uniform distribution when expert judgment is the main means used to evaluate the indicator value (e.g. ‘‘the influencing conditions are supposed to be quite beneficial (or not) for the reliability’’);
- Triangular distribution if the indicator value is deterministic and must be translated on a defined scale (e.g. the indicator value is given on a scale from 0 to 5 according to the ‘‘degree of suitability’’ for the reliability);

- Gaussian distribution when the quantitative indicator value is directly used (e.g. pressure, temperature, volume).

Step 6: influencing functions

The influencing functions aim at formulating the influencing coefficients according to the indicator values. The functions are defined by setting three particular values: one which corresponds to a medium indicator value (denoted by $C_j(I_{j,mean})$), two which correspond to the least and the most suitable indicator values (resp. $C_j(I_{j,worst})$ and $C_j(I_{j,best})$). They can be obtained by the equations given in... They take the previous steps into account, including the influencing factor weights. Linear relations are then assumed between these particular values. These functions are extrapolated all over the indicator scales [$I_{j,lower}, I_{j,upper}$].

The influencing reference coefficients are obtained by solving the following equations:

$$\lambda_{s,\max} = \lambda_{s,mean} \cdot \sum_{i=1}^{N} [c_i \cdot \prod\nolimits_{j \in J_i} (\psi \cdot w_j \cdot C_{ref}^{-})] \tag{7}$$

$$\lambda_{s,\min} = \lambda_{s,mean} \cdot \sum_{i=1}^{N} [c_i \cdot \prod\nolimits_{j \in J_i} (\frac{C_{ref}^{+}}{\psi \cdot w_j})] \tag{8}$$

Particular values of the influencing functions:

$$C_j(I_{j,,mean}) = 1 \text{ for } j = 1,...,M \tag{9}$$

$$C_j(I_{j,worst}) = w_j \cdot C_{ref}^{-} \text{ for } j = 1,...,M \tag{10}$$

$$C_j(I_{j,best}) = \frac{1}{w_j} \cdot C_{ref}^{+} \text{ for } j = 1,...,M \tag{11}$$

Step 7: final results

Given the indicator functions $(g_j(I_j))$ which express the states of the influencing factors, and the influencing functions $(C_j(I_j))$ which formulate the influencing coefficients, both according to the indicator values, the influencing coefficients (C_j^*) are calculated by:

$$C_j^* = \int_{I_{j,lower}}^{I_{j,upper}} C_j(I_j) \cdot g_j(I_j) \cdot dI_j \text{ for } j = 1,...,M \tag{12}$$

Finally, the final system failure rate is obtained by using Equation (1) and (2) with the input data from the first step. Note that the density function for indicator values in equation (3) mitigates the potential effects on the results of the assumptions from step 6 (i.e. about the influencing functions definition).

This methodology combines a quantitative part to integrate available data, with a qualitative analysis to compensate for a potential lack of feedback knowledge. Therefore, unlike statistical models, it does not require much reliability feedback data; and differs from predictive models, it is not necessary to know the influencing factors' states and properties well. The failure rate evaluations with influencing factors provide argued and coherent result.

3.2 The BORA Project

The BORA project has developed a model for both quantitative and qualitative risk analysis of platform specific hydrocarbon release frequency based on the use of event trees, fault trees, influence diagrams, and RIFs. The RIFs to be used are selected by expert judgment from the set of generic RIFs. The state of each RIF is classified into several states and a scoring and weighing process is used to determine the effect of each RIF. It is based on the initial methodology formulation as well as the experience from the case studies (Vinnem et al., 2009). By using BORA it is possible to analyze the effect of safety barriers introduced to prevent hydrocarbon releases, and how platform specific conditions of technical, human, operational, and organizational risk influencing factors influencing factors influence the barrier performance. The BORA project is limited to analysis of hydrocarbon release. However, the principle in BORA is relevant for analysis of the consequence barriers as well.

Several criteria the BORA should fulfill were developed. The criteria were developed as a result of discussions of the purpose of the analysis method (Aven et al., 2006). To what extent BORA fulfills these criteria are discussed in section 3.2.2. The aim was to develop a method that:

- Facilitates identification and illustration of safety barriers planned to prevent hydrocarbon releases.
- Contributes to an understanding of which factors (technical, human, operational, and organizational) that influence the performance of the safety barriers and the risk.
- Reflects different causes of hydrocarbon releases.

- Is suited for quantification of the frequency of initiating events and the performance of the barriers.
- Allows use of available input data as far as possible.
- Allows consideration of different activities, phases, and conditions.
- Enables identification of common causes and dependencies.
- Is practically applicable regarding use of resources.
- Provides a basis for "re-use" of the generic model in such a way that installation specific considerations may be performed in a simple and not too time-consuming manner.

The first step in the development of the model is to define work operations and equipment units that may cause a leak. To have a manageable risk model, a limited number of generic work operations are defined, covering operations which may directly cause a leak or introduce latent failures in the system which may cause a leak at a later point in time. The work operations are defined in such a way that they will have as many common characteristics as possible, such that the RIFs influencing the probability of making errors will be the same or very similar for all specific operations grouped together.

Further, generic equipment units or equipment packages are defined. This could be, for example, a compressor package. For each of these generic equipment packages, the number of flanges, valves, instrument connections, etc. is specified.

Based on this, an "average" platform with an average leak frequency can be established. A simplified approach is also proposed, using generic leak frequency data and adjusting these to take into account variations in the number of work operations for a specific installation.

To establish a suitable set of typical work operations, the starting point is to consider the types of equipment located in the process areas and which operations are being performed on this equipment. Principally, the equipment can be divided into two groups:

- Hydrocarbon-containing systems/equipment;
- Other equipment and structures (this will include all sorts of equipment in the process areas such as utility equipment, safety systems, electrical equipment, structures, etc.).

There will be a principal difference between work operations performed on these two groups of equipment as work on the second group of equipment only indirectly can lead to a leak of hydrocarbons, e.g. as a result of dropped or swinging objects (external impacts). However, when performing work on the hydrocarbon-containing equipment, the operation can lead directly to a release, e.g. if a wrong valve is opened.

The detailed procedure can be found in (Vinnem et al., 2009) and (Aven et al., 2006). The generic risk model is shown in Figure 3.

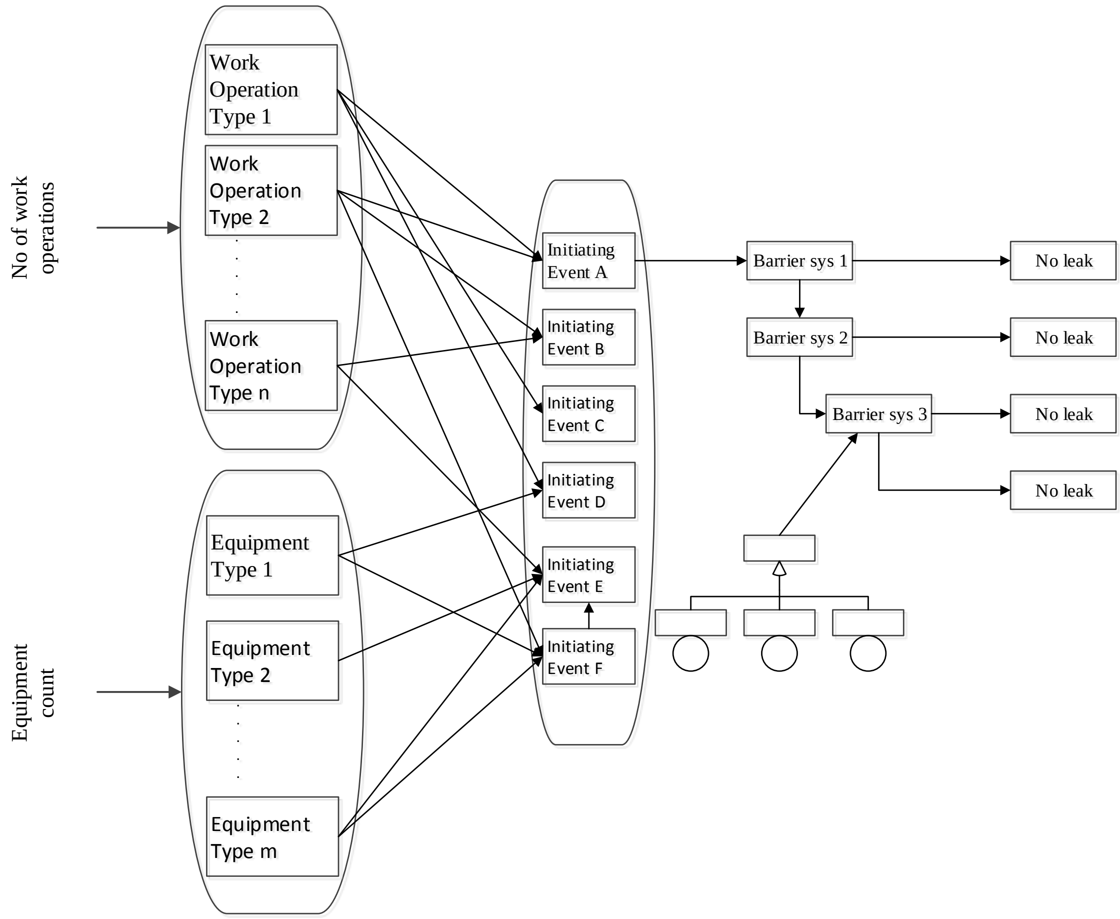

Figure 3 A generic risk model, generic information versus amplification-specific information

According to (Aven et al., 2006), the detailed steps followed BORA project are as follow:

1) Development of a basic risk model including release scenarios;
2) Modelling of the performance of safety barriers;
3) Assignment of industry average probabilities/frequencies and risk quantification based on these probabilities/frequencies;
4) Development of risk influence diagram;
5) Scoring of risk influencing factors;
6) Weighting of risk influencing factors;
7) Adjustment of industry average probabilities/frequencies;

8) Recalculation of the risk in order to determine the platform specific risk related to hydrocarbon release.

3.3 "3-step" Model: Functions-material Elements-fault and Failures

With the development of micro electro-mechanical systems (MEMS), the sensor systems are able to combine data acquisitions from physical or chemical properties, and internal data processing, to obtain the required information now. According to ISA and IEC international standards, such systems are therefore appropriately referred to as "transmitters" instead of "sensors" in the process industry (Brissaud et al., 2011). These advance functionalities of correction, self-adjustment, self-diagnosis and validation, online reconfiguration, and digital bidirectional communication play a role in generic functions: measure, configure, validate, and communicate. The use of intelligent transmitters may hence bring several benefits for industrialists. However, the "intelligent features" of transmitters give rise to several issues for dependability. A discussion on the advantages and disadvantages, with respect to reliability, maintainability, and safety, is provided in Table 9.

Reliability analysis of intelligent transmitters are required to determine safety integrities for SISs, but may also be used to obtain input data for self-diagnoses and validation, online configuration, and network design. However, even though reliability studies focus on certain specific aspects, notably on digital communication, intelligent transmitters are often assumed to be "black box" systems and are usually not taken into account for evaluations. In fact, a reliability analysis for intelligent transmitters, or more generally for new technology-based transmitters, has to deal with several issues:

i. System complexity, i.e. various interactions between both material elements and functions;
ii. System behavior under faulty conditions which is usually not well known and difficult to predict (especially due to programmable units and software);
iii. Several transmitted data which may be wrong (e.g. measurements, diagnostic information), and dependently of each other;
iv. Little available reliability feedback (e.g. failure modes and reliability data) due to new technologies.

Table 9 Advantages and disadvantages of intelligent transmitters

Criterion	Pros	Cons
Reliability	Self-adjustment may prevent drifts or other faults and failures which appear with aging.	The high amount of electronics, programmable units and software aspects implies new failure causes and modes which are usually not well known and difficult to predict.
	Faults and failures may be partly compensated using fault tolerant strategies (reconfiguration).	Each fault or failure may affect several functions and transmitted data (e.g. measurements, diagnoses).
	Digital communication is often assumed to be more reliable than analogue wires.	Digital communication reliability is questioned and may yield common cause failures.
Maintainability	Information on drifts, influencing factors, charge exceeding, previous faults and failures with corresponding circumstances etc. may be monitored over time and used for preventive maintenance.	Specific expertise is required to maintain such complex systems.
	Digital communication and online reconfiguration can make corrective maintenance easier and more efficiency.	
Safety	Self-diagnoses allow better fault and failure coverage, and safe states can be defined in more detail.	Transmitters are increasingly becoming “black box” systems.
	Centralized data processing and digital communication may improve risk management efficiency.	

These points make qualitative analysis such as FMECA hardly exhaustive for the identification of failure modes, with respect to (ii) and (iv), and for handling fault and failure interaction, with respect to (i) and (iii). Moreover, the binary reliability models (e.g. RBD and FT) are often inappropriate as it, especially due to (ii) and (iii), and transition states approaches (e.g. Markov models and Petri nets) have some difficulties in defining state boundaries and transition because of (i) and (ii).

Therefore, the 3-step model (functions-material elements-faults and failures), which is based on goal tree-success tree (GTST) approaches to present both the functional and material aspects, and includes the faults and failure as a third part for supporting the reliability analysis, is proposed for the reliability analysis of new technology-based transmitters. The behavioral aspects are provided by relationship matrices, also denoted master logic diagram (MLD), with statistic values which represent direct relationships between system elements. Relationship analyses are then proposed to assess the effect of any fault or failure on any material element or function. Taking these relationships into account, the probabilities of malfunction and failure modes are evaluated according to time. Furthermore, uncertainty analyses tend to show that even if the input data and system behavior are not well known, these previous results can be obtained in a relatively precise way.

3.3.1 Modeling of new technology-based transmitters

A new technology-based transmitter may present two levels of complexity: at the system level when various intra and inter relationships exist between material elements and functions; at the component level when behavior of units is difficult to define. Models for complex systems should be investigated, for example with regard to function-oriented and object-oriented approach.

Function-oriented approaches (i.e., functional analyses) allow the system to be analyzed according to goals and functions which are to be met or currently performed. They may be used in design phase to define functional requirements, or later to understand effective system operation. Examples of these approaches include the structure analysis and design technique (SADT), the functional analysis system technique (FAST), and the multilevel flow modeling (MFM).

Object-oriented approaches are usually more formal. These approaches may be used to describe the static or dynamic structure of a system by defining the material (and software) elements and their interactions (i.e. structural analysis). Examples of object-oriented approaches include the dynamic flow graph methodology (DFM), fault trees, and the UML class diagrams.

In practice, function-oriented and object-oriented approaches do not reflect opposing concepts and, in particular, they can be used as complementary techniques. The model developed in this model describes both the system functional and material aspects according to a common process. It is based on the GTST approach, combined with MLD. The basic idea of GTST is that complex systems can be best described by hierarchical frameworks. The system is breaking up according to it qualities (i.e. goals and functions) by the use of a goal tree (GT), and according to its objects (i.e. parts) by the use of a success tree (ST), as illustrated in Figure 4.

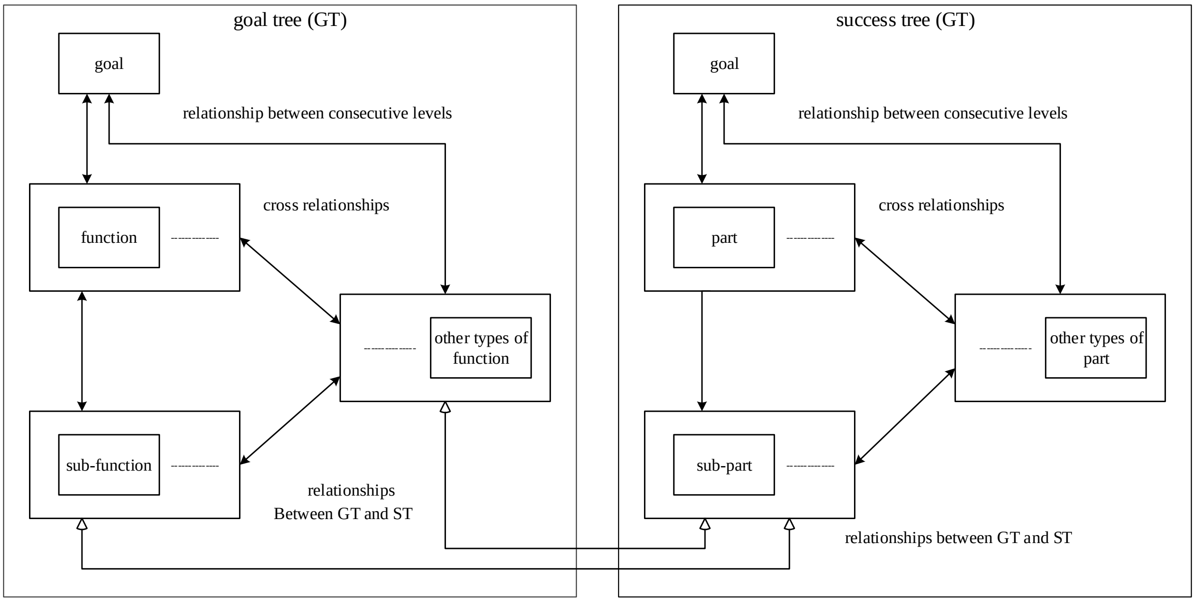

Figure 4 Conceptureal goal tree-sucess tree (GTST) with different tpyes of relationships

The first level of the GT defines the system goal, and the second level is formed by the functions which have to be achieved to attain this goal. Additional levels may then be added to specify sub-function s, as far as further development is possible without referring to objects. Different types of functions may also be distinguished (e.g. main and supporting functions) in order to facilitate the analysis of complex systems. Then the ST describes the system structure as a collection of objects which are the system parts (hardware, software and human) used to achieve the function given in the GT. Similarly to the GT, different levels and types of objects may be established.

In order to represent a compact and transparent fashion the relationships between GT functions and ST objects, or between different types of elements within GT or ST, MLD, where a simple example is illustrated in Figure 5, can be used.

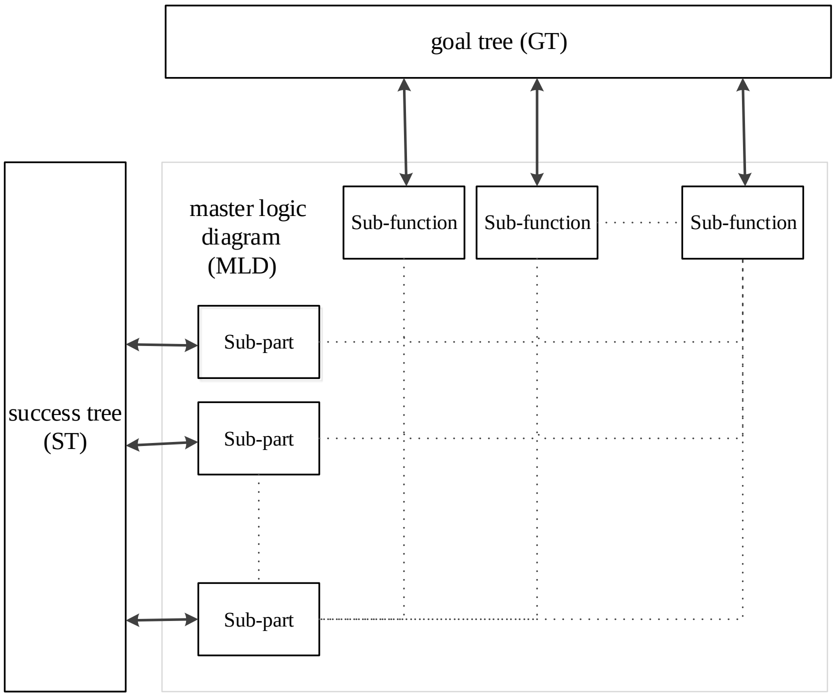

Figure 5 Conceptual GTST-MLD

The combined GTST-MLD model provides an efficient framework to describe the causal relations of complex systems, which is also basis of the 3-step model. The three parts of 3-stpe model will be discussed in the next section.

3.3.2 "3-step" model: functions-material elements-fault and failures

We only provide the conceptual description of this method, for more information and example of impalement, see (Brissaud et al., 2011).

Functional tree

The first part of this model provides the functional aspect of the system. The top function of the functional tree is then denoted by goal function. Classically, the goal function is safety function, that is, a function used to prevent hazardous event. The goal function is split into sub-functions on an increasing level of detail. The fulfillment of all these sub-functions assures that the goal function is achieved. These relationships may then be specified by "and" and "or" gates. In this approach, two types of functions are distinguished: main and supporting functions. The global and basic functions are main functions because they directly stemmed from the goal function splitting. On the other hand, the supporting functions have no final goal as far as users are concerned, but may be required or act on one or several main function.

Material tree

The second part of the model provides the material aspects of the system. The material elements collect all the objects of the system which are necessary to achieve any of the functions given in the functional tree. The material elements are then identified by breaking up the system into its parts. The material tree starts with top element which describes the whole system to be analyzed and stop when the material elements have been sufficiently described according to their distinctive roles in the fulfilment of the functions given in the functional tree. Similarly to the functional tree, two types of material elements are used: main and supporting material elements.

Faults and failures (Rausand and Øien, 1996)

To perform reliability analyses, faults and failures are introduced as a third full part of the model, which provides the dysfunctional aspects. According to the definitions from (IEC61508, 2010), a fault is an abnormal condition that may cause a reduction in, or loss of, the capacity of an entity, while a failure is the termination of the ability to perform a required function, or in any way other than as required, a fault is therefore prior to a failure because it may or may not result in a failure.

The faults and failures may be defined and set up according to different categories and levels of detail. In this model, a deductive approach may be used to identify possible faults and failures that are relevant for any material element given in the material tree (unlike FMECA).

The authors then model the effects of faults and failures, first by relationships between them and material elements, and second by relationship between material elements and functions. Both of them are represented by relationship matrices discussed in the next part.

Relationship matrices (MLD)

Relationship matrices also denoted by MLD, provide the behavioral aspects of the system. As such, they show the way any function is achieved. At this step of the modelling approach, qualitative relationships are assumed (no numerical values are used).

3.3.3 Relationship analyses based on 3-step model

Relationship analyses

The relationship analyses aim to assess the total relationships between any elements (faults and failures, material elements, functions) including, for example, the effects of faults and failures on functions, taking the direct and indirect relationships into account. Relationship event (direct, indirect, and total) are defined.

The direct relationship events are denoted by:

$$AB_{ab} \ \{\text{event } A_a \text{ directly implies (i.e. without request for any other event) event } \mathrm{B}_b\}$$

The total relationship events between the faults and failures and units are defined by:

$$DMtot_{d,m} = \{DM_{d,m} \cup_p (DP_{d,p} \cap PM_{p,m})\} \tag{13}$$

which means an occurrence of fault for failure *d* (directly or indirectly) implies a failed state of unit *m*.

It is often more relevant to analyze the global functions rather than the basic functions. Then, the total relationship between faults and failures and global functions are denoted by:

$$DG_{d,g} = \{\cup_{f(g)} DF_{d,f(g)}\} \tag{14}$$

which means that an occurrence of fault or failure d (directly or indirectly) implies a malfunction of global function *f*, where f(g) is the set of basic functions f that have to be fulfilled to achieve the global function *g*.

It is then possible to express the probability of global function g malfunctioning, as follow:

$$P[G_g] = P[\cup_d (D_d \cap DG_{d,g})] \tag{15}$$

Furthermore, a simple way to compute the total relationship values is then to use the following expression:

$$P[DG_{d,g}] = P[G_g / D_d \cap_{\sigma \neq d} \overline{D_\sigma}] \tag{16}$$

This is, if the fault or failure d occurs and no other, the global function g malfunctions with a probability equal to $P[\mathrm{DG}_{d,g}]$. The value can therefore be interpreted as the individual impact measure of fault or failure d on global function g.

Probabilities of malfunction and failure modes

The probabilities of malfunction and failure modes are assessed according to the following assumptions:

- The direct relationship events are independent, and the corresponding probabilities are time-independent;
- The occurrences of faults and failures are independent, and the corresponding probabilities are time-dependent and thus denoted $P[Dd](\mathrm{t})$;
- No maintenance action is performed during the study time.

The probabilities of the global functions malfunctioning at time t may then be assessed by:

$$\sum_{d}(P[DG_{d,g}]P[D_d](t)\prod_{\sigma\neq d}(1-P[D_\sigma](t))) \leq P[G_g](t) \leq \sum_{d}(P[DG_{d,g}]P[D_d](t)) \qquad (17)$$

The probabilities of failure modes at time t may then be obtained, for example by a fault tree-based approach, as in the previous analyses.

Uncertainty analyses

Input data uncertainty is a substantial issue for reliability amylases. It has been widely investigated in many references, especially by comparing the use of several sources, Monte Carlo simulation, method of moments, Bayesian networks, and other approaches such as fuzzy sets and possibility theory, evidence theory, and interval analyses. In fact, most of the models for reliability analysis first require the system's response to events to be strictly defined.

A probabilistic approach is preferred because mathematical criteria such as variances can be used to assess the uncertainties in result, compared with the uncertainties in inputs.

3.4 Failure Rate prediction of New Subsea Systems

Most of the new subsea equipment or systems are adapted from similar, well known topside (i.e. on the platform) system and the industry often talks about "marinization" of topside technology. Reliability information for topside systems is available from the OREDA handbook and the OREDA database (for participating companies). This information cannot be used directly for new subsea systems, because of design modifications, different environmental stresses, and different maintenance conditions. The reliability information in OREDA is presented as a constant failure rate, together with additional information related to failure modes, failure descriptors/mechanisms, and components that contributed to the system failures. Currently, no practical method is available for extrapolating the available reliability data from similar and known systems and come up to a failure rate prediction for new system operating in a different environment.

This is a practical approach to reliability prediction of new subsea systems based on available operational data from similar, known systems from the topside environment and a comparison between two systems. The application if the approach is illustrated by an example of a subsea pump.

As noted previously, most reliability data sources assume that the items have constant failure rates and that failures in a population of identical items occur according to a homogeneous Poisson process (HPP) where the time t is the accumulated time in service. Design variations and operational and environmental conditions may be accounted for by including covariates into the model. In some application areas (including the subsea oil and gas industry), the covariates are sometimes referred to as reliability-influencing factors (RIFs). A RIF is a relatively stable condition, which by being changed will increase or reduce the failure rate of the item. In (Ascher and Feingold, 1984), the authors listed 18 RIFs that influence the failure behavior of a repairable system. NSWC-1110 considers the effects of the environmental RIFs at the lowest part level of mechanical systems (Rahimi and Rausand, 2013).

3.4.1 Failure rate provision for new systems

How the subsea environment influences a system's failure rate will generally depend on the application of the system and its internal and external environmental conditions. Items that are not directly in contact with the subsea environment are mainly affected by internal stresses, while items that are in direct contact with the subsea environment are also affected by external stresses. Failure rate estimates for topside systems are available from (OREDA, 2009). Other sources, such as MechRel and the (RIAC-HDBK-217Plus, 2006) handbook may also give supplementary information. In many applications, reliability prediction is often performed under the assumption that the underlying failure time is exponential distributed. It is known that the accuracy of a prediction often depends on the completeness of product information and the appropriateness of a model for the underlying lifetime distribution (Jin et al., 2010).

The objective of this approach is to use the available topside data to predict the failure rate of a similar subsea system. Several categories of data and information are required.

- *Technical dat*a are usually s supplied by system manufacturers and are necessary for understanding the system functions and for developing system models. Based on this type of data, similarities among or between systems can be identified.
- *Environmental dat*a provide information about the operating conditions for the system and needs to be incorporated into the reliability analyses. Subsea environmental meta-data and ocean data can be used for a better understanding of influencing factors.
- *Operational and maintenance data* (field data) are collected under actual operating conditions by the customers, and are plant/system specific.
- *Expert judgment* plays a central role in the provision of data for new applications. Experts may possess valuable knowledge that can supplement the recorded data and provide important input to decision-makers.
- *Reliability prediction* methods are required to find or develop a suitable method for a more realistic estimation.

3.4.2 Stepwise procedure

This approach can be used early in the product development process, i.e. the design and development phases. During the operational phase, the predicted failure rate from previous phases has to be updated based on the real data that are collected.

Step 1. New system familiarization

The intended application of the new subsea system must be clearly defined and its physical boundaries and operational and environmental conditions must be specified. A suggestion on what may be included in the description of the system and its environment is given in (BS5760-4, 1986). It is recommended to represent the system as a hierarchical structure of subsystems and maintainable items. A maintainable item is a lowest level item in the system hierarchy at which maintenance is carried out.

(DNV-RP-A203, 2011) suggests that a critical items list is prepared, specifying key issues, such as materials, dimensioning loads, capacities, frequency of operation, and so on. The description may be in the form of drawings, text, data, or other relevant formats.

Step 2. Identification of failure modes and failure causes

A failure mode and failure cause analysis of the new subsea system should be carried out. A full FMECA is not required, but may already have been prepared for other purposes at this stage of the system development process. All potential failure modes must be considered, together with the failure causes and mechanisms that may contribute to each failure mode. The assessment must cover all operational modes. The failure modes and failure cause analysis may be based on a worksheet as shown in Figure 1. Some columns in the worksheet, such as ‘‘maintainable item’’ or ‘‘function’’, are not used specifically in the approach or in the calculations, but they are necessary in order to get insight related to failures, influencing factors, and so on. It is further recommended to establish an influence diagram to illustrate the potential causes, as shown in Table 10.

Table 10 Failure mode and failure cause worksheet

Description of unit				Description of failure		
Ref no.	Maintainable item	Function	Operational mode	Failure mode	Failure cause	Detection of failure

Step 3. Reliability information acquisition for the similar known system; comparison of the new and known system

It is assumed that data are available from a known topside system that performs similar functions and has a similar design and structure as the new system. Therefore, as much reliability information about the known topside system as possible should be acquired form OREDA. The information includes:

- Failure modes;
- Failure rate estimates for each failure mode, including confidence intervals;
- Failure descriptors, i.e. failure mechanisms and other factors contributing to each failure mode (qualified);
- Maintainable items contributing to each failure mode (qualified).

Let $\lambda^{(T)}$ denote the constant total failure rate given in OREDA for the topside system. The failure rate for failure mode FM_i is denoted by $\lambda_i^{(T)}$, for $i = 1, 2, ..., n$, such that $\lambda^{(T)} = \sum_{i=1}^{n} \lambda_i^{(T)}$, when the failure modes are disjoint. The failure modes may not be completely independent since they can have several failure causes in common. The relationship among reliability-influencing factors, failure causes, failure modes, and the total failure rate can be illustrated as shown in Figure 6.

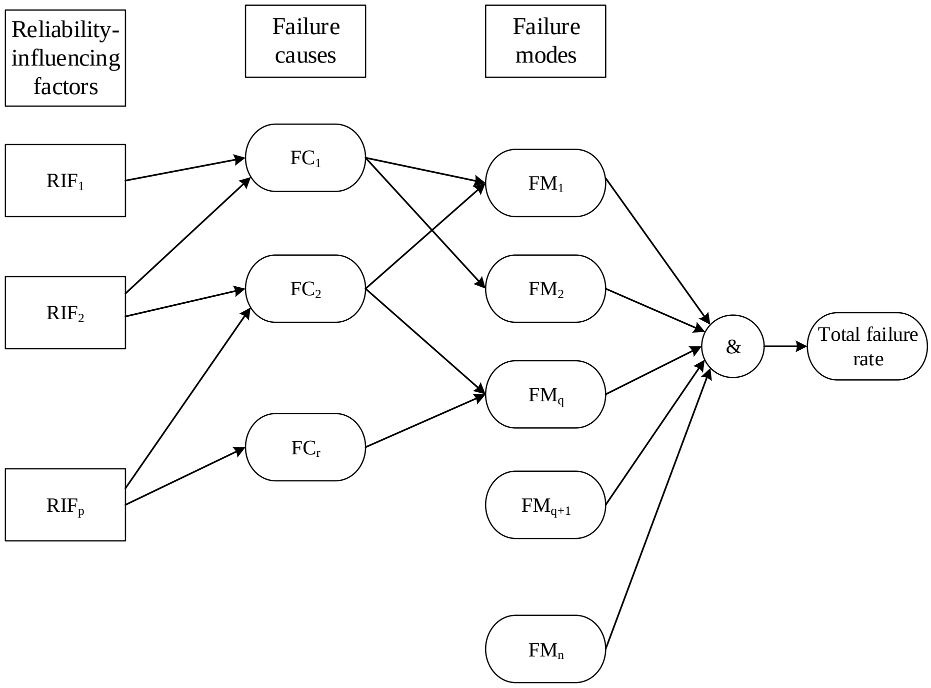

Figure 6 Factors contributing to the total failure rate of the subsea system

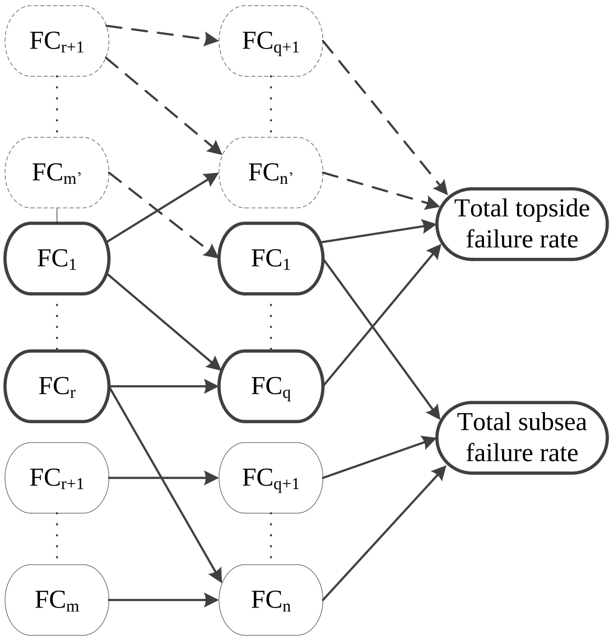

Figure 7 Subsea and topside system comparison

The new and known systems are compared with respect to structural, operational, and environmental conditions, and failure modes and failure causes (including failure mechanisms), and similarities and differences are recorded. The new and known system may not have exactly the same failure modes, and differences must be listed and described. Figure **7** illustrates the comparison of failure modes and failure causes between the new and the known systems. The dashed rounded rectangles and arrows indicate that they belong to the topside system, the thick rounded rectangles and arrows indicate that they are similar for both the offshore and the subsea systems, and the thin rounded rectangles and arrows indicate that they belong only to the subsea system.

Step 4. Selection of relevant RIFs

The RIFs influence the reliability, and when a RIF is changed, the failure rate of the system may change. Our goal is to determine how much the failure rate changes by evaluating the RIF's influences on the failure causes. The RIFs that are relevant for the new subsea system are identified based on the physical insight in step 3, combined with expert judgment. It is typically assumed that it is possible to measure or evaluate the states of the RIFs.

Table 11 provides a list of generic RIFs, partly based on the checklist presented in Table **8**. These RIFs are related to design and manufacturing, operation and maintenance, and environmental factors. This table can be used as a checklist to establish a set of specific RIFs for the particular topside and subsea systems. The selection of specific RIFs should be done by experts.

Table 11 Generic RIFs

Category	RIFs	
Design and manufacturing	System structure, Materials, Dimensions, Loads and capacities, Quality (manufacturing process, installation, logistics, assembly…)	
Operational and maintenance	Functional requirements, Time in operation, Mechanical constrains, Frequency of maintenance, Maintenance policy, Accessibility for maintenance	
Environmental	External	Temperature, Location of operation, Pressure, Corrosive environment, Pollution
	Internal	Pressure, Sand particles in the fluid, Chemical content

Furthermore, the specific RIFs must be ranked by experts according to their importance for each failure caused of the new subsea system. This can be done as repeated pairwise ranking by deciding whether or not RIF_{j,k_1} is more important than RIF_{j,k_2} , for all pairs (k_1, k_2) , for failure cause FC_j . The experts should next allocate weights to the carious RIFs for failure causes of the subsea system, such that ε_{kj} is the weight of RIF_k for FC_j. The weights should indicate the relative importance of the RIFs and be scaled such that $\sum_{k=1}^{p} \varepsilon_{kj} = 1$ for $j = 1, 2, ..., r$.

The selected RIFs are added to the influencing diagram, as shown in Figure 6, to illustrate their influences on the failure causes.

Step 5. Scoring the effects of the RIFs

The RIFs selected in step 4 may be different for the topside and the subsea system therefore, it is necessary to make clear description in order to help comparing the effects if these RIFs on the failure causes.

To indicate which of the p selected RIFs that influence the failure causes of the topside and subsea systems, the indicators $v_{kj}^{(T)}$ and $v_{kj}^{(S)}$ are used, where the topside indicator $v_{kj}^{(T)}$ is

$$v_{kj}^{(T)} = \begin{cases} 1, \text{ if } \mathrm{RIF}_k \text{ has effection (topside) failure cause } \mathrm{FC}_j \\ 0, \text{ if } \mathrm{RIF}_k \text{ has no effection (topside) failure cause } \mathrm{FC}_j \end{cases}$$

And the subsea indicator $v_{kj}^{(S)}$ is,

$$v_{kj}^{(S)} = \begin{cases} 1, \text{ if } \mathrm{RIF}_k \text{ has effection (subsea) failure cause } \mathrm{FC}_j \\ 0, \text{ if } \mathrm{RIF}_k \text{ has no effection (subsea) failure cause } \mathrm{FC}_j \end{cases}$$

The effects each RIF has on the subsea system are then compared with the effects the same RIF has on the topside system. For each failure cause FC_j and RIF_k, an influence score η_{kj} is used to indicate how much higher/lower influence RIF_k has on failure cause FC_j for subsea system compared with the topside system it is suggested to use seven-points scale in Table 12 to assign the score, but other scoring scales may be used if deemed more realistic.

Table 12 A seven-point scale for scoring RIFs

-3	-2	-1	0	+1	+2	+3
Much lower effect	Significantly lower effect	Slightly lower effect	No difference	Slightly higher effect	Significantly higher effect	Much higher effect

For example, the score +3 indicates that RIF_k has a much higher influence on failure cause FC_j subsea compared with topside. When $v_{kj}^{(T)} = 1$, all the seven points are applicable for scoring, while $v_{kj}^{(T)} = 0$, means that only three of the seven points (i.e. only positive points indicating higher influence) have to be considered. The scoring requires detailed physical and operational insight and judgments from experts.

Step 6. Weighing the contribution of the failure causes to failure modes

How much the failure cause FC*j* contributes to failure mode FM*i* for the topside is specified as a weight $w_{ji}^{(T)}$. The weights can be easily deduced from the data tables in OREDA. The corresponding weights for the subsea system have to be determined based on expert judgments, technical reports, operational data, feedback knowledge, interview of key staff, and comparison procedure in step 3, which are denoted by $w_{ji}^{(S)}$. The weights should be scaled such that

$$\sum_{j=1}^{r} w_{ji}^{(S)} = 1 \text{ for } i = 1, 2, ..., q \tag{18}$$

Where q is the number of failure modes that is similar for both subsea and topside system.

Step 7. Determination of the failure rate for similar failure mode

The failure rates for the failure modes of the subsea system are determined by adjusting the corresponding failure rates for the topside system based on the influences of the RIFs. This approach is similar to the BORA approach. It is assumed that the failure rate for failure mode FMi in the subsea environment can be expressed by the failure rate to the corresponding FMi in the topside environment as

$$\lambda_i^{(S)} = \lambda_i^{(T)} \cdot (1 + \kappa_i) \text{ for } i = 1, 2, ..., q \tag{19}$$

where $\kappa_i \geq -1$ is a constant scaling factor that needs to be determined. The weight can also be interpreted as the conditional probability, that is

$$w_{ji}^{(S)} = \Pr(\text{the failure is caused by } \mathrm{FC}_{ji} \,|\, \mathrm{FM}_i \text{ has occured}) \tag{20}$$

It is suggested that this influence is determined as a weighted average of the scores of the RIFs that influence FC*j*, and where the RIFs are weighted according to the relative importance of the RIFs, such that

$$\overline{\eta_j} = \sum_{k=1}^{p} \varepsilon_{kj} \cdot v_{kj}^{(S)} \frac{\eta_{kj}}{3} \text{ for } j = 1, 2, ..., r \tag{21}$$

The reason why the weighted average score is divided by 3 comes from the highest score in Table 12 and used for normalization.

The scaling factor κ_i can be calculated by

$$\kappa_i = c_i \cdot \sum_{j=1}^{r} w_{ji}^{(S)} \cdot \overline{\eta_j} \text{ for } i = 1, 2, ..., q \tag{22}$$

Where c_i a constant scaling factor that will be specified later in this step.

Given the assumption that the failure rate $\lambda_i^{(S)}$ of the subsea system with respect to failure mode FM*i* can be delimited such that

$$\lambda_i^{(S)} \in \left[\lambda_{Low,i}^{(S)}, \lambda_{High,i}^{(S)} \right]$$

Where the boundary values can be determined based on $\lambda_i^{(T)}$. The boundaries are defined by the two factors $\theta_{\min,i}$ and $\theta_{\max,i}$ for each failure mode such that

$$\theta_{\min,i} \cdot \lambda_i^{(T)} \le \lambda_i^{(S)} \le \theta_{\max,i} \cdot \lambda_i^{(T)} \tag{23}$$

Solving equations above, we can get

$$\theta_{\min,i} \le 1 + c_i \cdot \sum_{j=1}^{r} w_{ji}^{(S)} \cdot \overline{\eta_j} \le \theta_{\max,i} \tag{24}$$

Furthermore, they suggest that

$$c_i = \begin{cases} 1 - \theta_{\min.i} \text{ when } \sum_{j=1}^{r} w_{ji}^{(S)} \cdot \overline{\eta_j} < 0 \\ 0 \text{ when } \sum_{j=1}^{r} w_{ji}^{(S)} \cdot \overline{\eta_j} = 0 \\ \theta_{max,i} - 1 \text{ when } \sum_{j=1}^{r} w_{ji}^{(S)} \cdot \overline{\eta_j} > 0 \end{cases} \quad \text{for } i = 1, 2, ..., q \tag{25}$$

Then the result becomes

$$\lambda_i^{(S)} = \lambda_i^{(T)} \cdot (1 + c_i \cdot \sum_{j=1}^{r} w_{ji}^{(S)} \cdot \overline{\eta_j}) \text{ for } i = 1, 2, ..., q \tag{26}$$

Step 8. Determination of failure rates of new failure modes, calculation of new total failure rate

The failure rates of failure modes that are only relevant to the subsea system cannot be obtained from the topside system. Therefore, the values of $\lambda_{q+1}^{(S)}, ..., \lambda_n^{(S)}$ have to be determined by expert judgments, technical reports, and limited operational data from other similar systems operating in subsea environment. Finally, the total failure rate for the new subsea system can be calculated by

$$\lambda_{Total}^{(S)} = \sum_{i=1}^{n} \lambda_i^{(S)} \tag{27}$$

3.4.3 Applicability testing by a simple example

To verify the applicability of this approach, we consider a new subsea pump that is used to move fluids in a pipeline as an example of implement. The pump consists of components that are normally found in standard topside pumps, but the design and materials are improved and the application is new. The information about this "new" pump is based on open sources as development of new technology for the subsea industry is confidential. Moreover, subsea systems are commonly highly complex, and the number of failure modes, failure causes and RIFs therefore can be so high that we are not able to cover all of them in this thesis. The purpose of this example is to demonstrate the approach rather than present a realistic case study, thus it does not reach a final result that expresses the realistic failure rate of the new subsea pump.

Step 1: New system familiarization.

The pump is integrated in a single pressure-containing cartridge with statistic seals towards the environment. The pump is multi-stage pump with several impellers connected in series. This enables a higher pressure increase within a limited area. Critical features for this pump are as follows: (i) high reliability is required (i.e., all components require special considerations); (ii) the maintenance philosophy is not standard (i.e., not similar to topside application); (iii) the pump fluid is only partly conventional, and its properties may change over time.

Step 2: Identification of failure modes and failure causes.

In this example, we only consider the most important failure modes, and failure causes that have a significant contribution to corresponding failure modes. The selected failure modes and failure causes are listed in Table 13. Furthermore, to illustrate relevant relationships an influencing diagram is established in Figure 8.

Table 13 Important failure modes and failure causes of the new subsea pump

Category	Description
Failure modes	Fail to start on demand(FTS)
	Low output (LOO)
	Spurious stop (UST)
Failure causes	Mechanical failure-general (MFG)
	Blockage/plugged (BLK)
	Instrument failure-general (IFG)
	Control failure (CF)

Step 3: Reliability information acquisition for the similar known system; comparison of the new and the known system.

As the defined physical boundary of the known topside pump in OREDA, the items made up it are: pump unit, power transmission, control and monitoring, lubricating system, miscellaneous.

To simplify the analysis procedure, we assume that all the important failure modes of the subsea pump are similar to the topside pump. The same for failure causes, although with different effects.

Step 4: Selection of relevant RIFs.

According to the generic RIFs list in Table 11, the selected RIFs are: location of operation, frequency of maintenance, and loads and capacity. The weights of RIFs for each related failure cause are considered as equal.

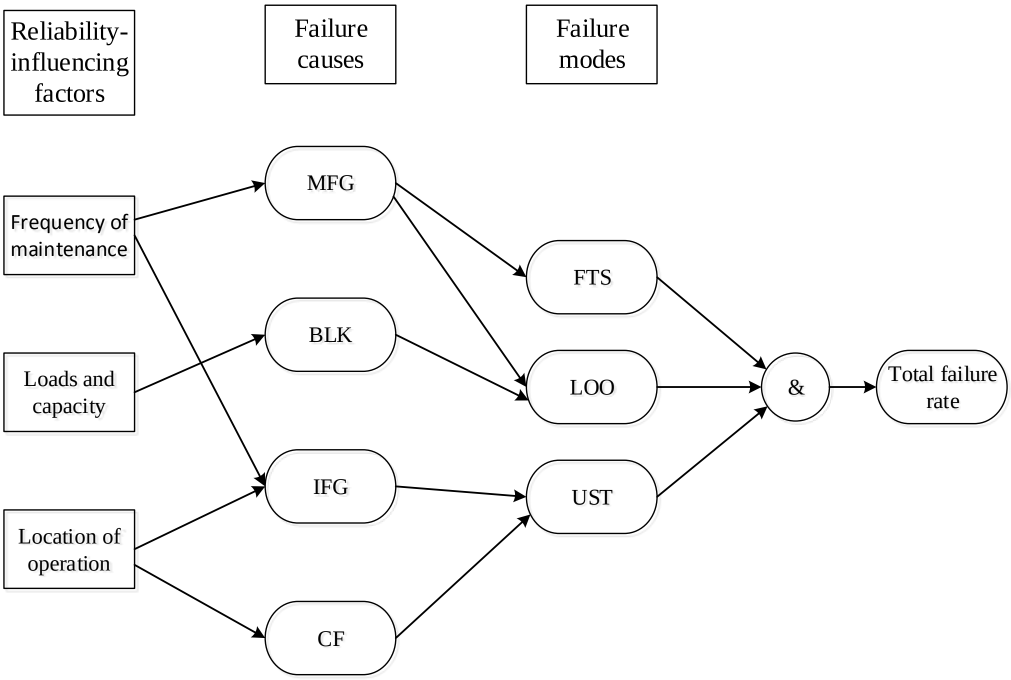

Figure 8 Reliability influencing diagram for the new subsea pump

*MFG: Mechanical failure-general; BLK: Blockage/plugged; IFG: Instrument failure-general; CF: Control failure; FTS: Fails to start on demand; LOO: Low output; UST: Spurious stop

Step 5: Scoring the effects of the RIFs.

The assessment of the RIFs for the topside and the subsea pump are summarized in Table 14.

Table 14 Scoring of RIFs for subsea pump by comparison with the topside pump

				Failure causes			
RIFs	Category	Interpretation		MFG	BLK	IFG	CF
Frequency of maintenance	TS	Every year	Relevance	1	0	1	0
	SS	Every 5 years	Relevance	1	0	1	0
			Score	1	0	0	0
Loads and capacity	TS	Normal	Relevance	0	1	0	0
	SS	Up to 2 times	Relevance	0	1	0	0
			Score	0	0	0	0
Location of operation	TS	Offshore	Relevance	0	0	1	1
	SS	Seabed	Relevance	0	0	1	1
			Score	0	0	-2	1

*RIF: Reliability influencing factor; MFG: Mechanical failure-general; BLK: Blockage/plugged; IFG: Instrument failure-general; CF: Control failure; TS: Topside; SS: Subsea.

The scores in this table are obtained based on Table 12, for example, the effect of location of operation on IFG for a subsea pump seems to be significantly lower than a topside pump, because the design of the subsea pump which located in a capsule, and therefore gives the value of “-2”.

Step 6: Weighing the contribution of the failure causes to failure modes.

The contributing weight of each failure cause to each failure mode for the topside pump is available in OREDA and from step 3. The new contributing weights for the subsea pump have to be determined. These are summarized in Table 15.

Table 15 The old and new contribution weights of failure causes for each failure modes

Failure modes	Failure causes								
	MFG	BLK	IFG	CF	MFC	BLK	IFG	CF	
	Old contributing weights				New contributing weights				Sum
FTS	1	-	-	-	1	-	-	-	1
LOO	0.67	0.33	-	-	o.75	0.25	-	-	1
UST	-	-	0.5	0.5	-	-	0.4	0.6	1

*MFG: Mechanical failure-general; BLK: Blockage/plugged; IFG: Instrument failure-general; CF: Control failure.

Step 7: Adjustment of old failure rates, calculation of total failure rate.

It is assumed that $\theta_{min,i} = 0.3$ and $\theta_{max,i} = 1.1$ for all the failure modes. The NJ,KI, and updated failure rats for failure modes of the subsea pump are summarized in Table 16, Table 17, and Table 18.

Table 16 The values of for each failure cause

Failure causes	MFG	BLK	IFG	CF
	0.33	0	-0.33	0.33

Table 17 The values of min and max for each failure mode

θ_{min}	θ_{max}	Failure modes	κ_i
0.3	1.1	FTS	0.033
0.3	1.1	LOO	0.025
0.3	1.1	UST	0.0066

Table 18 The old and updated failure rates for each failure mode

Failure modes	FTS	LOO	UTS
Failure rates for topside pump	40,73	81,46	101,82
Failure rates for subsea pump	40,86441	81,66365	101,8872

Step 8: Determination of failure rates, calculation of new total failure rate.

Since we have not analysis all failure modes, failure causes, and RIFs, we are not able to obtain any failure rate estimate for the subsea pump.

3.5 Discussion

All of the methods have their limitations and none of these methods mentioned above can be used directly to predict the failure rate of a new subsea system.

For example, the BORA approach is concerned with reliability assessment of safety barriers on offshore oil and gas installations, and considers a set of generic RIFs related to human and organizational factors. However, it requires extensive data to determine covariate values and related parameters. Besides, it mainly focuses on human and organizational factors that influence the risk of hydrocarbon releases. To use available field data from topside systems, this approach needs some extension in different levels, such as scoring and failure analysis.

The "3-step" model which is also based on PH model considers a set of RIFs that are classified according to life cycle phases. The estimation of the application-specific failure rate is comparable with the approach in MIL-HDBK-217F, but the determination of the multiplicative factors is done in another way by scoring and weighing procedure. However, it has difficulties in finding the influencing functions for the indicator.

The approach proposed by (Rahimi and Rausand, 2013) gives us a practical way to obtain the failure rate prediction for some new applications that can be considered as "marinization" of similar topside technology. Investigations of major accidents show that technical, human, operational, as well as organizational factors influence the accident sequences. However, this approach has considered only technical safety systems.

Chapter 4 A New Procedure to Predict the Plant-specific Failure Rates

The main objective of this chapter is to present a new approach for the failure rates prediction of plant-specific equipment, which could minimize the deficiencies of the traditional reliability prediction methods. The proposed approach takes advantage of the potentiality of different reliability prediction approaches. It combines the use of FMECA, reliability influence diagrams and hierarchical RIF model to predict failure rates using the available data from similar topside equipment. This approach makes it possible to analyze how plant-specific conditions of technical, human, as well as operational RIFs influence the predicted failure rates. It also allows realizing more realistic reliability prediction in case of new products or products without historic data. The approach is developed for but not limited to new subsea equipment.

This method tries to combine the evaluation made by means of a prediction model and the collection of results from the field and, when possible, with failure analysis. The analysis flow concerning the proposed reliability method is presented in Figure 9 (Cassanelli et al., 2005).

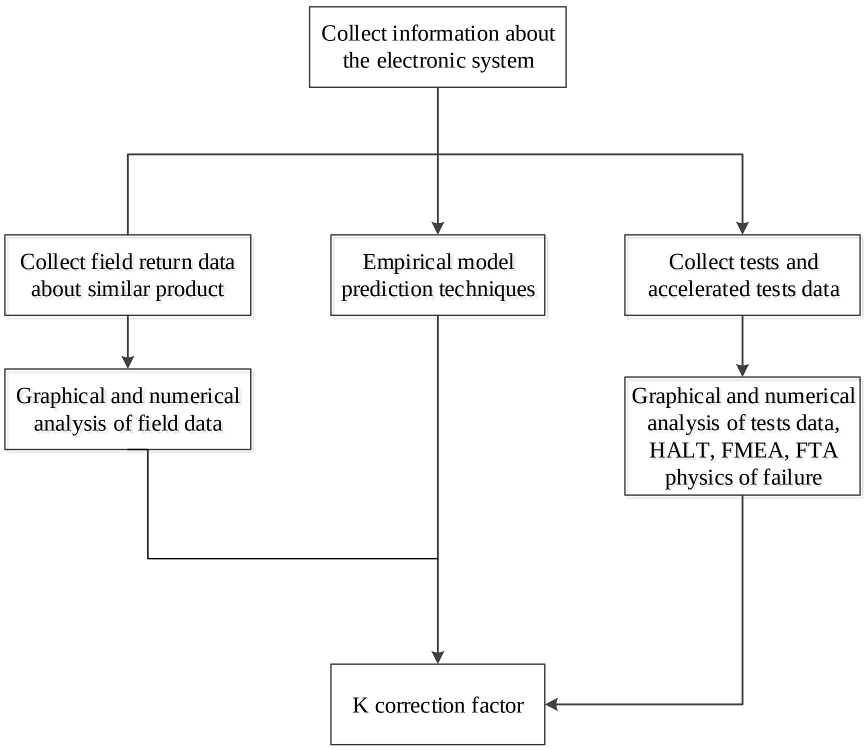

Figure 9 Analysis flow

4.1 Stepwise procedure

All aspects of the model are addressed in a principal manner, in order to illustrate the features of the model and its limitation. In order to make it easy to compare this new approach with existing models and methods, we are going to use the same case as in (Rahimi and Rausand, 2013), which is a simple multistage electric motor driven pump with power less than 500kW.

Step 1: new system familiarization

The study object is a pump that used to move fluids in a pipeline. The pump is made of components that are normally found in standard topside pumps, but the design and materials are improved and the application is new. The tasks in this step are almost the same as in the approach presented in (Rahimi and Rausand, 2013).

Step 2: functional analysis

It is necessary to delimit the scope of the study: which system to be applied and for what functions to achieve in the beginning. To this purpose, we first define the physical boundary of the system and analyze the critical failure modes and their corresponding failure causes, for which FMECA is recommended to be used. The physical boundary of the known topside is specified in (OREDA, 2009). The subunits of a topside pump are: pump unit, power transmission, control and monitoring, lubricating system, impellers, miscellaneous.

Step 3: reliability information acquisition from similar systems

The input data is collected from past experience data on system with a similar and comparable technology. The data are evaluated for form, fit and function compatibility with the new subsea system. If the new system is an item that is undergoing an enhancement, the collected data will provide a good basis for comparison to the new system. If the system does not have a direct similar item, the lower level similar circuits can be employed.

All the maintainable items related to each subunit are listed in detail in (OREDA, 2009). Several reliability data tables for topside pumps are also provided in (OREDA, 2009). For each type of pump, a main data table gives the failure rates for the different failure modes, together with 90% confidence bounds. Another table lists the relative contribution from each failure cause to the failure rate.

Step 4: model definition and selection of RIFs

As discussed in step 3, we try to consider not only technical factors, but also operational, human, and organizational factors, however, not including the influence due to design (e.g., system structure and material).

To analyze the RIFs in a more comprehensive way, we use the hierarchical model of RIFs presented in (Vinnem et al., 2012) as an improvement, where the RIF identification process results in a RIF structure of two levels. Level 1 consist RIFs with a theoretical and empirical justified direct influence on one or more of the failure causes. Level 2 represents different aspects of management that have a theoretically and empirically justified influence on the RIFs on level 1. The two-levels-RIF structure is chosen to emphasize and elucidate the underlying impact of managerial decisions on the probabilities of failure modes. Only the RIFs on level 1 are in our model considered to influence the probability of failure causes triggered. RIFs on level 2 are considered only to influence RIFs on level 1, and may regarded as a means to reduce the uncertainty implied by observations of RIFs only on level 1 with associated scores. Scores and influence from RIFs on level 2 are used together in order to provide information about the true value of the RIFs. To make the calculation procedure simpler, we are not going to score the influence from RIFs on level 2.

Step 5: RIF's importance measurement (Vinnem et al., 2012).

It is important to define the weight of each RIF for corresponding failure cause. In the approach presented in (Rahimi and Rausand, 2013), the weights of RIFs for each related failure cause are considered as equal. Similarly, in the BORA model, the RIF's structure used was one level structure, where all the RIFs were given the same structural importance. However, it is obviously not realistic.

Analysis of importance is well known in fault tree analysis, using which, we could find the most effective and economic solution to reliability improvement. It is usually established for classical sensitivity analysis. There are many important measures in the literature. We will use a Birnbaum like measure of reliability importance, which is one of the most commonly used measures, see (Rausand and Høyland, 2004). The Birnbaum's measure,$I_{(i)}^{B}$ is defined as the change in probability (denoted by Q_0) of top event due to the change in unreliability of component I (denoted by q_i), which can be expressed by $I_{(i)}^{B} = \frac{\partial Q_0}{\partial q_i}$. If $I_{(i)}^{B}$ is large, a small change in the reliability of component *i* will result in a comparatively large change in the top event. Similarly, the changes in RIFs with higher importance will result in bigger influences on the system failure rate.

The next challenge, therefore, is to develop a Birnbaum-like measure that could be applied for the RIFs. Since the RIFs are random variables not parameters as in fault tree or event tree, we need another definition of a “small change” in the value of the RIF. We define this change in a RIF in terms of a shift in the expected value of the RIF. Let π_j be the posterior distribution of RIF_i, and ΔE_j be the change in the expected value of π_j. Further let F be the frequency of the critical failure modes, (e.g., failure to start) where F depends on the posterior distribution of the RIFs, and in particularRIF_j. A Birnbaum-like measure for the importance of RIF_j is then given by:

$$I_{RIF}^{B}(j) = \left[F\left(\pi_j^{\Delta}\right) - F\left(\pi_j\right)\right] / \Delta E_j \qquad (28)$$

To interpret the philosophy behind the Birnbaum-like measure in an easier way, we can recall the meaning of it in fault tree, where reducing the basic event failure probability with Δq_i, system failure rate may be reduced by $I_{(i)}^{B} * \Delta q_i$. Similarly, the change in the system failure rate could be calculated by the combination of the Birnbaum-like measure $I_{(i)}^{B}$ and the shift in the expected value of the RIF given by $I_{RIF}^{B}(j) * \Delta E_j$.

The advantage of having this knowledge is that by focusing on the measures that have an influence on the RIFs with highest importance, one could expect that these measures would also have the largest effect on the overall system reliability. The detailed presentation can be found in (Vinnem et al., 2012) and (Gran et al., 2012).

Step 6: scoring the effects of RIFs

The scores indicate how much lower or higher are the effects of RIFs on a subsea pump compared with a topside pump. This is usually evaluated by expert judgment.

Step7: weighting the contribution of failure cause to the failure mode

The contributing weight of each failure cause to each failure mode for the topside pump is available in (OREDA, 2009) and in step 3.

Step 8: modeling of dependencies in terms of fault tree

(Podofillini et al., 2009) and (Čepin, 2008) reviewed the models for assessing human reliability analysis dependence. We will use the same dependence levels (i.e., zero, low, moderate, high and complete) to analysis our case. For each of these levels it corresponds a β factor which is the conditional probability of a subsequent failure given a first failure. It is commonly agreed that common cause failures is a more important issue after a component failure compared to our situation. Therefore, we assume lower common cause influence than found in the literature.

One way to include the common cause effects in the modeling is to do a recalculation of the minimal cut sets in the fault trees.

For example, if a minimal cut set comprises the following basic events: P=Planning error; CP=Control planning error; E=Execution error, CE=Control execution error. And let $\beta_{CP|P}$ and $\beta_{CE|E}$ denote common cause factors for controlling the plan, and controlling the execution respectively. We may use the following approximation to find the probability of failure contribution from this minimal cut set:

$$Q_j = \left[q_P q_{CP} + \beta_{CP|P} \min(q_P, q_{CP})\right] + \left[q_E q_{CE} + \beta_{CE|E} \min(q_E, q_{CE})\right] \qquad (29)$$

where we assume there is no common cause effects between planning and execution, and the β-values are found by equation:

$$\beta = \beta_0 \prod_i w_i^{S_i} \qquad (30)$$

where $\boldsymbol{\beta_0}$ is the baseline common cause factor, and $\boldsymbol{w_i}$ is the weight of factor *i*.

Step 9: modeling of interactions between RIFs

The influence of one RIF on the failure cause in assumed to be independent of the influence of the other RIFs in the models presented in chapter 3. However, there might be causes where a high score of one or more RIFs balances or neutralizes the low score of other RIFs (Vinnem et al., 2012).

Further explanation is that, the effect of a low (bad) observation of a RIF would be higher if one or more of other RIFs also have a low observation. Similarly it can be argued that the effect of one good RIF would be increased if one or more RIFs are good. The latter might represent a problem in the modelling where a RIF is represented in characters. To allow for a neutralization effect, the model has to be extended to also have negative characters, or one has to set the weight of such a set of RIFs equal to zero (Gran et al., 2012). The interaction effect will be triggered if both the involved RIFs have a low observation, and a weight (low, medium or high) is multiplied by the original weights.

The arguments in the modelling of interaction effects are as follows: interaction effects are only modelled between RIFs on level 1 due to the fact that no level 1 RIFs are influenced by more than one level 2 RIFs in the reliability influence diagram. Further the influence of the level 1 RIFs on the probability of failure cause triggered are essentially determined by a weighted sum of the level 1 RIFs, i.e.,

$$r = \sum_i w_i r_i \tag{31}$$

where r_i is a score of RIFs on level 1.

In the modelling of interaction effects subsets of the total set of RIFs are considered to represent a potential for interaction. However, we have assumed that interaction effects only come into play when all the RIFs in a subset have an observation worse than the average RIF score. We only consider subsets of two or three RIFs. In order to simplify the modelling of interaction effects we assign a weight, w_I of the interaction effect which is relative to the weight of the various RIFs in the interaction subset, say *I*. For each RIF in the subset I we then may find a total weight of the RIF in addition the original weight of the RIF, i.e.,

$$w_{I,i} = w_i f \tag{32}$$

where w_i is the original weight of the RIF, and *f* is a correction factor. If one or more of the RIFs have an observation better than the average RIF score we set $f = 0$. If all the RIF scores in *I* have the worst score, we set $f = 1$. For scores between we apply a linear transformation:

$$f = (\sum r - \sum C')/(\sum F' - \sum C') \tag{33}$$

where $\sum r$ is the sum of RIF scores in *I*, $\sum C'$ is the sum of the same RIFs if they are all equal to “C”, and $\sum F'$ is the sum if they all equal to “F”. Further the total impact of the RIFs on each failure cause is calculated from:

$$r = \sum_i w_i r_t + \sum_{i \in I} w_I i^r \tag{34}$$

where we have summed the interaction effects for one subset of interactions. In principle there might be more than one subset of interaction effects, and we also need to add these.

Step 10: determination of the failure rate for similar failure mode

Using the same method presented in (Rahimi and Rausand, 2013), given the assumption that $\theta_{min,i} = 0.3$ and $\theta_{max,i} = 1.1$ for all the failure modes. We can obtain the values of N calculated based on equation 22. Further the values of κ_i calculated based on equation 22 and equation 25. The failure rate related to each failure mode for topside pump are available from step 3. The updated failure rates for failure modes of the subsea pump are obtained based on equation 26.

Step 11: the total failure rate of the new subsea pump

Finally, the total failure rate for the new subsea pump can be calculated by summing up the failure rate of each failure mode. As mentioned previous, even though the contributing failure modes to the total failure rate are not completely independent, we consider it is sufficiently accurate estimate of the sum of failure rate of each failure mode.

However, since we only considered a few failure modes, failure causes and RIFs, it is not possible to obtain any failure rate estimate for the subsea pump. In a real case, a subsea pump should be able to survive five years with a probability of at least 95%. The case study has only illustrated the stepwise approach. Only four failure modes have been considered. Besides, a comprehensive and thorough consideration of RIF is very important for getting a reliable estimate of failure rate.

4.2 case study

Step 1: new system familiarization

The study object is a pump that used to move fluids in a pipeline. The pump is made of components that are normally found in standard topside pumps, but the design and materials are improved and the application is new. The tasks in this step are almost the same as in the approach presented in (Rahimi and Rausand, 2013). The purpose of this case study is to illustrate the new method, not to present a complete and accurate failure rate estimate; therefore we ignore some failure modes, failure causes and RIFs that do not give the biggest contribution to the system failure rate.

Step 2: functional analysis

To delimit the scope of the study, we first define the physical boundary of the system and analyze the critical failure modes and their corresponding failure causes, for which FMECA is recommended to be used. The physical boundary of the known topside is specified in

(OREDA, 2009). The subunits of a topside pump are: pump unit, power transmission, control and monitoring, lubricating system, impellers, miscellaneous.

As described in (Rahimi and Rausand, 2013), the subsea pump and the electric motor are integrated in a single pressure-containing cartridge with static seals towards the environment. Here we consider the cartridge and the pump as the study objects which will make it more reasonable to include the environmental condition factors in the analysis. In principle, all the critical failure modes and failure causes for the subsea pump have to be identified and listed. However, due to the complexity of subsea systems, the number of failure modes, failure causes, and RIFs can be very high that we are not able to cover all of them in this case. Therefore, we only consider the most important failure modes and the failure causes which are listed in Table 19. In addition, an influence diagram will be illustrated in Figure **12**. If we could have more detail about the design, we prefer to conduct a fault tree analysis to help us understand the system in component level. However, limited to the high confidential of new technology for the subsea industry, we hence only able to present a general structure of the subsea pump, see Figure 10.

Table 19 Important failure modes and failure causes

Category	Description
Failure modes	Fail to start on demand (FTS) Low output (LOO) Spurious stop (UST) Leakage to the environment (LTE)
Failure causes	Mechanical failure-general (MFG) Clogging/plugged (CLG) Instrument failure-general (IFG) Control failure (CF) Corrosion & erosion (CE) Human error (HE)

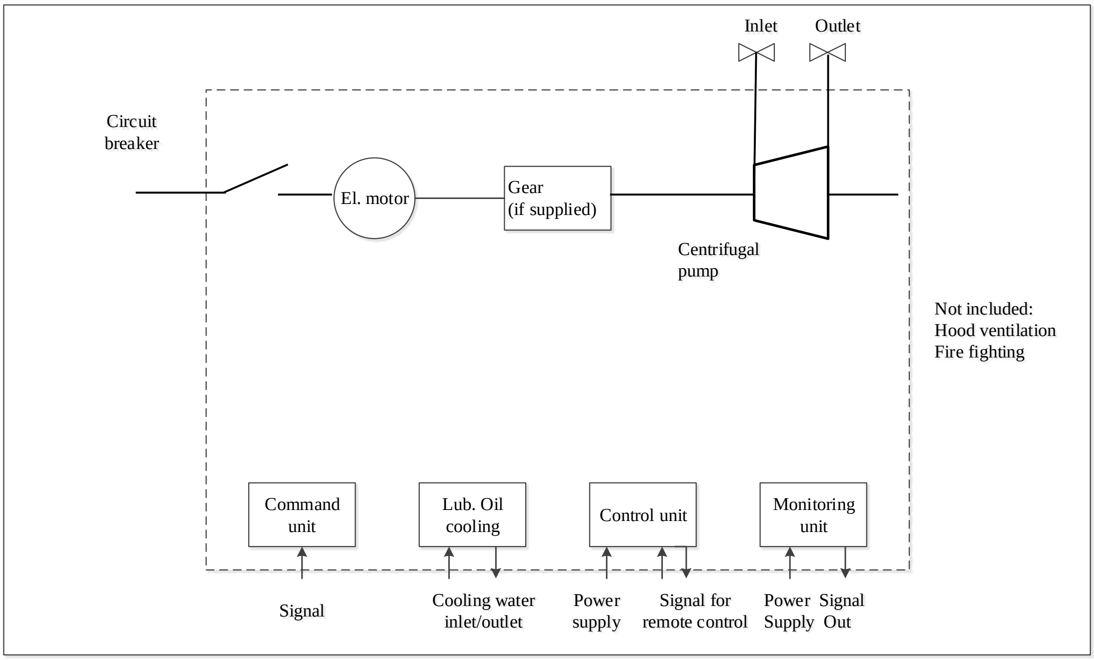

Figure 10 The physical structure of the new subsea pump

Step 3: reliability information acquisition from similar systems

The subsea pump and the topside pump have to be compared with respect to technological solutions, failure modes, failure causes. The topside lubrication system is not feasible subsea and a totally different design may be required, such as magnetic bearings. To assess the effect of this difference will require a detailed analysis and is outside the scope of this thesis. In this case, we therefore assume that all the important failure modes of the subsea pump are found to be similar to topside pump. The failure causes are also found to be similar, although with slightly differences.

Step 4: model definition and selection of RIFs

In this case, the main RIFs on level 1 are loads and capacity (LC), frequency of use, location of operation (LO), frequency of preventive maintenance (FOM), quality of maintenance, maintenance policy, corrosion and humidity (CH), working load/stress (WS) and competence (C) . Furthermore, they are illustrated in the hierarchical RIF model associated with their corresponding RIFs on level 2 (i.e., management task, management information, management general), see Figure 11. However, to simplify the analysis, we assume that the quality of maintenance and frequency of use for the new subsea pump are in the same condition comparing to the similar topside pump. Therefore, the selected RIFs are just FOM, LO, LC, CH, WS and C.

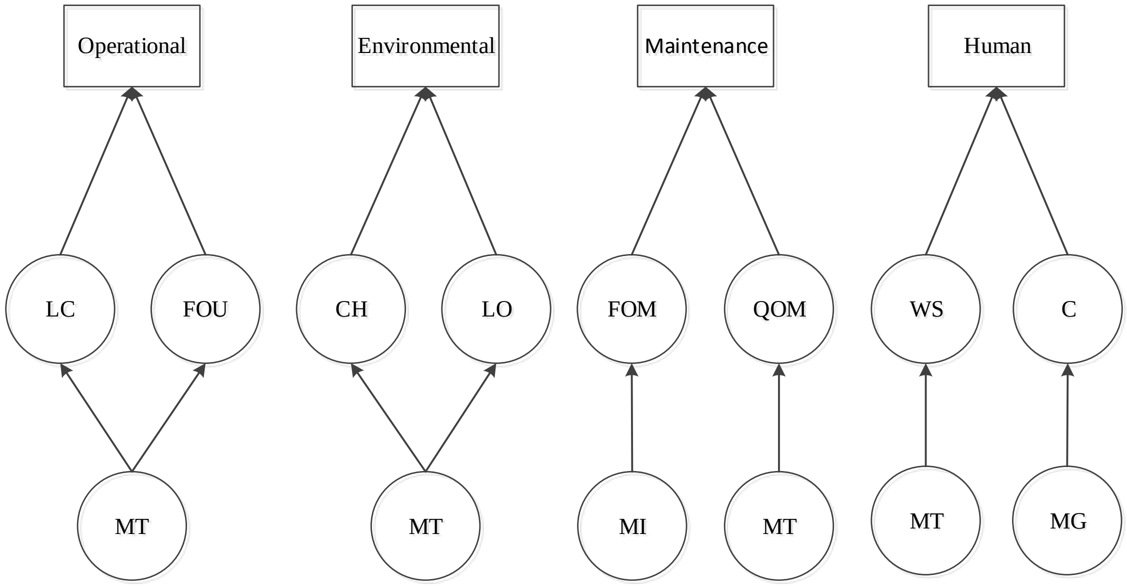

Figure 11 The hierarchical RIF model

Adding the functional analysis in step 2 we could conduct the reliability influence diagram to model the effect of operational, environmental, maintenance, and human factors, see Figure 12.

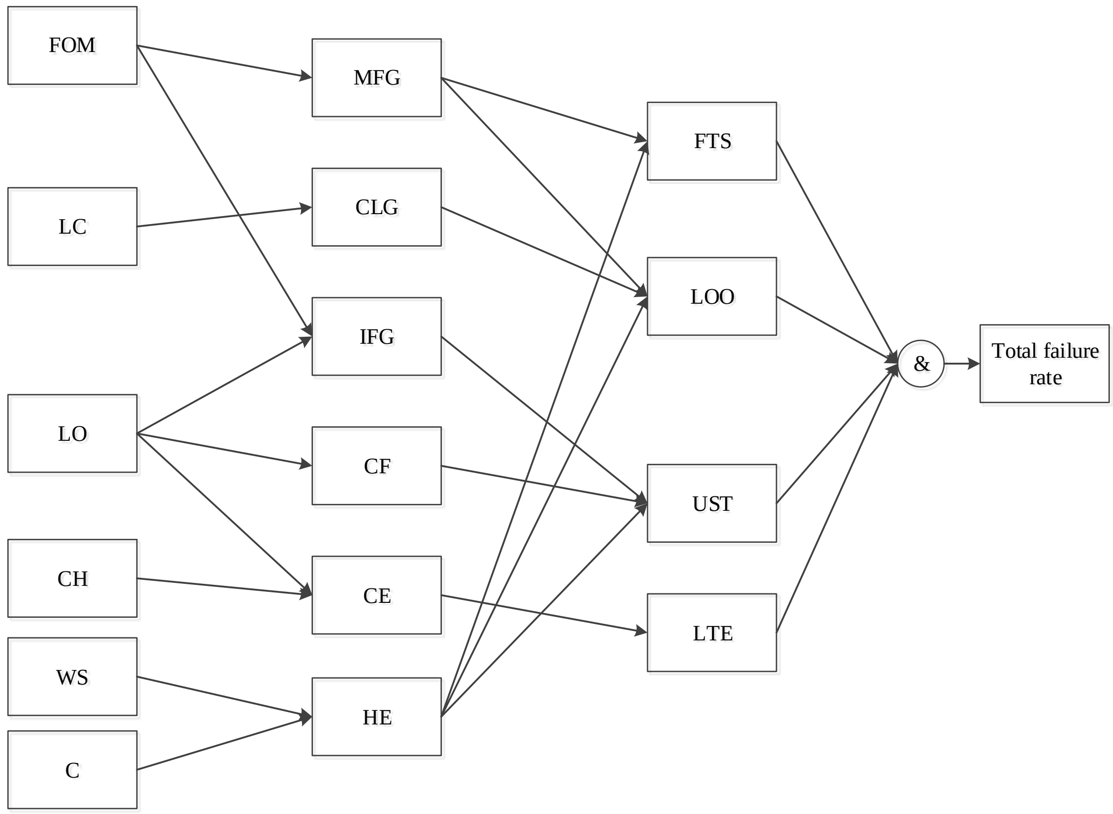

Figure 12 The reliability influence diagram

Step 5: RIF's importance measurement (Vinnem et al., 2012).

We use the Birnbaum-like measure to assess the importance of RIFS. However, since we are not aiming to get an accurate prediction we only provide the approximate weight of each RIF, see Table 20. The weighting of the RIFs is done by expert judgment. In practice, the assessment of the weights is based on a general discussion of the importance with platform personnel and the analysts. The weights are normalized as the sum of the weights for the RIFs influencing a failure cause should be equal to 1.

Table 20 The weight of RIF for each failure cause

	RIFs FOM	LC	LO	CH	WS	C
MFG	1	-	-	-	-	-
CLG	-	1	-	-	-	-
IFG	0.70	-	0.30	-	-	-
CF	-	-	1	-	-	-
CE	-	-	0.35	0.65	-	-
HE	-	-	-	-	0.5	0.5

Step 6: scoring the effects of RIFs

How we score the effect of RIFs is almost the same as in (Rahimi and Rausand, 2013) where we use the seven-point score for RIF given in Table 12. The assessment of the RIFs for the topside and the subsea pump is presented in Table 21 in the format of Table 14. The scores indicate how much lower or higher are the effects of RIFs on a subsea pump compared with a topside pump. For example, the RIF "location of operation" effects on the failure cause "corrosion and erosion" for both subsea pump and the topside pump, and therefore they are given value of 1 representing relevant. In addition the effect of location of operation on "CE" for a subsea pump seems to be significantly higher than a topside pump, owing to the depth of location will influence the corrosion rate, and therefore given the value of 2.

Table 21 Scoring of RIFs for subsea pump by comparison with the topside pump

				Failure causes					
RIFs	Category	Interpretation		MFG	CLG	IFG	CF	CE	HE
FOM	TS	Every year	Relevance	1	0	1	0	0	0
	SS	Every 5 years	Relevance	1	0	1	0	0	0
			Score	1	0	0	0	0	0
LC	TS	Normal	Relevance	0	1	0	0	0	0
	SS	Up to 2 times more	Relevance	0	1	0	0	0	0
			Score	0	0	0	0	0	0
LO	TS	Offshore (wind…)	Relevance	0	0	1	1	1	0
	SS	Sea bed (depth…)	Relevance	0	0	1	1	1	0
			Score	0	0	-2	1	2	0
CH	TS	In air	Relevance	0	0	0	0	1	0
	SS	Under water	Relevance	0	0	0	0	1	0
			Score	0	0	0	0	2	0
WS	TS		Relevance	0	0	0	0	0	1
	SS		Relevance	0	0	0	0	0	1
			Score	0	0	0	0	0	-1
C	TS		Relevance	0	0	0	0	0	1
	SS		Relevance	0	0	0	0	0	1
			Score	0	0	0	0	0	-1

Step7: weighting the contribution of failure cause to the failure mode

The new contributing weights for the subsea pump have to be determined based on the information in OREDA and in step 3. The weights are summarized in Table 22. The field data indicate that human error plays a critical role in major accidents; however, our focus is technical factors. We hence give relatively lower weight to HE. This may not be realistic.

Table 22 The topside and subsea contribution weights of failure causes of failure modes

Failure modes	Failure causes MFG	CLG	IFG	CF	CE	HE	MFG	CLG	IFG	CF	CE	HE	Sum
	Old contributing weights ()						New contributing weights ()						
FTS	0.60	-	-	-	-	0.40	0.75	-	-	-	-	0.25	1
LOO	0.60	0.30	-	-	-	0.10	0.67	0.23	-	-	-	0.10	1
UST	-	-	-	0.45	0.45	0.10	-	-	-	0.36	0.54	0.10	1
LTE	-	-	-	-	1	-	-	-	-	-	1	-	1

Step 8: modeling of dependencies in terms of fault tree

The simplified model of scoring regime for each common effect factor and a simple example can be found in (Vinnem et al., 2012). There are two feasible ways to include them in the modeling. One way is to model explicitly the common cause effects by including additional basic events in the fault tree and the event tree. This can be done easily in both the BNN model and the hybrid model. The other alternative, which can only be implemented by the hybrid model, is to do a recalculation of the minimal cut sets in the fault trees. The challenge then is to describe the possible dependencies for various classes of basic events, and then add common cause effects when the minimal cut set contributions are calculated. For both of the two practical ways, it will also require an assessment of the size of the common causes.

Step 9: modeling of interactions between RIFs

We only present the principle of how to model the interactions between RIFs, not intend to adjust the scores listed Table 21.

Step 10: determination of the failure rate for similar failure mode

Table 23 shows the values of η_j calculated based on equation21. Since only frequency of maintenance affects MFG, which is the only case will contribute in the value of average score of MFG, where the weight of failure of maintenance for MFG is equal to 1, and the average η_j is equal to $\frac{1}{3}$, The value of average score for MFG is calculated by $1 * 1 * \frac{1}{3} = 0.3$.

Table 23 Table of the value of $\boldsymbol{\eta_j}$ for each failure cause

Failure cause	MFG	CLG	IFG	CF	CE	HE
nj	0.33	0	-0.2	0.33	0.33	-0.33

The values of κ_i calculated based on equation 22 and equation 25 are summarized in Table 24. The sum of $w_{ji}^{S} n_j$is calculated by:

$$0.6 * \frac{1}{3} + 0.4 * \frac{-1}{3} + 0.6 * \frac{1}{3} + 0.1 * \frac{-1}{3} + 0.45 * \frac{1}{3} + 0.45 * \frac{1}{3} + 0.1 * \frac{-1}{3} + 1 * \frac{1}{3} = 0.83,$$

which is greater than 1. Therefore, $C_i = \theta_{max,i} - 1 = 0.1$. Further we can get κ_i, for example, for FTS, the κ is equal to $0.1 * (0.6 * \frac{1}{3} + 0.4 * \frac{-1}{3}) = 0.0066$.

Table 24 Table of the values of .. for each failure mode

θ_{min}	θ_{max}	Failure modes	C_i	κ_i
0.3	1.1	FTS	0.1	0.0066
0.3	1.1	LOO	0.1	0.0167
0.3	1.1	UST	0.1	0.0267
0.3	1.1	LTE	0.1	0.0330

The failure rate related to each failure mode for topside pump are available from step 3. The updated failure rates for failure modes of the subsea pump are obtained based on equation 26 and listed in Table 25. The failure rates are given per 10^6 hours.

Table 25 The failure rates for each failure mode from topside and subsea

Failure modes	FTS	LOO	UST	LTE
Failure rates for topside pump	40.15	82.91	96.00	49.75
Failure rates for subsea pump	40.42	84.29	98.56	51.39

Step 11: the total failure rate of the new subsea pump

Finally, the total failure rate for the new subsea pump can be calculated by summing up the failure rate of each failure mode. However, since we only considered a few failure modes, failure causes and RIFs, it is not possible to obtain any failure rate estimate for the subsea pump.

In principle, we could predict the failure rate of the new subsea pump if we conduct a comprehensive analysis following the procedure introduced in section 4.1.

The case study has demonstrated that the model gives a good basis for ranking the proposed failure rates prediction method. In addition, the general model can be successfully applied to various installations. When analyzing subsea equipment or systems, the reliability prediction process can be extremely important and difficulty. Therefore, there is no attempt made here to present a thorough analysis.

Chapter 5 Summary and recommendations for further work

This chapter is divided into two parts. In the first section, the applicability and limitation of these approaches are discussed. Furthermore, on the basis of the case study following the new procedure for failure rates prediction of plant-specific equipment, a comparison between the new reliability prediction approach and existing approaches is conducted which shows that it is applicable and more comprehensive. In the second section, existing problems to be solved are enumerated and recommendations for further work are proposed.

5.1 Summary and Conclusion

Based on the philosophy of reliability prediction methodologies introduced in Chapter 2, we have chosen several feasible models and methods, which are specific in an industrial area, to discuss. Most of them give reasonably accurate values for the failure rates; however, they all have significant weaknesses, see section 3.5.

Based on these existing approaches, we combined some of them and developed a new approach capable of prediction complex new subsea systems that are adapted from similar topside. There are several improvements in the new approach.

First of all, we provide more comprehensive model for RIF analysis. On one hand, the plant-specific conditions of technical, human, operational, as well as organizational RIFs that influence the predicted failure rates are all considered and illustrated by a hierarchical RIF model. A complete list of RIFs is very important owing to the comparative characteristics of the approach. On the other hand, a Birnbaum-like measure is applied for measuring the importance of RIFs. Differ from giving RIFs equal weight as in other approaches, the Birnbaum-like measure helps us figure out which RIF influence the system reliability most. This gives us a practical way of making design decision more cost effective. In other words, it confirms that the control of probability of failure on demand can be achieved through the control of changes in RIFs

Furthermore, taking the fact that influences of RIFs on one failure cause are not independent each other into consideration, the interactions between RIFs are modeled quantitatively and conceptually. In the case study, although a numerical calculation is not performed, neither the interactions influence how we predict the failure rate of new subsea pump. This is just due to the limitation of information. The principle is totally applicable.

In addition, we include common cause effects in analyzing the dependences between different failure modes so that the system failure rate is no longer the simple sum of failure rates for all failure modes, which is more realistic in industry application. One way to model explicitly the common cause effects by including additional basic events in the fault trees. The other way in to a recalculation of the minimal cut sets in the fault trees, which is demonstrated by a simple example. To carry out a dependency analysis, further knowledge of the BNN model and the hybrid model.

5.2 Recommendations for Further Work

The usefulness of a reliability prediction is a dependent on how well the prediction satisfies the user's objectives. However, the accuracy of the prediction results is dependent on the accuracy and completeness of the information used to perform he prediction, and in the method used to conduct the prediction. Many manufactures have stated that the carious reliability prediction methodologies based on statistical analysis of limited historical data can be significantly inaccurate and inconsistent when compared to actual field performance.

Investigation of major accidents has shown that human error is the most common cause of system failure. However, it is difficult to give quantitative analysis on human error and organizational defects. Moreover, the assessment of RIF scores, failure causes contribution weights for failure modes and many other data are dependent on expert judgment. Both of the two issues are somehow subject to perception of experts.

Besides, these approaches presented in this project all have a weakness that they do not take uncertainty into consideration. We may relate uncertainty to model and data, which is also called sensitivity analyses in some papers.

All in all, it is our belief that the best reliability prediction could only be achieved by a combined use of different methods. A specific reliability figure is of less concern compared to the confidence in the effective reliability level of the product to be sold. The use made of the reliability prediction concepts should also be coherent, i.e., based on sound principles, explained to the customer throughout the whole process.

However, what industries really want is a risk factor and not only a reliability prediction: they want to know the risk of new equipment compared to a consolidate equipment.

Appendix A

Acronyms

AF	Accelerate factor
BNN	Bayesian belief network
BORA	Barrier and operational risk analysis
CCA	Circuit card assembly
COTS	Commercial off the shelf
CPT	Conditional probability table
DFM	Dynamic flow graph methodology
DoD	Department of defense
ETA	Event tree analysis
EUC	Equipment under control
FAST	Functional analysis system technique
FT	Fault tree
FMECA	Failure modes, effects and criticality analysis
GTST	Goal tree-success tree
HEP	Human error probability
MEMS	Micro electro-mechanical systems
MFM	Multilevel flow modeling
MLD	Master logic diagram
MTTF	Mean time to failure
RIF	Reliability-influencing factor
SADT	Structure analysis and design technique
SIS	Safety instrumented system
PFD	Probability of failure on demand
PH	Proportional hazards
PSA	The petroleum safety authority Norway
PoF	Physics-of-failure
QRA	Quantitative risk analysis
RBD	Reliability block diagram
RID	Reliability influencing diagram
RIF	Reliability influencing factor
TQP	Technology quantification program

Appendix B

Comparison of Reliability Prediction Methodologies (Pechta et al., 2002)

	Field data	Test data	Stress and damage Models	Handbook Methods				
				MIL-HDBK-217	RAC's PRISM	SAE's HDBK	Telecordia SR-32	CNET's HDBK
Does the methodology identify the sources used to develop the prediction methodology and describe the extent to which the source is known?	Yes	Yes	Yes	No	Yes	No	No	No
Are assumptions used to conduct the prediction according to the methodology identified, including those used for the unknown data?	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Are sources of uncertainty in the prediction results identified?	Can be	Can be	Can be	No	No	No	No	No
Are limitations of the prediction results identified?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Are failure modes identified?	Can be	Can be	Yes	No	No	No	No	No
Are failure mechanisms identified?	Can be	Can be	Yes	No	No	No	No	No
Are confidence levels for prediction results identified?	Yes	Yes	Yes	No	No	No	No	No
Does the methodology account for life cycle environmental conditions, including those encountered during a) product usage (including power and voltage conditions), b)packaging, c)handling, d) storage, e) transportation, and f) maintenance conditions?	Can be	Can be	Yes	No	No	No	No	No
Does the Methodology account for material, geometry, and architectures that comprise the parts?	Can be	Can be	Yes	No	No	No	No	No
Does the methodology account for part quality?	Can be	Can be	Yes					
Does methodology allow incorporation of reliability data and experience?	Yes	Yes	Yes	No	Yes	No	Yes	No

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Internship & Projects

NTNU:

- **Prediction of plant-specific failure rates (Master Thesis)**

  Perform a survey of existing reliability prediction approaches and discuss pros and cons of each approach. Further, to suggest a suitable approach for failure rate prediction of new subsea process equipment that can be considered as "marinized" from topside equipment.

- **Reliability Assessment of Safety-instrumented Systems in High-demand Mode (Specialization Project)**

  Present different approaches to calculating the PFH for SISs operating in high-demand mode with common cause failures considered. Discuss and compare these approaches to find the most suitable reliability performance measure. In the end an example of calculation on the ships' dynamic positioning (DP) system was performed to confirm the applicability of these approaches.

- **Risk Analysis of A Catenary Anchor Leg Mooring Buoy**

  Using PHA, FMECA, HAZOP, ETA to present hazardous events, further, develop risk matrix and give recommendations.

- **Reliability Analysis of a Steam Boiler**

  Analysis the structure of the system and how the top event could be triggered using FMECA & FTA. Based on CARA software calculate different

PFDs for subsystems and the top event. Further, recommendations and improvements are given to achieve required SIL.

- **RAMS Requirements of a Lubrication System for the Norwegian Cruise Liner MS Polarlys**

  Build up hierarchical function tree and FMECA on vital components, estimate RAMS performances based on industrial data, and calculate the LCC of the whole system considering risk and operational cost.

- **World-class Maintenance and Reliability**

  Theoretical research on challenges and solutions in applying TPM, RCM & lean maintenance models.

CSU:

- Internship in Railway Bureau of Weihai, Shandong Province 07/2009
- Internship in Freight Section, Railway Bureau of Zhuzhou, Hunan Province 05/2011
- Internship in Passenger Section, Railway Bureau of Nanchang, Jiangxi Province 04/2012-05/2012
- Research on Factors that affecting Urban Transit Attraction 01/2012-06/2012

  Graduate thesis for Bachelor degree. Comparing the occupancies of public transit in all trips in different cities and analyzing data to work out the affecting factors. Taking Changsha city as an example, proposing some available options to increase the percentage of public transit in all trips.

Computer Skills and Language

- Excellent at Microsoft Office, AutoCAD, Matlab, Minitab, SPSS, C++ & Visual Foxpro
- Language: English (proficiency), Chinese (mother tongue), Japanese and Norwegian (beginner)

Honors (2008-2012)

- Outstanding Scholarship, 1st, 2nd and 3rd year in CSU (Top 5%)
- Brilliant Graduate Award (5%)

Extracurricular Roles

- Student Assistant of Risk Management in Project 08/2013-12/2013
- Vice-president in Chinese Students and Scholars Association, NTNU 08/2013-present
- Diplomacy department in the Students Union, CSU 09/2008-06/2011
- Journalist in Medium Center, CSU 09/2008-06/2010
- Secretary in Center of Career Development, CSU 09/2008-06/2010

Hobbies

Swimming, badminton, skiing, travelling, cooking, jazz and country music, traslating movies & billiards

Reference

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