DEVELOPMENT OF DYNAMIC MODELS TO ESTIMATE ICE ACCUMULATION RATE AND RISK-BASED INSPECTION INTERVAL

by

© Karan Bhatia

A Thesis Submitted to the

School of Graduate Studies

in partial fulfilment of the requirements for the degree of

Master of Engineering

Faculty of Engineering and Applied Science

Memorial University of Newfoundland

October, 2018

St. John’s Newfoundland and Labrador.

Abstract

Evolving process operations in harsh environments and stringent safety regulations have created increasing complexity in the assessment and management of risks. This demands an advanced approach to monitor and manage the process system's risk profile. This thesis presents two contributions: i)a model for dynamic risk-based inspection planning, and ii)a predictive model for the ice-accumulation rate for operations in extremely cold conditions.

The traditional risk-based inspection (RBI) guidelines assume that the system is safe for operation throughout the planned interval. This assumption has led to several unfortunate accidents. A novel dynamic RBI model has been proposed in this study to monitor the system's degradation rate and estimate its impact on the risk profile. The results were compared with the risk profile obtained industrial guideline: API-581. It is demonstrated that the use of this framework would provide a better understanding and monitoring of the system's risk. This will help to plan for optimal inspection intervals rendering the maximum cost savings possible while ensuring the system's safety.

A new model is developed to predict the ice accumulation rate on sea vessels and offshore rigs operating in harsh and cold regions. This model use Bayesian approach to predict the icing rate. It be easily be applied to a wide range of vessels and rigs and can include several parameters. The model was tested and validated using an experimental setup designed to simulate the spray-icing observed on sea vessels. It was concluded that the ice accumulation rate predicted using the proposed model was reasonably close to the values observed in the experiment.

Acknowledgement

Many people have supported me in my research. Here, I attempt to thank all who in one way or another helped me in the completion of this thesis. I would like to thank Dr. Faisal Khan for his invaluable encouragement and supervision throughout this work. I am eternally grateful to him for not only guiding me during this research but also for providing a supportive and inclusive learning environment.

I would like to thank all my university colleagues, members of C-RISE and my friends for cheering me up and motivating me during the roadblocks in my research. I would like to acknowledge the support from the Queen Elizabeth II diamond jubilee scholarship program and its sponsors for financing my studies and making me part of the prestigious and global QEScholars community. I thank the school of graduate studies and the international office, especially Ms. Carol Sullivan, Ms. Lynn Walsh, and Dr. Aimée Surprenant, for providing me several opportunities to develop, learn and engage with the community.

I want to acknowledge the help from Peiwei Xin and Dinesh Herath, Dan Chen and Dr. Ming Yang for their contributions in designing and documenting the experimental setup used in this research.

Finally, I thank my parents and family to whom I owe my success. I am indebted for their constant care and support for the last twenty-five years. Most of all, I thank Ms. Hiral Patel for her love. She is the source of my motivation and strength in difficult times. I dedicate this work to them.

Table of Contents

List of Tables

List of Figures

List of symbols Nomenclature and Abbreviations

POF	Probability Of Failure
COF	Consequences Of Failure
DRA	Dynamic Risk Assesment
IM	Inspection and Maintenance
RBIM	Risk-Based Inspection and Maintenance
RBI	Risk-Based Inspection
DRBI	Dynamic Risk-Based Inspection
API	American Petroleum Institute
ASME	American Society Of Mechanical Engineers
RBM	Risk-Based Maintenance
HVAC	Heating, Ventilation, And Air Conditioning
DNV	Det Norske Veritas
HSE	Health And Safety Executive (Uk)
GFF	Generic Failure Frequency
ASTM	American Society For Testing And Materials
NACE	National Association Of Corrosion Engineers

CFD	Computational Fluid Dynamics
LWC	Liquid Water Content
BN	Bayesian Network
RH	Relative Humidity
CPT	Conditional Probability Table
MSE	Mean Square Error
LSR	Least Squared Residue
ABS	American Bureau of Shipping

1. Introduction

In spite of developments in methods to predict industrial hazards, unfortunately, we still fail to foresee many accidents. The real question is: are the techniques adequate to detect the changes in complex and dynamic systems? Today, industries have adopted sophisticated procedures for inspection and maintenance to ensure the system's safe operation. Complex probabilistic models are developed to predict and prevent accidents accurately. However, to ensure a safe operation or prepare for unavoidable consequences, updating of estimated parameters is equally essential. In a fast changing system, the efficiency of a probabilistic model depends on how quickly it responds to variations in the operation. There is a need for a system that can not only monitor the process but also calculate and predict the effects of the changes happening in the process in real time.

1.1 Evolution of Dynamic Risk Assessment:

Risk assessment is the process of quantifying the risk associated with hazards, which includes calculating the entailed probabilities and consequences(Crowl & Louvar, 2011). Risk estimation is one of the most critical tasks to be performed by management. Several methodologies have been developed in the last three decades by scholars and industrialists. These methodologies can be classified into two main principal groups: i) qualitative methods and ii) quantitative methods. Qualitative methods are used to estimate the risks and hazards of a large group of systems. The risk calculated is relative and the analysis is usually performed as a screening process to plan for detailed analysis. Quantitative methods involve comprehensive analysis conducted over a limited number of components that are identified as high risk. The risk is quantified with an absolute value of consequences and probability of failure. The methodologies can also be classified as deterministic and probabilistic methods. Deterministic analysis focus on the impact of the hazards on the environment, personnel and equipment. Probabilistic methods center around estimating the frequency of occurrence of a potential accident (Tixier, Dusserre, Salvi, & Gaston, 2002). Modern risk analysis includes both probabilistic and deterministic approaches.

In conventional risk analysis, the probability of failure (POF) is often calculated based on mean failure frequencies observed across the process industries. Also, the approaches are static; the complete analysis has to be redone to update the risk estimation (Meel & Seider, 2006). To have a better understanding of risk and use it to make an operational decision, it is necessary to update the risk continuously with the variations in the process parameters (Hashemi, Ahmed, & Khan, 2014). Even though the idea for modelling risk based on the dynamic situation has existed for a long time (Swaminathan & Smidts, 1999), it was not until the last decade that (Meel & Seider, 2006, 2008) developed a unique approach to provide a real-time failure frequency for a system. Based on this framework, (Kalantarnia, Khan, & Hawboldt, 2009) developed a model for Dynamic Risk Assessment (DRA) using Bayesian theory to update the likelihood of failure. A detailed case study was provided and it was claimed that using the DRA method, accidents like the BP Texas City refinery explosion and fire could have been predicted and prevented (Kalantarnia, Khan, & Hawboldt, 2010).

DRA is a recent approach to define the risk as a function of time and other critical parameters; the value of risk changes in real time upon observing any change in the system. In a heterogeneous system, the occurrence of specific events may alter the risk value from initial calculations. This difference can be more extensive with a combination of certain critical events. It is not reliable to use the risk estimated initially to decide on the safe operation of the system. Hence, there is a need for an approach that can update the initially calculated risk with the availability of new evidence from the process monitoring system, accident/near miss data or inspection activities.

1.2 Risk-based Inspection and Maintenance Optimization

To ensure the reliability and continuous operation of equipment, proper inspection and maintenance are necessary. The goal is to maintain the safety of the system employing minimal resources. Risk-Based Inspection and Maintenance (RBIM) is a concept of prioritizing the inspection of high-risk equipment. RBIM can be considered as an extension of risk assessment to plan for inspection and maintenance process.

Simply increasing the frequency of inspection and maintenance (IM) is not sufficient to decrease the risk of failure. Figure 1.1 Comparison of risk profile using RBI and interval-based approach displays a simplified comparison between two scenarios, as identified by (API, 2016), where inspection and maintenance activities are carried out using i) interval based planning ii) risk-based planning. It is established that increasing the frequency of IM decreases the risk initially up to a point where it cannot be reduced any further. However, there is a significant difference in the reduction of risk depending on the approach followed. The solid curve indicates that the risk-based approach with the same number of inspection and maintenance activities reduces risk more substantially. This is because the RBIM program focuses on prioritizing high-risk components. Based on risk ranking, the equipment with the highest risk in the industry will be the primary focus for risk mitigation activities which delivers a significant reduction in risk with minimal investment(API, 2016).

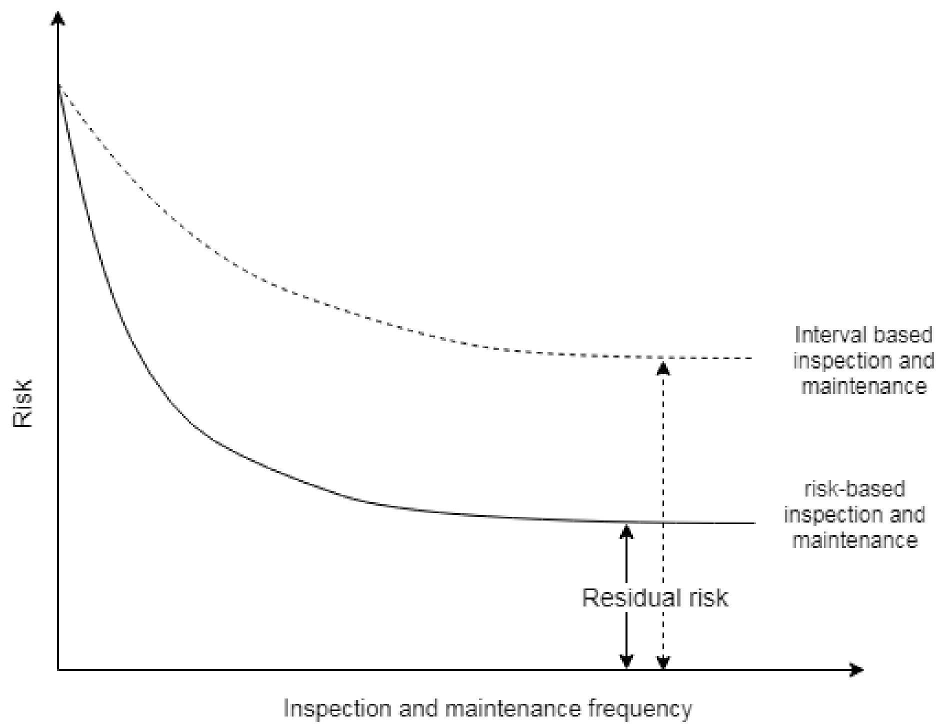

Figure 1.1 Comparison of risk profile using RBI and interval-based approach

The earliest attempts of RBIM, as reviewed by (Thodi, 2011), was made to plan inspections of steel structures in offshore industries (Fujita, Schall, & Rackwitz, 1989) (Madsen, Sørensen, & Olesen, 1990). Several innovative works to develop RBIM for process industries were completed in the early 21st century (Geary, 2002). A model was proposed that employs a Bayesian decision model to choose an optimal inspection plan constructed with the uncertainty of degradation mechanism (Kallen & van Noortwijk, 2005). The application of this method was demonstrated on a pressurized steel vessel. A similar approach of using Bayesian updating was combined with a gamma distribution model to define a risk function (Khan, Haddara, & Bhattacharya, 2006). The optimal interval was calculated using this risk function and it was subsequently used for integrity inspection. In the last few years, attempts have been made to develop RBIM methodology to calculate risk with greater precision; however, there is no verified model that can calculate the risk in real time and update the inspection interval dynamically. While industries are implementing Risk-Based Inspection (RBI) codes like API-581, which is expanding its scope to include various equipment and material, they still lack an ability to make use of real-time data to update risk dynamically.

1.3 Risk-Based Approach for Winterization

Winterization is defined as the modification of conventional sea vessels or oil rigs for operation in extreme cold and harsh offshore conditions. Such conditions are found at oil basins in arctic regions. With increasing oil explorations in the Arctic region, there is a need for adopting winterization approaches to operate safely in an extremely cold environment. The major issues of operating in these climates centers around ice accumulation causing slippery decks and unsafe conditions for workers to maintain the system's integrity. In harsh conditions, the systems are functioning close to the designed limit, which means there is a significantly higher risk compared to that for similar equipment operating onshore (Yang et al., 2013). Hence, it is necessary to have a proper framework to design vessels and rigs to operate safely in these conditions.

To enable equipment to operate safely several methods are employed to maintain the operating temperature and infrastructure including heat tracing, insulation, ice-repellant coating, de-icing chemicals etc. However, such techniques often require certain resources and constant observation. It is also not economical to apply winterization techniques to all the equipment on the vessel. There is a lack of proper guidelines for selecting the proper winterization method for the right equipment. A reliability and performance-based approach is proposed to correctly identify the extent of winterization required for the operation in an artic environment (Khan et al., 2015). Risk-based winterization; prioritizes the winterization process based on the risk ranking of the equipment.

To perform any Risk-Based Winterization, it is necessary to understand the underlying phenomena and parameters that may affect the safety of the equipment. One such parameter is the estimation of the correct design temperature. Type and category of material are selected based on the design temperature; hence, an incorrect assumption of design temperature may lead to a poor design of the system. Climate data may not directly give precise indications of design temperature and the current standards provide very limited guidance to accurately predict it (Sulistiyono et al., 2014). A statistical model has been developed to accurately evaluate this cold region design temperature (Sulistiyono, Khan, Lye, & Yang, 2015).

Another serious obstruction for safe operation in a cold offshore environment is ice and snow buildup on the equipment and working area. Slippery ice surfaces along with falling ice are hazardous for workers. In the event of an emergency, the hazardous conditions may obstruct the access to safety systems such as lifeboats (Khan et al., 2015). To properly design a system to operate under such condition it is crucial to understand the ice accumulation phenomenon in the Arctic regions.

Intriguingly, a plethora of scholarly research shows that humidity, condensation, snow, rain and drizzle accounts for very little ice accumulation on sea vessels (Makkonen, 1984) (Lozowski, Szilder, & Makkonen, 2000) (Zakrzewski, 1987) (Dehghani, Muzychka, & Naterer, 2016). The most significant cause is the freezing of water droplets formed due to waves splashing the vessel. When a wave collides with a vessel or rig, the water disperses and rises upwards in the form of small droplets. These droplets are then carried by the wind over various parts of the vessel or rig. Cooling of these droplets starts as soon as they are formed and continues until they are in contact with the vessel's structure. While the droplets that have not frozen will disperse as runoff, based on the conditions, a significant amount of droplets will keep freezing and accumulate on the surface of the structure.

Even though years of efforts have been made to investigate and predict the ice accumulation on sea vessels, there are still several knowledge gaps in the understanding of this phenomenon (Fein & Freiberger, 1965; Hay, 1956; Lackenby, 1960; Sutherby, 1951). Several numerical and experimental methods were reviewed by (Dehghani-Sanij, Dehghani, Naterer, & Muzychka, 2017); however, since ice accumulation involves several complex modeling for spray generation, calculation of droplets trajectory, freezing of salt water and formation of ice layer, it was concluded that the models available may not provide a reliable prediction of Ice accumulation. There is a need for a predictive model that can be easily modified for application in a wide range of environmental conditions.

Moreover, the climate in a harsh environment can change rapidly, so the model must be robust and dynamic to update the estimation with the availability of new data.

1.4 Research objectives of the thesis:

Based on the research gaps identified in the previous subsections, the need for dynamic estimation approaches has been identified in two specific areas:

i) Risk-based inspection methodologies

ii) Risk due to ice accumulation on marine vessels and offshore rigs.

Figure 1.2 shows two research objectives that are defined to address these identified research gaps. The first objective is to develop a model to calculate dynamic or real-time risk to help with inspection optimization. It includes a brief study of the industrial codes that are used as standard guidelines for risk-based inspections. Because most industries have already adopted several standard guidelines, it is necessary that the proposed dynamic model must be integrated with those standards and codes. This study is undertaken to provide a better decision-making tool for determining inspection intervals.

The second objective of the thesis is to develop a dynamic tool for predicting ice accumulation in harsh and extreme cold artic conditions. From the literature reviewed in this chapter, it was identified that several numerical and experimental models failed to give reliable results. The second part of the research objective aims to overcome this by developing a dynamic statistical tool that can be updated instantly upon the availability of new data. The goal is to reduce uncertainty in estimation of the spray-icing in an extremely cold environment, to plan risk-based winterization activities. The scope includes the identification of several factors affecting the icing rate. To test the accuracy of the model, once developed, an experimental setup is designed. This setup, constructed in a controlled cold chamber, consists of a spray atomizer connected with a programmable control system that can simulate the periodic spray identically to the spray formed by waves splashing an offshore structure of a vessel.

With these identified research objectives, the thesis aims to demonstrate two novel approaches that will provide a foundation for developing dynamic models that can be integrated with current practices in i) Risk-based inspection and ii) Marine icing estimation.

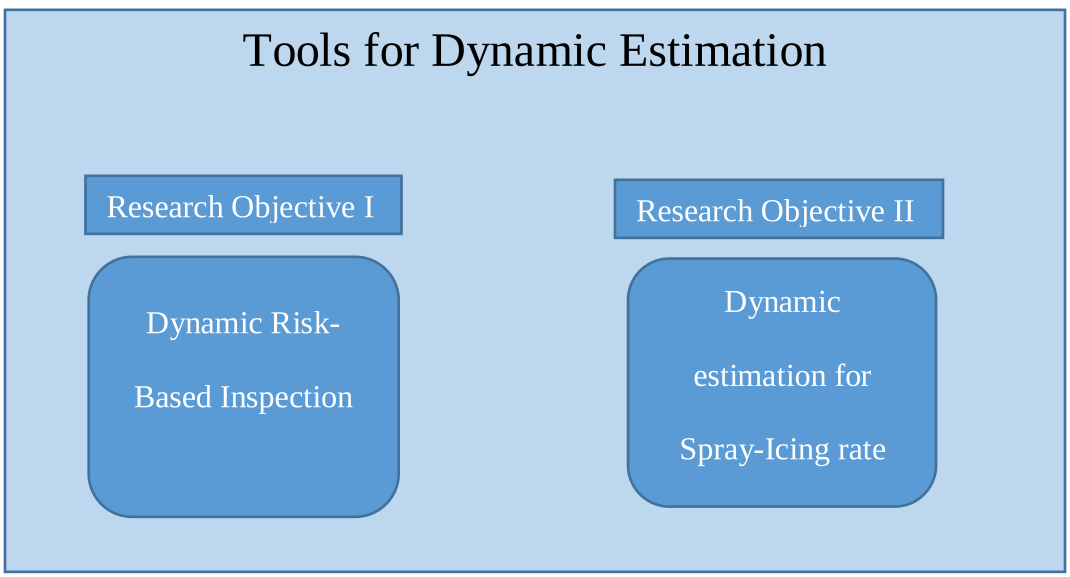

Figure 1.2 Representation of the research objectives

1.5 Thesis Structure:

The thesis is written in manuscript format. It includes two manuscripts submitted to peer-reviewed journals: the manuscript in chapter 2 is submitted to the Journal of Loss Prevention in the Process Industries and the manuscript in chapter 3 is submitted to Ocean Engineering journal.

Chapter 2 is based on the first research objective. It proposes a dynamic risk-based inspection (DRBI) technique which is developed using widely accepted industrial guidelines for RBI: API-581. It includes a brief review of several other industrial codes for RBI. The model's ability to provide a real-time risk estimation based on the systems monitored parameters is also discussed. The proposed module can be integrated with the current industrial framework for RBI without significant investment. A case study is provided to demonstrate the technique and is compared with the results obtained using API-581 guidelines. A sensitivity analysis is done to illustrate the impact of fluctuation of the system parameters on the risk profile, something that is ignored in conventional RBI methods.

Chapter 3 provides a predictive method for wave generated marine ice estimation on vessels operating in arctic conditions. The framework identifies the influencing parameters for the ice accumulation. It employs a Bayesian belief network to estimate the icing rate based on the environmental parameters. This section provides steps to update the estimation in real time upon identifying the change in environmental conditions. Details of the experimental setup used to validate the model are also provided in the chapter, followed by the comparison of the results obtained using the predictive model and the observed ice accumulation rate in the experiments.

Chapter 4 summarizes the results of the research. Based on the conclusion of the work in chapter 2 and chapter 3, it provides several recommendations for future work.

1.6 References:

API, R. (2016). 580 Risk-Based Inspection. In: American Petroleum Institute.

Crowl, D. A., & Louvar, J. F. (2011). Chemical Process Safety : Fundamentals with Applications: Fundamentals with Applications (Vol. 3rd ed). Upper Saddle River, NJ: Prentice Hall.

Dehghani-Sanij, A., Dehghani, S., Naterer, G., & Muzychka, Y. (2017). Marine icing phenomena on vessels and offshore structures: Prediction and analysis. Ocean Engineering, 143, 1-23.

Dehghani, S. R., Muzychka, Y. S., & Naterer, G. F. (2016). Droplet trajectories of wave-impact sea spray on a marine vessel. 127, 1-9.

Fein, N., & Freiberger, A. (1965). A survey of the literature on shipboard ice formation. Naval Engineers Journal, 77(6), 849-855.

Fujita, M., Schall, G., & Rackwitz, R. (1989). Adaptive reliability-based inspection strategies for structures subject to fatigue. Paper presented at the Structural Safety and Reliability.

Geary, W. (2002). Risk based inspection: a case study evaluation of offshore process plant. Retrieved from

Hashemi, S. J., Ahmed, S., & Khan, F. (2014). Risk-based operational performance analysis using loss functions. 116, 99-108.

Hay, R. (1956). Ice accumulation upon trawlers in northern waters. Meteorol. Mag, 85(1010), 225-229.

Kalantarnia, M., Khan, F., & Hawboldt, K. (2009). Dynamic risk assessment using failure assessment and Bayesian theory. Quantitative Risk Analysis - Special issue devoted to Norberto Piccinini, 22(5), 600-606.

Kalantarnia, M., Khan, F., & Hawboldt, K. (2010). Modelling of BP Texas City refinery accident using dynamic risk assessment approach. 88(3), 191-199.

Kallen, M.-J., & van Noortwijk, J. M. (2005). Optimal maintenance decisions under imperfect inspection. Reliability Engineering & System Safety, 90(2-3), 177-185.

Khan, F., Ahmed, S., Yang, M., Hashemi, S. J., Caines, S., Rathnayaka, S., & Oldford, D. (2015). Safety challenges in harsh environments: lessons learned. Process Safety Progress, 34(2), 191-195.

Khan, F., Haddara, M., & Bhattacharya, S. (2006). Risk-Based Integrity and Inspection Modeling (RBIIM) of Process Components/System. Risk Analysis: An International Journal, 26(1), 203-221.

Lackenby, H. (1960). Formation of ice on trawlers. Fish. Boats World, Vol. 2-Sea Behav., 511-514.

Lozowski, E. P., Szilder, K., & Makkonen, L. (2000). Computer simulation of marine ice accretion. Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences, 358(1776), 2811-2845.

Madsen, H., Sørensen, J. D., & Olesen, R. (1990). Optimal inspection planning for fatigue damage of offshore structures. Paper presented at the International Conference on Structural Safety and Reliability.

Makkonen, L. (1984). Atmospheric icing on sea structures. (No. CRREL-MONO-84-2). Cold regions research and engineering lab hanover nh.

Meel, A., & Seider, W. D. (2006). Plant-specific dynamic failure assessment using Bayesian theory. 61(21), 7036-7056.

Meel, A., & Seider, W. D. (2008). Real-time risk analysis of safety systems. Festschrift devoted to Rex Reklaitis on his 65th Birthday, 32(4), 827-840.

Sulistiyono, H., Khan, F., Lye, L., & Yang, M. (2015). A risk-based approach to developing design temperatures for vessels operating in low temperature environments. 108, 813-819.

Sulistiyono, H., Lye, L. M., Khan, F. I., Yang, M., Oldford, D., & Dolny, J. (2014). Estimating design temperatures in Arctic environments: A new approach. Paper presented at the Oceans-St. John's, 2014.

Sutherby, F. (1951). Icing Problems on Ships. Journal of Glaciology, 1(10), 546-548.

Swaminathan, S., & Smidts, C. (1999). The event sequence diagram framework for dynamic probabilistic risk assessment. Reliability Engineering and System Safety, 63(1), 73-90.

Thodi, P. (2011). Risk based integrity modeling for the optimal maintenance strategies of offshore process components. (NR82010), Memorial University of Newfoundland (Canada),

Tixier, J., Dusserre, G., Salvi, O., & Gaston, D. (2002). Review of 62 risk analysis methodologies of industrial plants. 15(4), 291-303.

Yang, M., Khan, F. I., Lye, L., Sulistiyono, H., Dolny, J., & Oldford, D. (2013). Risk-based winterization for vessels operations in arctic environments. Journal of Ship Production and Design, 29(4), 199-210.

Zakrzewski, W. P. (1987). Splashing a ship with collision-generated spray. Cold Regions Science and Technology, 14(1), 65-83.

2. Dynamic Risk-Based Inspection Methodology

Preface

A version of this manuscript has been submitted to the Journal of Loss Prevention in the Process Industries. I am the primary author of this manuscript along with Co-authors Faisal Khan, Hiralben Patel and Rouzbeh Abbassi. I developed the framework for the proposed method, its implementation and analysis of the result. I prepared the first draft. The framework concept was proposed by co-author Faisal Khan. Dr. Khan also reviewed the developed framework, its implementation and provided feedback for improvement. Dr. Khan also reviewed results and provided feedback. His valuable feedback helped me to improve the manuscript. The Co-author Hiralben Patel helped to implement the feedback and finalize the framework and drafting of the manuscript. Co-author Rouzbeh Abbassi reviewed the results and manuscript and provided constructive suggestions for improving the model its presentation in the manuscript.

Abstract

Inspection methodologies have evolved in the past decades to explore optimal interval and inspections methods. The American Petroleum Institute has published several standards such as API-510, API 653, API 570 and API-580 to assist in determining inspection intervals based on equipment life, consequences of failure, degradation rate, and environmental impact. The most recent approach is the Risk Based Inspection, API-580 and API-581. The underlying assumption of this approach is that risk remains acceptable between two planned inspection or maintenance intervals. This condition may not hold true

in a complex, fast-changing or degrading engineering system. This study presents an innovative method to assess risk for a dynamically changing system based on the system parameters that are continuously monitored. The calculated dynamic risk is used to plan optimal inspection and maintenance intervals. The proposed method is tested on different process systems. Efforts are also made to align and integrate the proposed method with API-581. This would help to implement a more accurate approach while maintaining the required industry standard to ensure safe operation with low uncertainty.

Keywords: risk-based inspection; reliability; asset integrity, dynamic risk; risk-based maintenance

2.1 Background:

In recent years increasing regulations and accountability have made operational failure a major economic, political and public relations issue. Inspection and maintenance activity are necessary to ensure continuous operation and to avoid losses and damage to the reputation of the company. The maintenance methodologies can be classified as corrective maintenance and preventive maintenance. Basic preventive maintenance can be categorized as time-based maintenance and condition-based maintenance. In the competitive market, a major failure could cost an organization much more than just repair expenditure, and this has made industries lean towards predictive maintenance policies. Historically, inspection has been a vital tool to detect potential failures. Inspection intervals were scheduled on dates with prespecified duration or prescribed fitness for service life. With the improvement in inspection approaches, instead of duration or rule-based approaches, inspections are planned based on the equipment's condition. The goal is to obtain the right balance between the benefits of inspection and the cost of inspection and maintenance. These have led to the evolution of a new area of inspection-maintenance optimization called risk-based inspection (RBI). This is based on the logical concept that the majority of high-risk components are concentrated within a small portion of the plant. Hence, priority and extra investment must be made for the maintenance of this equipment, and this extra cost can be counterbalanced with reduced maintenance for other equipment with lower risk.

In the1990s, the American Society of Mechanical Engineers published several guidelines which offered a foundation for organized RBI (ASME, 1991, 1996, 1997). The American Petroleum Institute (API) published API-580 in 2002, which provided a framework for an inspection methodology that ranks the inspection program based on its risk value (API, 2002). It was rewritten in 2009 and further revised in 2016 (API, 2009, 2016a). The three fundamental goals of RBI are: i) to define and measure risk; ii) to allow the organization to review the risk thoroughly, and iii) to optimize inspection based on the probability of failure. Further, API 581 provides a comprehensive method to calculate the probability and consequences of failure, environmental impact, and inspection planning. It includes the consideration for thinning, stress corrosion cracking, high-temperature hydrogen attack, mechanical fatigue for pipe, long-term creep, short-term overheating, brittle fracture, damage to the equipment linings and external damage degradation models. It also provides a framework for assessment of environmental and financial consequences (API, 2016b).

2.1.1 Risk-based inspection and maintenance approaches

Apart from API and ASME, a great deal of research has been conducted in the past two decades to develop risk-based maintenance and inspection methodologies. A comprehensive and qualitative risk-based maintenance (RBM) method was developed which focused on all possible failure scenarios of the equipment. (Khan & Haddara, 2003). Another model that combines a reliability approach and RBM was developed and applied on an offshore process facility developed later (Khan & Haddara, 2004). A different approach for RBM planning is based on fitness-of-service criteria, where equipment is inspected critically to obtain the data for its reliability which is then converted to ascertain its remaining life. Application of this approach was demonstrated for offshore wind structures that are unmanned and not frequently monitored, compared to process plants (Brennan, 2013). A model that is driven by data to predict the probability and consequences of failure has been proposed for a cross-country oil pipeline (Dawotola, Trafalis, Mustaffa, Van Gelder, & Vrijling, 2012). RBI has also been applied to structural systems, and involves a different approach by considering the entire system instead of planning to inspect a single component (Straub & Faber, 2005). RBI that uses historical data for accidents and near misses to estimate the risk at two specific stages in the maintenance activities, turnarounds and work order management, claims to provide improvements in maintenance quality in an oil refinery (Bertolini, Bevilacqua, Ciarapica, & Giacchetta, 2009). Several RBI methods have been reviewed and classified based on input, output, modules and techniques (Arunraj & Maiti, 2007). Table 2-2 summarizes the recent RBI and RBM approaches reviewed for this study. Their applicability and unique features are also summarized in the table.

Table 2-1 Recently proposed RBI methods and their application

Model	Classification of the Model	Demonstrated application in	Data based modelling	Experience-based modelling	Provides risk ranking/indexing	Unit of risk
Khan & Haddara (2003)	Quantitative	Heating, ventilation, and air conditioning (HVAC)	✓		✓	Performance loss
Abbassi, Bhandari, Khan, Garaniya, & Chai (2016)	Quantitative	Thermal power plant	✓	✓		NA
Pui, Bhandari, Arzaghi, Abbassi, & Garaniya (2017)	Semi-quantitative	Managed pressure drilling		✓	✓	NA
Fujiyama et al. (2004)	Quantitative	Steam-turbine	✓		✓	Financial loss

Model	Classification of the Model	Demonstrated application in	Data based modelling	Experience-based modelling	Provides risk ranking/indexing	Unit of risk
Krishnasamy, Khan, & Haddara (2005)	Quantitative	Power-generating plant	✓	✓	✓	Financial loss
Dey (2001)	Qualitative	Cross-country pipeline		✓		Financial loss
Arzaghi et al. (2017)	Semi-quantitative	Subsea pipeline		✓		NA
Brennan (2013)	Qualitative	Offshore wind structure	✓			NA

Model	Classification of the Model	Demonstrated application in	Data based modelling	Experience-based modelling	Provides risk ranking/indexing	Unit of risk
Bertolini et al. (2009)	Semi-quantitative	Oil refinery	✓		✓	NA
Khan & Haddara, (2004)	Quantitative	Offshore process platform	✓		✓	Financial loss
Hu, Cheng, Li, & Tang (2009)	Semi-quantitative	Petrochemical reforming reaction plant		✓	✓	Financial loss
Khan, Sadiq, & Haddara (2004)	Semi-quantitative	Molecular sieve tank, hydroterater, autoclave, methanol storage drum		✓	✓	Asset and environmental loss

Model	Classification of the Model	Demonstrated application in	Data based modelling	Experience-based modelling	Provides risk ranking/indexing	Unit of risk
Straub & Faber (2005)	Qualitative	Generic engineering structures		✓		NA
Melani, Murad, Caminada Netto, Souza, & Nabeta (2018)	Qualitative	Coal-fired power plant	✓	✓		NA
Pui et al. (2017)	Semi-quantitative	Offshore process platform	✓	✓	✓	Financial loss
Mancuso, Compare, Salo, Zio, & Laakso (2016)	Semi-quantitative	Sewerage network		✓	✓	Financial loss

Model	Classification of the Model	Demonstrated application in	Data based modelling	Experience-based modelling	Provides risk ranking/indexing	Unit of risk
Dawotola et al. (2012)	Quantitative	Cross-country pipeline	✓		✓	Financial / environmental
Mancuso et al. (2016)	Quantitative	Power plant		✓		NA
Kamsu-Foguem (2016)	Qualitative	Process production system	✓	✓		Production loss
Wang, Cheng, Hu, & Wu (2012)	Semi-quantitative	Petrochemical catalytic reforming plant		✓	✓	Financial loss

2.1.2 Standards, Codes, and Recommend Practices

Standards, codes and recommended practices for RBI for application in the offshore oil and gas industry include the DNV-RP-G101 by Det Norske Veritas. This relies heavily on the degradation mechanism and provides direction for predicting Probability Of Failure (POF) for a specific list of materials under certain service conditions (DNV, 2010). RBI guidelines by ASME, PCC-3 provide a strategy and basic concepts for application in fixed pressure-containing equipment and components. This guideline provides a brief overview of RBI and can be compared with the API-580 recommended practice (ASME, 2007). Unlike the codes mentioned above, API-581 provides detailed and widely applicable RBI guidelines for the process industry. Several industries are now following these guidelines as they offer stepwise calculations for a wide range of fluids and materials. They provide two levels of consequences assessment: level 1 and level 2. For a predefined list of common fluids, straightforward lookup tables and charts are provided in level 1. Steps mentioned in level 1 provide relatively simple calculations based on certain assumptions. Level 2 offers a rigorous calculation for when data is not provided for the fluids mentioned in level 1, or when assumptions made in level one are not valid (API, 2016b).

While reviewing the industrial guidelines for RBI, the calculation of the risk function is found to be derived from data, and the predicted value is established for the equipment's age (API, 2016a, 2016b; ASME, 2007; DNV, 2010). There are three possible scenarios based on this prediction.

1) The value of risk is exceeding an acceptable risk value before the first RBI planned date. This is shown by curve A in Figure 2.1. In this condition, RBI is recommended before the planned date to employ risk mitigation plans.

2) The value of risk is exceeding the acceptable risk between the RBI intervals. This is shown by curve B in Figure 2.1. In this case, the duration of RBI should be reduced to keep the risk at an acceptable level.

3) The risk value stays below acceptable risk throughout both inspection intervals. This is shown by curve C in Figure 2.1. It is implied that if the risk values are below the acceptable risk value, then the equipment is safe to operate in that time period.

Review of industrial RBI codes identifies various knowledge and technological gaps that need to be studied to have better optimization of inspection and maintenance activities:

- Considering the rate for deterioration remains the same for years based on one inspection may give a false sense of security and may lead to an unpredicted failure. There is a need for a system that can track the changes in the risk profile in real time to ensure safe operation.
- Guidelines like ASME-PCC-3 require the user to have effective management of the change in system parameters and initiate an inspection to update the risk value. They also present various key elements that can trigger a reanalysis of RBI. However, inspection and maintenance activities require significant resources, and a frequent reanalysis or inspection may not always be practical. There is a need for

a tool to have a continuous estimation of risk against an acceptable limit that can help make the decision for reinspection.

- Despite having an RBI system in place, accidents such as that at the ConocoPhillips Humber refinery still occur. At the refinery, failure to understand the actual condition of the pipe led to an explosion just three months before a planned RBI date. Such incidents can be avoided by having an accurate perception of risk in real time. (Carter, Dawson, & Nixon, 2006)

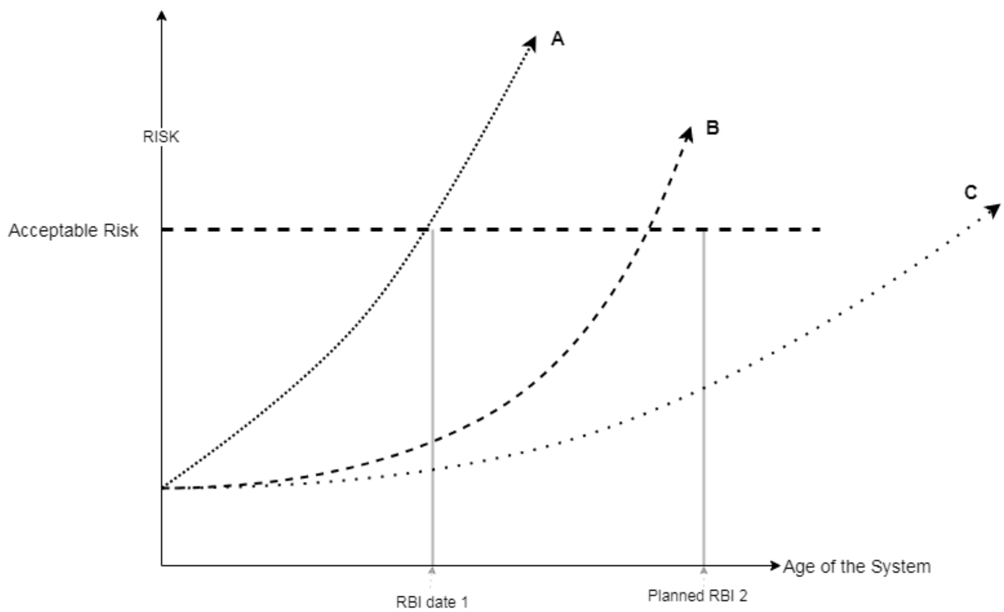

Figure 2.1 Risk trend as calculated by traditional RBI

2.1.3 The Concept of dynamic risk

Dynamic risk is defined as a risk profile that provides the status of risk at any given time and can be updated upon the availability of new information. Several attempts have been made to assess the risk in dynamic conditions. A detailed classification of risk assessment methodologies based on the approach followed has been reviewed by(Khan et al., 2016; Zio, 2018). To simplify this classification, dynamic risk models can be divided into three basic categories. Table 2-2 provides references for the dynamic risk-based approaches proposed in the past two decades. These approaches can be divided into three main categories:

1. Data-based approach: In this approach, the risk is updated based on accident or near miss data. Once new data are available, they are integrated into the model to update the risk profile. This approach makes use of statistical tools such as fault tree, event tree and Bayesian belief networks to define relationships among the initiating events. The issue with statistical approaches is that they require failure data or accident precursor data to update the risk. The risk profile may only change after critical events have occurred, which is insufficient for risk mitigation.

2. Process-based approach: Any deviation in the process parameters from its optimum condition is likely to increase the risk. Such changes are monitored to update the risk value. The magnitude and the duration of deviation of process parameters define the dynamic risk profile. Traditionally, mathematical tools are used to predict failure and provide an alert. To use different mathematical tools to predict risk requires having process failure information with multiple correlated marginal distributions (Khan et al., 2016). This is not feasible to apply to a complex process.

3. Degradation-based approach: The risk is defined based on the system's actual condition. If the degradation rate is continuously monitored, then the risk profile can be updated in real time. The degradation mechanism rate has to be estimated based on experience and available data. The efficiency of the model depends on the assumptions used to estimate the degradation mechanism.

These above approaches could be used for asset integrity management, however, they need to improve for modelling inspection, maintenance activity and optimization of the inspection interval. In addition, these approaches need to be compatible with industry codes and standards. Substantial resource allocation is required for data collection to implement these methods. This study attempts to fill this gap by developing a novel dynamic risk-based inspection methodology that is compatible with RBI guidelines such as API-581.

Table 2-2 Dynamic risk models reviewed based on classification

Data-driven approach			Degradation-based approach
Logic and probability based analysis	**Loss function**	**Derivatives of Principal component analysis**	
Kalantarnia, Khan, & Hawboldt (2009), Meel & Seider (2006, 2008), Hashim, Hidekazu, Takeshi, & Ming (2014), Roy, Srivastava, & Sinha (2015), Khakzad, Khan, & Paltrinieri (2014), Khakzad, Khan, & Amyotte (2012), Pariyani, Seider, Oktem, & Soroush (2012), Abimbola, Khan, & Khakzad (2014), Zeng & Zio (2018)	Hashemi, Ahmed, & Khan (2014), Pan & Chen (2013)	Alrowaie, Gopaluni, & Kwok (2012), Zadakbar, Imtiaz, & Khan (2013), Zadakbar, Khan, & Imtiaz (2015), Baraldi, Mangili, & Zio (2012)	Kim et al., (2015), Lewandowski (2013), Zeng, Kang, & Chen (2016), Zhiguo, Yunxia, Enrico, & Rui (2017), Baraldi et al. (2012), Zeng & Zio (2018)

2.2 Dynamic risk-based inspection (DRBI) Methodology

This study presents an approach that is built on the API-580, and 581 guidelines but expands further to continuously monitor the risk values, fulfilling the knowledge gaps identified in the previous sections. The dynamic risk is calculated based on risk indicators of degradation mechanisms that are applicable for the given system. This would enable the user to monitor the risk profile of the plant in realtime. Figure 2.2 shows an example of a typical scenario where risk is calculated using the proposed DRBI and plotted against time. The risk derived from and based on system parameters is presented with a solid line, and the risk calculated using traditional RBI is displayed with a dotted line for reference. At point x, the actual dynamic risk curve shown in the figure is exceeding the acceptable risk, which could not have been predicted using other RBI codes. This buildup in risk can be caused by a number of factors, including specific processes such as stem blowout, system flushing/cleaning etc. Management factors such as a change in operator or external environmental factors may also affect the risk value.

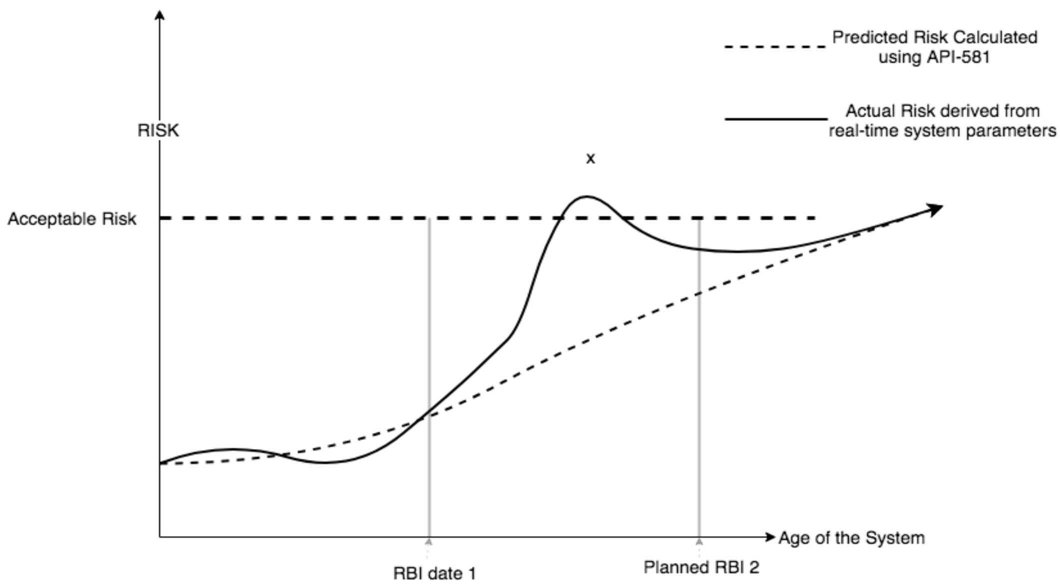

Figure 2.2 Comparison of risk trend of proposed DRBI with traditional RB

This section provides a stepwise framework to implement this methodology. Figure 2.3 provides a basic flowchart for application of the procedure. A comparison with API-581 recommended guidelines has also been drawn in this section. These steps are shown with dotted blocks in Figure 2.3.

2.2.1 Identify the system

System identification is the first step in the calculation of the risk. This includes the classification of the fundamental factors that are critical for the safe operation of the system. The team responsible for performing the DRBI must collect relevant information about the components of the system and analyze it for the inspection plan. Proper care should be taken if the system's integrity is contingent on other systems' condition or any outside factors. Successful implementation of this step will ensure that the focal point of the DRBI remains established throughout the process. It will clarify the underlying issues and identify the crucial drivers for the risk. Organizations may already have a high-level summary of the process and its operation. Information such as corrosion circuit diagrams and their boundary conditions should be collected and studied in the initial stage.

API-581 suggests similar steps to identify the system. However, API-581 has compiled data and provided a lookup table and charts to guide the identification process. The user must also decide between level 1 or level 2 of the consequences' calculation for the RBI. If a level 2 calculation is to be considered, plan for data collection must be established at this point while performing the API-581 prescribed approach.

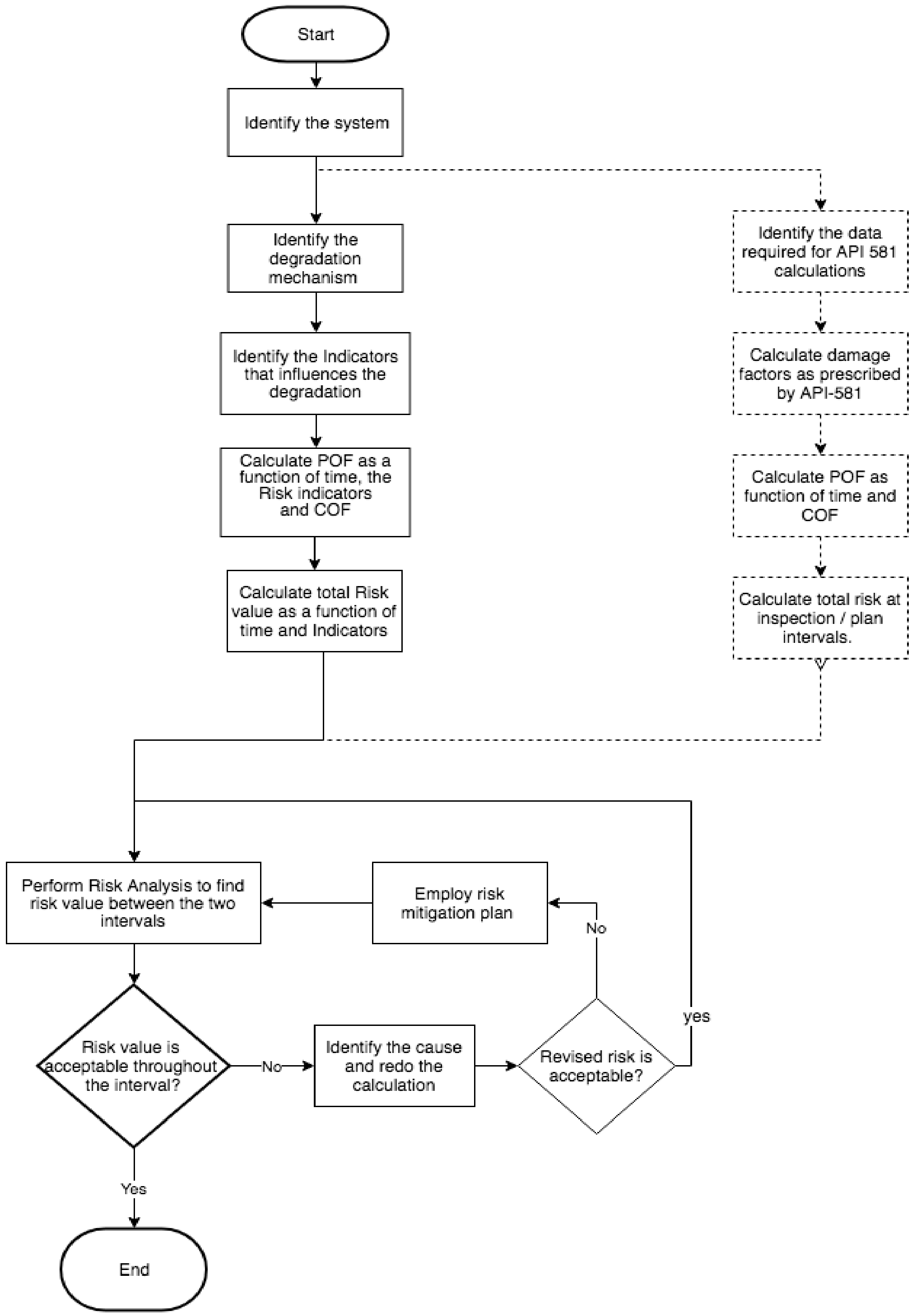

Figure 2.3 Details of the proposed methodology

2.2.2 Identify the degradation mechanism

Once the system is studied, the next step is to identify the degradation mechanism that poses a threat to the safe operation of the system. The effectiveness of the RBI depends on correct identification of the actual degradation mechanism. For the scope of the proposed DRBI, it is necessary to recognize a degradation mechanism that has the most influence on the system's safe operation. This degradation mechanism is used to calculate the POF. The next step is to prioritize the degradation mechanisms if more than one is present. This degradation mechanism is driven by several causal events, and the deterioration rate may change along with it. The state of the system may remain the same for several years or change drastically, based on variation in certain operational and environmental conditions such as a change in pH, temperature, etc. The user should identify these parameters while studying the degradation mechanism. These parameters are discussed in the next step. If a corrosion control document for the equipment is available, it can provide a building block to identify the applicable degradation mechanism. Examples of basic degradation mechanisms can be, but are not limited to:

- Local, general or pitting corrosion leading to thinning of the wall thickness
- Change in material's strength due to process conditions
- Crack development or welding defects
- Loss of insulation that protects the material.

A similar method in API-581 provides steps for calculation of damage factors. These damage factors are derived from the applicable degradation mechanism present in the system. API-581 delivers a descriptive list of the degradation mechanisms, including steps to identify their rates. This includes corrosion, brittle failure, stress cracking due to sulfide, alkaline carbonate etc. Annex 2.B of API-581 gives a detailed description of calculating the corrosion rate in several conditions.

2.2.3 Identify the Risk Indicators

In this study, a risk indicator is defined as a continuously monitored parameter that would directly or indirectly affect the prevalent degradation mechanism of the equipment. Examples of system specific indicators could be pressure, temperature, oxygen or pH levels. External indicators such as atmospheric temperature, humidity, storm, or snow can also be considered for equipment exposed to varying climates. It is essential that these indicators are already being monitored in the system. If an extra inspection is required to measure the indicators that need additional resources, the goal of this methodology will not be met.

Copious scholarly works have been conducted to identify the indicators of risk. Asset integrity indicators were classified into mechanical, operational and personnel indicators (Hassan & Khan, 2012). Another study proposes an approach of safety performance indicators which are based on UK's health and safety executive (HSE) recommended framework (Khan, Abunada, John, & Benmosbah, 2010) (HSE, 2006). Indicators can be classified into leading and lagging types, based on their predictive nature. Methods to identify the safety indicators for offshore facilities and nuclear plants are proposed by (LIU & WU, 2006), (Sharp, Ersdal, & Galbraith, 2008).

While these models provide a foundation to identify the indicators, the majority of them are not continuously monitored, hence cannot be applied to the DRBI. Recommendations are provided here to distinguish the indicators correctly:

The DRBI Indicators can be identified by asking the following questions:

- What will cause a change in the rate of the degradation?
- Is the identified parameter monitored continuously (directly or derived)?

Once the indicators are known, their relationship with the degradation mechanism has to be recognized. It can be done by asking the following questions:

- How does the change in the value of indicator affect the degradation rate?
- What is the magnitude of this change?
- Does the magnitude have any boundary limits?

The inclusion of the indicators makes the DRBI a unique approach compared to the API-581, which assumes that the degradation rate calculated in the initial stage will remain valid for the entire inspection interval.

2.2.4 Calculate POF and COF

The risk value is a product of the probability and consequences of failure (POF × COF). The model proposed in this study provides a unique approach of employing the risk indicators identified to calculate the POF. Since the risk indicators are based on factors that are monitored continuously, the POF becomes a dynamic value. The COF, however, is based on the same traditional concept: what the potential loss can be if the system fails. Since the identified possible outcome of the failure is established initially, COF will remain static throughout the period.

To calculate the probability of failure, the first step is to develop a condition for failure based on the degradation mechanism. This can be done by static/dynamic reliability models or based on generic failure frequency. To implement the static reliability models, it is mandatory to establish failure criteria based on the monitored condition. It can be allowable stress for the given material, or the magnitude of the load applied. Another approach to calculating the POF can be based on the generic failure frequency (GFF), an approach that API-581 has implemented. A modifying factor has to be defined based on the risk indicators. Its value changes based on the deterioration and defined condition of failure. This damage factor is multiplied with the GFF to obtain the POF.

Dynamic reliability models are applicable under certain conditions when the load is placed on the system repetitively over time (Ebeling, 1997). The numerical model developed based on this concept considers that the reliability of the system is not just a function of time, but also a function of the available wall thickness. For the fitness of service, a minimum wall thickness of 50% is assumed to be required. The reliability of the system is calculated based on the available thickness which is derived from the dynamic value of the corrosion rate. The failure condition is considered when more than 50% thickness of the pipeline is lost. The static reliability at a given time is determined by using Equation 1.

Here R is the static reliability at a given condition and s is the shape factor. The dynamic reliability is given by the Equation 2 where R is the static reliability when the system is operating calculated, using equation 1. Here t is the age of the system and α is the frequency of operation per unit time. This process must be carried out in real time as the new corrosion rate is calculated based on the risk indicators.

$$R = \varphi\left(\frac{1}{s} ln \frac{h_{min}}{h}\right) \tag{1}$$

$$R(t) = e^{-(1-R)\alpha t} \tag{2}$$

The other popular approach is to use a generic failure frequency (GFF) model. If the data for the failure is available for similar equipment, it can be modified to calculate an adjusted failure frequency. A modifier based on the corrosion rate and the available thickness is multiplied by the generic failure frequency to obtain the POF. A similar approach is applied in API-581 to define POF. The lookup table for the damage factor is provided in Part 2 of API-581: Table 4.7. In this study, an empirical equation is developed to fit the data provided in this table. This will enable the model to capture even smaller changes in the parameters in a continuous manner. For this case study, the empirical equation for damage factor (df) was defined by a third-degree polynomial equation (3) where x is the wall loss fraction estimated in the previous step.

$$\mathrm{df} = 980.11\mathrm{x}^3 + 470.76\mathrm{x}^2 - 61.457\mathrm{x} + 2.2789 \tag{3}$$

In API-581, the Probability of Failure (POF) is based on the generic failure frequencies of particular equipment. The API-581 provides several modification factors that change the failure frequency, based on the management system and several degradation mechanisms such as thinning (corrosion), insulation deterioration and stress cracking. Once these factors are identified, they are multiplied with the GFF to obtain the probability of failure. The next step is to calculate the consequences of failure (COF). As mentioned in the previous section, API-581 provides an option of level 1 or level 2 calculation for COF. The consequences categories can be flammable and explosive consequences, toxic consequences, non-flammable and non-toxic consequences and financial consequences.

2.2.5 Calculate Risk as a function of time and indicators.

Total risk is the combination of COF and POF, as defined in the previous step. There can be several ways to quantify the risk based on the consequences. The most common unit for risk is in terms of financial, casualties or the area involved dollar loss, death/injuries, or m^2 area affected. Whenever the equipment is operating, there is always some risk present. The risk value can be reduced using mitigation techniques, but it cannot be zero as long as the equipment is operating. To produce safe operation of the equipment, it is essential to have an acceptable risk limit such that if the risk value is higher than this limit, equipment is no longer safe for operation. This limit is often also necessary for regulatory and insurance purposes. The risk limit is normally defined by management based on the local regulations or the company's policy. While performing the DRBI, a constant comparison between current risk value and continuous risk value has to be carried out to ensure safe operation.

In API-581 however, risk value for an entire inspection interval is predicted at the beginning. Based on the POF and COF, a risk value is obtained for the inspection interval dates. A risk curve is established based on the obtained values. API-581 provides three possible cases based on the predicted risk which was discussed in the previous section and in Figure 2.1.

2.2.6 Perform DRBI and compare with the risk limit

Once the risk function is developed, it can be implemented for the system to perform a predictive DRBI analysis. Continuous data from the monitored system parameters must be provided to update the risk in real time. The risk calculated with DRBI is compared with the acceptable risk limit. Any unusual trend in the risk value must be identified and investigated for the cause, especially if the risk value is approaching the acceptable risk limit. If needed, a detailed RBI must be carried out using other established methods to check the accuracy of the defined risk function. Unlike API-581, the POF value calculated with DRBI will change dynamically with the change in the process parameters. API-581 does not require a continuous input of data, since the POF trend is pre-established.

Table 2-3 summarizes the main difference between the proposed DRBI and the API-581 methodology based on the input/output, nature or risk, uncertainty due to inspection and data required.

Table 2-3 Comparison of API-581 and proposed DRBI method

	API-581 recommended RBI	Proposed DRBI
Input type	Data from inspection and manufacturer provided data.	Real-time risk indicator value, the age of the equipment
Output type	Risk value as a function of time and other factors measured at the inspection date.	Actual risk value as a function of continuously monitored indicators and time.
Uncertainty	Provides lookup table to address inspection uncertainty using an effectiveness factor	Since the risk is a function of parameters that are monitored continuously, uncertainty due to data estimation is not present.
Data required	Based on the component type, fabrication material and fluid type, API-581 provides several lookup tables for the type of data required.	Information about the applicable degradation along with continuously monitored parameter which is responsible for it.

2.3 Implementation of DRBI framework

This section provides a case study for the illustrative application of the DRBI. The predictive dynamic risk is calculated for a pipeline carrying a mixture of sulfuric acid. The framework mentioned in the previous section is applied to this system. The result is also compared with the values calculated by the guidelines provided in API-581.

2.3.1 Description of the scenario

In this study, a 4-inch carbon steel pipeline carrying sulfuric acid is provided. The properties of the system are logically assumed to demonstrate the concept. Details of the system properties are summarized in Table 2-4. Sulfuric acid has a corrosive nature that can deteriorate carbon steel. Ferrous sulfate is formed as a byproduct of the corrosion and forms a layer over the metal, which prevents any further corrosion. Due to this phenomenon, the corrosion rate is low for a near stagnant flow rate. If the flow rate is high, it will increase the mass loss of the ferrous sulfate film and accelerate the corrosion rate. The corrosive nature of sulfuric acid also depends on its concentration: corrosion rate increases with the increase in concentration up to around 80%, higher concentration of sulfuric acid is less corrosive. Despite the corrosive characteristics of sulfuric acid with carbon steel, it is typically accepted as piping material. If the specified condition is maintained, then the corrosion rate is very low. In this simulation, the concentration, temperature and the velocity of the sulfuric acid mixture are set at optimum values, and they are continuously monitored.

Table 2-4 Important equipment properties

Age of Pipe at time of study	3 years
Outside Diameter	4 in
Inside diameter	3.213in
Thickness	10 mm
Pipe Material	ASTM 304 Grade A
Length	40m
Fluid density	1.67 kg/L
Temperature set point	10 C
H2SO4 concentration	75%
Inspection period if acceptable risk target is not reached	3 years

2.3.2. Stepwise application of DRBI

The following steps are considered to simply illustrate the application of the developed methodology on the aforementioned case study.

Step 1. The first step for the DRBI is to summarize all the information necessary for the calculation. The integrity of the pipe is based on the wall thickness and it is necessary to have the data for the internal and external diameters in the initial stage. For this case study, generic data have been used to demonstrate the methodology. To mimic the continuously monitored data, a simulation approach has been taken.

Step 2. Due to the corrosive nature of the fluid, the degradation mechanism is identified as corrosion. The integrity of the pipe is based on its available thickness. A low flow rate of the sulfuric acid will cause general corrosion or thinning of the carbon steel. The effect of other degradation mechanisms such as local corrosion or pitting will be negligible if the conservative approach is taken for general corrosion calculation.

Step 3. The next step is to identify the indicators. As mentioned in the framework section, the factors that will affect the corrosion rate of the pipe are temperature, flow velocity, acid concentration, the presence of oxidants, atmospheric parameters such as moisture content and system vibration, etc. Of these parameters, fluid temperature, acidic concentration, and flow velocity are set and monitored by the control system. Hence, these three parameters are identified as indicators for the risk. The next step is to identify the relationship of the indicators with the degradation mechanism. NACE has provided data for corrosion caused by sulfuric acid as a function of temperature, concentration and flow velocity (NACE, 1985). Based on NACE data, API-581 has provided a lookup table in Table 2.B.5.2 in Annex 2.B along with brief details of the corrosion mechanism (API, 2016b). This table is used in this study to construct the corrosion rate as a function of the temperature, concentration and flow velocity.

Step 4. Once the corrosion rate is obtained, the POF can be defined using several approaches. In this study, as discussed in section 2, dynamic reliability models and a generic failure frequency (GFF) model have been used to calculate the POF. The POF calculated by both approaches, reliability models and GFF models, are dynamic in nature. For reliability based DRBI model The POF(t) is calculated as 1- R(t). Whereas for GFF-Based model POF is defined as the product of df and GFF.

Step 5: To calculate the risk, possible failure scenarios have been identified. The underlying financial and area loss due to identified leakage scenario was calculated. The COF for the case study has been calculated using an API-581 level 1 approach. A detailed discussion of the calculation is out of the scope of this work and interested readers can refer to API-581 part 3 for more details on this (API, 2016b). The risk is then calculated as a product of COF and POF.

Step 6: The final step is the predictive analysis. In this case, a spreadsheet program is developed to simulate the value of the temperature, acidic concentration and the flow velocity. The simulation is carried out for three years, a typical inspection and maintenance period for the pipeline. The programme derives the value for the corrosion rate and the thickness lost based on the references discussed in the step 3 of this section. This value is fed into static reliability models and the GFF model. The output is in terms of the probability of failure. The results are discussed in more detail in the following section.

2.4 Result analysis

A DRBI is calculated based on the monitored parameters simulated for three years. For the simulation, it is assumed that the temperature of the fluid, acidic concentration and the velocity of fluid follow normal distributions with mean and standard deviations as mentioned in Table 2-5. This assumption is logical since process systems employ a proportional control system or a PID control system to regulate the system parameters. Values of these parameters are simulated for each day of operation between the inspection period. The graph in Figure 2.4 presents the daily variation of temperature. It reproduces the effect of a control system that is programmed to adjust the temperature to a set point of 10°C. The fluctuation in the value mimics the temperature regulator's on-off cycle. Similarly, the graphs in Figure 2.5 and Figure 2.6 provide the value of acid concentration and the flow velocity based on the simulation of the control system that has been set to 75% concentration and 0.91 m/s respectively.

Corrosion rate was calculated based on the result of simulation for each period. Even though the monitored parameters fluctuate frequently, the corrosion taking place due to the indicators may not change as rapidly. To correctly quantify the corrosion resulting from the indicator's value, a conservative corrosion rate is selected based on the moving percentile value of the observations in each month. Figure 2.7 shows the variation in the corrosion rate resulting from variation in the indicator's value. Based on the corrosion rate derived from the indicators, a wall thickness loss is estimated. Figure 2.8 shows the available wall thickness as a function of the age of the system. This wall thickness, along with the corrosion rate, is used to calculate the POF based on i) Dynamic Reliability models ii) the GFF based model.

Table 2-5 Set points of system parameters and variations

Fluid parameters	Type of distribution	Mean	Std Dev
Temperature	Normal	10°C	5°C
Acidic concentration	Normal	75%	5%
Flow velocity	Normal	0.91 m/s	0.25 m/s

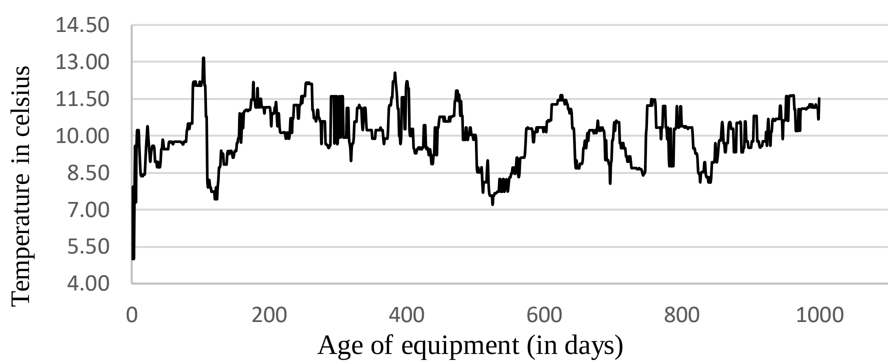

Figure 2.4 Simulated temperature of the fluid measured continuously

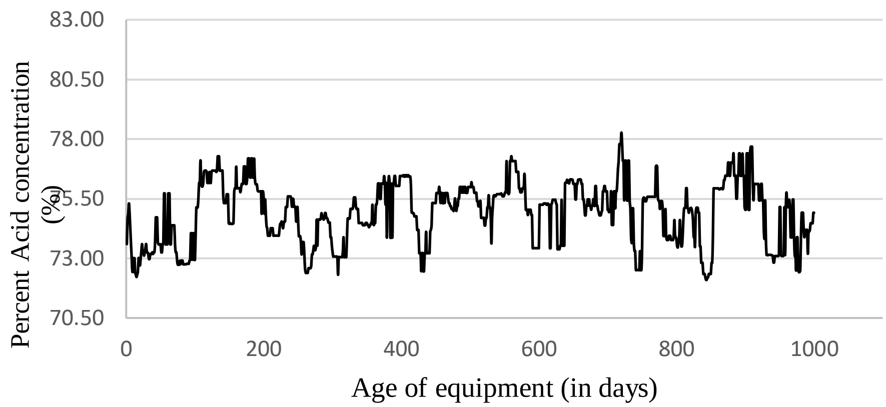

Figure 2.5 Simulated acidic concentration of the fluid measured continuously

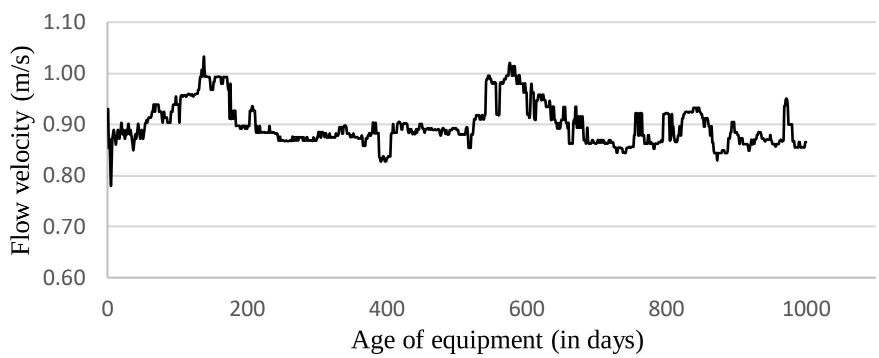

Figure 2.6 Simulated velocity of the fluid measured continuously

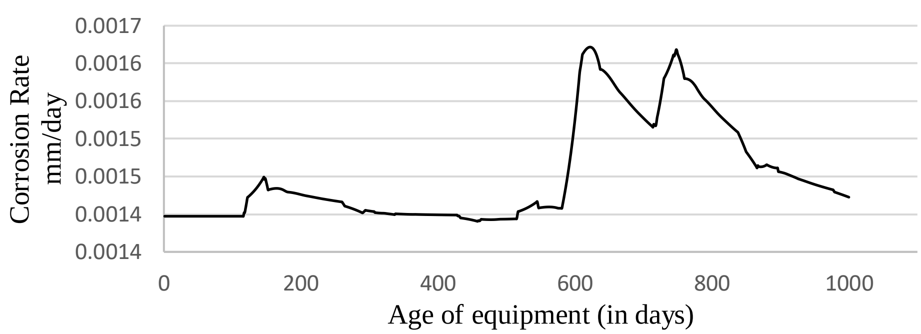

Figure 2.7 Real-time corrosion rate calculated from the Risk Indicators

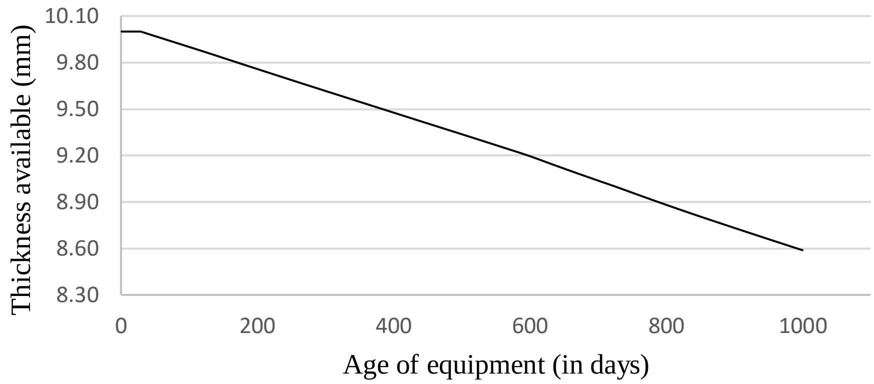

Figure 2.8 Calculated thickness available as a function of time

2.4.1 Dynamic Reliability model

For the calculation of the POF using the reliability model, the failure of the pipeline based on the available thickness is assumed to follow a lognormal distribution. This provides an option to adjust the reliability trend specific to the system by changing the shape parameter. The wall thickness at a given time is h and minimum wall thickness, hmin, is 5 mm, which is based on a 50% thickness failure criterion. The graph in Figure 2.9 shows the result of the POF between two inspection intervals.

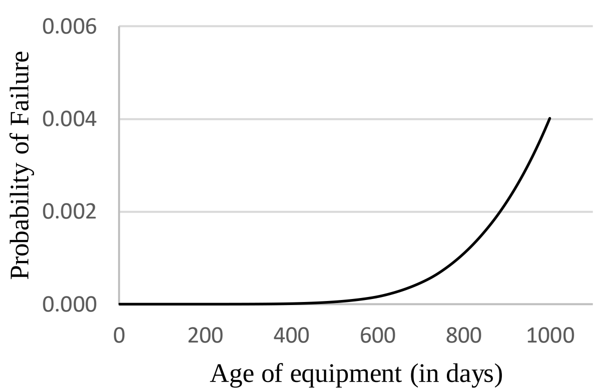

Figure 2.9 Probability of failure calculated using DRBI- reliability based model.

2.4.2 Results of using GFF based model

To calculate the POF using the GFF model, a failure frequency is determined for the pipe using generic data. The modifiers for the corrosion rate are defined based on the system's properties and experiential learning. As the system parameters change, the value of modifiers will increase or decrease in accordance with the established conditions. The POF is determined as a product of the failure frequency and modifiers. POF, calculated using the GFF approach, is summarized in Figure 2.10. The graph shows the value of POF on the vertical axis and the duration between inspection intervals on the horizontal axis.

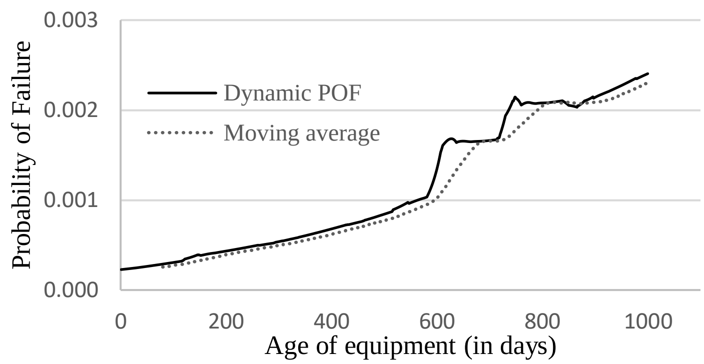

Figure 2.10 Probability of failure calculated using DRBI- GFF model

2.4.3 Comparison with API-581 RBI

An RBI calculation has been carried out using the API-581's recommended practice for the same system. According to the guidelines, the POF function is $P_f(t) = gff_{total} \cdot D_f(t) \cdot F_{MS}$, where $P_f(t)$ is the probability of failure as a function of time, which is obtained as a product of generic failure frequency gff_{total}, a damage factor, $D_f(t)$, and a facility management factor, F_{MS}.

In API-581 methodology, the $D_f(t)$ is obtained based on the A_{rt} value which is defined as the component wall thickness factor, calculated using the most recent inspection data. The inspection effectiveness of B is assumed for this study. POF is generated based on the $D_f(t)$ determined by the A_{rt} value at the given age of the system. A summary of the calculation is provided in Table 2-6. Figure 2.11 shows the POF value obtained by API-581 as a function of time. Note that since the A_{rt} value will only increase or remain constant, the POF will also show the same trend: it will increase in interval-based steps and never decrease.

Table 2-6 Summary of API-581 recommended RBI values

Generic failure frequency	3.06 E-05
Management system factor	1
Corrosion ate	0.55 mm/year
Art value	0.165
Thinning damage factor at inspection date	8
Thinning damage factor at next planned inspection date	53
POF at inspection date	0.00024
POF at next planned inspection	0.00162

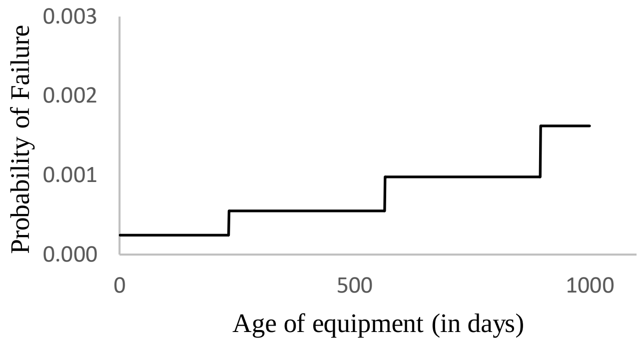

Figure 2.11 Probability of failure calculated using API-581 recommended RBI

2.4.4 Sensitivity Analysis

Sensitivity analysis is performed on the GFF model to check the effect of the indicators on the POF value at the beginning of the DRBI. API-581 also uses these parameters in its risk estimation. However, it is assumed that these values remain constant over the entire interval. All three indicators in this study: temperature, acidic concentration, and velocity have units on different measurement scales. To examine the effect of variation in POF, a change of one standard deviation is applied to the indicators. Figure 2.12 shows the magnitude of increase in POF with an increase in the value of the indicator.

Raising the temperature and concentration by one standard deviation increases the POF 1.25 times. However, an increase in the velocity of the fluid by one standard deviation causes the POF to increase 5.63 times. It is clear that POF is most sensitive to the velocity, followed by temperature and acid concentration. The sensitivity of the POF justifies the correct identification of indicators for the system.

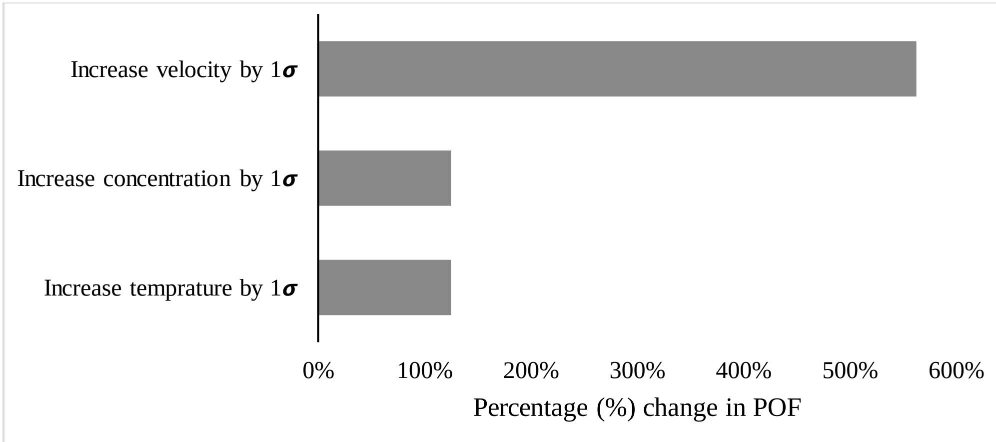

Figure 2.12 Effect of Risk Indicators on the initial probability of failure

2.5 Discussion:

The result of the simulation of the proposed DRBI calculation gives a clear picture of the system's condition. Considering Figure 2.11 which illustrates the POF calculated by API-581 recommended practice, a step-wise increase in the probability is observed. This is because the damage factor is defined based on a lookup table. Due to the assumption that the corrosion rate will remain constant, the POF will always increase after a specified interval at a predefined rate. This may not always be true, and this is proved with the calculation of the proposed DRBI.

Of the two approaches used for calculation of POF in DRBI: the reliability model and GFF model, the latter provides the more sensitive results for the case study under consideration. This is due to the fact that the reliability based model only calculates POF based on the current thickness and does not consider the risk indicators directly in the calculation. However, unlike the API-581 calculated value, the reliability model gives a continuous failure profile, as shown in Figure 2.9. The increase in the corrosion rate at around 600 days from the initial inspection causes a rise in the POF calculated in the graph. Since the thickness lost during this period is not recovered, the POF will not decrease even if the corrosion rate is brought under control.

The POF calculated from the GFF model gives an active prediction of the probability. This POF calculation not only considers the available thickness, but also the recent indicator value and the corrosion rate. Due to the spike in the corrosion rate at around 600 days, an abrupt change is reflected in the POF value, as shown in Figure 2.10. However, here the POF becomes stable as soon as the corrosion rate is brought under control. The API-581 recommended RBI fails to capture this fluctuation and this will give a false sense of security if only API-581 is used.

Further, to check the influence of the involved parameters in the calculation, a sensitivity analysis was carried out. The result is discussed in the previous section. It is observed that the increase in the indicator's value by one standard deviation causes a significant change in the POF value. Of the three indicators, the velocity of the fluid was found to be the major driver for the POF. An increase of one standard deviation caused the probability to increase over five times. This is due to the corrosion mechanism explained in section 3 which explains that at a higher velocity, the ferrous sulfate film will erode and accelerate the corrosion process.

The probability curves obtained by API-581, the reliability-based DRBI model and the GFF-based DRBI model overlap for comparison in Figure 2.13. It is clear that the probability value obtained by API-581 failed to identify the degradation due to the dynamically changing corrosion rate. After around 600 days, the actual POF value doubled, and this was registered in real time using GFF-based DRBI. Furthermore, in the proposed model, Risk is a product of POF and COF where only POF is modelled as a dynamic function. Due to this risk profile will be similar to that of POF and change dynamically with the system parameters.

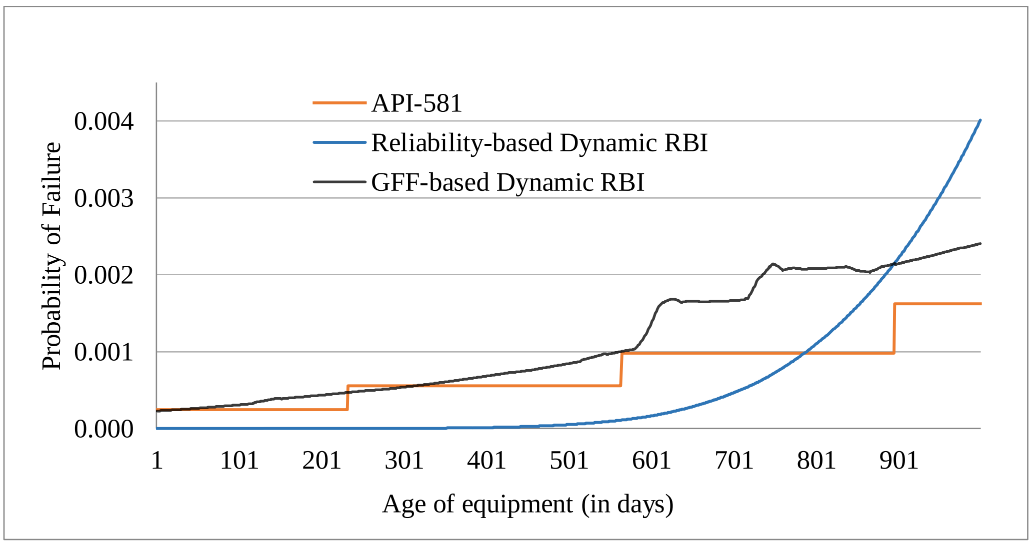

Figure 2.13 Comparison of POF obtained from DRBI and API-581

A comparison of the results obtained from the API-581 recommended RBI and the proposed DRBI has been summarized in Table 2-7.

Table 2-7 Comparison of advantages of proposed DRBI

API-581 Recommended RBI	**DRBI**	
	Reliability-based model	**GFF-based model**
A stepwise increase in POF with time is observed between inspections	A continuous increase in POF with time is witnessed.	A continuous increase or decrease in POF is observed with time.
Changes in actual corrosion rate, available thickness or system parameter are not captured in the POF	Change in actual thickness available and **indirect** influence of corrosion rate and system parameters are captured with real-time POF	Changes in actual thickness available and **direct** influence of corrosion rate and system parameters are captured with real-time POF
POF will always increase at a predefined rate regardless of the changes in system parameters.	POF will always increase; however, the rate of increase will depend on the system parameters.	POF will increase or decrease based on the actual condition of the system's condition and its parameters.
Ability to include effects of several process and management parameters to calculate the POF.	POF is calculated based on the continuously monitored parameters.	POF is calculated based on the continuously monitored parameters.

2.6 Conclusions and Recommendations

This study presents a new approach that can be integrated with the current RBI practices to overcome several shortcomings discussed in section 2. A detailed stepwise framework along with a demonstrative case study for DRBI is presented for application in process systems. Upon analyzing the results of the case study, the following can be concluded:

1) **Confidence in safety of the system**: The proposed DRBI model provides direct and real time insights nto the actual risk value of the system. This will decrease the uncertainty of risk estimation in real time and provide an accurate sense of safety of the system.

2) **Effective monitoring and alert system**: The degradation rate may change drastically due to a certain combination of process fluctuations. The DRBI adequately captures this change, and the information can be combined with the monitoring system to provide an alert. This will give adequate time to prepare and implement risk mitigation plans. This is not possible with other traditional RBI methods. Even though advanced process systems have a monitoring system in place to provide alerts, if a certain parameter exceeds allowable limits, these systems do not consider its effect on the degradation mechanism. This study shows that a combination of certain fluctuations in the process parameters, even though within allowable limits, may increase the degradation rate significantly, leading to an increase in POF.

3) **A reward for safe operation:** Most traditional RBI uses a conservative approach when there is considerable uncertainty in the risk estimation. A risk-aversive approach is taken by increasing the inspection frequency due to this uncertainty in risk. It is shown in this

study that under certain conditions, the risk may decrease if the system parameters are optimized. With the DRBI, this can be recognized with minimal uncertainty and can be used for rescheduling inspection intervals. This can provide an immediate cost saving by extending planned inspection intervals and maintenance.

4) **Effective process optimization tool**: The unique approach used to define the risk based on the indicators provides an ability to identify the actual cause for the sudden or gradual increase in the risk value in real time. Sensitivity analysis was performed in this study to identify the influence of the indicators. Based on this analysis, recommendations for optimization of the system parameters can be provided.

Although the proposed DRBI provides numerous unique advantages over traditional RBI methods, it is heavily dependent on the system parameters and defined risk indicators. Due to the continuous requirements of data, factors such as management system parameters are not used in the calculation of POF. A solution to this would be to use the proposed DRBI along with well-established guidelines like API-581. Initial risk value from the DRBI can be adjusted or benchmarked with widely accepted API-581. This would have the ability to include the benefits of both methods at the same time without making any significant extra investment. This study provides a foundation for the development of a new module that can be incorporated with the API-581 to enable dynamic risk calculation.

2.7 References

Abbassi, R., Bhandari, J., Khan, F., Garaniya, V., & Chai, S. (2016). Developing a quantitative risk-based methodology for maintenance scheduling using Bayesian network. *Chemical Engineering Transactions*, 48, 235-240.

Abimbola, M., Khan, F., & Khakzad, N. (2014). Dynamic safety risk analysis of offshore drilling. *Journal of Loss Prevention in the Process Industries, 30*, 74-85.

Alrowaie, F., Gopaluni, R. B., & Kwok, K. E. (2012). Fault detection and isolation in stochastic non-linear state-space models using particle filters. *4th Symposium on Advanced Control of Industrial Processes (ADCONIP), 20*(10), 1016-1032.

API, R. (2002). 580. *Risk-Based Inspection", American Petroleum Institute, Washington, DC.*

API, R. (2009). 580 Recommended Practice for Risk-Based Inspection. *American Petroleum Institute, Washington, DC*.

API, R. (2016a). 580 Risk-Based Inspection. In: American Petroleum Institute.

API, R. (2016b). 581, 2016. *Risk-based Inspection Methodology. API Recommended Practice, 581*.

Arunraj, N. S., & Maiti, J. (2007). Risk-based maintenance—Techniques and applications. *Papers Presented at the 2005 Symposium of the Mary Kay O'Connor Process Safety Center, 142*(3), 653-661.

Arzaghi, E., Abaei, M. M., Abbassi, R., Garaniya, V., Chin, C., & Khan, F. J. E. F. A. (2017). Risk-based maintenance planning of subsea pipelines through fatigue crack growth monitoring. *Engineering Failure Analysis, 79*, 928-939.

ASME. (1991). *Risk-based inspection : development of guidelines*. New York: American Society of Mechanical Engineers.

ASME. (1996). *Risk-based inservice testing : development of guidelines : an ASME research report*. New York: American Society of Mechanical Engineers.

ASME. (1997). *Applications of risk-based technologies to U.S. Coast Guard systems : workshop proceedings*. New York: American Society of Mechanical Engineers.

ASME. (2007). PCC-3 Inspection Planning Using Risk-Based Methods. In: American Society of Mechanical Engineers.

Baraldi, P., Mangili, F., & Zio, E. (2012). A Kalman filter-based ensemble approach with application to turbine creep prognostics. *IEEE Transactions on Reliability, 61*(4), 966-977.

Bertolini, M., Bevilacqua, M., Ciarapica, F. E., & Giacchetta, G. (2009). Development of Risk-Based Inspection and Maintenance procedures for an oil refinery. *22*(2), 244-253.

Brennan, F. (2013). Risk based maintenance for offshore wind structures. *Procedia CIRP, 11*, 296-300.

Carter, J., Dawson, P., & Nixon, R. (2006). EXPLOSION AT THE CONOCO HUMBER REFINERY–16TH APRIL 2001. *IChemE J. LPB, 188*, 14-20.

Dawotola, A. W., Trafalis, T., Mustaffa, Z., Van Gelder, P., & Vrijling, J. (2012). Risk-based maintenance of a cross-country petroleum pipeline system. *Journal of pipeline systems engineering and practice, 4*(3), 141-148.

Dey, P. K. (2001). A risk-based model for inspection and maintenance of cross-country petroleum pipeline. *Journal of Quality in Maintenance Engineering, 7*(1), 25-43.

DNV, D. N. V. (2010). Recommended Practice DNV-RP-G101: Risk Based Inspection of Offshore Topsides Static Mechanical Equipment.

Ebeling, C. E. (1997). *An introduction to reliability and maintainability engineering*. New York: McGraw Hill.

Fujiyama, K., Nagai, S., Akikuni, Y., Fujiwara, T., Furuya, K., Matsumoto, S., . . . Kawabata, T. (2004). Risk-based inspection and maintenance systems for steam turbines. *29th MPA Seminar in the series Safety and Reliability of Pressure Components - Stuttgart, October 9th and 10th, 2003, 81*(10), 825-835.

Hashemi, S. J., Ahmed, S., & Khan, F. (2014). Risk-based operational performance analysis using loss functions. *116*, 99-108.

Hashim, M., Hidekazu, Y., Takeshi, M., & Ming, Y. (2014). Application case study of AP1000 automatic depressurization system (ADS) for reliability evaluation by GO-FLOW methodology. *278*, 209-221.

Hassan, J., & Khan, F. (2012). Risk-based asset integrity indicators. *Journal of Loss Prevention in the Process Industries, 25*(3), 544-554.

HSE. (2006). *Developing process safety indicators: a step-by-step guide for chemical and major hazard industries*: Health and Safety Executive.

Hu, H., Cheng, G., Li, Y., & Tang, Y. (2009). Risk-based maintenance strategy and its applications in a petrochemical reforming reaction system. *Journal of Loss Prevention in the Process Industries, 22*(4), 392-397.

Kalantarnia, M., Khan, F., & Hawboldt, K. (2009). Dynamic risk assessment using failure assessment and Bayesian theory. *Quantitative Risk Analysis - Special issue devoted to Norberto Piccinini, 22*(5), 600-606.

Kamsu-Foguem, B. (2016). Information structuring and risk-based inspection for the marine oil pipelines. *Applied Ocean Research, 56*, 132-142.

Khakzad, N., Khan, F., & Amyotte, P. (2012). Dynamic risk analysis using bow-tie approach. *Reliability Engineering & System Safety, 104*, 36-44.

Khakzad, N., Khan, F., & Paltrinieri, N. (2014). On the application of near accident data to risk analysis of major accidents. *Reliability Engineering & System Safety, 126*, 116-125.

Khan, F., Abunada, H., John, D., & Benmosbah, T. (2010). Development of risk-based process safety indicators. *Process Safety Progress, 29*(2), 133-143.

Khan, F., & Haddara, M. (2003). Risk-based maintenance (RBM): a quantitative approach for maintenance/inspection scheduling and planning. *Journal of loss prevention in the process industries, 16*(6), 561-573.

Khan, F., & Haddara, M. (2004). Risk-based maintenance (RBM): A new approach for process plant inspection and maintenance. *Process safety progress, 23*(4), 252-265.

Khan, F., Hashemi, S. J., Paltrinieri, N., Amyotte, P., Cozzani, V., & Reniers, G. (2016). Dynamic risk management: a contemporary approach to process safety management. *Biotechnology and bioprocess engineering / Process systems engineering, 14,* 9-17.

Khan, F., Sadiq, R., & Haddara, M. (2004). Risk-based inspection and maintenance (RBIM): multi-attribute decision-making with aggregative risk analysis. *Process safety and environmental protection, 82*(6), 398-411.

Kim, H., Lee, S.-H., Park, J.-S., Kim, H., Chang, Y.-S., & Heo, G. (2015). Reliability data update using condition monitoring and prognostics in probabilistic safety assessment. *Special Issue on ISOFIC/ISSNP2014, 47*(2), 204-211.

Krishnasamy, L., Khan, F., & Haddara, M. (2005). Development of a risk-based maintenance (RBM) strategy for a power-generating plant. *Journal of Loss Prevention in the Process Industries*, *18*(2), 69-81.

Lewandowski, R. (2013). *Incorporation of Corrosion Mechanisms into a State-dependent Probabilistic Risk Assessment.* (Doctoral dissertation, The Ohio State University).

LIU, Y., & WU, Z. (2006). Operational safety performance indicators for nuclear power plants [J]. *Journal of Tsinghua University (Science and Technology), 3,* 028.

Mancuso, A., Compare, M., Salo, A., Zio, E., & Laakso, T. (2016). Risk-based optimization of pipe inspections in large underground networks with imprecise information. *Reliability Engineering & System Safety, 152*, 228-238.

Meel, A., & Seider, W. D. (2006). Plant-specific dynamic failure assessment using Bayesian theory. *61*(21), 7036-7056.

Meel, A., & Seider, W. D. (2008). Real-time risk analysis of safety systems. *Festschrift devoted to Rex Reklaitis on his 65th Birthday, 32*(4), 827-840.

Melani, A. H. A., Murad, C. A., Caminada Netto, A., Souza, G. F. M. d., & Nabeta, S. I. (2018). Criticality-based maintenance of a coal-fired power plant. *147*, 767-781.

NACE. (1985). *Corrosion in sulfuric acid : proceedings of the Corrosion/85 Symposium on Corrosion in Sulfuric Acid*. Houston, Tex.: National Association of Corrosion Engineers.

Pan, J.-N., & Chen, S.-C. (2013). A loss-function based approach for evaluating reliability improvement of an engineering design. *Expert Systems with Applications*, *40*(14), 5703-5708.

Pariyani, A., Seider, W. D., Oktem, U. G., & Soroush, M. (2012). Dynamic risk analysis using alarm databases to improve process safety and product quality: Part II—Bayesian analysis. *AIChE Journal*, *58*(3), 826-841.

Pui, G., Bhandari, J., Arzaghi, E., Abbassi, R., & Garaniya, V. (2017). Risk-based maintenance of offshore managed pressure drilling (MPD) operation. *Journal of Petroleum Science and Engineering 159*, 513-521.

Roy, A., Srivastava, P., & Sinha, S. (2015). Dynamic failure assessment of an ammonia storage unit: A case study. *Process Safety and Environmental Protection*, *94*, 385-401.

Sharp, J., Ersdal, G., & Galbraith, D. (2008). *Development of key performance indicators for offshore structural integrity*. Paper presented at the ASME 2008 27th international conference on offshore mechanics and Arctic engineering.

Straub, D., & Faber, M. H. (2005). Risk based inspection planning for structural systems. *Structural safety, 27*(4), 335-355.

Wang, Y., Cheng, G., Hu, H., & Wu, W. (2012). Development of a risk-based maintenance strategy using FMEA for a continuous catalytic reforming plant. *Journal of Loss Prevention in the Process Industries*, *25*(6), 958-965.

Zadakbar, O., Imtiaz, S., & Khan, F. (2013). Dynamic risk assessment and fault detection using a multivariate technique. *Process Safety Progress, 32*(4), 365-375.

Zadakbar, O., Khan, F., & Imtiaz, S. (2015). Dynamic Risk Assessment of a Nonlinear Non-Gaussian System Using a Particle Filter and Detailed Consequence Analysis. *The Canadian Journal of Chemical Engineering, 93*(7), 1201-1211.

Zeng, Z., Kang, R., & Chen, Y. (2016). Using PoF models to predict system reliability considering failure collaboration. *Chinese Journal of Aeronautics*, *29*(5), 1294-1301.

Zeng, Z., & Zio, E. (2018). Dynamic risk assessment based on statistical failure data and condition-monitoring degradation data. *IEEE Transactions on Reliability*, *67*(2), 609-622.

Zhiguo, Z., Yunxia, C., Enrico, Z., & Rui, K. (2017). A compositional method to model dependent failure behavior based on PoF models. *Chinese Journal of Aeronautics*, *30*(5), 1729-1739.

Zio, E. (2018). The future of risk assessment. *Reliability Engineering & System Safety*, *177*, 176-190.

3. A Predictive model to estimate Ice Accumulation on Sea Vessels and Offshore Rigs

Preface

A version of this manuscript has been submitted to the Journal of Ocean Engineering. I am the primary author of this manuscript while Faisal Khan is the co-author. The experimental setup used in the study was developed earlier by Peiwei Xin and Dinesh Herath. I have developed the experiment protocol, the framework of the data gathering and analysis; this development was reviewed and revised by Faisal Khan. I have calibrated the experiment, conducted experiments, collected data, and did programming of the controller used in the experiment. Faisal Khan has reviewed the data and provided feedback and guidance on how to analyze and made conclusive observations. I have prepared the first draft of the manuscript and subsequent revisions. Co-author Faisal Khan has reviewed the manuscript multiple times, suggested revisions and provided constructive technical feedback.

Abstract

Ice accumulation on the ships and offshore rigs creates unsafe working condition and may damage the critical equipment. Several approaches have been developed in the past to predict the ice accumulation; this includes analytical models, experimental investigations, computational fluid dynamics simulations, empirical and statistical models. This work proposes a probabilistic causal relationship based model to predict the ice accumulation on the ships or offshore rigs. The model uses the Bayesian probabilistic approach to establish the relationship among the factors affecting the icing. The model is successfully tested on

an experimental setup designed to simulate the spray icing condition observed in the subzero environment on a sea vessel. The result of the experimental testing was compared with the outputs from the predictive model. It was observed that the predicted values gave the reasonably good match with the observed values.

The proposed model considered a range of environmental and processes parameters that affect the ice accumulation. The model has the flexibility to include more parameters affecting icing based on the location and system. The model can be used for dynamically changing conditions with minimum computational load and time.

Keywords: Ice load; Ice conditions; Harsh environment; Ice accretion; Arctic conditions; Icing prediction

3.1 Introduction

Ice accumulation occurs on the sea goings vessels and offshore rigs that operate in subzero temperature. When water droplets come in contact with the cold object, it is necessary that process of heat extraction occur such that all or some of the water freeze before getting drained away. Also, if the surface is dry and the droplets freeze before coming in contact with the surface, the crystals with not stick to the surface and no ice accumulation will occur (Jessup, 1985). Icing can cause a severe threat to the stability of the vessel structure; this is more significant in the case of small ships. Many small ships still use manual deicing methods that involve Wooden or metal mallets, baseball bats to remove the ice layer. This traditional method is useful in some cases. However it can damage the equipment from being a strike by the mallets, and it also possesses a high risk to the person carrying out this operation on the deck (Ryerson, 2011). Several deicing chemicals are now restricted as per the new regulation due to its environmental impacts. (Ryerson, 2013)

Calculation of icing rate is a very complicated process. Several models are proposed to predict icing rate for various vessels and rigs. Most commonly used model is the one developed by (Overland, Pease, Preisendorfer, & Comiskey, 1986). This empirical model was based on several observations from Alaskan waters. It provides clear steps to calculate the value of icing predictor (PR) which can be categorized from light to extreme icing. Even though this model overcame several complexities involved in icing prediction, it considers only limited variables affecting icing rate and is based on many simplifying assumptions. The model proposed by (T. Myers & Hammond, 1999) focus on the growth of the ice accumulation and calculation of its thickness. Some research on the formation of saline icicles on the vessels has also been carried out (Chung & Lozowski, 1990). The results show very little difference in the growth of saline icicles concerning freshwater icicles. A mathematical model developed by (T. G. Myers & Charpin, 2004) uses a modified model to show ice formation on various surfaces. However, it only considers fresh water in its calculation. (Kulyakhtin & Tsarau, 2014) develops a 3-dimensional time-dependent model they named MARICE using calculations of freshwater icing by (T. G. Myers & Charpin, 2004) and salinity conservation equations used by (Ivar Horjen, 1990). (Shipilova et al., 2012) studied the effect of water droplet temperature, air temperature and wind velocity on the ice accumulation rate. A more complex numerical model like ICEMOD (Ivar Horjen, 2013; I Horjen & Vefsnmo, 1986), RIGICE04 (Forest, Lozowski, & Gagnon, 2005) are also available. These models focus more on the spray generation based on the splashing of waves with the vessel. Airflow and some heat transfer process are approximated for specific shapes. Recently model was developed for Norwegian Coast Guard by (Samuelsen, Edvardsen, & Graversen, 2017), this model was tested using data from the coast guard ship. In real condition, the process is even more complicated: several other parameters affect the generation of spray and the heat transfer process which are very difficult to integrate. Another approach of using a numerical model based on computational fluid dynamics (CFD) simulation has been developed by (Kulyakhtin, Shipilova, & Muskulus, 2014) which simulates the icing rate over the whole vessel.

Some models discussed models are developed and test based on a specific location or vessel type. The numerical models that are based on mass and heat transfer calculations or CFD simulation require much computational power which makes it less efficient for predictions on a dynamically changing environment(Dehghani-Sanij, Dehghani, Naterer, & Muzychka, 2017). Although the concern for icing problem exists for almost a century, there is still very little understanding on this topic (Dehghani-Sanij et al., 2017). This study aims to present a different approach for predicting Icing load. The uniqueness of this model is that it is dynamic such as it can be implemented in changing scenarios. Once the data has been converted in the form of the likelihood that is required for this model, the prediction of icing load can be made with minimum computational power. This can give the ability to predict the icing load in real time on a moving system. As observed in the previous models, (Jessup, 1985; Overland et al., 1986) only some parameters are considered necessary for icing rate calculation, and new parameters cannot be introduced without modelling from the beginning. The model proposed here overcomes this limitation. The additional parameters can be introduced without changing the entire model quickly and effectively. The model was further verified on an experimental setup designed to simulate the spray icing observed on a vessel.

3.2 Model development

This section gives descriptions of the method to estimate the ice accretion load on equipment on sea vessel or offshore platform. The main steps for developing the model is shown in Figure 3.1. The method starts with the identification of the factors affecting icing, and the final step is the interpreting the output into a numerical value. The steps also include the formulating of a predictive model, which is a crucial step for this model. Bayesian network is used as a predictive tool to develop the model.

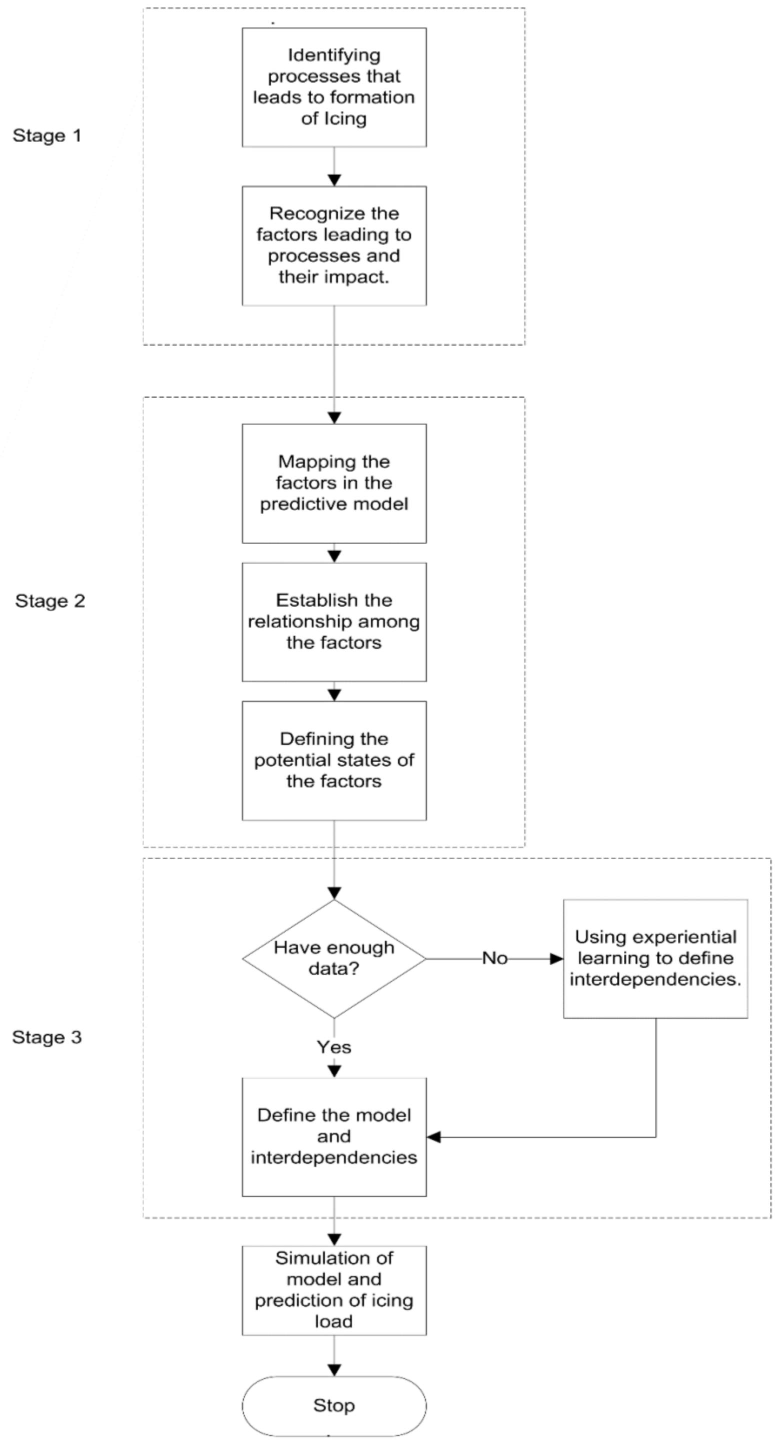

Figure 3.1 Steps involved in the development of the model

3.2.1 Stage 1: Identification of processes and factors affecting Marine Icing

Several factors affect ice accumulation such as wave height, wind velocity, ambient air temperature, sea water temperature as well as vessel velocity(Fukusako, Horibe, & Tago, 1989). Several complex processes are leading to ice accumulation.(Kulyakhtin, Kulyakhtin, & Løset, 2016) divides the process into four types including the generation of spray flux, the flow of spray cloud, impingement of droplets and freezing of the spray. The spray flux formation and heat transfer among the droplets are critical processes in ice accumulation hence it must be calculated very carefully(Lozowski, Szilder, & Makkonen, 2000). In this study, two main processes are considered: 1) formation of spray flux, 2) droplet cooling. The goal is to predict the icing based on the observed data, so the dynamics of spray formation and icing is not considered here.

Spray flux is defined by the amount of droplet of the cloud interacting with the structure (Kulyakhtin & Tsarau, 2014). It is mainly influenced by the wind velocity and the liquid water content (LWC) in the air. The LWC is dependent on wind velocity and waves splashing with the vessel which leads to the formation of droplets. As the vessel is in motion, it needs to consider the relative wind velocity. This dependency can be shown in Figure 3.2a. The directional arrow signifies the influence of the factors on the directed phenomenon.

Significant cooling of spray droplets is necessary to form ice on impacting. The droplet cools as it travels through the air. The temperature of the droplets approaches the temperature of the atmospheric air. In real conditions, this temperature will always be higher than atmospheric temperature. The main parameters affecting the droplet cooling are atmospheric temperature, relative humidity of the air, and velocity (Hoes, 2016). The velocity in this study is approximated by the relative speed of the vessel. Figure 3.2b shows the relation of these factors. Finally, these factors leading to two phenomena of droplet cooling and spray flux causes the ice accumulation on the object as shown in the Figure 3.2c.

3.2.2 Stage 2: The Structure of the predictive model:

Bayesian network (BN) is used as a probabilistic predictive tool for this study. In the BN, nodes represent the variables, and unidirectional arrows representing the dependencies connect them. The formation of the structure of the BN can be divided into three main steps: 1) mapping the factors into nodes 2) Connecting the nodes 3) defining the states of the nodes.

1) After identifying different factors affecting the phenomenon, they can be defined as nodes in the BN. These nodes can be divided into evidence, intermediate nodes, and query nodes. The evidence is the inputs entered based on the observations made. Whereas the query nodes are the final node of the BN. This is also output nodes of the system. To establish proper relations between the evidence and terminal nodes intermediate nodes are defined based on the nature of the processes. This node connects the evidence nodes to the query nodes based on the logical relationships. The factors represented in Figure 3.2are considered as nodes in the BN. The BN predictive model is shown in Figure 3.3. The factors responsible for initiating the process of Flux

formation and droplet cooling are considered as the evidence. They act as input nodes to the Bayesian Network. Spray flux and droplet cooling are determined as an intermediate node. The intermediate nodes define the causes of the final node of ice accumulation, which is the output of the system.

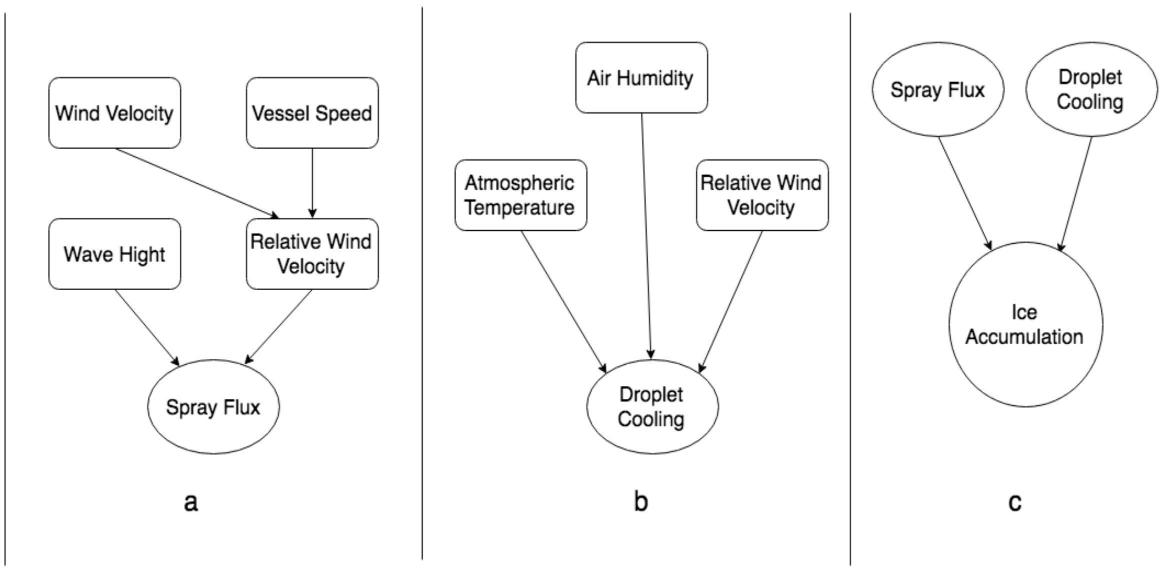

Figure 3.2 Relationship of factors and processes affecting Ice Accumulation

2) The next step is to connect the nodes. Cause and impact relationship usually do this. To illustrate this process wind velocity, vessel speed and waves are considered as the inputs to the system as shown in Figure 3.2a. This is defined as evidence or primary input nodes in the BN in Figure 3.3. Note that the relative velocity is defined based on the wind velocity and the vessel speed. Hence node "relative velocity" becomes an intermediate node which is linked to wind velocity and vessel speed. Now Spray flux is dependent on the "waves" and the "relative velocity" so it is connected with the

directional arrows from waves and relative velocity. Finally, the flux and the droplet cooling are the prior distribution of the ice accumulation which is also the output of our system. This can be connected to the directional arrow shown in Figure 3.3.

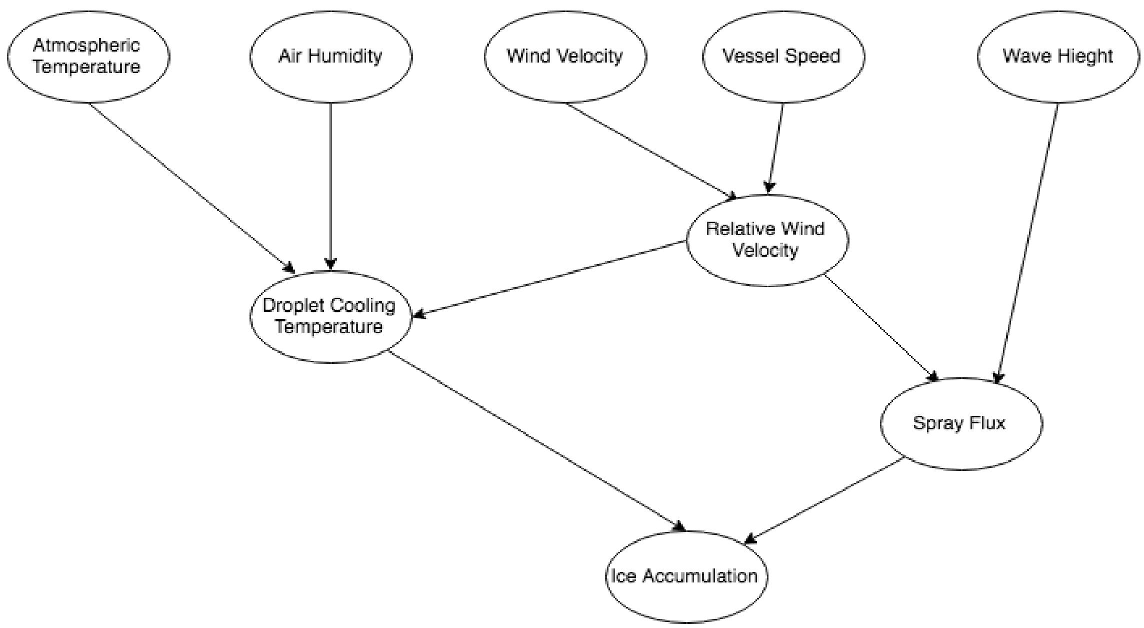

Figure 3.3 Bayesian network structure showing dependencies of the factors affecting ice accumulation

3) Before defining the conditional relationships known as the conditional probability data, it is needed to develop the states in each node. The nodes in BN could have several states. This is dependent on the nature of the system.

Each node can be divided into several states. However, if we define many states, the system will become very complicated, and the number of conditional interdependency for the next node will inherit longer multitudes. To keep the system consistent and straightforward, the nodes are defined to have three states. For instance, Atmospheric Temperature can be High, medium and low, corresponding to more than -5, -5 to -12 and below -12 respectively. Similarly, the classification for all other nodes can be defined into three stages as shown in the Table 3-1. This classification of states is an essential step in this model. This classification is based on the observed range and experiential learning. This range can be tweaked for the different data set, once available.

Table 3-1 Classification of states of the nodes

Parameters	Classification	Range of parameters
Air Temperature	High Med Low	Greater than -5 C -5.01C to -12 C Less than -12 C
Wind velocity	Low Moderate High	up to 3 m/s 3 to 12 m/s more than 12 m/s
Humidity	Low Med High	0 to 50 % RH 20 to 80 % RH 80- 100% RH
Vessel speed	Normal Moderately Fast Fast	up to 5 m/s 5 to 10 m/s more than 10 m/s
Wave Height	Calm Moderate Rough	up to 1.25 m 1.26 to 4 m more than 4 m
Relative Speed of vessel	Normal Moderately Fast Fast	up to 5 m/s 5 to 10 m/s more than 10 m/s

Droplet cooling temp	High Med Low	Greater than -5 C -5.01C to -12 C Less than -12 C
Spray Flux	Low Med High	up to 3.25 ml/m2 s 3.26 to 5.44 ml/m2 s 5.45 to 8.16 ml/m2 s
Ice accumulated	Low Med High	0 to 0.149 g/s 0.15 to .299 g/s 0.3 to .499 g/s

3.2.3 Stage 3: Defining Conditional Probability

The third step is defining the conditional probability data table (CPT). The CPT is defined for every node other than the primary node. The marginal probability values in the CPT defines the relation between the prior and posterior nodes in the Bayesian Network. If enough data is available, then the data frequency can be converted to the marginal probabilities by dividing the frequency of occurrence of a given state by the total number of observations. If enough data is not available, then the empirical relationship, numerical simulation, or experience-based judgment can be used to construct the CPT.

In this study, ten experimental runs have been done to create the data for ice accumulation. Details of the experimental setup are described in the next section. The frequency table has been generated based on the data available. In this study, experiential learning along with the experimental data was used in defining the conditional probabilities. These values are used to define the Conditional Probability Table (CPT) and completes the Bayesian network.

3.2.4 Interpretation of the output

In the proposed model every node, including ice accumulation node, has three states. The Bayesian network will give an output based on the probability of occurrence of each state. For Icing, the states defined are Low, Med, and high. The output probabilities of each state must be converted to a specific value to get a proper estimation of accuracy in prediction. This can be done by two simple approaches using the Mean and Mode values of the distribution:

1) Mode value: The mode value is defined as the mean value of classification with the highest probability multiplies by the probability of occurrence of the same class. For instance, if the probability of Medium comes highest of all three, the mode value will be the central value of the class, multiplied by the probability of that class.
2) Mean value: The mean value is the weighted average of all the class. It can be defined as the average of the sum of the products of probabilities of occurrence of all class and its central value.

3.3 The Experimental Setup

In this section, the model proposed above has been applied to the experimental setup designed to study the spray icing. The experiment is designed to mimic a spray icing condition on a sea vessel.

3.3.1 Overview of the experimental setup:

The spraying rig consists of a pump, compressor, sprayer, vales and pipes as shown in Figure 3.4. An air atomizing unit supplied with water and pressurized air is used to generate water spray. The nozzle height is adjustable to allow variations of spray directions. Pressurized air (~35 psi) is supplied from an air compressor. A blower is placed carefully behind the spraying rig to mimic wind. Water spray will be carried in the direction of wind and freezes due to low temperature and windy conditions. The icing object is placed inside an enclosure to minimize the effect of disturbances to the air flow (due to air flow created by the fans inside the cold room). The setup is built on two separate mobile trolleys: spray unit with the tank, pump and valves on one trolley and icing object with the enclosure on another. A temperature control system is adapted to control and maintain the temperature of the water tank. Stainless steel pipes are used to resist corrosion and withstand low temperatures.

The test specimen object is a steel cylinder, which is a standard shape found on many vessel equipment and pipes. The Specimen is kept in a cuboidal glass tunnel. The tunnel is kept at a certain distance to allow proper formation of the spray cloud. The blower blows the droplet cloud formed by the air atomizer uniformly into the tunnel. The specimen is positioned on two single point load cells sensors, which transmits the weight data to the data acquisition system. The amount of the ice deposited is calculated by calculating the difference in the weight observed at the end of each cycle.

3.3.2 Testing Protocol:

Parameters considered in the experiment run:

Temperature: The setup has several temperature sensors in the system including tank, in the cold room and at the side of the nozzle. In this study, only the data from the sensor next to the nozzle is considered. This will give a more accurate temperature of the spray cloud generated.

Flux: The flux is calculated with some conditions. It is assumed that all of the discharge of water droplets from the spray nozzle generates the cloud and the flux is uniform across the cross-sectional area of the tunnel. The discharge per cycle is observed at the beginning of the experimental run. The amount of water droplets per cross-section area of the tunnel is obtained by dividing the discharge by the cross-sectional area of the tunnel. Based on the dimension of the cylindrical object the cross-sectional area is about 16.7% of the total area of the tunnel. This factor is multiplied by the tunnel flux to obtain the Flux.

Wind: The blower used to produce air in this study operates at constant speed. In the experiment setup, an extremely delicate hot wire anemometer is used which is positioned along with the temperature sensor near the spray nozzle. Since the blower speed is constant the readings from the anemometer remains around 12 m/s. The nature of the flow generated is turbulent.

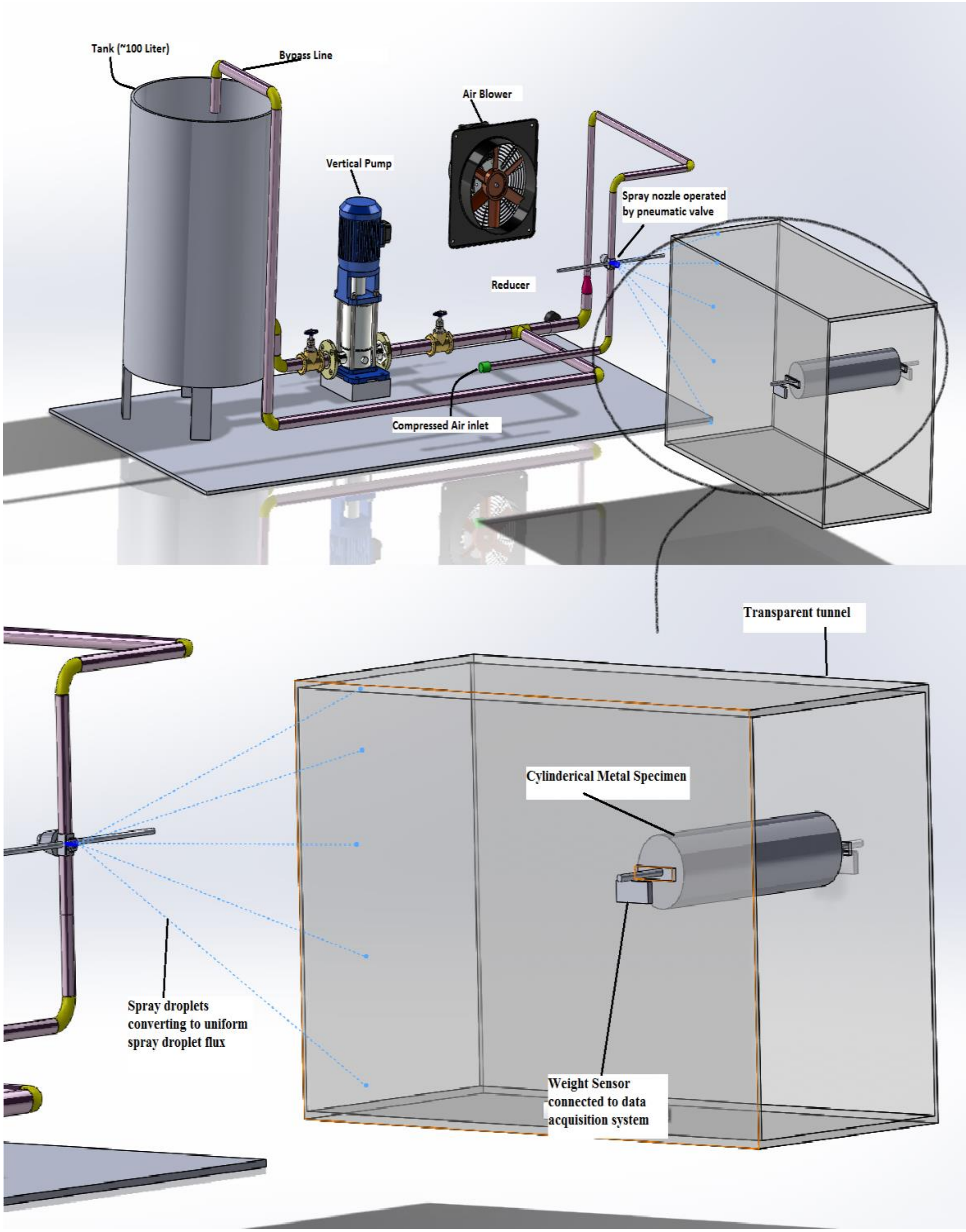

Figure 3.4 Experiment setup overview: the figure is not up to scale.

3.3.3 The test conditions:

Periodic spray for the 3-second duration is carried out after an interval of every 3 seconds. This allows proper formation of spray cloud which is quite similar to conditions observed at sea due to the splashing of waves. The experiment is carried out for 100 cycles, which is about 600 seconds. The water discharge from the nozzle is monitored. Temperature and wind velocity is also monitored for the experiment from the digital sensors. At the end of the experiment, the weight of the ice deposited on the steel cylinder is obtained from the data accusation system connected with the setup. This test is carried out at a wide range of temperature and discharge of spray.

3.3.4 Limitation of the Experimental Setup

Even though the experimental setup creates a similar condition to spray cloud generated by the wave splashing, we cannot measure all the parameters defined in Figure 3.3. For example, waves height, vessel velocity, salinity, and humidity are not valid in this experiment. Flux is dependent on the wave height and the vessel speed, which is also not considered in this experimental setup.

3.4 Testing of the model

To validate the prediction capability of the model a simple method has been proposed. Same input parameters entered into the predictive model and the experimental system. The predictive model gave the result in term of the probability of the icing. These probabilities can be compared with the actual ice accumulation observed in the system. To estimate the quality of the prediction; it is necessary to convert the probability distribution obtained from the of the Bayesian network into the measurable parameter. Based on the definition of the state of the output node the probabilities are converted to mean or mode state's central value as described in section 2.4. Then these values are used for estimating the error in prediction. Necessary steps followed for the testing of this model are summarized in Figure 3.5.

3.4.1 Equivalent model to adjust with a limitation:

As discussed in the limitations of the experiment setup, several parameters cannot be measured in the experimental setup used for testing and validation. Experimental setup directly generates the spray cloud, making parameters like wave height, vessel speed invalid or not measurable in this setup. To demonstrate the procedure and validate the proposed method, only the atmospheric temperature and spray flux are considered as input in this model. Since the flux is dependent on the wave height and the vessel speed, which doesn't exist in this experimental setup, the spray flux along with temperature is considered as direct input to the system.

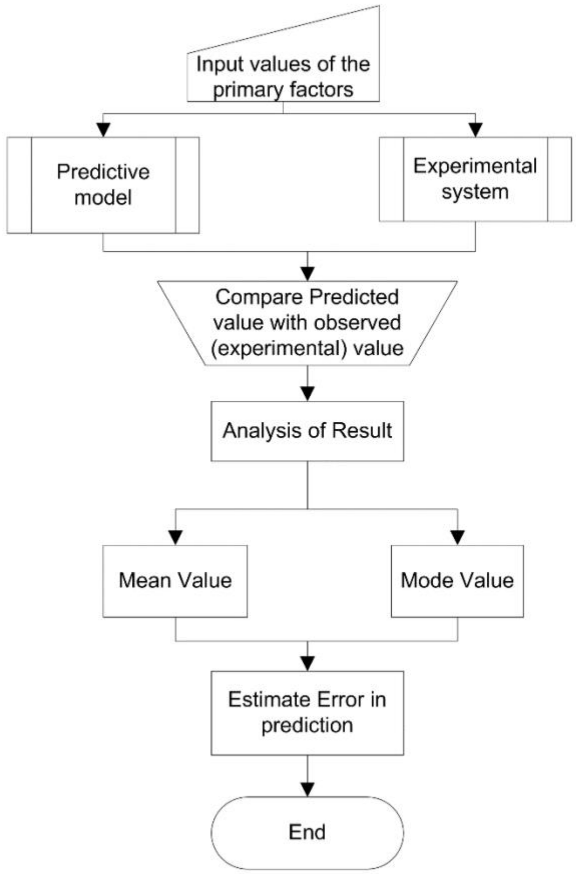

Figure 3.5 Framework for the testing of the model

To do this, the BN model has to be modified to consider only two inputs. Two primary nodes of Atmospheric temperature and Spray flux will act as input to the system. The Bayesian Network is modified as shown in Figure 3.6. Also, since, the parameter of wind is constant in the experiment, its effect is not considered in this study. The CPT of droplet cooling is defined as unity, meaning observing high, medium and low temperature will result in high, med, low droplet cooling respectively with a probability of 1.

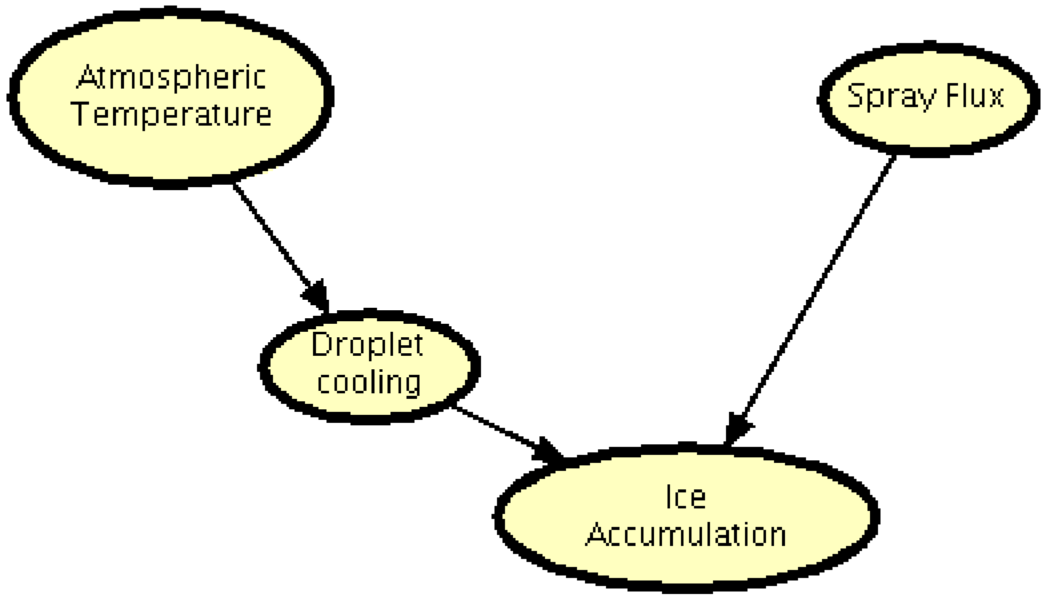

Figure 3.6 Modified Bayesian network for the experiment setup's limitations

3.4.2 Testing:

A different set of preliminary readings are taken for 11 independent conditions from the same experimental setup with varying temperature and flux values. It is to be noted that these 11 data sets are different from the ten data sets used in the construction of the CPT. Same values of the spray flux and temperature are entered into experimental setup and the predictive model. The experiment is carried out following the same testing conditions mentioned in section 3.3 and for the same duration of 100 cycles or 600 secs. The real icing observed in the experiment is compared with the predicted values obtained by the BN model. All other parameters including wind speed (blower speed) are kept same. These steps are repeated for all the observations taken in the experiment setup.

3.5 Results and Discussion

Total of 21 data sets has been observed from the experimental setup. As mentioned earlier, along with experiential learning 10 data sets had been used to develop CPT. Other 11 data sets have been used for testing and validation of the model. Following the testing procedure mentioned in the above section, the same values of temperature and spray flux are entered into the predictive model and the experimental setup. The outputs from both have been summarized in Table 3-2. Temperature is given in the second column, followed by the corresponding state it is classified according to Table 3-1. Similarly, spray flux, and its states are mentioned in the 4th and 5th column. Next three column gives the predicted probability distribution for each state of Ice accumulation namely low, med and high. For comparison, the last two column shows observed ice accumulation along with its corresponding state. For each input values of Temperature and Flux, the BN model gives probabilities of occurrence of each class. For instance, for first reading, there is 60% probability of low icing, 30% chances of medium icing and 10% chances of high occurrence of ice accumulation of the corresponding classification. As described in the methodology section, these probabilities can be converted to a numerical value based on Mean and Mode of the probability distribution.

Table 3-2 Comparision of results from the model and experiment

Inputs				**Predicted (probability in percentage)**			**Observed**	
Average temperature (°C)	Class	Spray Flux ml/sec	Class	P (low)	P (med)	P (high)	Average Ice rate g/sec	Class
-13.6	Low	3.44	low	60	30	10	0.14	Low
-11.5	med	6.74	med	30	60	10	0.09	Low
-10.8	med	8	high	5	35	60	0.3	High
-10	med	7.2	med	30	60	10	0.12	Low
-9.3	med	6.44	med	30	60	10	0.22	med
-8	med	6.67	med	30	60	10	0.13	Low
-7.8	med	1	low	85	10	5	0.08	Low
-7.8	med	9.1	high	5	35	60	0.22	Med
-6.5	med	5.55	med	30	60	10	0.08	Low
-4.5	High	8	high	10	40	50	0.27	High
-4.44	High	5.2	med	15	85	0	0.2	Med

The analysis of the testing of the model is discussed in this section.

3.5.1 Estimating error in prediction:

To check the efficiency of the model, it is essential to calculate the error in the prediction. The error in prediction is defined as the difference in the predicted and the observed ice accumulation value divided by the observed value. It is calculated on both mode and means the value of the probability distribution from the output of the predictive model.

1. Mode Table 3-3 shows the predicted value obtained from the BN, and it is compared with the observed value. The observed value is given in the first column, along with the class it falls in. The method mentioned in the methodology calculates the mode. For

example, for the first test, we have the highest probability of low icing, 60%. Hence the mode value is 60*(0.149/2)/100.

Table 3-3 Calculation of mode value of icing rate (g/s) from the probability distribution

	Observed		Predicted					
	Value	**Class**	**P(low) (%)**	**P(med) (%)**	**P(high) (%)**	**Mode**	**Weighted mode value**	**Error in prediction**
1	0.14	Low	60	30	10	Low	0.045	-0.683
2	0.09	Low	30	60	10	med	0.135	0.494
3	0.3	High	5	35	60	high	0.24	-0.197
4	0.12	Low	30	60	10	med	0.135	0.126
5	0.22	med	30	60	10	med	0.135	-0.391
6	0.13	Low	30	60	10	med	0.135	0.016
7	0.08	Low	85	10	5	Low	0.045	-0.461
8	0.22	Med	5	35	60	high	0.24	0.088
9	0.08	Low	30	60	10	med	0.135	0.611
10	0.27	High	10	40	50	High	0.2	-0.262
11	0.2	Med	15	85	0	Med	0.191	-0.069

2. Similarly, the mean value is calculated considering all the classes. The result of the mean value analysis is summarized in Table 3-4. The mean value is calculated based on the definition given in the methodology section. For instance, the mean value for the first row will be:

$$\left(\frac{0+0.149}{2}\right)*0.6+\left(\frac{0.15+0.299}{2}\right)*0.3\ +\left(\frac{0.3+0.449}{2}\right)*0.1.$$

Table 3-4 Calculation of mean value of icing rate (g/s) from a probability distribution

	Observed		Predicted				
	Value	**Class**	**P(low)**	**P(med)**	**P(high)**	**Weighted mean value**	**Error in prediction**
1	0.141	Low	60	30	10	0.15	0.06
2	0.09	Low	60	30	10	0.195	1.157
3	0.298	High	5	70	25	0.307	0.029
4	0.12	Low	60	30	10	0.195	0.625
5	0.221	med	60	30	10	0.195	-0.121
6	0.133	Low	60	30	10	0.195	0.467
7	0.083	Low	85	10	5	0.105	0.26
8	0.22	Med	5	70	25	0.307	0.393
9	0.084	Low	60	30	10	0.195	1.326
10	0.27	High	10	40	50	0.285	0.052
11	0.205	Med	15	85	0	0.202	-0.014

In Table 3-4 the estimated error [(observed-weighted mean)/observe]}are reasonable except for two observations, second and the ninth observation. To analyze this, we may refer to the Table 3-2, for the same set of the input condition the observed icing is very low. The icing observed for these two sets of data (temperature and flux are medium) lesser compared to what is observed at high temp and low spray flux condition, which logically should not be. It was further discovered from the observation notes of the experiment, that there was clogging of the spray nozzle which could have led to lower flux then actual observation. This may explain the reason for the high error for this particular reading. Figure 3.7 shows the comparison of the icing load predicted based on mean and mode value with the observed value.

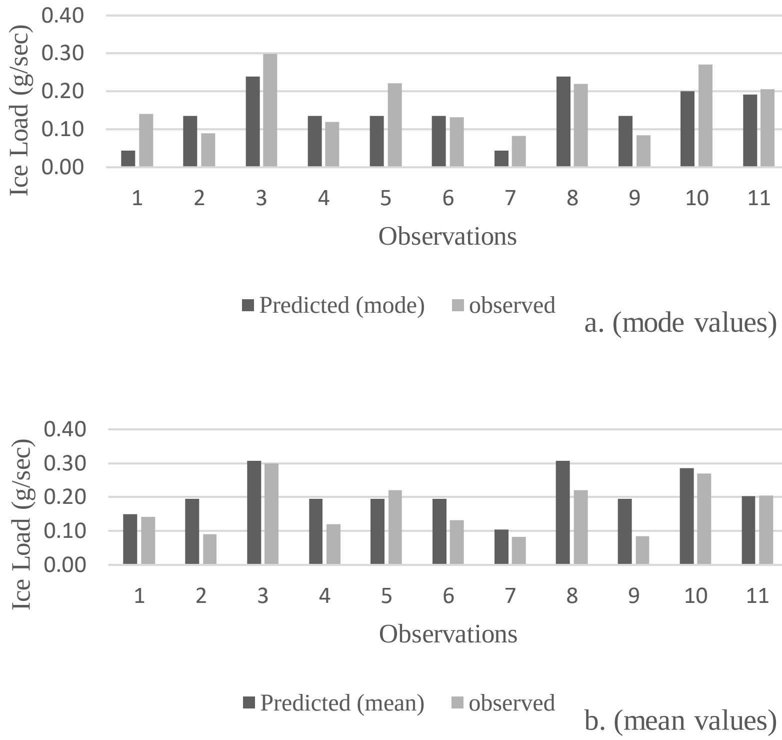

Figure 3.7 Comparison of predicted vs observed Icing Load for (a) mode and (b) mean values

3.5.2 Quality check:

To check the model's estimation, the mean square error (MSE) approached is used. The least squared residue (LSR) is calculated for each observation. LSR can be defined as the square of the difference in the observed and predicted values. These values are converted to MSE. It is defined as the average of the sum of squared errors. MSE represents the overall quality of the prediction of the model. The MSE should be as low as possible for the model to be acceptable. The MSE values obtained by mean and mode values are compared with each other.

Next step is to find the LSR. The LSR value for each observation is summarized in Table 3-5 based on the mean and mode approach. Once the LSR value for each observation is obtained, its average is taken. This value is a MSE. MSE for mode values is obtained as 0.003, and that for mean values is 0.004. The low value of MSE obtained from the results of this study signify that the model is robust and useful in predicting the icing load.

Table 3-5 LSR value for each observation and total MSE

Test runs: Observations	**LSR (Mode)**	**LSR (Mean)**
1	0.009	0.000
2	0.002	0.011
3	0.003	0.000
4	0.000	0.006
5	0.008	0.001
6	0.000	0.004
7	0.001	0.000
8	0.000	0.008
9	0.003	0.012
10	0.005	0.000
11	0.000	0.000
MSE	**0.003**	**0.004**

3.6 Conclusions

A new probabilistic predictive model to estimate ice accumulation on the sea vessel or offshore rigs is proposed here. The model is built on a Bayesian network approach to represent causal dependence of the design, operational and environmental parameters on the ice accumulation. This study also presents the design of an experimental setup to test ice accumulation. The experimental setup is successfully used to run a range of ice accumulation tests. These test data is used to compare predicted results with the observed results. Below is the main observations:

- Experimental results are in matching well with the predicted values by the proposed model. The low MSE vindicate the efficiency and robustness of the model.
- The proposed model can analyze the relationship of the factors and its impact on Ice accretion based on several methods, including experiential learning, observed values, empirical relations or simply expert's knowledge. It can also enable the combination of more than one parameter.
- The model requires minimum computational load once it has been developed. This gives it the ability to predict icing load in the changing system.
- The method gives the flexibility of adding or removing the factors affecting icing easily. The BN can be updated upon the availability of new evidence of the data. It can be tweaked easily for different environmental conditions, vessel types or rigs.
- The experimental validation using atmospheric temperature and spray flux data to predict the amount of ice accreted provides foundation and motivation for further

testing to include other factors that might affect the ice accretion process like salinity and waves.

- The model has the flexibility to include more parameters affecting icing based on the location and system. The model can be used for dynamically changing conditions with minimum computational load and time.

This study presents a novel approach for icing prediction and demonstrates the accuracy using experimental observations. However, due to experimental limitations, several parameters such as vessel speed, wave height, salinity and humidity are not considered in the study. The current work proposes subsequent testing at field level to further development of the model including more parameters. Testing of ice accumulation under varying wind condition is important and may be considered for subsequent studies. Once the model is successfully field tested, it can provide a paradigm change in icing load prediction methods used on sea vessels and offshore structures.

3.7 References

Chung, K. K., & Lozowski, E. P. (1990). On the growth of marine icicles. *Atmosphere-Ocean, 28*(4), 393-408.

Dehghani-Sanij, A., Dehghani, S., Naterer, G., & Muzychka, Y. (2017). Marine icing phenomena on vessels and offshore structures: Prediction and analysis. *Ocean Engineering, 143*, 1-23.

Forest, T., Lozowski, E., & Gagnon, R. (2005). Estimating marine icing on offshore structures using RIGICE04.

Fukusako, S., Horibe, A., & Tago, M. (1989). Ice accretion characteristics along a circular cylinder immersed in a cold air stream with seawater spray. *Experimental Thermal and Fluid Science, 2*(1), 81-90.

Hoes, C. (2016). Marine Icing: A probabilistic icing model from sea generated spray.

Horjen, I. (1990). Numerical modelling of time-dependent marine icing, anti-icing and de-icing.

Horjen, I. (2013). Numerical modeling of two-dimensional sea spray icing on vessel-mounted cylinders. *Cold Regions Science and Technology, 93,* 20-35.

Horjen, I., & Vefsnmo, S. (1986). Calibration of ICEMOD-extension to a time-dependent model. *Trondheim: Norwegian Hydrodynamic Laboratories*.

Jessup, R. (1985). Forecasting techniques for ice accretion on differenttypes of marine structures, includingships, platforms and coastal facilities. *Marine Meteorology and Related Oceanographic Activities, Rep, 15*, 50-60.

Kulyakhtin, A., Kulyakhtin, S., & Løset, S. (2016). The role of the ice heat conduction in the ice growth caused by periodic sea spray. *Cold Regions Science and Technology, 127,* 93-108.

Kulyakhtin, A., Shipilova, O., & Muskulus, M. (2014). Numerical simulation of droplet impingement and flow around a cylinder using RANS and LES models. *Journal of Fluids and Structures, 48*, 280-294.

Kulyakhtin, A., & Tsarau, A. (2014). A time-dependent model of marine icing with application of computational fluid dynamics. *Cold Regions Science and Technology, 104,* 33-44.

Lozowski, E. P., Szilder, K., & Makkonen, L. (2000). Computer simulation of marine ice accretion. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences, 358*(1776), 2811-2845.

Myers, T., & Hammond, D. (1999). Ice and water film growth from incoming supercooled droplets. *International Journal of Heat and Mass Transfer, 42*(12), 2233-2242.

Myers, T. G., & Charpin, J. P. (2004). A mathematical model for atmospheric ice accretion and water flow on a cold surface. *International Journal of Heat and Mass Transfer, 47*(25), 5483-5500.

Overland, J., Pease, C., Preisendorfer, R., & Comiskey, A. (1986). Prediction of vessel icing. *Journal of climate and applied meteorology, 25*(12), 1793-1806.

Ryerson, C. C. (2011). Ice protection of offshore platforms. *Cold Regions Science and Technology, 65*(1), 97-110.

Ryerson, C. C. (2013). *Icing management for coast guard assets*. Retrieved from http://acwc. sdp. sirsi. net/client/search/asset/1027480

Samuelsen, E. M., Edvardsen, K., & Graversen, R. G. (2017). Modelled and observed sea-spray icing in Arctic-Norwegian waters. *Cold Regions Science and Technology, 134*, 54-81.

Shipilova, O., Kulyakhtin, A., Tsarau, A., Libby, B., Moslet, P., & Loset, S. (2012). *Mechanism and dynamics of marine ice accretion on vessel archetypes.* Paper presented at the OTC Arctic Technology Conference.

4. Summary, Conclusions and Recommendations

As oil and gas industries develop, the processes are becoming increasingly complex. Variation in the process parameters may rapidly change the state of the system. It is necessary to have an arrangement not only to monitor of the process, but also to estimate its impact on the long-term safety of the plant. To address this need for dynamic estimation, the thesis presents two dynamic prediction tools that can be applied for risk-based decision making. The DRBI model is developed to provide a real-time risk estimation based on the degradation mechanism that can be applied along with industrial RBI codes like API-581. Another tool for the dynamic prediction of ice accumulation on marine vessels and oil rigs based on the climate and operational conditions is also developed in this study.

Chapter 1 provides a background of RBIM methods that are developed to date. Concepts of dynamic risk assessment are also introduced in this chapter. It was identified that industrial RBI assumes that the risk profile will the remain same between IM intervals but the risk calculated based on the initial inspection may give a false perception of safety. The concept of Risk-based Winterization is also presented in the section. With increasing oil exploration in the extremely cold arctic region, this is an emerging field and relevent research is needed. Application of risk-based winterization has been discussed followed by the identification of the research objective of the thesis.

Chapter 2 proposes a new model for dynamic risk-based inspection. The model is defined with system parameters that are continuously monitored, giving the ability of real-time updating. The model is tested for its efficiency using a simulation approach and the results are compared with the risk profile generated using the API-581 recommended approach. It was found that due to several fluctuations in system parameters, even though the fluctuations were within the allowable limit, the actual degradation rate was higher than initially calculated. This caused the actual risk to deviate from the API-581 calculated risk. The results were plotted on the same graph for clarity. With successful validation of the proposed DRBI model, it can provide a better confidence in the system's safety and effective optimization of the inspection interval.

Chapter 3 presents a unique method for predicting the ice accumulation on sea vessels and offshore rigs. A review of the existing models calculating the ice load is provided. The predictive model is developed to fill the gaps identified in the review. This model uses a Bayesian approach to construct the dependencies between the influencing parameters. A stepwise guide is provided to implement the model for a wide range of vessels. The model was tested on an experimental setup designed to generate periodic spray in a controlled cold room. The test was carried out at various temperatures and spray flux. The observed ice accumulation was compared with the predicted value using the proposed model. A close comparison of the results showed that the predicted ice accumulation rate was reasonably close to the observed value. Unlike several numerical models reviewed for this study, the proposed predictive model requires a minimal computational load and has an ability to update dynamically with the availability of new data.

Finally, this chapter provides a summary of the work and highlights the achievements of this research. The following recommendations are provided for future work to improve the dynamic tools presented in this thesis.

The proposed DRBI methodology could be extended for application in the process industry by updating both the probability and consequences of failure dynamically. Future study may focus on identifying ways to consider multiple degradation mechanisms to define the risk function.

It was identified that further development of the predictive model for spray icing needs to be carried out using field data. Even though the effect of water salinity is negligible, future research could aim to verify this. As many factors affect the icing rate, a Copula Bayesian network will provide an interesting topic for future studies to capture the dependency in the predictions more accurately.