PREDICTIVE ACCIDENT MODELING THROUGH BAYESIAN NETWORK

MD. AL-AMIN BAKSH

PREDICTIVE ACCIDENT MODELING THROUGH BAYESIAN NETWORK

by

© Md. Al-Amin Baksh

A thesis submitted to the School of Graduate Studies in partial fulfillment of the requirements for the degree of

Master of Science

Department of Computer Science

Memorial University

June 2013

St. John's Newfoundland

ABSTRACT

Accident modeling methodologies in literature such as System Hazard Identification, Prediction and Prevention (SHIPP) [1] consider accident precursors to assess the likelihood of accident occurrence and to design preventive, controlling and mitigating measures for improving the industrial process safety. The SHIPP methodology considers five engineering safety barriers represented using fault and event tree to model the cause-consequence relationship between the failure of safety barriers and potential adverse events [1, 2]. In this method, to evaluate the probabilities of end events' occurrence, a restrictive assumption is used that the severity of the adverse events increases only through sequential failures of the five safety barriers considered.

First, it is strengthen by appending two important non-mechanical safety barriers viz. human and management & organizational factors. We propose to improve the shortcoming of the SHIPP methodology in the following ways. First, we relax the restrictive sequential event assumption in SHIPP methodology by allowing non-sequential failure of safety barriers to cause adverse event of any order. Secondly, in the prediction of posterior probabilities of adverse events for real time industrial data, we include an important mechanical safety barrier viz. 'Damage Control and Emergency Management Barrier (DCEMB)' and as a result we include an adverse event of highest order viz. 'Catastrophe'. Further, posterior probabilities of adverse events are calculated using Bayesian network approach. The posterior probabilities are used to update the safety barrier failure probabilities through a backward analysis and in turn update the estimates of the likelihood continually. The utility of this approach is tested and

demonstrated with the data from a liquefied natural gas (LNG) process facility. The method allows for continual updating of occurrence probability for adverse events and failure probabilities of safety barriers for successive monthly data from industry.

ACKNOWLEDGEMENTS

All praises are for Almighty Allah, who has given me the opportunity to accomplish the work.

My adviser, Professor Faisal Khan, deserves thanks not only for his wisdom and guidance but also for his unending patience with me. He has strengthened my understanding of how to research effectively and continues to serve as an important role-model for me. Any accurate understanding that I have of Bayesian Network is entirely due to Professor Veeresh Gadag. The tangible and intangible benefits of collaboration with him are too numerous to list. I am an interloper in his field, and he has not only tolerated my intrusion but has welcomed me and provided me with instructions on how I might proceed deeper into new spaces. My thanks are also extended to them not only for their continuous support, encouragement and guidance, but also for their optimism and kindness.

I also owe thanks to Dr Refaul Ferdous and Samith Rathnayaka for helping me about improving my ability to understand the language of Process Engineering and being a part of the research team.

I would also like to give thanks to my colleagues in the group at the INCO Innovation Center and friends at Memorial University for their kind help and inspiration.

I appreciate and acknowledge the financial support of Vale research project. I also thank the School of Graduate Studies and Faculty of Computational Science, Memorial University of Newfoundland, for their financial and relevant support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

SHIPP	System Hazard Identification, Prediction and Prevention
LNG	Liquefied Natural Gas
HFB	Human Factor Barrier
MOB	Management & Organizational Barrier
RPB	Release Prevention Barrier
DPB	Dispersion Prevention Barrier
IPB	Ignition Prevention Barrier
EPB	Escalation Prevention Barrier
DCEMB	Damage Control and Emergency Management Barrier
BN	Bayesian Network
BP	British Petroleum
HSE	Health and Safety Executive
GDP	Gross Domestic Product
IC	Industrial Commission
NOHSC	National Occupational Health and Safety Commission
IEC	International Electrotechnical Commission
ALARP	As Low As Reasonably Practicable
CCPS	Center for Chemical Process Safety
RIDDOR	Reporting of Injuries, Diseases and Dangerous Occurrences Regulations
AIChE	American Institute of Chemical Engineers

NRC	National Response Center
TAMU	Texas A&M University
CSB	Chemical Safety Board
STAMP	Systems-Theoretic Accident Model and Processes
SCMM	Safety Culture Maturity Model
SEI	Software Engineering Institute
OSHA	Occupational Safety & Health Administration
OSHEU	Occupational Safety, Health and Environment Unit
CCOHS	Canadian Centre for Occupational Health and Safety
RoSPA	Royal Society for the Prevention of Accidents
UCIL	Union Carbide India Limited
LPG	Liquefied Petroleum Gas
DAG	Directed Acyclic Graph
LFL	Lower Flammable Limit
UFL	Upper Flammable Limit
CEE	Center for Energy Economics

CHAPTER 1

Introduction and Overview

Process accidents are major cause of concern in industrial process facilities. These accidents are often caused by equipment malfunction, process deviation, structural failure, and human error [3]. Their inadequate control can increase the probability of occurrence of industrial accidents. These are reflected in a few accident examples that have occurred in the last few decades, such as the Ocean Ranger, North Atlantic accident, the British Petroleum (BP), Texas City disaster [4-7], BP's deepwater horizon offshore drilling rig explosion and oil spill [8-13], Imperial sugar refinery dust explosion (Figure 1.1) on February 7, 2008 in Port Wentworth, Georgia [14]. Between 1926 and 1997, 3222 accidents have occurred, of which a large number of accidents belong to chemical process facility [15-23]. Major process accidents between 1944 and 2012 are well described in literature, and experts' opinions [16-21, 24-30]. Hence, only the LNG accident occurrences are highlighted in Table 1.1.

Recent advancement in science and engineering is helping to decrease the number of incidents; however, the level of damage from these few incidents has radically increased [19, 31, 32]. During the 90s, Health and Safety Executive (HSE) of UK studied on 600 accidents and found average cost per accident on oil platform £2951 [33]. In Australia, the estimated safety pay for injuries was about $20 billion in same era which is equivalent to 5% Australia's GDP [34, 35]. Bhopal (1984) chemical plant disaster cost at least 2000 lives, injuries over 200,000 [36] and a hefty pay of $470 million to the victims

[35]. Aftermath of these disasters leaves an unpleasant past of losses which is unbearable. A long term health survey (1985-2007) at Sambhavna Trust Clinic in Bhopal confirms high pregnancy loss, acute deaths and even effect on offspring [37]. Financial impact of catastrophic events is briefly discussed in Kim et al. [31], Cutler & James [33], IC [34], Hopkins [35], Kletz [36], Lepkowski [38] and NOHSC [39].

Figure 1.1: Imperial Sugar Refinery Explosion [14]

Table 1.1: Major Accidents in LNG Process Facility (1944-2012)

Year	Location	Chemical	Event	Deaths/injured
1944	Cleveland, OH	LNG	Fire and explosion	128/300
1973	Staten Island, NY	LNG	Fire	40
1979	Lusby, Maryland	LNG	Fire	1/1
2004	Skikda, Algeria	LNG	Explosion	27/56

Industrial facilities including the offshore process facilities can never be made completely safe and risk free. Safety of the process facility specifies risk free environment which means, prevention from any accident or damages that might cause personal health hazard. According to IEC 61508 [40] safety means, "Freedom from unacceptable risk of physical injury or of damage to the health of people, either directly, or indirectly as a result of damage to property or to the environment" [41]. However, experts review suggest that a proper accident model and likelihood assessment technique can improve the degree of inherent safety [3, 42-49] and ensure the maintenance of risk level as low as reasonably practicable (ALARP) [3, 12, 49-52]. To limit or avoid hazard at source, Kletz [44] developed the concept of inherently safer design in the late 70s [47].

Industrialists, researchers, workers, - members of regulatory bodies, policy makers can all learn from past incidents. So it is essential to collect data and maintain a database for research purpose. The Center for Chemical Process Safety (CCPS) of US was established aftermath of Bhopal tragedy to implement safety practice in workplaces. Since 1st of April, 1996, RIDDOR 95 (The Reporting of Injuries, Diseases and Dangerous Occurrences Regulations 1995) act mandate to report all work related injuries, diseases and dangerous occurrences to HSE (Health Safety Executive) [53]. Organizations and Research center viz. Wharton Risk Management and Decision Processes Center established in 1984 [54, 55], the American Institute of Chemical Engineers (AIChE) Center for Chemical Process Safety (CCPS) established in 1985 [56], National Response Center (NRC) [57] and Mary Kay O'Connor Process Safety Center at Texas A&M University (TAMU) established in 1995 [58] have taken initiatives to collect and share incident database with industrialists, researchers and experts. Past Industrial accident investigation and review clearly identify that most of the accidents occurred due to improper likelihood assessment of risk contributors and correlations of these contributors to occurrence of a potential accident. Experts' judgment emphasize on learning from past accidents [19, 31, 59, 60] to prevent further occurrences in future. The Cullen report on Piper Alpha disaster [61] made a significant change to manage safety process by the industry and the regulator [47]. Baker Panel [62] proposed 10 recommendations to improve process safety after its investigations on process safety management in BP's US refineries [63]. Process safety leadership, process safety knowledge & expertise, process safety cultures are among those recommendations which are thoroughly practiced nowadays by many US companies. The US Chemical Safety Board (CSB) strictly emphasizes process safety culture in highly hazardous industries [5].

1.1 Motivation

In order to improve industrial safety, it is essential to predict the likelihood and posterior probabilities of adverse events through an accident modeling mechanism. The System Hazard Identification, Prediction and Prevention (SHIPP) methodology is one such method recently proposed by Rathnayaka et al. [1]. It is assumed in this method that an adverse event occurs only as a result of the failure or otherwise of the safety barriers in a sequential manner [1, 2, 66]. In a real life industrial system, the safely barriers need not fail in a sequential manner to cause an adverse end event. In the current dissertation we propose a new mechanism to improve this situation.

1.2 Objective

Fault and event tree methods are widely used in process facility to estimate risk of accident occurrence though they are inadequate to show the conditional dependency in a rather sequential approach. The objective of this analysis is to present a Bayesian network based non-sequential accident model which will include two non-mechanical safety barriers viz. human and management & organizational factors with other five engineering safety barriers. This model is able to address the limitation of current accident models such as: non-sequential, conditional and the interdependence relationships of safety barriers. In addition, this model is able to calculate the occurrence of adverse events in any order using Bayesian network approach. It can perform real time occurrence and posterior probability estimation using industrial data. Furthermore, a Bayesian updating mechanism is able to update the probabilities of end events' as well as success/failure of safety barriers' when real time information becomes available. In this case, Bayesian network is an ideal approach which not only describe the dependency and evaluate the likelihood of end events' occurrence but also able to demonstrate the conditional likelihood assessment for different scenarios. The improved methodology presented here can be extended easily to other process facilities or accident scenarios.

1.3 Goal of the Project

The goal of the project is to develop a Bayesian network based accident model that helps to predict the occurrence likelihood of end events and update as usual when real time information becomes available in the system. Bayesian updating mechanism is being integrated to update the occurrence likelihood of end events' when real time information becomes available. Further, developed accident model will be implemented on a case study of LNG process facility.

1.4 Approach

In this work, analyses of event trees and Bayesian network modeling have been applied. Theoretical explanation of the model and analysis will be laid out. Analysis will consist of five parts; (i) Design Bayesian network model, (ii) Calculation and analyses of the likelihood results using forward analysis on Bayesian network, (iii) Calculation of posterior results using prior and likelihood results, (iv) Estimation of each barrier contribution on occurrence of end events using backward analysis on Bayesian network, and (v) Updating safety barrier probabilities in real time. Further, the model will be able to update the occurrence likelihood of end events' with real time information from the system. The process will continue every time new information becomes available.

1.5 Result

The result of this analysis will drive the users to use this improved accident model for different accident scenarios and estimate the occurrence likelihood of the end events. It will also help to update prior safety barrier failure probabilities real time for the given system and incorporate necessary steps to mitigate or minimize end events' occurrences.

1.6 Layout of the Thesis

In the background, several accident models are discussed along with the concept of safety barriers together with end events' definition in chapter 2. A brief review of SHIPP methodology is also included in chapter 2. A brief discussion of revised event tree (3.1.1) and Bayesian network modeling (3.1.2) along with fundamentals of Bayesian network are included in chapter 3. Conditional probability assessment technique, Bayesian inference, likelihood and updating model are also included under mathematical formulation and discussed in chapter 4. This is followed by the implementation of the developed model on a case study of LNG process facility with a step-by-step explanation, in chapter 5. The findings are analyzed in chapter 6. A brief discussion followed by conclusions is included in chapter 7. Recommendations for further analysis in future are provided in chapter 8.

CHAPTER 2

Background: Accident Model

An effective accident modeling approach along with an appropriate likelihood assessment technique can help prevent and mitigate the process accident in industrial facility. Hollnagel [64] defines accident model as a causal mechanism of conventional rules. Leveson [65] states, "Accident models form the basis for investigating and analyzing accidents, preventing future ones, and determining whether systems are suitable for use (risk assessment)". Rathnayaka et al. [66] simply illustrate accident model as "a theoretical and simplified representation of incidents occurring in real life". Huang et al. [67] implies accident model as a theoretical demonstration of incidence and progression.

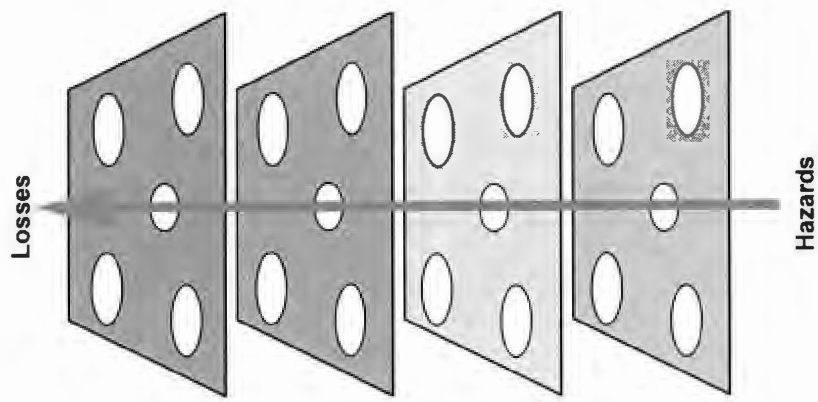

Figure 2.1: Swiss Cheese Model [70]

Domino theory proposed by Heinrich [68] is one of the first sequential accident models, where an accident event is described as a chain of independent events that occurs in a particular order and terminates from the system as an injury. According to Domino theory, an accident can be prevented by removing one of the factors from the chain of events [1, 69]. Non-mechanical accident factors viz. human and management and cause-effect relationship between these factors are ignored in this model.

Swiss Cheese model by Reason [70] in Figure 2.1, is another example of conventional sequential accident model where hazard propagates and ends up with losses. It demonstrates the influence of human and organizational failures in accident process. Currently, aviation industry uses Reasons' Swiss Cheese model to replicate human error [71].

Among the accident model, Kujath's model uses successive safety barriers to minimize end events [72]. It comprises both sequential and epidemiological models. It was demonstrated in offshore accident analysis with the safety barrier concept. The SHIPP model by Rathnayaka et al. [1, 2] is also based on the concept of Kujath's model where successful integration of human and management factor is illustrated. However, no guidance has been given on how to implement these factors for evaluating the likelihood (i.e. probability) of final events' occurrence. SHIPP model [1, 2] uses four successive safety barriers in accident analysis viz. release prevention, dispersion prevention, ignition prevention and escalation prevention. In a subsequent paper, Rathnayaka et al. [66] included human and management barriers in SHIPP model and demonstrated the failure probability through fault and event tree simulation. In the SHIPP methodology, the safety barriers have to be arranged in sequential order, which restrict the escalation of different end events' occurrence sequentially rather than randomly.

Another accident model, called Systems-Theoretic Accident Model and Processes (STAMP) is based on system theory to evaluate system accidents [65, 73]. This accident model demonstrates no quantitative analysis and has limited graphical illustration. In the

STAMP model, "an accident is described as an event that occurs from inappropriate or inadequate control or enforcement of safety-related constraints on the development, design, and operation of the system, rather than simply occurring due to independent component failures" [1, 41].

Fleming [74] introduced the Safety Culture Maturity Model (SCMM) in Health and Safety Executive. The concept of SCMM was being used for a potential safety culture improvement in the offshore oil and gas industry. The concept was developed by the Software Engineering Institute (SEI) which possessed five level processes for organizations safety. Later ten elements were included in the safety culture maturity model. It was assumed based on research that safety performance improves in organization with increasing levels of maturity. More details about SCMM can be found in Fleming [74].

Table 2.1 lists number of accident models that are available for accident scenario analysis e.g. Domino theory, Swiss Cheese model, Kujath's model, SHIPP model and proposed Bayesian network model and comparison among these models. These accident models are well summarized in Rathnayaka et al. [1]. All of these existing accident models consider that the occurrences of end events have to be sequential with the failure of safety barriers; however, in real life events occurrence is not always sequential and could be happened in any order. Furthermore, human and management & organizational barrier have been ignored in all models except SHIPP which have significant influence to the occurrence of end events. Moreover, end event occurrences are conditional to the functional and non-functional states of safety barriers.

Table 2.1: Comparison of Available Accident Models

Features	Domino Theory [68]	Swiss Cheese model [70]	Kujath's Model [72]	SHIPP Methodology [1]	Bayesian Network (Proposed) [75]
Cause integration of accident occurrence	Not well defined	Defined	Not defined	Use fault tree to integrate the potential causes	Use Bayesian network to integrate the potential causes
Likelihood assessment of safety barriers	Qualitative	Qualitative	Qualitative	Quantitative and qualitative	Quantitative and qualitative
Accident precursor data integration	Not defined	Not defined	Not defined	Utilize previous accident data to predict end event probabilities	Utilize previous accident data to predict end event probabilities
Updating mechanism	Never used	Never used	Never used	Able to update prior information	Able to update prior information
Accident modeling	Sequential	Sequential	Sequential and Epidemiological	Sequential	Non-sequential
Human and Management barrier	Ignored	Ignored	Ignored	Defined, and used	Included and used

2.1 End Events' Definition

Consequence and occurrence of events in every stage of the accident model is defined as end events. End events are occurring frequently in process facility; however, end events' occurrence probability estimation has received little attention until experts, researchers taking initiatives to keep in account. End events get initiated, as deviation from safe state (e.g. failure of safety barriers) propagates and gradually toward catastrophic accident. Sklet [76] has briefly defined 'initiating events' as, "An initiating event for a release scenario is the first significant deviation from a normal situation that under given circumstances may cause hydrocarbon release (loss of containment). A 'normal situation' is a state where the process functions as normal according to design specifications without significant process upsets or direct interventions in the process plant". For example, a safety valve placed in wrong position during regular production hour (s) is an initiating event; and prevention of materials' release due to wrong position of safety valve (by detecting wrong position) is the barrier function.

In the description of end events, severity of end events' occurrence is categorized as 'safe', 'near miss', 'mishap', 'incident', 'accident' and 'catastrophe'. The categorization may vary from industry to industry based on different definitions. Following definition of end events is available in literature:

Safe: According to online Oxford dictionary, the term 'safe' means, "protected from or not exposed to danger or risk" [77].

Near miss: Health and Safety Executive (HSE) of UK defines 'near miss' as "any incident, accident or emergency which did not result in an injury" [78]. In literature 'near miss' is defined as "a hazardous situation and/or an unsafe action where the event chain could lead to an accident if it had not been interrupted" [79-81]. According to OSHA (Occupational Safety & Health Administration), "near misses describe incidents where no property was damaged and no personal injury sustained, but where, given a slight shift in time or position, damage and/or injury easily could have occurred" [82]. According to OSHEU (Occupational Safety, Health and Environment Unit), a near miss can be defined as, "any event, which under slightly different circumstances, may have resulted in injury or ill health of people, or damage or loss to property, plant, materials or the environment or a loss of business opportunity" [83]. For example, during the liquefaction process, contaminant such as Nitrogen (N2) is leaked but would not harm workers in production area. After reviewing incident occurrence in process industry, it can be observed that for every severe accident, a large number of incidents occurred with little or no damage at all. This is well-observed and illustrated in the safety pyramid (Figure 2.2) by Phimister et al. [54] which highlights "the ratio of one serious injury to the number of near misses is very small" [48, 54]. However, near miss can provide more information compare to accident occurrence about the source of serious accidents [84].

Mishap: The term 'mishap' has been defined by HSE, as "an event that, causes any person to be harmed; or in different circumstances, might have caused any person to be harmed" [78]. Rathnayaka et al. [1] defines it as a sequence of events that might cause minor damages to human health, property or environment. For example, oil spill on production floor might cause work hour (s) loss.

Figure 2.2: Safety Pyramid [54]

Incident: OSHA defines 'incident' as, "an unplanned, undesired event that adversely affects completion of a task" [82]. According to CCOHS (Canadian Centre for Occupational Health and Safety), the term 'incident' can be referred "to an unexpected event that did not cause injury or damage this time but had the potential" [85].

Accident: The term 'accident' may be defined by Skogdalen & Vinnem [12], RoSPA [86], and Sklet [87], as undesired and unplanned events which has led to loss of human lives, injury to people, damage to plant, machinery or the environment. Khan & Abbasi [19], and Suchman [88] classified 'accident' as, "unexpected", "unavoidable" and "unintended". HSE clarifies 'accident' as "an undesired circumstance(s) which gives rise to ill health, injury, damage, production losses or increased liabilities" [78]. According to CCOHS, 'accident' can be defined as "an unplanned event that interrupts the completion of an activity, and that may (or may not) include injury or property damage" [85].

Catastrophe: The term 'catastrophe' can be defined as an event that could cause major damages to human health, property or environment for a significant time period or forever [1]. For example, Bhopal disaster - the worst industrial disaster in history [35, 38] caused permanent shutdown of the UCIL (Union Carbide India Limited) pesticide plant.

The definition of end events is available in several publications, journals, expert opinions [1, 54, 90].

2.2 Safety Barrier Definition

The concept of safety barrier is introduced by several authors in different ways which shows the same functionality. During the 60s, Gibson [91] and Haddon [92] used "the concepts of energy and barriers as a basis" in accident analysis [93]. Skogdalen & Vinnem [12], Sklet [87], Bento [94], and Duijm et al. [95] use words i.e. 'limit', 'control', 'prevent', 'mitigate', 'minimize' to define the function of safety barriers in a similar pattern. Bento [94] defines safety barrier as a solution or a system to minimize occurrences of events. Skogdalen & Vinnem [12] and Sklet [87] define it as a "physical and/or nonphysical" source to "prevent, control, or mitigate undesired events or accidents". For example, after the liquefaction process in the LNG process facility, liquid gas is transferred from system A to system B for shipping purposes and the safety barrier works in every stage of this process to prevent, control or mitigate any consequences of hazardous events. Barrier functions are well described in experts' review [1, 12, 87, 96].

Safety barriers work as a shield in every stage of accident propagation until it reaches catastrophic accident. The safety barriers that we consider in the current dissertation are (i) 'Release Prevention Barrier' - which mitigates chemical or energy release, (ii) 'Dispersion Prevention Barrier' - which restricts the propagation of chemical or energy release, (iii) 'Ignition Prevention Barrier' – which prevents the flammable release to ignite, (iv) 'Escalation Prevention Barrier' - which prevents the escape of release materials, and (v) 'Damage Control and Emergency Management Barrier' - as a final stage to shield against catastrophic incident.

'Human factors' and 'human error' are two terms often exchanged in the offshore process industry without clear explanation [97]. These two terms are often used as the general cause of an accident. According to Rasmussen et al. [98] and Rasmussen [99-101], "Accidents are typically judged to be caused by 'human error' on the part of a train driver, a pilot, or a process operator". Traditionally, human factor is defined as "the scientific study of the interaction between man and machine" [97]. According to HSE [102], human factors refer here is to the environmental, work related factors, and individual characteristics which influence human behavior at work in a way that affect health and safety. In present study, we are considering human factor barrier to reflect above elements. Failure of human factor barrier reflect human induced by one or more of these factors. The other term 'human error' is defined by Rasmussen [100] as "human acts which are judged by somebody to deviate from some kind of reference act…they are subjective and they vary with time". Human factor was largely ignored in the past in evaluation of accident analysis. Early research shows human factor involvement in the causation of accidents. In the 60s, several human factors specialists (i.e. Altman [103]; Chapanis [104]; Christensen [105]) associated 'human error' in accident causation; however, American Research Institute used this concept in accident analysis [101]. Brazier [106] studied on human factor involvement in accident causation in various process industries. Wagenaar & Groeneweg [107] researched on marine industry in findings of human factor causes. Table 2.2 represents statistical analysis of human factor contribution in various fields, industry and discipline [70, 108-113].

Table 2.2: Human Error Involvement in Different Fields

Field	Failure rate
Nuclear industry	over 90%
Chemical and petro-chemical industry	over 80%
Marine and Offshore	over 75%
Aviation	over 70%
Drinking water distribution and hygiene	over 75%

The process operator under the supervision of management/organizational factor has the vital responsibility to assure a safe operational environment. A study by the Institute of Nuclear Power Operations [114] showed that at least 92% of the underlying causes of accidents were caused by people. According to Cullen [61] report on Piper Alpha disaster, insufficient qualified and trained personnel were involved in production for long time. A report by the UK P&I Club [115] indicates that more than 62% error resulted by one or more individuals [116]. In workplace, human interaction advances as a cycle through chain of command, as manager affects supervisor, supervisor affects subordinates and vice versa, organization's safety culture (training) which might affect the workplace safety. Recent study shows, thirty three major factors might be involved in human factor barrier failure [1] which is influenced by the leadership, training, safety management procedure etc., under the management of different industry. Kim et al. [31] emphasize on root causes responsible for human error such as, 'fatigue', 'inadequate supervision', 'failure of sight navigation', 'lack of effective pilot and escort system' after the analysis of the Valdez oil spill incident. For detailed descriptions of human error refer to Reason [70], Rasmussen [100] and Gordon [117].

Organizational factors are also involved in accident causation. According to Jacobs & Haber [118], organizational factors encourage unsafe acts and ultimately produce system failures. Sklet [87] acknowledges with Hopwood [119] about "administrative, social and self-control" under the organizational controls. Johnson & Gill [120] clarifies administrative control as "to control the organizational behavior(s) of other individuals, groups and organizations" [87]. The Swiss Cheese model [70, 121] illustrates the overall organizational framework for accident causation. In addition, it also demonstrates accidents' contributing factors which include organizational influences, unsafe supervision, preconditions for unsafe acts and unsafe acts in an organizational accident. Failure to ensure any of the organizational safety procedures may lead to accident causation. Aven et al. [122] commented on Norwegian oil and gas industry safety issue: ''Investigation of major accidents shows that technical, human, operational as well as organizational factors influence the accident sequence" [59]. Johnson & Holloway [123] shows a clear statistics for the period between 1996-2006 on aviation and maritime accidents in terms of human and organizational factor error. Based on this analysis, it has been revealed that 48% organizational factors and 12% human factors contribute on USA aviation accidents. In case of maritime accidents, it is 53% organizational and 24-29% human factors error. Therefore, human and management factor receive prime attention from the perspective of safety culture in accident causation. In the current work, our model allows for human and management & organizational factors to influence and contribute at every stage of safety procedure. More information on safety culture management in industry can be found on Mearns et al. [97], Reason [121], Cox & Cox [124], and Turner & Pidgeon [125].

Human and management & organizational factor barriers are included in proposed work and kept common in every stage of event sequence, so they are more emphasized. Leveson [65] highlighted that communication lacking between human and machine operating system can be an alarming factor in occurrence of accidents. Hence, all influential risk contributing factor including the human communication error have to be addressed in each step of accident modeling approach for a comprehensive safety assessment and improving overall safety for a system. In the SHIPP methodology, human and management & organizational barrier were suggested; however, limited information was discussed on these barriers.

2.3 Accident Modeling: SHIPP

Recently, Rathnayaka et al. [1, 2, 66] proposed SHIPP (System Hazard Identification, Prediction and Prevention) methodology as a quantitative safety assessment approach to evaluate safety at different stage of probable accident sequence analysis. In process industry, liquid and gas leaks, cryogenic temperature, flammability, and vapor dispersion are potential hazards [66, 126]. "Cryogenic temperature and flammability and vapor dispersion characteristics are potential safety issues" among the physical properties of LNG [66]. SHIPP is applicable in LNG process facilities to maintain and manage these safety issues by identifying potential hazards (i.e. end events) through assessing accident scenarios using safety barriers and forecast the future happening. SHIPP methodology is a sequential accident model technique, which encompassed the human and management factors, however, Rathnayaka et al. [1, 2] provided no guidance on how to implement these factors for evaluating the likelihood (i.e. probability) of final events' occurrence. T he conceptual diagram of the SHIPP methodology is shown in Figure 2.3, which is translated into an event tree as shown in Figure 2.4 for calculating occurrence probability of end events. The end events i.e. safe, near miss, mishap, incident, accident and catastrophe are the outcome events of safe sate deviation for an abnormal operation (e.g., LNG release). In SHIPP methodology, events' consequence follows the hierarchy and sequence viz. first near miss, next mishap, then incident and accident to follow, which is exactly analogous to the structural development of event tree. In real life scenario, end events' occurrence can happen in any random order (i.e. near miss can escalate to an incident or accident). However, in the SHIPP methodology, the safety barriers have to be arranged in sequential order, which restrict the escalation of different end events' occurrence sequentially rather than randomly.

Sklet [87] identified five release factors responsible for hydrocarbon release (i.e. human and operational errors, technical failures, process upsets, external events and design failures). Following release factor or, safety barrier has been classified in the SHIPP methodology for the accident prevention strategies;

1. Human Factor Barrier (HFB)
2. Management and Organizational Barrier (MOB)
3. Release Prevention Barrier (RPB)
4. Dispersion Prevention Barrier (DPB)

5. Ignition Prevention Barrier (IPB)

6. Escalation Prevention Barrier (EPB)

7. Damage Control and Emergency Management Barrier (DCEMB)

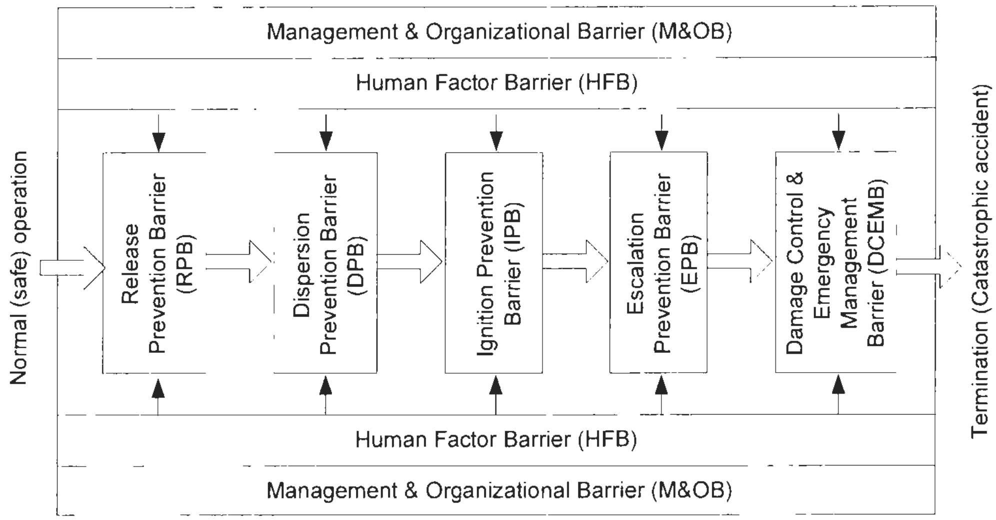

Figure 2.3: SHIPP Model [1, 2, 66]

The SHIPP methodology incorporates four steps to accomplish accident progression and likelihood assessment for a given abnormal operation i.e. system definition, hazard identification and analysis, accident modeling and prediction, updating, decision making and implementations of the prevention strategies [1, 2, 66]. However, while implementing the SHIPP method for LNG data, Rathnayaka et al. [2] used only four safety barriers excluding Damage Control and Emergency Management Barrier, Human Factor Barrier and Management and Organizational Barriers. In a subsequent paper, Rathnayaka et al. [66] included Human and Management Barriers but still neglected the Damage Control and Emergency Management Barrier. In the current work we include the entire seven safety barrier and as a result include an adverse event of highest order 'Catastrophe'. The end events' occurrence can be estimated if the prior information of safety barrier is available. This model with predictive capabilities can be applied to any real-life accident situation in process industry (i.e. LNG, LPG). The proposed Bayesian network model presented by Baksh et al. [75] adopted the same source of the basic event probability data as used by other researchers such as Rathnayaka et al. [66].

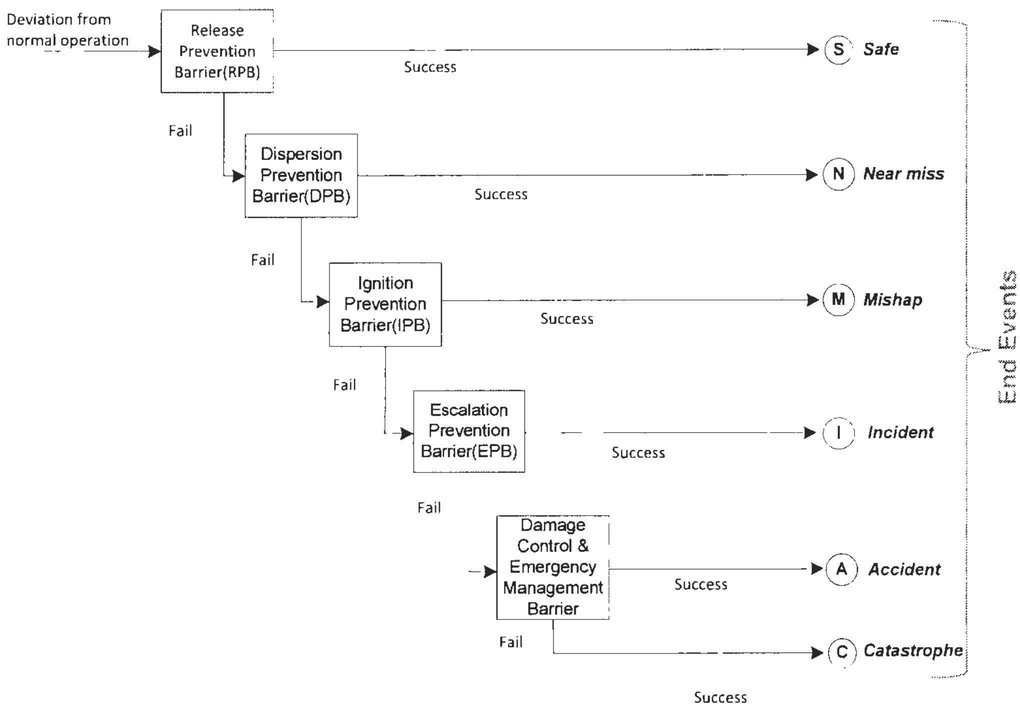

Figure 2.4: Accident Sequence [1, 2]

CHAPTER 3

Methodology

3.1 Model Development

3.1.1 Event tree modeling

Revised event tree, which is translated from the SHIPP model, is illustrated in Figure 3.1. The failure probability of each safety barrier is denoted by X_i (i = 1 to 7) as seven safety barriers (i.e. human, management, release prevention, dispersion prevention, ignition prevention, escalation prevention and damage control prevention factor) are utilized in revised event tree model to prevent, mitigate or control an end event i.e. safe (S) to escalate to a near miss (N), mishap (M), incident (I), accident (A) or catastrophe (C). Failure probabilities for each safety barrier are assigned in the event tree viz. HFB (2.90×10^{-3}), MOB (4.21×10^{-2}), RPB (5.27×10^{-2}), DPB (6.16×10^{-2}), IPB (10.60×10^{-2}), EPB (2.71×10^{-2}), and DCEMB (10.88×10^{-2}). There are twenty four potential consequences which have been identified exaggerating from the initial safe state in an LNG process facility. First twelve consequences are: (i) S (All X_1, X_2, X_3 safety barriers work properly), (ii) N (X_1, X_3 both work, but X_2 fails), (iii) S (X_1 fails, but both X_2 and X_3 work), (iv) N (X_1, X_2 both fail, but X_3 works), (v) N (X_3 fails, but X_1, X_2 and X_4 work), (vi) M (X_2, X_3 both fail, but both X_1 and X_4 work), (vii) N (X_1, X_3 both fail, but both X_2 and X_4 work) and (viii) M (X_1, X_2 and X_3 fail, but X_4 works), (ix) M (X_3, X_4 both fail, but X_1, X_2 and X_5 work), (x) I (X_2, X_3 and X_4 fail, but X_1, and X_5 both work), (xi) M (X_1, X_3 and X_4 fail, but X_2, and X_5 both work), (xii) I (X_1, X_2, X_3 and X_4 fail, but X_5

work). Similarly, following twelve consequences can be explained. All the consequences in event tree network are translated in Table 3.1.

Table 3.1: Revised Event Tree Network Consequences

No.	Barrier success	Barrier failure	Consequences
1	X_1, X_2, X_3	None	Safe
2	X_1, X_3	X_2	Near miss
3	X_2, X_3	X_1	Safe
4	X_3	X_1, X_2	Near miss
5	X_1, X_2, X_4	X_3	Near miss
6	X_1, X_4	X_2, X_3	Mishap
7	X_2, X_4	X_1, X_3	Near miss
8	X_4	X_1, X_2, X_3	Mishap
9	$X_1, X_2 X_5$	X_3, X_4	Mishap
10	X_1, X_5	X_2, X_3, X_4	Incident
11	X_2, X_5	X_1, X_3, X_4	Mishap
12	X_5	X_1, X_2, X_3, X_4	Incident
13	$X_1, X_2 X_6$	X_3, X_4, X_5	Incident
14	X_1, X_6	X_2, X_3, X_4, X_5	Accident
15	X_2, X_6	X_1, X_3, X_4, X_5	Incident
16	X_6	X_1, X_2, X_3, X_4, X_5	Accident
17	$X_1, X_2 X_7$	X_3, X_4, X_5, X_6	Accident
18	X_1, X_7	X_2, X_3, X_4, X_5, X_6	Catastrophe
19	X_2, X_7	X_1, X_3, X_4, X_5, X_6	Accident
20	X_7	$X_1, X_2, X_3, X_4, X_5, X_6$	Catastrophe
21	X_1, X_2	X_3, X_4, X_5, X_6, X_7	Accident
22	X_1	$X_2, X_3, X_4, X_5, X_6, X_7$	Catastrophe
23	X_2	$X_1, X_3, X_4, X_5, X_6, X_7$	Catastrophe
24	None	$X_1, X_2, X_3, X_4, X_5, X_6, X_7$	Catastrophe

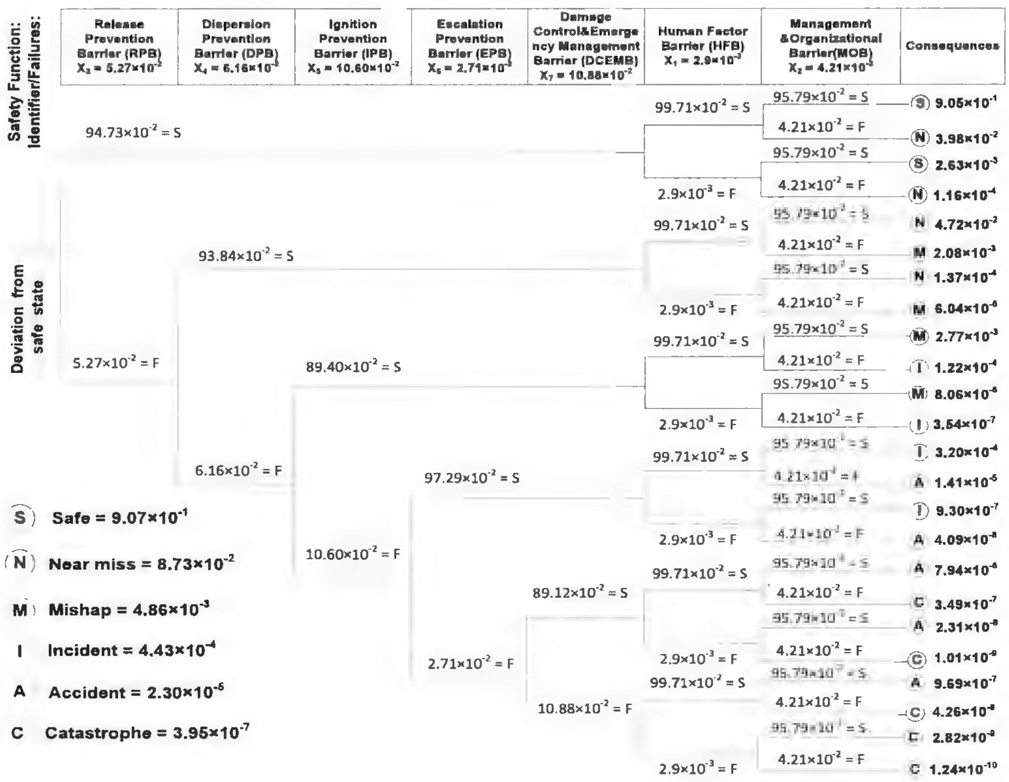

Figure 3.1: Revised Event Tree Accident Model

3.1.2 Bayesian network modeling

Bayesian inference is one of the emerging thought got much attention to scholars. Nowadays Bayesian theory is implemented in fault diagnosis while engineers, experts are using in safety and risk analysis of the system process. Bayesian network can be defined by its characteristics; a set of variables, a set of edges (directed), finite set of mutually exclusive states in each variable and form of a directed acyclic graph [127]. Bayesian network is called a directed acyclic graph (DAG) due to representation of its conditional interdependency [128]. In Bayesian Network, "probability inference of an event is conditional on the observed evidence" [129]. Bayesian network can implement forward or prediction analysis; however, it can perform backward or diagnosis analysis as well [130].

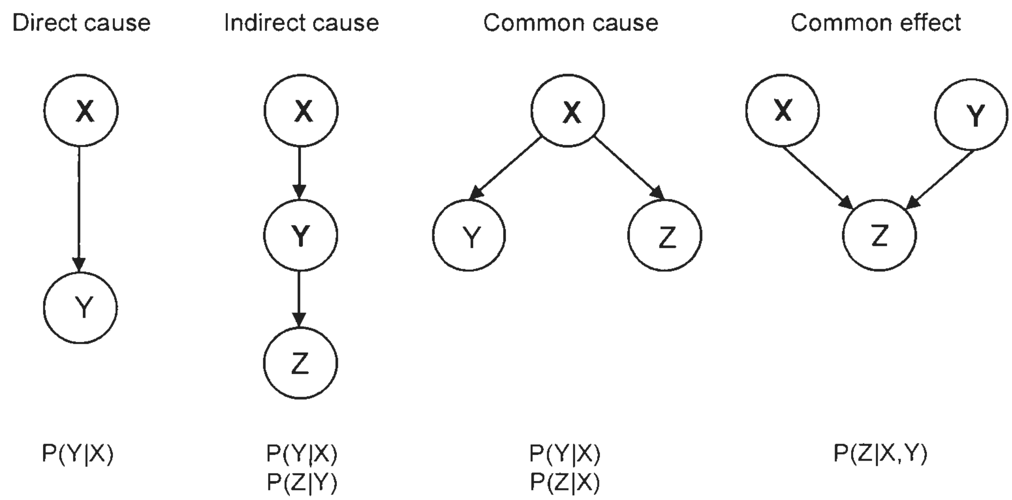

Figure 3.2: Cause and Effect Relationship

Figure 3.2 represents causal network with a set of variables (i.e. X, Y, Z) and a set of directed edges between those variables. If there is an edge from X to Y, we can say that X is a parent of Y and Y is a child of X. It can be represented by P(Y|X). Similarly, if there is link or edges from X to Y and Z, we can say that Y and Z are children of X and X is parent of Y and Z. This structure is known as directed graph [127].

A general Bayesian network is presented in Figure 3.3 where we can see influence of **A** on C and E, influence of **C** on B and D and influence of **E** on D. Here, C and E are descendants or children of **A** and **A** is parent of C and E. Similarly, B and D are descendants of **C** and **C** is parent of B and D. C and E both influence D. Hence, **C** and **E** both are parents of D. This network can be explained using chain rule as follows:

$$P(A,B,C,D,E) = P(A)\ P(B|C)\ P(C|A)\ P(D|C,E)\ P(E|A,C)$$

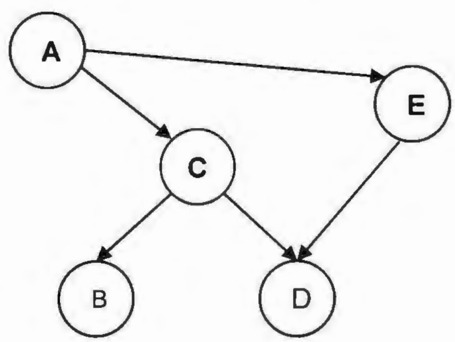

Figure 3.3: General Bayesian Network

The general chain rule for Bayesian network as follows:

$P(U) = \prod_{i=1}^{n} P(A_i \mid \mathrm{pa}(A_i))$, where pa ($A_i$) are the parents of A_i in Bayesian network.

Both converging and diverging connections exist in Figure 3.3. From top node **A**, connection diverges to C and E; from **C** it diverges to B and D; from **C** and **E** it converges to D. If any information exists in **A**, it will pass between all the children of **A** (i.e. C and E). Similarly, any existing information known to **C** will pass between its children B and D. If no information is available about D, only the information of **C** and **E** exist, then the parents **C** and **E** are independent. Evidence of C or E cannot influence each other certainties through D. Figure 3.4 represents both converging and diverging connections between its variables. From parent node X_1 and X_2, connection diverges to all consequences (i.e. safe, near miss, mishap, incident, accident and catastrophe). For each consequence, connection converges such as X_1, X_2 and X_3 converge to safe consequence. Here, X_1, X_2 and X_3 are safety barriers to prevent unwanted consequences. These are possible causes as well since failure of these barriers might cause near miss or other consequences deviated from safe state. If we know a possible condition of "how" and "why" a near miss occurs, it might lead us to possible causes; otherwise one possible cause cannot tell about other causes. Relevant details regarding Bayesian network can be found on Jensen & Nielsen [127], Neil et al. [131] and Pearl [132].

Networking

Bayesian network diagram includes nodes and edges. The failure probability of each safety barrier is denoted by X_i in the relative Bayesian network (Figure 3.4) which comprises 'circular' nodes as safety barriers as well as parents from X_1 to X_7 (i.e. human, management, release prevention, dispersion prevention, ignition prevention, escalation prevention and damage control prevention factor) and 'oval' shaped nodes as end events as well as children (i.e. safe, near miss, mishap, incident, accident, and catastrophe). Safety barriers (parents) are linked through edges with end events (children). In current network, only dotted line represents edges from Human factor (X_1) barrier to all end events. Management factor is connected through breaking lines/edges to all end events. Other listed barriers are connected through hard lines/edges.

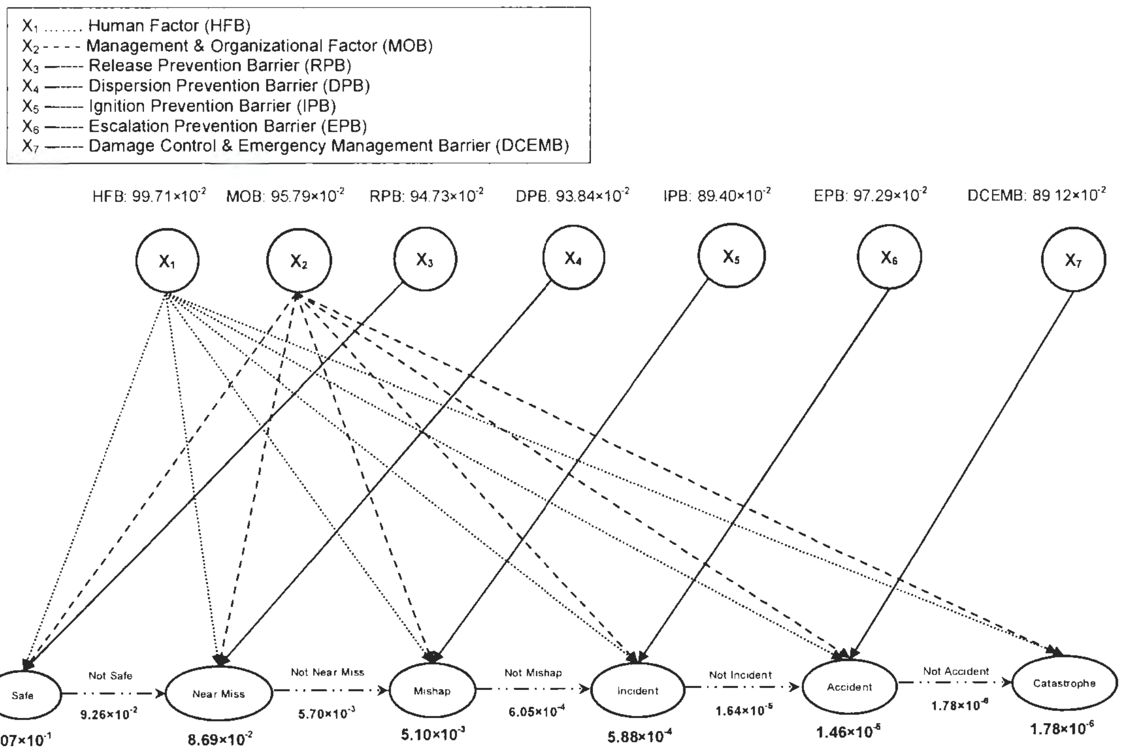

Figure 3.4: Proposed Bayesian Network Model [75]

Considering the SHIPP conceptual model, but non-sequential array, Bayesian network model (Figure 3.4) has been proposed which is based on revised event tree (The revised event tree includes human and management & organizational barriers). Bayesian network model is superior for real time accident scenarios and designing accident model and analysis and hereby, preferred due to its ability for successive approximation and handle uncertainty. Moreover, it can describe the dependency and conditionality of the prior causes and consequences. The current Bayesian model can depict the accident scenarios and help to determine the occurrence probability of end events in any order conditional to any given state of safety barriers. It requires only a small number of directed edges in addition to small number of probabilities to add a new piece of information in Bayesian network. In the proposed Bayesian model, Bayesian network is developed for each safety barrier and their relevant links with the end events. Edges between safety barriers and end events are considered as non-sequential; however, events' occurrence is sequential. Bayesian theory can be implemented in the current Bayesian model to update prior belief of safety barriers with observations of actual performance [130, 133]. Figure 3.4 represents the sequences of safety barriers to prevent and mitigate potential end events in an LNG process facility. It also depicts failure of relevant barriers individually and collectively leading to end states. Depending on the failure consequences, the end results might be near miss to catastrophic accident deviated from a safe state.

CHAPTER 4

Mathematical Formulation and Analysis

4.1 Conditional Probability Assessment

The nodes of a Bayesian network are associated with the conditional probability which determines the nodes' probability distribution [131]. In present analysis, Bayesian network is used to estimate prior conditional events' occurrence probability. Further, using the prior occurrence probability of safety barriers in revised event tree (Figure 3.1), end states occurrence probability has been estimated using forward analysis (Equation 4.1). Moreover, failure probabilities of the safety barriers are updated with the help of backward conditional probability approach (Equation 4.2) by using the posterior probabilities of adverse events and the newly observed data.

4.1.1 Forward analysis (Posterior probability estimation)

Bobbio et al. [130] nicely defined forward analysis as, "predictive analysis, in which the probability of occurrence of any node of the network is calculated on the basis of the prior probabilities of the root nodes and the conditional dependence of each node".

$$P(z) = \sum_{x_1,x_2,x_3} P(x_1,x_2,x_3,z)$$

$$P(z = success) = \sum_{x_1,x_2,x_3} P(x_1,x_2,x_3,z = success)$$

$$= \sum_{x_1,x_2,x_3} P(x_1)P(x_2)P(x_3)P(z = success \mid x_1,x_2,x_3) \qquad (4.1)$$

$$\ldots \qquad \ldots \qquad \ldots$$

To estimate the probability of an end event' occurrence in a given time period, the specific safety barrier contribution in every stage is kept in count by summing over the possible situations. For each end state (i.e. safe, near miss, mishap, incident, accident, and catastrophe), forward analysis has been implemented in following ways:

$$P(Safe = yes) = \sum_{x_1} P(X_1)P(X_2)P(X_3)P(Safe = yes \mid X_1, X_2, X_3)$$

$$P(Nearmiss = yes)$$
$$= \sum_{x_1,x_2} P(X_1)P(X_2)P(X_4)P(NotSafe)P(Nearmiss = yes \mid X_1, X_2, X_4, NotSafe)$$

$$P(Mishap = yes)$$
$$= \sum_{x_1,x_2} P(X_1)P(X_2)P(X_5)P(NotNearmiss)P(Mishap = yes \mid X_1, X_2, X_5, NotNearmiss)$$

$$P(Incident = yes)$$
$$= \sum_{x_1,x_2} P(X_1)P(X_2)P(X_6)P(NotMishap)P(Incident = yes \mid X_1, X_2, X_6, NotMishap)$$

$$P(Accident = yes)$$
$$= \sum_{x_1,x_2} P(X_1)P(X_2)P(X_7)P(NotIncident)P(Accident = yes \mid X_1, X_2, X_7, NotIncident)$$

$$P(Catastrophe = yes)$$
$$= \sum_{x_1,x_2} P(X_1)P(X_2)P(NotAccident)P(Catastrophe = yes \mid X_1, X_2, NotAccident)$$

4.1.2 Backward analysis (Bayesian failure probability estimation)

"Backward (diagnostic) analysis concerns the computation of the posterior probability of any given set of variables given some observation (the evidence), represented as instantiation of some of the variables to one of their admissible values" [130].

$$P(x_1 = work \mid z = success) = \frac{P(x_1 = work \;\&\; z = success)}{P(z = success)}$$

$$= \frac{\sum_{x_2, x_3} P(x_1 = work, x_2, x_3, z = success)}{P(z = success)} \tag{4.2}$$

... ...

The preferred method for estimating $P(X_i \mid Safe = yes)$ or $P(X_i \mid Nearmiss = yes)$ is using the statistical analysis of accident data. Contribution of each barrier in end events' occurrence is estimated by taking probabilities of X_i (i = 1,..,7) given that system is in end state (i.e. safe, near miss, mishap, incident, accident and catastrophe) and summing over the possible situations. Here, X_1, X_2, X_3, X_4, X_5, X_6 and X_7 are identified as safety barriers (i.e. human, management, release prevention, dispersion prevention, ignition prevention, escalation prevention and damage control prevention factor). Backward analysis has been implemented to check the contribution of each safety barrier in occurrence of any end events in following ways:

$$P(X_1 \mid Safe = yes) = \sum_{x_2, x_3} P(X_1 = s, X_2, X_3, Safe = yes) / P(Safe = yes)$$

$$P(X_2 \mid Safe = yes) = \sum_{x_1, x_3} P(X_1, X_2 = s, X_3, Safe = yes) / P(Safe = yes)$$

$$P(X_3 \mid Safe = yes) = \sum_{x_1, x_2} P(X_1, X_2, X_3 = s, Safe = yes) / P(Safe = yes)$$

$$P(X_1 \mid Nearmiss = yes)$$
$$= \sum_{x_2, x_4} P(X_1 = s, X_2, X_4, NotSafe = yes, Nearmiss = yes) / P(Nearmiss = yes)$$

$$P(X_2 \mid Nearmiss = yes)$$
$$= \sum_{x_1, x_4} P(X_1, X_2 = s, X_4, NotSafe = yes, Nearmiss = yes) / P(Nearmiss = yes)$$

$$P(X_4 \mid Nearmiss = yes)$$
$$= \sum_{x_1, x_2} P(X_1, X_2, X_4 = s, NotSafe = yes, Nearmiss = yes) / P(Nearmiss = yes)$$

... ...

In similar way, mishap, incident, accident and catastrophe have been included to estimate the barrier contribution in causation of end events.

4.2 Bayesian Updating Model

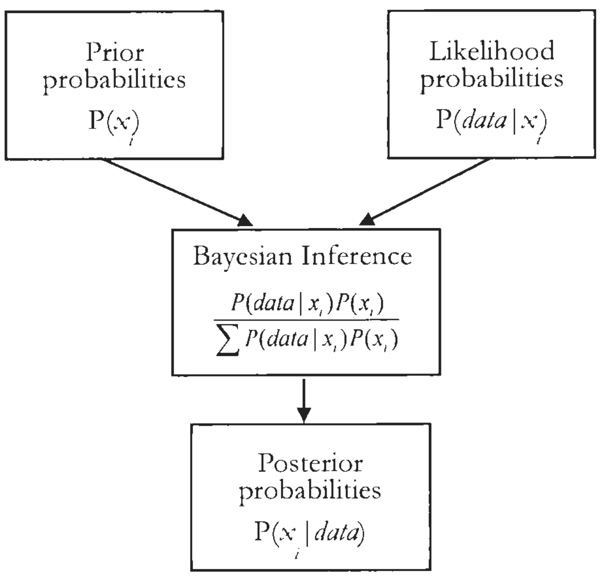

Figure 4.1: Bayesian Updating Process

Bayesian inference estimates the updated consequence results in case of failure of safety barriers through Bayesian network analysis. Once the prior failure probabilities of safety barriers, $P(x_i)$ are available and likelihood probabilities, $P(data \mid x_i)$ are estimated, posterior probabilities, $P(x_i \mid data)$ can be calculated. Bayesian updating mechanism is illustrated in Figure 4.1. Subsequently, Bayesian backward conditional probability approach helps to update safety barrier success/failure probabilities. The whole consequence is demonstrated through a flowchart diagram for an LNG process facility in Figure 4.2.

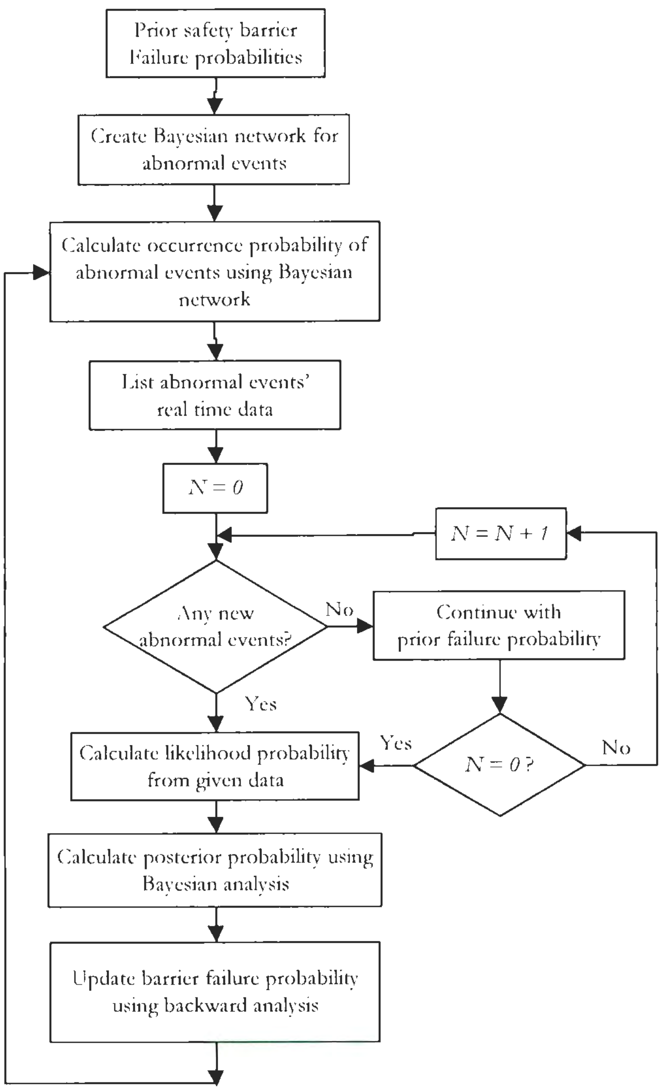

Figure 4.2: Flowchart for Updating Barrier Failure Probabilities for LNG Process Facility

4.2.1 Likelihood estimation

Using the real life site specific data, likelihood probabilities are estimated for the specific scenario. To define likelihood, identification of end events for a given time duration (each month) in each category is essential which is denoted by $N_{e,i}$. After estimating the occurrence probabilities of each end state, the likelihood probabilities, $P(E|X)$ is calculated for each end state using the following Equation (4.3):

$$N_{e,1}, N_{e,2}, N_{e,3}, \ldots\ldots, N_{e,6}$$

$$\sum_{i=1}^{6} N_{e,i} = N_{e,1} + N_{e,2} + N_{e,3} + N_{e,4} + N_{e,5} + N_{e,6}$$

$$P(E \mid X) = \frac{N_{e,i}}{\sum_{i=1}^{6} N_{e,i}}, where \sum_{i=1}^{6} N_{e,i} \neq 0 \tag{4.3}$$

4.2.2 Bayes' theorem

Bayes' theorem updates probabilities [134] for given new pieces of evidence using the following Equation (4.4).

$$P(X \mid E) = \frac{P(X,E)}{P(E)} = \frac{P(X,E)}{\sum P(X,E)} = \frac{P(E \mid X)P(X)}{\sum P(E \mid X)P(X)} \tag{4.4}$$

where,

X represents a specific hypothesis (may or may not be some null hypothesis).

E represents observed evidence.

P(X) is called the prior probability of *X*.

P(E|X) is called the conditional probability of seeing the evidence *E* if the hypothesis *X* happens to be true.

P(E) is called the marginal probability of *E*.

Here, occurrence probability of the safety barrier X is an identical independent random variable and $P(E|X)$ is likelihood probabilities whereas, $P(X|E)$ is posterior probabilities. Prior probabilities, $P(X)$ and likelihood probabilities, $P(E|X)$ are replaced in Bayes' theorem (Equation 4.4) to estimate posterior probabilities, $P(X|E)$ or, updated occurrence probabilities. The denominator represents the normalizing factor.

CHAPTER 5

Model Testing

Bayesian theory is convenient to estimate posterior probabilities of end events. Safety barriers' success/failure probability estimation using backward conditional probability approach is another advantage of this method. Before testing the improved model, expert opinion, literature review and process component failure data are used to estimate prior failure probabilities of the *i*-th safety barrier for different values of *i* (1, 2, 3,...,7) through relevant fault tree simulation [2, 66, 135] (Table 5.1) and is presented in Appendix A.

Table 5.1: Prior Occurrence Probability for Each Primary Safety Barrier

Safety Barrier(X_i)	Failure Probability, P(X_i)
Human Factor Barrier (HFB)	2.90×10^{-3}
Management and Organizational Barrier (MOB)	4.21×10^{-2}
Release Prevention Barrier (RPB)	5.27×10^{-2}
Dispersion Prevention Barrier (DPB)	6.16×10^{-2}
Ignition Prevention Barrier (IPB)	10.60×10^{-2}
Escalation Prevention Barrier (EPB)	2.71×10^{-2}
Damage Control and Emergency Management Barrier (DCEMB)	10.88×10^{-2}

5.1 LNG Process Facility Data Evaluation

5.1.1 LNG and process train

LNG (Liquefied Natural Gas) is a highly demanded condensed natural gas (boiling temperature ranges from -166° C to -157° C at atmospheric pressure). It is a mixed component of methane, ethane, propane, nitrogen and other particles which are combustible with a LFL (Lower Flammable Limit) limit of 4-5% by volume in air and an UFL (Upper Flammable Limit) limit of 15%, depending on temperature [136]. To make it more economical and meet global energy demand, it is liquefied for easy shipping for different regions. According to CEE [137], it needs to follow a LNG train which is comprised four stages, (1) Exploration and production, (2) Liquefaction, (3) Shipping, and (4) Regasification and storage. Liquefaction is an important step in LNG process train since it transforms natural gases in a liquid form to make it usable for customers. The liquefaction plant is fed with gas sourced from the production field. During this process, contaminants such as, carbon dioxide (CO_2), water (H_2O), Nitrogen (N_2) is removed to avoid freezing up or, any unwanted damages [66]. Liquefaction facilities are well established with several parallel trains where LNG is stored in double-walled inner and outer tanks at atmospheric pressure. Several safety measures are taken in LNG process facilities though any catastrophic hazards have not taken place until today. The hazardous nature of LNG can be found on Rathnayaka et al. [66], Bernatik et al. [136], and Horn & Wilson [139].

5.1.2 Case study application of proposed model

The proposed Bayesian model is applied to LNG process facilities to evaluate past accident data as well as accident scenarios. In this section, an LNG process plant (Figure 5.1) data is studied to demonstrate the application of the proposed Bayesian accident model. In this case study, six possible end states/events (i.e. safe, near miss, mishap, incident, accident and catastrophe) are identified. From the revised sequential event tree (Figure 3.1), it has been observed that the process system is deviated from its normal operation which results in 'safe' events; however, no harm/loss is occurred. If the management and organizational factor barrier (MOB) fails (i.e. poor safety culture), release might occur and human factor barrier (HFB) might not be able to stop/prevent it which results in a 'near miss'. Now if the HFB fails (i.e. operator error) and release occurs, MOB still can manage it through strong safety culture management and prevent the release causing no harms, which is still a 'safe' event. If both HFB and MOB fail (i.e. operator error, wrong decision), release would happen and 'safe' will escalate to a 'near miss'. Similarly, other end events' consequences can be explained from the given event tree. However, all the consequences are happening sequentially and that is a drawback of this improved sequential SHIPP model. In real life scenario, end events' occurrence can happen in any order (i.e. near miss can escalate to an incident or accident). So it is crucial to use this updated and improved non-sequential approach which is defined as Bayesian network approach [75]. Now if the non-sequential concept is applied on Bayesian network model in Figure 3.4, the end events' consequences can be explained in any order. For example, a mishap just happened due to HFB, RPB (Release prevention barrier) and DPB (Dispersion prevention barrier) failure which might escalate to an accident and the chances of occurrences can be estimated if the 'not incident', HFB, MOB and DCEMB (Damage control and emergency management barrier) success probabilities are available. In similar way, probabilities of other consequences can be estimated. Both revised event tree and Bayesian network model are useful to validate the assumption. Prior failure probabilities can be applied in the revised event tree model as well as in the Bayesian network model to estimate the occurrence probabilities for both models. The results are listed in Table 5.2. It may be observed from the listed results that the occurrence probabilities for both models closely match.

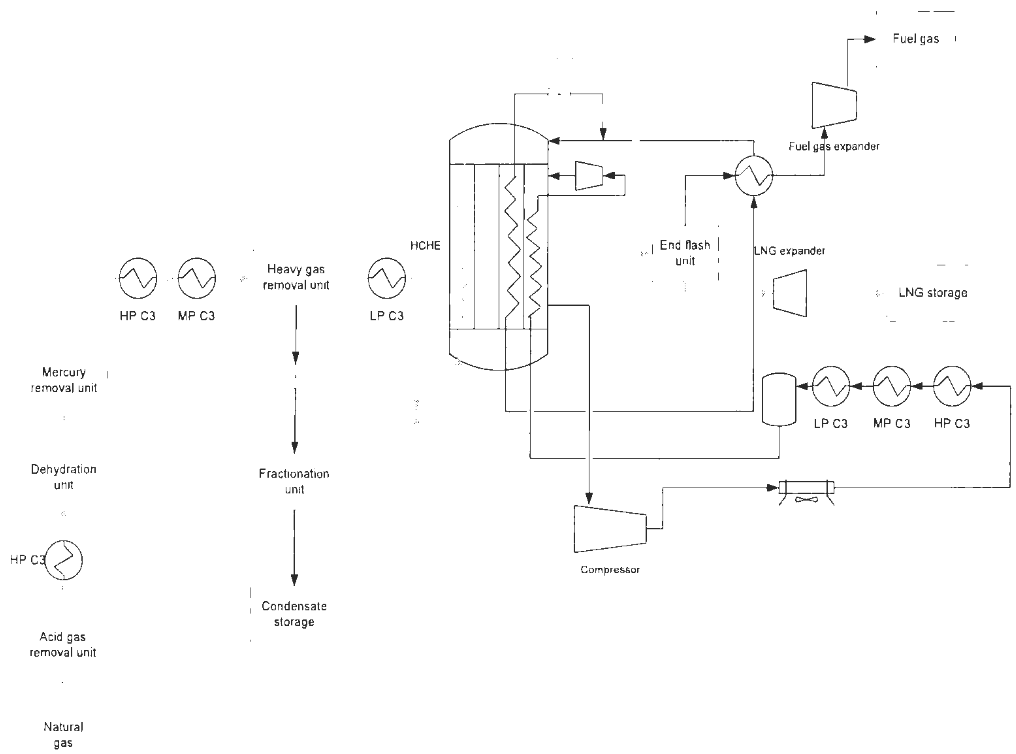

Figure 5.1: LNG Process Plant [66, 140]

Table 5.2: Prior Occurrence Probabilities of End Events Using SHIPP and Bayesian Model

End Events(E)	Event Tree Occurrence Probability P(E_k)	Conditional Event Occurrence Probability P(E_k)
Safe (E_1)	9.07×10^{-1}	9.07×10^{-1}
Near miss (E_2)	8.73×10^{-2}	8.69×10^{-2}
Mishap (E_3)	4.86×10^{-3}	5.10×10^{-3}
Incident (E_4)	4.43×10^{-4}	5.88×10^{-4}
Accident (E_5)	2.30×10^{-5}	1.46×10^{-5}
Catastrophe (E_6)	3.95×10^{-7}	1.78×10^{-6}

5.1.3 Model validation

End events' occurrence in a process facility on a regular basis is not unusual. Hence, first 10 months end events' data (2008) [2] of an LNG process plant is presented in Table 5.3 to proof that evidence. This raw data is used in the proposed Bayesian network model (Figure 3.4).

Table 5.3: Real Monthly Data of the First 10 Months of the Year 2008 [2]

Month	Safe (E_1)	Near miss (E_2)	Mishap (E_3)	Incident (E_4)	Accident (E_5)	Catastrophe (E_6)	Total Events
1	5	4	2	1	0	0	12
2	4	6	2	0	0	0	12
3	5	7	2	1	0	0	15
4	18	44	12	8	1	0	83
5	5	18	5	2	0	0	30
6	3	9	1	1	0	0	14
7	4	6	0	1	1	0	12
8	4	7	3	1	0	0	15
9	3	10	3	1	0	0	17
10	2	3	2	2	0	0	9

The estimated likelihood and posterior probabilities are listed in Table 5.4 and 5.5. Here, the posterior probabilities are calculated using both prior occurrence and likelihood probabilities of end events.

Table 5.4: Likelihood of Events Occurrence of the First 10 Months of the Year 2008

Month	Safe (E_1)	Near miss (E_2)	Mishap (E_3)	Incident (E_4)	Accident (E_5)	Catastrophe (E_6)
1	4.17×10^{-1}	3.33×10^{-1}	1.67×10^{-1}	8.33×10^{-2}	0.0	0.0
2	3.33×10^{-1}	5.00×10^{-1}	1.67×10^{-1}	0.0	0.0	0.0
3	3.33×10^{-1}	4.67×10^{-1}	1.33×10^{-1}	6.67×10^{-2}	0.0	0.0
4	2.17×10^{-1}	5.30×10^{-1}	1.45×10^{-1}	9.64×10^{-2}	1.20×10^{-2}	0.0
5	1.67×10^{-1}	6.00×10^{-1}	1.67×10^{-1}	6.67×10^{-2}	0.0	0.0
6	2.15×10^{-1}	6.43×10^{-1}	7.14×10^{-2}	7.14×10^{-2}	0.0	0.0
7	3.33×10^{-1}	5.00×10^{-1}	0.0	8.33×10^{-2}	8.33×10^{-2}	0.0
8	2.67×10^{-1}	4.67×10^{-1}	2.00×10^{-1}	6.67×10^{-2}	0.0	0.0
9	1.76×10^{-1}	5.88×10^{-1}	1.76×10^{-1}	5.88×10^{-2}	0.0	0.0
10	2.22×10^{-1}	3.33×10^{-1}	2.22×10^{-1}	2.22×10^{-1}	0.0	0.0

Table 5.5: Posterior Events' Occurrence of the First 10 Months of the Year 2008

Month	Safe (E_1)	Near miss (E_2)	Mishap (E_3)	Incident (E_4)	Accident (E_5)	Catastrophe (E_6)
1	9.27×10^{-1}	7.10×10^{-2}	2.08×10^{-3}	1.20×10^{-4}	0.0	0.0
2	8.72×10^{-1}	1.25×10^{-1}	2.45×10^{-3}	0.0	0.0	0.0
3	8.80×10^{-1}	1.18×10^{-1}	1.98×10^{-3}	1.14×10^{-4}	0.0	0.0
4	8.08×10^{-1}	1.89×10^{-1}	3.03×10^{-3}	2.33×10^{-4}	7.22×10^{-7}	0.0
5	7.40×10^{-1}	2.55×10^{-1}	4.16×10^{-3}	1.92×10^{-4}	0.0	0.0
6	7.76×10^{-1}	2.23×10^{-1}	1.45×10^{-3}	1.68×10^{-4}	0.0	0.0
7	8.74×10^{-1}	1.26×10^{-1}	0.0	1.42×10^{-4}	3.52×10^{-6}	0.0
8	8.53×10^{-1}	1.43×10^{-1}	3.60×10^{-3}	1.38×10^{-4}	0.0	0.0
9	7.55×10^{-1}	2.41×10^{-1}	4.24×10^{-3}	1.63×10^{-4}	0.0	0.0
10	8.70×10^{-1}	1.25×10^{-1}	4.89×10^{-3}	5.64×10^{-4}	0.0	0.0

Despite careful steps in accident modelling it is a requirement to validate the model and verify numerical calculation. As a first step, the model can be validated and compare all numerical values with other models. For the proposed Bayesian model to pass the validation, it is necessary to compare the posterior end results with prior months. For example, if the '0'*th* (prior) and later month end events' values closely match for both SHIPP and proposed Bayesian model then the proposed model will be acceptable. For the comparison, the end events' posterior probabilities for the '0'*th* (prior) and the '10'*th* month are obtained from the revised event tree and Bayesian network and are listed in Table 5.6. Further, these two results are compared. It may be observed from Table 5.6 that posterior values for both SHIPP and Bayesian model closely match. Graphical representation of 10 months occurrence probability is available in Figure 5.2. Another case study of Macondo blowout well accident is presented in Appendix B.

Table 5.6: Model Comparison for End Events' Probabilities

Month	End Events	SHIPP Model	Proposed Model
0^{th} month (prior)	Safe (E_1)	9.07×10^{-1}	9.07×10^{-1}
	Near miss (E_2)	8.73×10^{-2}	8.69×10^{-2}
	Mishap (E_3)	4.86×10^{-3}	5.10×10^{-3}
	Incident (E_4)	4.43×10^{-4}	5.88×10^{-4}
	Accident (E_5)	2.30×10^{-5}	1.46×10^{-5}
	Catastrophe (E_6)	3.95×10^{-7}	1.78×10^{-6}
10^{th} month	Safe (E_1)	8.50×10^{-1}	8.70×10^{-1}
	Near miss (E_2)	1.45×10^{-1}	1.25×10^{-1}
	Mishap (E_3)	4.00×10^{-3}	4.89×10^{-3}
	Incident (E_4)	3.00×10^{-4}	5.64×10^{-4}
	Accident (E_5)	9.21×10^{-7}	0.0
	Catastrophe (E_6)	0.0	0.0

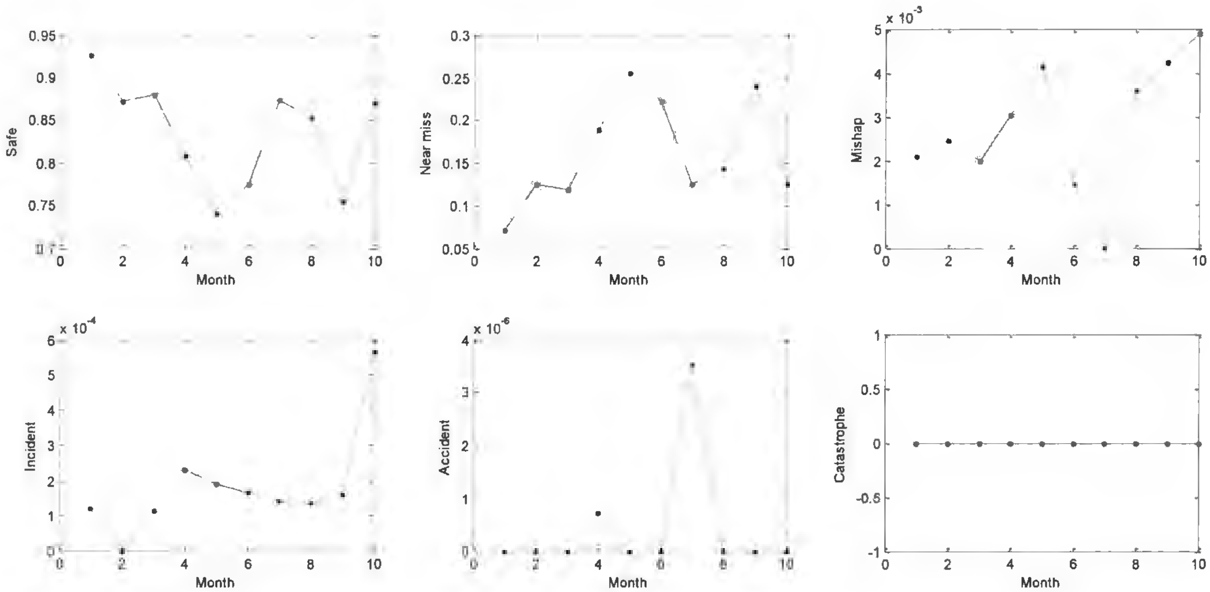

Figure 5.2: Posterior Occurrence Probabilities of End Events Over 10 Months

5.2 Application to 24 Months Data

5.2.1 Likelihood failure probability estimation

The 24 months real time data from LNG process plant is listed in Table 5.7. From this raw data four end events (safe, near miss, mishap and incident) are identified with frequent number of occurrence. Only three accident occurrence in 24 months period and no catastrophe has been observed. Columns 2-7 of Table 5.7 represent each end event occurrence and column 8 represents total occurrence for each month. To calculate likelihood probabilities of the given data, Equation (4.3) is used.

The likelihood probabilities are estimated using following steps:

- Identify end events for each month in each category denoted by $N_{e,i}$
- Assess total number of end events by taking sum on $N_{e,i}$,where i is the i-th barrier.
- Estimate the likelihood for each event of each month by dividing each corresponding months' total.

  For example, in the 2nd month, Safe (E_1) events happened twice (i.e. i =2). Total events for the 2nd month are 7.

$$
\begin{aligned}
&\sum_{i=1}^{6} N_{e,i} \\
&= N_{e,1} + N_{e,2} + N_{e,3} + N_{e,4} + N_{e,5} + N_{e,6} \\
&= 2 + 2 + 2 + 1 + 0 + 0 \\
&= 7
\end{aligned}
$$

- Now the likelihood P($E|X$) is calculated using the following equation as illustrated in Equation (4.3),

$$
\begin{aligned}
& P(E \mid X) \\
& = \frac{N_{e,i}}{\sum_{i=1}^{6} N_{e,i}} \\
& = \frac{2}{7} \\
& = 2.857 \times 10^{-1}
\end{aligned}
$$

Likewise, likelihood probabilities for other end events for each month have been calculated using above equation. Updated likelihood probabilities are listed in Table 5.8.

Table 5.7: Real Monthly Data of the Years 2008 and 2009 [66]

Month	Safe (E_1)	Near miss (E_2)	Mishap (E_3)	Incident (E_4)	Accident (E_5)	Catastrophe (E_6)	Total Events
1	3	4	0	0	0	0	7
2	2	2	2	1	0	0	7
3	5	2	0	0	0	0	7
4	11	26	8	1	0	0	46
5	3	5	1	0	0	0	9
6	2	3	0	0	0	0	5
7	4	2	1	1	0	0	8
8	1	2	0	3	0	0	6
9	2	1	0	0	0	0	3
10	2	3	1	0	1	0	7
11	1	4	2	0	0	0	7
12	4	2	0	0	0	0	6
13	5	4	2	1	0	0	12
14	4	6	2	0	0	0	12
15	5	7	2	1	0	0	15
16	10	27	6	3	1	0	47
17	3	15	6	2	0	0	26
18	3	7	1	1	0	0	12
19	4	6	0	1	1	0	12
20	4	7	3	1	0	0	15
21	3	10	3	1	0	0	17
22	2	3	2	2	0	0	9
23	7	10	2	0	0	0	19
24	4	4	2	0	0	0	10

Table 5.8: Likelihood of Events Occurrence of the Years 2008 and 2009

Month	Safe (E_1)	Near miss (E_2)	Mishap (E_3)	Incident (E_4)	Accident (E_5)	Catastrophe (E_6)
1	4.29×10^{-1}	5.71×10^{-1}	0.0	0.0	0.0	0.0
2	2.86×10^{-1}	2.86×10^{-1}	2.86×10^{-1}	1.43×10^{-1}	0.0	0.0
3	7.14×10^{-1}	2.86×10^{-1}	0.0	0.0	0.0	0.0
4	2.39×10^{-1}	5.65×10^{-1}	1.74×10^{-1}	2.17×10^{-2}	0.0	0.0
5	3.33×10^{-1}	5.56×10^{-1}	1.11×10^{-1}	0.0	0.0	0.0
6	4.00×10^{-1}	6.00×10^{-1}	0.0	0.0	0.0	0.0
7	5.00×10^{-1}	2.50×10^{-1}	1.25×10^{-1}	1.25×10^{-1}	0.0	0.0
8	1.67×10^{-1}	3.33×10^{-1}	0.0	5.00×10^{-1}	0.0	0.0
9	6.67×10^{-1}	3.33×10^{-1}	0.0	0.0	0.0	0.0
10	2.86×10^{-1}	4.29×10^{-1}	1.43×10^{-1}	0.0	1.43×10^{-1}	0.0
11	1.43×10^{-1}	5.71×10^{-1}	2.86×10^{-1}	0.0	0.0	0.0
12	6.67×10^{-1}	3.33×10^{-1}	0.0	0.0	0.0	0.0
13	4.17×10^{-1}	3.33×10^{-1}	1.67×10^{-1}	8.33×10^{-2}	0.0	0.0
14	3.33×10^{-1}	5.00×10^{-1}	1.67×10^{-1}	0.0	0.0	0.0
15	3.33×10^{-1}	4.67×10^{-1}	1.33×10^{-1}	6.67×10^{-2}	0.0	0.0
16	2.13×10^{-1}	5.74×10^{-1}	1.28×10^{-1}	6.38×10^{-2}	2.13×10^{-2}	0.0
17	1.15×10^{-1}	5.77×10^{-1}	2.31×10^{-1}	7.69×10^{-2}	0.0	0.0
18	2.50×10^{-1}	5.83×10^{-1}	8.33×10^{-2}	8.33×10^{-2}	0.0	0.0
19	3.33×10^{-1}	5.00×10^{-1}	0.0	8.33×10^{-2}	8.33×10^{-2}	0.0
20	2.67×10^{-1}	4.67×10^{-1}	2.00×10^{-1}	6.67×10^{-2}	0.0	0.0
21	1.76×10^{-1}	5.88×10^{-1}	1.76×10^{-1}	5.88×10^{-2}	0.0	0.0
22	2.22×10^{-1}	3.33×10^{-1}	2.22×10^{-1}	2.22×10^{-1}	0.0	0.0
23	3.68×10^{-1}	5.26×10^{-1}	1.05×10^{-1}	0.0	0.0	0.0
24	4.00×10^{-1}	4.00×10^{-1}	2.00×10^{-1}	0.0	0.0	0.0

5.2.2 Posterior events' occurrence probability estimation

In this step, Bayesian theory is applied to calculate the posterior probability of each end state. Using prior occurrence probabilities from Table 5.2 and likelihood probabilities from Table 5.8, posterior probabilities have been estimated using Bayes' Equation (4.4). The posterior probabilities are estimated using subsequent steps:

- Numerator can be written as for each event:

  $(l_{e_k,i} * p_{e_k,i})$;

  where, i = 1, 2, 3, 4, 5, 6;

  k = 1, 2, 3, 4,.......23, 24;

- Denominator can be written for the 2nd month as:

$$\sum_{i=1}^{6} P(E|X)P(X) = \left(l_{e_2,1} * p_{e_2,1}\right) + \left(l_{e_2,2} * p_{e_2,2}\right) + \dots \dots \dots + \left(l_{e_2,6} * p_{e_2,6}\right)$$

To calculate the denominator, above approach has been used:

$$\sum_{i=1}^{6} P(E|X)P(X) = (2.857 \times 10^{-1} * 9.074 \times 10^{-1}) + (2.857 \times 10^{-1} * 8.688 \times 10^{-2}) + \cdots + (0.0 * 1.782 \times 10^{-6}) = 2.856 \times 10^{-1}$$

Now, $\frac{P(E|X)P(X)}{\sum_{i=1}^{6} P(E|X)P(X)}$

$$= \frac{2.593 \times 10^{-1}}{2.856 \times 10^{-1}}$$

$= 9.079 \times 10^{-1}$, posterior value for the 'Safe' event for the 2nd month.

Likewise, posterior probabilities for other events for each month have been calculated using Bayes' Equation (4.4). Updated posterior values are listed in Table 5.9.

Table 5.9: Posterior Events' Occurrence of the Years 2008 and 2009

Month	Safe (E_1)	Near miss (E_2)	Mishap (E_3)	Incident (E_4)	Accident (E_5)	Catastrophe (E_6)
1	8.87×10^{-1}	1.13×10^{-1}	0.0	0.0	0.0	0.0
2	9.08×10^{-1}	8.69×10^{-2}	5.10×10^{-3}	2.94×10^{-4}	0.0	0.0
3	9.63×10^{-1}	3.69×10^{-2}	0.0	0.0	0.0	0.0
4	8.13×10^{-1}	1.84×10^{-1}	3.32×10^{-3}	4.79×10^{-5}	0.0	0.0
5	8.61×10^{-1}	1.37×10^{-1}	1.61×10^{-3}	0.0	0.0	0.0
6	8.74×10^{-1}	1.26×10^{-1}	0.0	0.0	0.0	0.0
7	9.53×10^{-1}	4.56×10^{-2}	1.34×10^{-3}	1.54×10^{-4}	0.0	0.0
8	8.38×10^{-1}	1.60×10^{-1}	0.0	1.63×10^{-3}	0.0	0.0
9	9.54×10^{-1}	4.57×10^{-2}	0.0	0.0	0.0	0.0
10	8.72×10^{-1}	1.25×10^{-1}	2.45×10^{-3}	0.0	7.02×10^{-6}	0.0
11	7.17×10^{-1}	2.75×10^{-1}	8.06×10^{-3}	0.0	0.0	0.0
12	9.54×10^{-1}	4.57×10^{-2}	0.0	0.0	0.0	0.0
13	9.27×10^{-1}	7.10×10^{-2}	2.08×10^{-3}	1.20×10^{-4}	0.0	0.0
14	8.72×10^{-1}	1.25×10^{-1}	2.45×10^{-3}	0.0	0.0	0.0
15	8.80×10^{-1}	1.18×10^{-1}	1.98×10^{-3}	1.14×10^{-4}	0.0	0.0
16	7.92×10^{-1}	2.05×10^{-1}	2.67×10^{-3}	1.54×10^{-4}	1.27×10^{-6}	0.0
17	6.71×10^{-1}	3.21×10^{-1}	7.54×10^{-3}	2.90×10^{-4}	0.0	0.0
18	8.16×10^{-1}	1.82×10^{-1}	1.53×10^{-3}	1.76×10^{-4}	0.0	0.0
19	8.74×10^{-1}	1.26×10^{-1}	0.0	1.42×10^{-4}	3.52×10^{-6}	0.0
20	8.53×10^{-1}	1.43×10^{-1}	3.60×10^{-3}	1.38×10^{-4}	0.0	0.0
21	7.55×10^{-1}	2.41×10^{-1}	4.24×10^{-3}	1.63×10^{-4}	0.0	0.0
22	8.70×10^{-1}	1.25×10^{-1}	4.89×10^{-3}	5.64×10^{-4}	0.0	0.0
23	8.78×10^{-1}	1.20×10^{-1}	1.41×10^{-3}	0.0	0.0	0.0
24	9.10×10^{-1}	8.72×10^{-2}	2.56×10^{-3}	0.0	0.0	0.0

5.2.3 Bayesian updating

To update the existing safety barrier success probabilities real time, backward or diagnosis analysis has been done. In addition, conditional probability table listed in Table 5.10 is used to calculate the end events' occurrence as well as each safety barrier contribution in occurrence of any end events.

Table 5.10: Conditional Probability Table

End Events	Safety Barrier						
	HFB (X_1)	MOB (X_2)	RPB (X_3)	DPB (X_4)	IPB (X_5)	EPB (X_6)	DCEMB (X_7)
Safe	Success	Success	Success	-	-	-	-
	Fail	Success	Success	-	-	-	-
Near miss	Success	Success	Fail	Success	-	-	-
	Fail	Success	Fail	Success	-	-	-
	Success	Fail	Fail	Success	-	-	-
	Fail	Fail	Fail	Success	-	-	-
Mishap	Success	Success	Fail	Fail	Success	-	-
	Fail	Success	Fail	Fail	Success	-	-
	Success	Fail	Fail	Fail	Success	-	-
	Fail	Fail	Fail	Fail	Success	-	-
Incident	Success	Success	Fail	Fail	Fail	Success	-
	Fail	Success	Fail	Fail	Fail	Success	-
	Success	Fail	Fail	Fail	Fail	Success	-
	Fail	Fail	Fail	Fail	Fail	Success	-
Accident	Success	Success	Fail	Fail	Fail	Fail	Success
	Fail	Success	Fail	Fail	Fail	Fail	Success
	Success	Fail	Fail	Fail	Fail	Fail	Success
	Fail	Fail	Fail	Fail	Fail	Fail	Success
Catastrophe	Success	Success	Fail	Fail	Fail	Fail	Fail
	Fail	Success	Fail	Fail	Fail	Fail	Fail
	Success	Fail	Fail	Fail	Fail	Fail	Fail
	Fail	Fail	Fail	Fail	Fail	Fail	Fail

t = 'N' -*th* time barrier success probabilities for X_1, X_2, X_3, X_4, X_5, X_6 and X_7 are listed in following table:

Safety Barrier(X_i)	Success Probability, P(X_i)
Human Factor Barrier (HFB)	99.71×10^{-2}
Management and Organizational Barrier (MOB)	95.79×10^{-2}
Release Prevention Barrier (RPB)	94.73×10^{-2}
Dispersion Prevention Barrier (DPB)	93.84×10^{-2}
Ignition Prevention Barrier (IPB)	89.40×10^{-2}
Escalation Prevention Barrier (EPB)	97.29×10^{-2}
Damage Control and Emergency Management Barrier (DCEMB)	89.12×10^{-2}

Posterior information of the 19th and 20th months is adopted from the case study (Table 5.9):

Month	Safe P(E_1)	Near miss P(E_2)	Mishap P(E_3)	Incident P(E_4)	Accident P(E_5)	Catastrophe P(E_6)
19	8.74×10^{-1}	1.26×10^{-1}	0.0	1.42×10^{-4}	3.52×10^{-6}	0.0
20	8.53×10^{-1}	1.43×10^{-1}	3.60×10^{-3}	1.38×10^{-4}	0.0	0.0

From conditional probability table we can see the system is in safe state while all three barriers respectively, HFB(X_1), MOB(X_2) and RPB(X_3) are in success/working state. Even the failure of HFB(X_1) still keeps the system safe. Since the system is in safe state, all three barriers related to safe sequence have significant contribution to keep it safe. This individual contribution can be estimated through backward analysis approach. Now to estimate HFB(X_1) contribution while the system is in safe state, following equation has been used:

$$P(X_1 \mid Safe = yes) = \frac{\sum_{X_2, X_3} P(X_1 = S, X_2, X_3, Safe = yes)}{P(Safe = yes)}$$

The numerator can be simplified further using chain rule as follows:

$$\sum_{x_2, x_3} P(X_1 = S, X_2, X_3, Safe = yes)$$

$= \boldsymbol{P(X_1 = S, X_2 = S, X_3 = S, Safe = yes)} + P(X_1 = S, X_2 = F, X_3 = S, Safe = yes)$

$+ P(X_1 = S, X_2 = S, X_3 = F, Safe = yes) + P(X_1 = S, X_2 = F, X_3 = F, Safe = yes)$

$= \boldsymbol{P(Safe = yes \mid X_1 = S, X_2 = S, X_3 = S)\ P(X_1 = S)\ P(X_2 = S)\ P(X_3 = S)}$

$+ P(Safe = yes \mid X_1 = S, X_2 = F, X_3 = S)\ P(X_1 = S)\ P(X_2 = F)\ P(X_3 = S)$

$+ P(Safe = yes \mid X_1 = S, X_2 = S, X_3 = F)\ P(X_1 = S)\ P(X_2 = S)\ P(X_3 = F)$

$+ P(Safe = yes \mid X_1 = S, X_2 = F, X_3 = F)\ P(X_1 = S)\ P(X_2 = F)\ P(X_3 = F)$

$= (\mathbf{90.48 \times 10^{-2}} * 99.71 \times 10^{-2} * 95.79 \times 10^{-2} * 94.73 \times 10^{-2}) + 0 + 0 + 0$

$= 81.86 \times 10^{-2}$

[Since, $P(Safe = yes \mid X_1 = S, X_2 = S, X_3 = S) = 99.71 \times 10^{-2} * 95.79 \times 10^{-2} * 94.73 \times 10^{-2} = \mathbf{90.48 \times 10^{-2}}$]

Here, only success state of all three barriers is considered. Failure of other barriers resulted in system fail and '0' probabilities. The *P(Safe)* value in denominator is available from 19th month as 87.43×10^{-2}. The final result 93.63×10^{-2} is contributed by human factor barrier (HFB) to keep the system safe.

$\boldsymbol{P(X_1 \mid Safe = yes)} = P(X_1 \ \&\ Safe = yes) / P(Safe = yes)$

$= 81.86 \times 10^{-2} / 87.43 \times 10^{-2}$

$= \mathbf{93.63 \times 10^{-2}}$

Similarly, following conditional probability table contribution of each factor barrier can be estimated in occurrence of end events. The contribution of safety barriers viz. X_1, X_2, X_3, X_4, X_5, X_6 and X_7 are listed here while the system is in 'safe' to 'catastrophic' state.

State	$P(X_1)$	$P(X_2)$	$P(X_3)$	$P(X_4)$	$P(X_5)$	$P(X_6)$	$P(X_7)$
Prior Values	99.71×10^{-2}	95.79×10^{-2}	94.73×10^{-2}	93.84×10^{-2}	89.40×10^{-2}	97.29×10^{-2}	89.12×10^{-2}
Safe	93.64×10^{-2}	93.64×10^{-2}	93.64×10^{-2}	-	-	-	-
Near miss	2.99×10^{-2}	2.98×10^{-2}	-	2.99×10^{-2}	-	-	-
Mishap	0.0	0.0	-	-	0.0	-	-
Incident	5.83×10^{-7}	5.83×10^{-7}	-	-	-	5.83×10^{-7}	-
Accident	8.36×10^{-12}	8.36×10^{-12}	-	-	-	-	8.36×10^{-12}
Catastrophe	0.0	0.0	-	-	-	-	-

Here 'success' contribution of the safety barriers X_1, X_2, X_3 are estimated while these are in 'safe' state and rest X_4, X_5, X_6 and X_7 are in 'failure' state. Adding up all the contribution in all state for X_1, X_2, X_3 and $(1 - contribution)$ for X_4, X_5, X_6 *and* X_7 are listed as follows:

Barrier Success Probabilities	$P(X_1)$	$P(X_2)$	$P(X_3)$	$P(X_4)$	$P(X_5)$	$P(X_6)$	$P(X_7)$
	96.63×10^{-2}	96.62×10^{-2}	93.64×10^{-2}	97.01×10^{-2}	1.0	1.0	1.0

Matlab code and step by step analysis is available in Appendix C and D.

Now, updated barrier success probabilities have been estimated after using 'prior' success values of the safety barriers and 19th month 'posterior' information of the end events. To estimate new values for the barriers, updated barrier success probabilities need to be considered as prior information from the above table and the 20th month 'posterior' information of the end events as normalizing factor in denominator.

State	$P(X_1)$	$P(X_2)$	$P(X_3)$	$P(X_4)$	$P(X_5)$	$P(X_6)$	$P(X_7)$
Prior Values	96.63×10^{-2}	96.62×10^{-2}	93.64×10^{-2}	97.01×10^{-2}	1.0	1.0	1.0
Safe	89.54×10^{-2}	89.65×10^{-2}	89.65×10^{-2}	-	-	-	-
Near miss	3.25×10^{-2}	3.25×10^{-2}	-	3.25×10^{-2}	-	-	-
Mishap	1.09×10^{-4}	1.09×10^{-4}	-	-	1.09×10^{-4}	-	-
Incident	0.0	0.0	-	-	-	0.0	-
Accident	0.0	0.0	-	-	-	-	0.0
Catastrophe	0.0	0.0	-	-	-	-	-

Adding up all the contribution in all state for X_1, X_2, X_3 and (1 – *contribution*) for X_4, X_5, X_6 and X_7 follows:

Barrier Success Probabilities	$P(X_1)$	$P(X_2)$	$P(X_3)$	$P(X_4)$	$P(X_5)$	$P(X_6)$	$P(X_7)$
	92.80×10^{-2}	92.91×10^{-2}	89.65×10^{-2}	96.75×10^{-2}	99.99×10^{-2}	1.0	1.0

These barrier success probabilities will be updated in the next time interval, t+1, as new information is available in the system.

Matlab code for the step by step analysis is given in Appendix C.

CHAPTER 6

Analysis of Results

Activities in LNG processing facilities are dynamic in nature. Any change in system performance, deviation from a safe state to any abnormal state is alarming. Current study has used real life end events data from such LNG process facilities. The improved accident model used for current case study comprises of seven non-sequential safety barriers; human, management & organizational, release prevention, dispersion prevention, ignition prevention, escalation prevention and damage control prevention barrier to illustrate the accident scenario. It is important to study the performance of the human factor barrier (HFB) and management & organizational barrier (M&OB) as they play a critical role in well integrity and decision making. The prior failure probabilities of safety barriers indicate vulnerability of the system or performance of safety barriers to intercept the accident sequence. The failure probabilities (prior values) of each safety barrier were estimated through relevant fault tree simulation [2, 66, 135] of a particular LNG processing unit to test the models' validity. In the improved methodology, the 24 months LNG process facility data are analyzed related to end events. In subsequent steps, plant real-time end event data is used to formulate the likelihood probabilities. Using the prior belief and likelihood data, posterior occurrence probabilities for end events have been estimated. As the new information is received, the prior failure probabilities of safety barriers are updated using Bayesian theorem. It is noticed that the results were directly supported by plant specific data. The posterior probabilities of end events' viz. safe, near miss, mishap, incident, accident and catastrophe are shown in Figures 6.1 to 6.6.

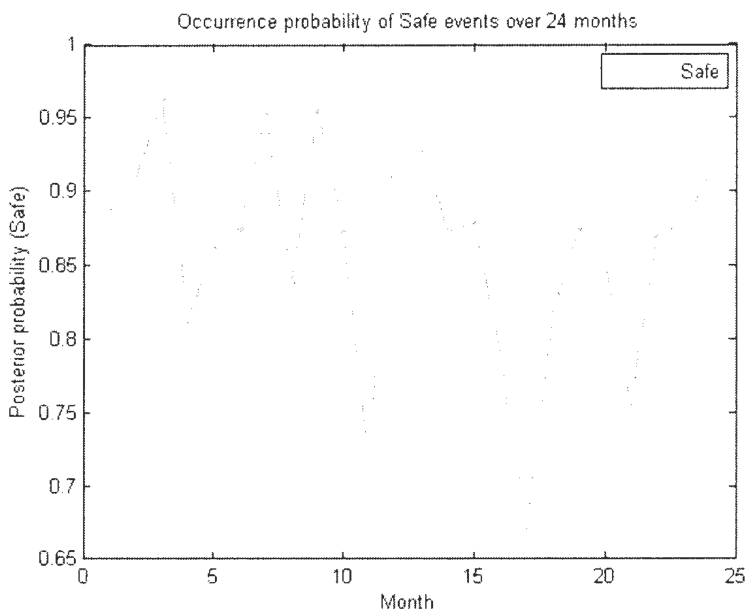

Figure 6.1: Posterior Occurrence Probabilities of Safe Events Over 24 Months

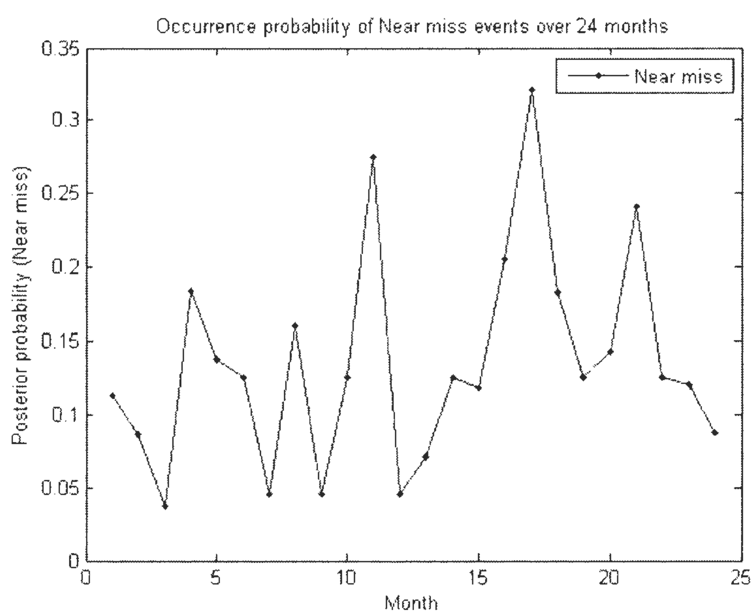

Figure 6.2: Posterior Occurrence Probabilities of Near miss Events Over 24 Months

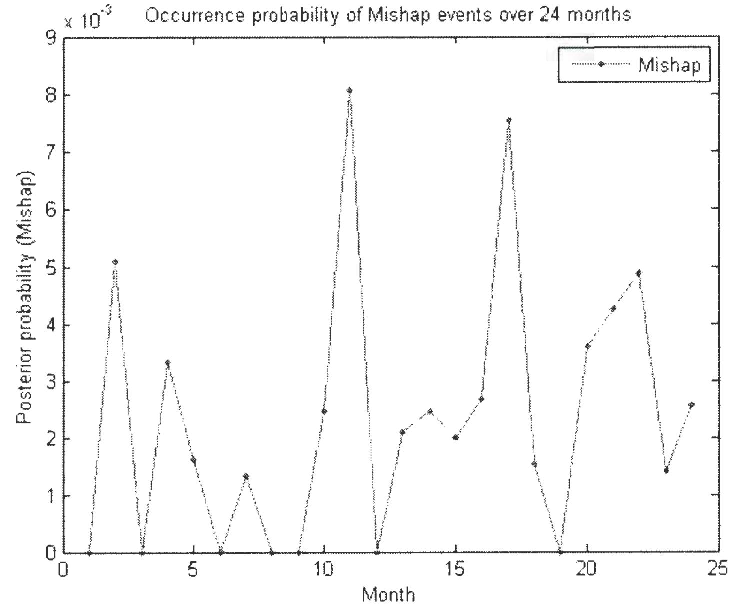

Figure 6.3: Posterior Occurrence Probabilities of Mishap Events Over 24 Months

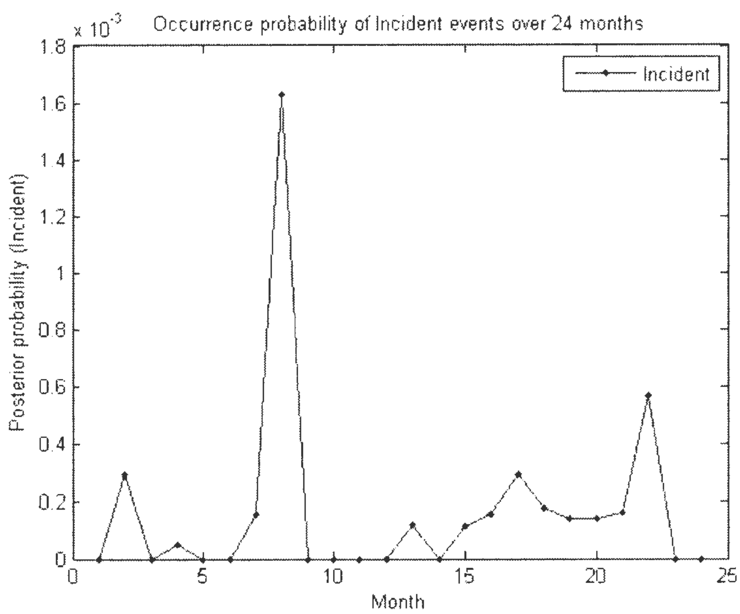

Figure 6.4: Posterior Occurrence Probabilities of Incident Events Over 24 Months

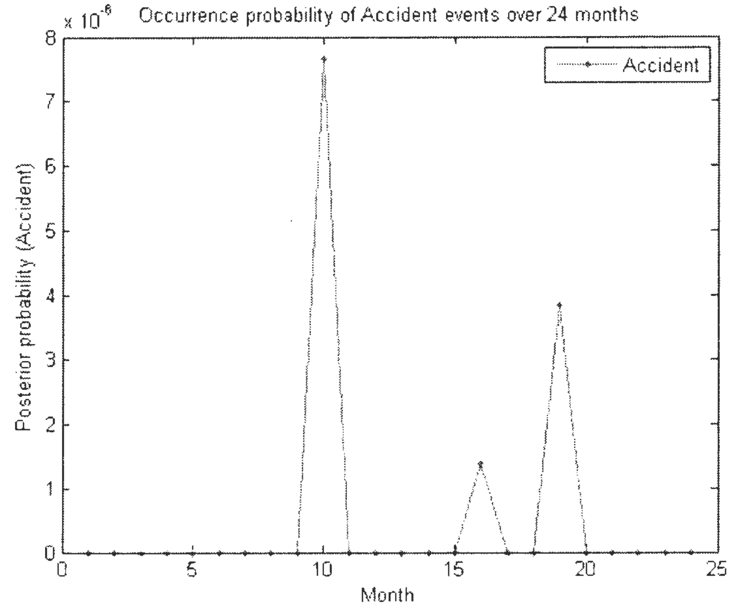

Figure 6.5: Posterior Occurrence Probabilities of Accident Events Over 24 Months

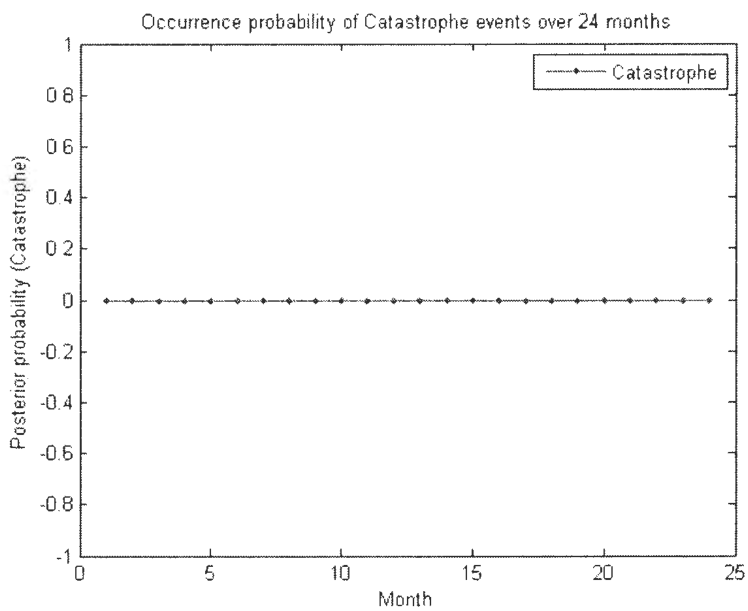

Figure 6.6: Posterior Occurrence Probabilities of Catastrophe Events Over 24 Months

Analysis of above Figures highlight that the end events' occurrence probabilities over the time period have been changed drastically as new information is integrated into the analysis. Occurrence probabilities have been changed significantly from its initial belief. With some exception in the month of April of 2008 and 2009, end events' occurrence is relatively higher compare to other months from the beginning of year 2009. Probability of 'Safe' events' occurrence is reduced and as a result, 'near miss' and 'mishap' are getting increased. 'Incident' and 'accident' are gradually decreased. In the month of April, it's comparatively higher than any other months though near miss events are high in those months. It is evident that the safe events have a higher occurrence probability at the beginning of the analysis. As it can be seen from Figure 6.1, the posterior probability is fluctuating all over the months which are never been steady. Near miss occurrence in Figure 6.2 shows almost same but upward fluctuation. The number of occurrences is on top in the month of April of the year 2009 as it reaches to the peak. Rest of the Figures (6.5 and 6.6) show a little fluctuation as there are not enough incident and accident events have taken place. Only three accident occurrences with low priority (7.02×10^{-6}, 1.27×10^{-6}, 3.52×10^{-6}) has been observed; however no catastrophe has been detected in that time period. The performance of the system is degraded with time which might result in higher occurrence probability of near misses and mishap events. Therefore, the prior estimation of consequences indicates that this particular LNG facility observes accidents with very low frequency whereas the observation of near misses is frequent. The past accident statistical data in different process industries displayed the same phenomena. In reality, events such as near misses and mishaps are more frequent than incidents or accidents. Therefore, the model results are significantly supported by real data. However, end event probabilities over the months of the year 2008 and 2009 change significantly as new data are integrated into the analysis. The safe event has a high probability of occurrence at the beginning and as time goes by the probability is reduced from 9.07×10^{-1} to 8.87×10^{-1} at the beginning of January 2008 and then increased to 9.07×10^{-1} at the beginning of January 2009. The lowest occurrence probability has been observed to 6.71×10^{-1} in the month of May of 2009. Furthermore, high severity events have low probabilities of occurrence at the beginning. As time goes by, the likelihood of event occurrence dramatically increases. The probability of "accident" occurrence changes from 1.46×10^{-5} to 3.52×10^{-6}.

For model comparison, occurrence probabilities are estimated using the prior failure probabilities of safety barriers in both revised event tree and Bayesian network and the outcome are relatively favorable. After observing these results, it is assumed that the chance of system being safe is 9.07×10^{-1} which is relatively high compare to other end events' results. The probability of accident and catastrophic accident causation are respectively, 1.46×10^{-5} and 1.78×10^{-6}. Similar prior belief or failure probabilities of the safety barrier are used in revised event tree which gives 9.07×10^{-1} for system being safe whereas, 2.30×10^{-5} for being an accident and 3.95×10^{-7} for a catastrophic accident. From both observations, it is clear that the improved model is applicable to real life accident scenarios in any process industry with minor adjustment. Due to end event occurrence in process facility, safety measures are undertaken whether it's mechanical or management concern. Variation of posterior probability (Figure 6.1 to 6.6) distribution over time period indicates impairment of the LNG process facility.

Bayesian network analysis is engaged to estimate updated occurrence probabilities of end events. Forward and backward conditional probability approach help to identify the contribution of each safety barrier in occurrence of any end events. In addition, conditional probability table (Table 5.10) is used to identify safety barrier's contribution in occurrence of end events. For justification, posterior probability of the 19^{th} and 20^{th} month has been taken into consideration. Updated barrier success probabilities have been estimated after using prior success values of the safety barriers and 19^{th} month posterior information of the end events. To estimate new values for the barriers, updated barrier success probabilities has been considered as prior information and the 20^{th} month posterior information of the end events as normalizing factor in denominator. Adding up all the contribution of safety barriers in each occurrence level provides updated success probabilities to end. These updated safety barriers' success probability can be used to predict the probabilities of end events' occurrence in the next time interval.

CHAPTER 7

Discussion and Conclusions

A review of existing accident modeling approaches provides a complex picture of accident occurrence in process facility. Fault and event tree sequential method is fairly common in industrial accident modeling while non-sequential approach Bayesian network methodology is fairly a new concept. It is evident that the majority of existing models focus on sequential accident approach. As in real life, occurrence of non-sequential events' might happen in any stage. The improved methodology with non-sequential characteristics gives the ability to overcome this issue. In the current study, the restrictive sequential event assumption in SHIPP methodology is relaxed by allowing non-sequential failure of safety barriers to cause adverse event of any order. Hence, Bayesian updating methodology is proposed to model LNG process safety. In existing model, end event's sequence has been clearly demonstrated in every stage. The proposed non-sequential model has been translated from the original SHIPP model with inclusion of improved feature. The methodology is applicable for modeling probable accident scenarios, and evaluating their occurrence probability using industry specific data. The application of the proposed Bayesian network based accident model has been demonstrated on a typical LNG process facility. The model has been validated using the plant specific 24 month's real time data. Current case study analysis uses seven non-sequential safety barriers; human, management & organizational, release prevention, dispersion prevention, ignition prevention, escalation prevention and damage control prevention barrier to illustrate the accident scenario. This case study shows that inclusion of two more important safety barriers viz. human and management & organizational factors, has made a significant difference in current study. In addition, an important mechanical safety barrier viz. Damage Control and Emergency Management Barrier (DCEMB) is included in the prediction of posterior probabilities of adverse events for real time industrial data and as a result an adverse event of highest order viz. Catastrophe is included in the study. The end events i.e. safe, near miss, mishap, incident, accident and catastrophe are the outcome events of safe sate deviation for an abnormal operation (e.g., LNG release).

The 24 months real time raw data from LNG process plant are used for the current study with frequent number of adverse event occurrence in every month. Bayes' theorem is convenient to estimate posterior probabilities of end events for the current study. Similarly, to obtain the posterior information or update the safety barrier success/failure probabilities real-time, Bayes' theorem has been used. For LNG release case study, occurrence probabilities of end events are estimated using forward analysis. From the graphical representation, it is clear that the posterior probability is fluctuating over the months except for the catastrophe events. In studied example, near misses and mishaps are more frequent than incidents or accidents. It also demonstrates a higher probability of occurrence of safe events; as time goes by, the system degrade and safety barrier performance is reduced which causes incidents and accidents to occur in the process facility. From the prior data, it has been observed accident occurrence with very low frequency whereas the occurrence of near miss is frequent. The end event probabilities over the months of the year 2008 and 2009 change significantly as new data are integrated into the analysis. The posterior probabilities are used to update the safety barrier failure probabilities through a backward analysis and in turn update the estimates of the likelihood continually. To test the improved model, expert opinion, literature review and process component failure data are used to estimate prior failure probabilities of the safety barrier through relevant fault tree simulation. The result (prior estimation) obtained through revised event tree and Bayesian network analysis is directly supported by the updated (posterior estimation) result, which supports the numerical validation.

The proposed improved methodology can predict the occurrence probability of the next time internal as soon as the updated barrier success/failure probabilities are available. The method helps to identify and estimate contribution of different barriers in accident causation. From the analysis, it has been observed that the model is flexible to incorporate new knowledge or evidence and yields updated probabilities and provides revised likelihood estimates for the end events. Based on the current study, it can be concluded that the improved methodology can be applied to real-life accident prediction and development of accident prevention strategies. The proposed accident model is applicable to offshore oil and gas process industry; however, with further modification it can be applied to other industrial facilities including mechanical pipeline and marine industries for analyzing likelihood of possible accident scenarios.

CHAPTER 8

Future Works

There are several improvements can be implemented in proposed methodology:

- **Uncertainty analysis:** Uncertainty analysis or error propagation needs to be included as the value has been calculated from several measured numbers.
- **Non-cyclic network:** To display an event's consequence, sometimes non-cyclic network is essential in real life analysis. Therefore it needs to be considered during graphical illustration.
- **Testing and validation:** The model can be tested and validated with a new set of data which is required.
- **Tools:** Several tools are recommended for testing and analysis. Hence, a tool needs to be developed for easy and effective use.
- **Results:** Results can be altered to suite the need of the user; they can be displayed graphically in a chart.

Bibliography

[1] Rathnayaka, S., Khan, F., and Amyotte, P. R. SHIPP methodology: Predictive accident modeling approach. Part I: Methodology and model description. *Journal of Process Safety and Environmental Protection*, 89:151-164, 2011. DOI: 10.1016/j.psep.2011.01.002

[2] Rathnayaka, S., Khan, F., and Amyotte, P. R. SHIPP methodology: Predictive accident modeling approach. Part II: Validation with case study. *Journal of Process Safety and Environmental Protection*, 89:75-88, 2011. DOI: 10.1016/j.psep.2010.12.002

[3] Pula, R., Khan, F., Veitch, B., Amyotte, P. R. Revised fire consequence models for offshore quantitative risk assessment. *Journal of Loss Prevention in the Process Industries*, 18(4-6):443-454, 2005. DOI: 10.1016/j.jlp.2005.07.014

[4] CSB. *Refinery Explosion and Fire*. Investigation Report No. 2005-04-I-TX, Washington, DC, 2007. Available at: http://www.csb.gov/assets/document/CSB FinalReportBP.pdf, Accessed on Dec. 28, 2012.

[5] Kalantarnia, M., Khan, F., and Hawboldt, K. Dynamic risk assessment using failure assessment and Bayesian theory. *Journal of Loss Prevention in the Process Industries*, 22(5):600-606, 2009. DOI: 10.1016/j.jlp.2009.04.006

[6] Mogford, J. *Fatal accident investigation report, isomerization unit explosion final report*, BP Texas City, Texas, USA, Dec. 9, 2005. Available at: http://www.bp.com/liveassets/bp_internet/us/bp_us_english/STAGING/local_ assets/downloads/t/final_report.pdf. Accessed on Dec. 28, 2012.

[7] Vinnem, J. E. On the analysis of hydrocarbon leaks in the Norwegian offshore industry. *Journal of Loss Prevention in the Process Industries*, 25(4):709-717, 2012. DOI: 10.1016/j.jlp.2012.03.009

[8] Bozeman, B. The 2010 BP Gulf of Mexico oil spill: Implications for theory of organizational disaster. *Technology in Society*, 33(3-4):244-252, 2011. DOI: 10.1016/j.techsoc.2011.09.006

[9] Fruedenburg, W., and Gramling, R. *Blowout in the Gulf: the BP Oil Spill Disaster and the Future of Energy in America*. Cambridge, MA: MIT Press, 2010.

[10] Presidential Commission. *Deepwater, the Gulf oil disaster and the future of offshore drilling*. Report to the President, National commission on the DP Deepwater Horizon oil spill and offshore drilling, 2011. Available at: http:// www.oilspillcommission.gov/sites/default/files/documents/DEEPWATER_ ReporttothePresident_FINAL.pdf, Accessed on Nov. 18, 2012.

[11] Reed, S., and Fitzgerald, A. *In: Too Deep: BP and the Drilling Race That Took It Down*. Wiley/Bloomberg Press, 2011.

[12] Skogdalen, J. E., and Vinnem, J. E. Quantitative risk analysis offshore - Human and organizational factors. *Reliability Engineering & System Safety*, 96(4): 468-479, 2011. DOI: 10.1016/j.ress.2010.12.013

[13] Transocean Ltd. *Update on semisubmersible drilling rig deepwater horizon*. News Release, Apr. 21-22, 2010. Available at: http://www.deepwater.com/fw/ main/News-748.html?c=113031&p=irol-news&nyo=0, Accessed on Nov. 18, 2012.

[14] CSB. *Sugar Dust Explosion and Fire*. Investigation Report No. 2008-05-I-GA, Washington, DC, 2009. Available at: http://www.csb.gov/assets/document/Imperial_Sugar_Report_Final_updated.pdf, Accessed on Dec. 20, 2012.

[15] Chowdhury, J., and Parkinson, G. OSHA tightens its hold. *Chemical Engineering*, 99(5):37, 1992.

[16] Haastrup, P., and Brockhoff, L. Severity of accidents with hazardous materials: A comparison between transportation and fixed installations. *Journal of Loss Prevention in the Process Industries*, 3(4):395-405, 1990. DOI: 10.1016/0950-4230(90)80010-8

[17] Khan, F., and Abbasi, S. A. Simulation of accidents in a chemical process industry using software MAXCRED. *Indian Journal of Chemical Technology*, 3:338-344, 1996.

[18] Khan, F., and Abbasi, S. A. Risk analysis of an epichlorohydrin manufacturing industry using the new computer automated tool MAXCRED. *Journal of Loss Prevention in the Process Industries*, 10(2):91-100, 1997. DOI: 10.1016/S0950-4230(96)00042-3

[19] Khan, F., and Abbasi, S. A. Major accidents in process industries and an analysis of causes and consequences. *Journal of Loss Prevention in the Process Industries*, 12(5):361-378, 1999. DOI: 10.1016/S0950-4230(98)00062-X

[20] Lees, F. P. *Loss Prevention in Chemical Process Industries*. London: Butterworth, 1996.

[21] Nash, J. R. *Darkest Hours*. Chicago: Nelson Hall, 1976.

[22] Taylor, J. R. Use of simulation for emergency planning and training. *Health, Safety and Loss Prevention*, 387:114-119, 1993.

[23] Thomas, I. F. The politics of safety. *Chemical Engineering of Australia*, 20(1):14-20, 1995.

[24] CH-IV International. *Have there been any serious LNG accidents*? Available at: http://www.ch-iv.com/lng_information.html, Accessed on November 18, 2012.

[25] Lees, F. P. Accident fatality number - a supplementary risk criterion. *Loss Prevention and Safety Promotion*, 3(2), 426, 1980.

[26] Lees, F. P. Major accident inquiries - lawyers or engineers? *Process Safety Environment*, 72B, 10, 1994.

[27] Lees, F. P., and Ang, M. L. *Safety Cases in Control of Industrial Major Accident Hazards (CIMAH - regulation 1984)*. London: Butterworth, 1984.

[28] Lewis, D. J. Case histories of past accidents, the causes and consequences. In Petts, J. I., *Major Hazard Installation: Planning and Assessment*. Loughborough University of Technology, UK, 1984.

[29] Lewis, D. J. *Case Histories: Accidents*. Department of Chemical Engineering, Loughborough University of Technology, UK, 1993.

[30] Wikipedia. *Liquefied natural gas*. Available at: http://en.wikipedia.org/wiki/Liquefied_natural_gas, Accessed on Nov. 18, 2012.

[31] Kim, B. K., Krams, J., Krug, E., Leaseburge, M., Lemley, J., Alkhawaldeh, A., Mentzer, R. A., Mannan, M. S. Case study analysis of the financial impact of catastrophic safety events. *Journal of Loss Prevention in the Process Industries*, 25(5):780-787, 2012. DOI: 10.1016/j.jlp.2012.05.006

[32] Kletz, T. A. Process safety: An engineering achievement. In Proceedings of the Institution of Mechanical Engineers. Part E: *Journal of Process Mechanical*

Engineering, 205(1):11-15, Feb. 1991. DOI: 10.1243/PIME_PROC_1991_205_190_02

[33] Cutler, T., and James, P. Does safety pay? A critical account of the Health and Safety Executive document: 'The Costs of Accidents'. *Work, Employment & Society*, 10(4):755-765, 1996. DOI: 10.1177/0950017096104008

[34] Industry Commission (IC). *Work, Health and Safety*, Vol. 2. AGPS, Canberra, 1995.

[35] Hopkins, A. For whom does safety pay? The case of major accidents. *Safety Science*, 32(2-3):143-153, 1999. DOI: 10.1016/S0925-7535(99)00017-X

[36] Kletz, T. A. *Learning from Accidents*. Oxford: Butterworth - Heinemann, 1994.

[37] Sarangi, S., Zaidi, T., Pal, R. K., Katgara, D., Gadag, V. G., Mulay, S., Varma, D. R. Effects of exposure of parents to toxic gases in Bhopal on the offspring. *American Journal of Industrial Medicine*, 53(8):836-841, 2010. DOI: 10.1002/ajim.20825

[38] Lepkowski, W. The restructuring of Union Carbide. In: Jasanoff, S. (Ed.), *Learning from Disaster: Risk Management after Bhopal*. University of Pennsylvania, Philadelphia, pages 22-43, 1994.

[39] NOHSC. *The Cost of Work - Related Injury and Disease*. AGPS, Canberra, 1994.

[40] IEC 61508. *Functional safety of electrical/electronic/programmable electronic safety related system*. Parts I to VII, Geneva, Switzerland: International Electrotechnical Commission, 1998-2000.

[41] Qureshi, Z. H. A review of accident modeling approaches for complex socio-technical systems. In *Proceedings of the twelfth Australian workshop on Safety*

critical systems and software and safety-related programmable systems - Volume 86 (SCS '07), Tony Cant (Ed.), 86:47-59. Darlinghurst, Australia: Australian Computer Society, Inc., 2007.

[42] DNV Technica Ltd. Update of the UKCS Risk Overview. *HSE: Offshore Technology Report*, OTH 94 458, London, UK: HSE Books, 1995.

[43] Khan, F., and Amyotte, P. Inherent safety in offshore oil and gas activities: a review of the present status and future directions. *Journal of Loss Prevention in the Process Industries*, 15(4):279-289, 2002. DOI: 10.1016/S0950-4230(02) 00009-8

[44] Kletz, T. A. "What you don't have, can't leak". *Chemistry and Industry*, 6:287-292, 1978.

[45] Mannan, M. S., West, H. H., Krishna, K., Aldeeb, A. A., Keren, N., Saraf, S. R., Liu, Y., Gentile, M. The legacy of Bhopal: The impact over the last 20 years and future direction. *Journal of Loss Prevention in the Process Industries*, 18(4-6):218-224, 2005. DOI: 10.1016/j.jlp.2005.06.037

[46] Mansfield, D. P., Kletz, T. A., and Al-Hassn, T. Optimizing Safety by Inherent Offshore Platform Design. In *Proceedings of 1996 OMAE Conference*-Volume 2 (Safety and Reliability), Florence, Italy, Jun 16-20, 1996.

[47] Mansfield, D. P., Poulter, L., and Kletz, T. A. Improving inherent safety. *HSE: Offshore Technology Report*, OTH 96 521, Suffolk, UK: HSE Books, 1996.

[48] Meel, A., and Seider, W. D. Plant-specific dynamic failure assessment using Bayesian theory. *Chemical Engineering Science*, 61(21):7036-7056, 2006. DOI: 10.1016/j.ces.2006.07.007

[49] Pula, R., Khan, F., Veitch, B., Amyotte, P. R. A grid based approach for fire and explosion consequence analysis. *Process Safety and Environmental Protection*, 84(2):79-91, 2006. DOI: 10.1205/psep.05063

[50] Ferdous, R., Khan, F., Sadiq, R., Amyotte, P., Veitch, B. Analyzing system safety and risks under uncertainty using a bow-tie diagram: An innovative approach. *Process Safety and Environmental Protection*, 91(1-2):1-18, 2013. DOI: 10.1016/j.psep.2011.08.010

[51] HSE. *A guide to the Offshore Installations (Safety Case) Regulations 2005*, 3rd ed. Surrey, UK: HSE Books, 2006.

[52] Mearns, K., and Flin, R. Risk perception and attitudes to safety by personnel in the offshore oil and gas industry: a review. *Journal of Loss Prevention in the Process Industries*, 8(5):299-305, 1995. DOI: 10.1016/0950-4230(95)00032-V

[53] RIDDOR. A Guide to the Reporting of Injuries, Diseases and Dangerous Occurrences Regulations 1995. *Health and Safety Executive*, London, UK, 1995.

[54] Phimister, J. R., Oktem, U., Kleindorfer, P. R., Kunreuther, H. Near-miss incident management in the chemical process industry. *Risk Analysis*, 23(3):445-459, 2003. DOI: 10.1111/1539-6924.00326

[55] Wharton Risk Management and Decision Processing Center. Available at: http://www.wharton.upenn.edu/riskcenter/about.cfm, Accessed on Dec. 28, 2012.

[56] CCPS. Process Safety Incident Database (PSID). Available at: http://www.aiche.org/ccps/resources/psid, Accessed on Dec. 28, 2012.

[57] NRC. National Response Center. Available at: http://www.nrc.uscg.mil/nrchp.html, Accessed on Dec. 28, 2012.

[58] Mannan, M. S., O'Connor, T. M., and West, H. H. Accident history database: An opportunity. *Environmental Progress*, 18(1):1-6, 1999. DOI: 10.1002/ep.670180113

[59] Andersen, S., and Mostue, B. A. Risk analysis and risk management approaches applied to the petroleum industry and their applicability to IO concepts, *Safety Science*, 50(10):2010-2019, 2012. DOI: 10.1016/j.ssci.2011.07.016

[60] Hollnagel, E. The four cornerstones of resilience engineering. In: Nemeth CP, Hollnagel E, Dekker S (Ed.), *Resilience Engineering Perspectives*, Vol 2. (pages 117-134). Farnham, UK: Ashgate Publishing Co., 2009.

[61] Cullen, W. D. *The Pubic Inquiry into the Piper Alpha Disaster*. Vols 1 & 2. London: HMSO, 1990.

[62] Baker Panel. *The BP U.S. refineries independent safety review panel report*, Jan. 2007. Available at: http://www.bp.com/liveassets/bp_internet/globalbp/globalbp_uk_english/SP/STAGING/local_assets/assets/pdfs/Baker_panel_report.pdf, Accessed on Nov. 28, 2012.

[63] Pitblado, R. Global process industry initiatives to reduce major accident hazards. *Journal of Loss Prevention in the Process Industries*, 24(1):57-62, 2011. DOI: 10.1016/j.jlp.2010.08.006

[64] Hollnagel, E. Understanding accidents - from root causes to performance variability. In *IEEE 7 human factors meeting*, Scottsdale, Arizona, 2002.

[65] Leveson, N. A new accident model for engineering safer systems. *Safety Science*, 42(4):237-270, 2004. DOI: 10.1016/S0925-7535(03)00047-X

[66] Rathnayaka, S., Khan, F., and Amyotte, P. R. Accident modeling approach for safety assessment in an LNG processing facility. *Journal of Process Safety and Environmental Protection*, 25(2):414-423, 2012. DOI: 10.1016/j.jlp.2011.09. 006

[67] Huang, Y. H., Ljung, M., Sandin, J., Hollnagel, E. Accident models for modern road traffic: changing times creates new demands. In *SMC (1): International conference on systems, man and cybernetics*, pages 276-281, 2004.

[68] Heinrich, W. H. *Industrial Accident Prevention*, 2nd ed. New York: McGraw-Hill, 1941.

[69] Ferry, T. S. *Modern Accident Investigation and Analysis*, 2nd ed. New York: Wiley, 1988.

[70] Reason, J. *Human Error*. Cambridge: Cambridge University Press, 1990.

[71] Shappell, S. A., and Wiegmann, D. A. *The human factors analysis and classification system - HFACS*. Virginia: National Technical Information Service, 2000.

[72] Kujath, M. F., Amyotte, P., and Khan, F. A conceptual offshore oil and gas process accident model. *Journal of Loss Prevention in the Process Industries*, 23(2):323-330, 2010. DOI: 10.1016/j.jlp.2009.12.003

[73] Lindøe, P. H., Engen, O. A., and Olsen, O. E. Responses to accidents in different industrial sectors. *Safety Science*, 49(1):90-97, 2011. DOI: 10.1016/j.ssci.2009.12. 007

[74] Fleming, M. Safety Culture Maturity Model. Report 2000/049. *Health and Safety Executive*. Colegate, Norwich. Available at: http://www.hse.gov.uk/research/otopdf/2000/oto00049.pdf, 2001.

[75] Baksh, A., Khan, F., Gadag, V., Ferdous, R. Predictive accident modeling through Bayesian network. *Reliability Engineering & System Safety*, (manuscript submitted, RESS-D-13-00125), 2013.

[76] Sklet, S. Hydrocarbon releases on oil and gas production platforms: Release scenarios and safety barriers. *Journal of Loss Prevention in the Process Industries*, 19(5):481-493, 2006. DOI: 10.1016/j.jlp.2005.12.003

[77] OED. Oxford English dictionary online. Available at: http://oxforddictionaries.com/us/definition/american_english/safe, Accessed on Nov. 28, 2012.

[78] HSE. Health and Safety Executive [online]. Available at: http://www.hse.gov.uk/aala/guidance/108-near-miss-reporting.htm, Accessed on Nov. 28, 2012.

[79] Gnoni, M. G., and Lettera, G. Near-miss management systems: A methodological comparison. *Journal of Loss Prevention in the Process Industries*, 25(3):609-616, 2012. DOI: 10.1016/j.jlp.2012.01.005

[80] Jones, S., Kirchsteiger, C., and Bjerke, W. The importance of near miss reporting to further improve safety performance. *Journal of Loss Prevention in the Process Industries*, 12(1):59-67, 1999. DOI: 10.1016/S0950-4230(98)00038-2

[81] Meel, A., O'Neill, L. M., Levin, J. H., Seider, W. D., Oktem, U., Keren, N. Operational risk assessment of chemical industries by exploiting accident databases. *Journal of Loss Prevention in the Process Industries*, 20(2):113-127, 2007. DOI: 10.1016/j.jlp.2006.10.003

[82] OSHA. Occupational Safety & Health Administration [online]. Available at: http://www.osha.gov/SLTC/etools/safetyhealth/mod4_factsheets_accinvest.html, Accessed on Nov. 28, 2012.

[83] OSHEU. Occupational Safety, Health and Environment Unit [online]. Available at: http://www.cardiff.ac.uk/osheu/toolkit/incindex.html#, Accessed on Nov. 28, 2012.

[84] Bea, R. G. Human and organizational factors in reliability assessment and management of offshore structures. *Risk Analysis*, 22(1):29-45, 2002. DOI: 10.1111/0272-4332.t01-1-00003

[85] CCOHS. *Accident investigation*. Available at: http://www.ccohs.ca/oshanswers/hsprograms/investig.html, Accessed on Dec. 20, 2012.

[86] RoSPA. *What is the definition of an accident*? Available at: http://www.rospa.com/faqs/detail.aspx?faq=255, Accessed on Dec. 28, 2012.

[87] Sklet, S. Safety barriers: definition, classification, and performance. *Journal of Loss Prevention in the Process Industries*, 19(5):494-506, 2006. DOI: 10.1016/j.jlp.2005.12.004

[88] Suchman, E. A. A conceptual analysis of the accident phenomenon. *Social Problems*, 8(3):241-253, 1961. DOI: 10.2307/798914

[89] Lepkowski, W. The Restructuring of Union Carbide. In: Jasanoff, S. (Ed.), *Learning from Disaster: Risk Management after Bhopal* (pages 22-43), Philadelphia: University of Pennsylvania, 1994.

[90] Mannan, M. S. *Lees' Loss Prevention in the Process Industries*, 3rd ed. Butterworth-Heinemann, 2005.

[91] Gibson, J. J. Contribution of experimental psychology to formulation of the problem of safety. In *Behavioural Approaches to Accident Research*. Association for the Aid of Crippled Children, London, 1961.

[92] Haddon, W. Jr. *The Prevention of Accidents. Preventive Medicine*. Little, Brown and Co., Boston, MA, 1966.

[93] Rasmussen, J. Risk management in a dynamic society: a modeling problem. *Safety Science*, 27(2-3):183-213, 1997. DOI: 10.1016/S0925-7535(97)00052-0

[94] Bento, J. P. *Review from an MTO-perspective of five investigation reports from BP (Draft)*. Norway: Stavanger, 2003.

[95] Duijm, N. J., Andersen, H. B., Hale, A., Goossens, L., Hourtolou, D. Evaluating and managing safety barriers in major hazard plants. In *PSAM 7-ESREL '04*, Berlin, Germany, 2004.

[96] Sklet, S. *Safety Barriers on Oil and Gas Platforms*. Trondheim: NTNU, 2005.

[97] Mearns, K., Flin, R., Fleming, M., Gordon, R. Human and organizational factors in offshore safety. *HSE: Offshore Technology Report* OTH 97 543. Suffolk: HSE Books, 1997.

[98] Rasmussen, J., Nixon, P., and Warner, F. Human error and the problem of causality in analysis of accidents. *Philosophical Transactions of the Royal Society of London*, B327(1241):449-462, 1990.

[99] Rasmussen, J. The role of error in organizing behaviour. *Ergonomics*, 33(10-11):1185-1199, 1990. DOI: 10.1080/00140139008925325

[100] Rasmussen, J. Perspectives on the Concept of Human Error. Keynote address at: *Human Performance and Anaesthesio Technology*. Society for Technology in Anaesthesia. Conference: New Orleans, Feb. 1993.

[101] Rasmussen, J. Risk management in a dynamic society: a modeling problem, *Safety Science*, 27(2-3):183-213, 1997. DOI: 10.1016/S0925-7535(97)00052-0

[102] HSE. Breaking down the barriers to safety. *Offshore Technology Report*, OTO 1999 090, London, UK: Health and Safety Executive, 2000.

[103] Altman, J. W. Behavior and accidents. *Journal of Safety Research*, 2(3):109-122, 1970.

[104] Chapanis, A. The Error Provocative Situation. Symposium on measurement of safety performance. *National Safety Council Industrial Conference*, Chicago, Sep 14-17, 1970.

[105] Christensen, J. *Overview of Human Factors in Design*. National Safety Congress, 1972.

[106] Brazier, A. J. A summary of incident reporting in the process industry. *Journal of Loss Prevention in the Process Industry*, 7(3):243-248, 1994. DOI: 10.1016/0950-4230(94)80072-3

[107] Wagenaar, W. A., and Groeneweg, J. Accidents at sea: multiple causes and impossible consequences. *International Journal of Man-Machine Studies*, 27:587-598, 1987.

[108] French, S., Bedford, T., Pollard, S. J. T., Soane, E. Human reliability analysis: A critique and review for managers, *Safety Science*, 49(6):753-763, 2011. DOI: 10.1016/j.ssci.2011.02.008

[109] Helmreich, R. L. On error management: lessons from aviation. *British Medical Journal*, 320:781–785, 2000. DOI: 10.1136/bmj.320.7237.781

[110] Kariuki, S. G., and Löwe, K. Integrating human factors into process hazard analysis. *Reliability Engineering & System Safety*, 92(12):1764-1773, 2007. DOI: 10.1016/j.ress.2007.01.002

[111] United States Nuclear Regulatory Commission. Review of Findings for Human Performance Contribution to Risk in Operating Events (NUREG/CR-6753). US GPO, Washington, DC, 2002. Available at: http://pbadupws.nrc.gov/docs/ML0209/ML020930077.pdf, Accessed on Dec. 28, 2012.

[112] Ren, J., Jenkinson, I., Wang, J., Xu, D. L., Yang, J. B. A methodology to model causal relationships on offshore safety assessment focusing on human and organizational factors. *Journal of Safety Research*, 39(1):87-100, 2008. DOI: 10.1016/j.jsr.2007.09.009

[113] Wu, S., Hrudey, S., French, S., Bedford, T., Soane, E., Pollard, S. A role for human reliability analysis (HRA) in preventing drinking water incidents and securing safe drinking water. *Water Research*, 43(13):3227-3238, 2009. DOI: 10.1016/j.watres.2009.04.040

[114] Institute of Nuclear Power Operations. *An Analysis of Root causes in 1983 Significant Event Reports*. INPO 85-027. Institute of Nuclear Power Operations, Atlanta, 1985.

[115] UK P&I Club. Just waiting to happen: The work of the UK P&I Club. *International Maritime Human Element Bulletin*, 1:3-4, 2003.

[116] Eleye-Datubo, A. G., Wall, A., and Wang, J. Marine and offshore safety assessment by incorporative risk modeling in a fuzzy-Bayesian network of an induced mass assignment paradigm. *Risk Analysis*, 28(1):95-112, 2008. DOI: 10.1111/j.1539-6924.2008.01004.x

[117] Gordon, R. P. E. The contribution of human factors to accidents in the offshore oil industry. *Reliability Engineering & System Safety*, 61(1-2):95-108, 1998. DOI: 10.1016/S0951-8320(98)80003-3

[118] Jacobs, R., and Haber, S. Organizational processes and nuclear power plant safety. *Reliability Engineering & System Safety*, 45(1-2):75-83, 1994. DOI: 10.1016/0951-8320(94)90078-7

[119] Hopwood, A. G. *Accounting and Human Behavior*. London: Haymarket Publishing, 1974.

[120] Johnson, P., and Gill, J. *Management and Organizational Behavior*. London: Paul Chapman Publishing Ltd., 1993.

[121] Reason, J. *Managing the Risks of Organizational Accidents*. Aldershot: Ashgate, 1997.

[122] Aven, T., Sklet, S., and Vinnem, J. E. Barrier and operational risk analysis of hydrocarbon releases (BORA-Release). Part I. Method description. *Journal of Hazardous Materials*, 137(2):681-691, 2006. DOI: 10.1016/j.jhazmat.2006.03.049

[123] Johnson, C. W., and Holloway, C.M. A Longitudinal Analysis of the Causal Factors in Major Maritime Accidents in the USA and Canada (1996-2006). In Proceedings of the 15th Safety-Critical Systems Symposium, Bristol, UK, Feb. 13-15, Redmill, F. and Anderson, T. (Eds.). *The Safety of Systems*, 85-94, Springer, 2007.

[124] Cox, S., and Cox, T. The structure of employee attitudes to safety: a European example. *Work and Stress*, 5(2):93-106, 1991. DOI: 10.1080/02678379108257007

[125] Turner, B., and Pidgeon, N. *Man-made Disasters*, 2nd ed. London: Butterworth, 1997.

[126] Woodward, J. L., and Pitblado, R. M. *LNG Risk Based Safety: Modeling and Consequence Analysis*. New Jersey: John Wiley & Sons, Inc, 2010.

[127] Jensen, F. V., and Nielsen, T. D. *Bayesian Networks and Decision Graphs*, 2nd ed. New York: Springer, 2007.

[128] Detcher, R., and Mateescu, R. Mixtures of deterministic-probabilistic networks and their search space. In *Proceedings of the 20th conference on uncertainty in artificial intelligence*, 120-129, 2004.

[129] Wang, Y. F., Xie, M., Chin, K., Fu, X. J. Accident analysis model based on Bayesian network and evidential reasoning approach, *Journal of Loss Prevention in the Process Industries*, 26(1):10-21, 2013. DOI: 10.1016/ j.jlp.2012.08.001

[130] Bobbio, A., Portinale, L., Minichino, M., Ciancamerla, E. Improving the analysis of dependable systems by mapping fault trees into Bayesian networks. *Reliability Engineering & System Safety*, 71(3):249-260, 2001. DOI: 10.1016/ S0951-8320(00)00077-6

[131] Neil, M., Fenton, N., and Nielson, L. Building large-scale Bayesian networks. *The Knowledge Engineering Review*, 15(3):257-284, 2000.

[132] Pearl, J. *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference, Series in Representation and Reasoning*. San Mateo, CA: Morgan Kaufmann Publishers, 1988.

[133] Khakzad, N., Khan, F., and Amyotte, P. Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches. *Reliability*

Engineering & System Safety, 96(8):925-932, 2011. DOI: 10.1016/j.ress.2011.03.012

[134] Hubbard, D. *How to measure anything: Finding the Value of Intangibles in Business*. Manhattan: John Wiley & Sons, 2007.

[135] Rathnayaka, S., Khan, F., and Amyotte, P. R. Accident modeling and risk assessment framework for safety critical decision-making: application to deepwater drilling operation. Proceedings of the Institution of Mechanical Engineers, Part O: *Journal of Risk and Reliability*, 227(1):86-105, 2013. DOI: 10.1177/1748006X12472158

[136] Bernatik, A., Senovsky, P., and Pitt, M. LNG as a potential alternative fuel - Safety and security of storage facilities. *Journal of Loss Prevention in the Process Industries*, 24(1):19-24, 2011. DOI: 10.1016/j.jlp.2010.08.003

[137] CEE. *The LNG value chain*. Available at: http://www.beg.utexas.edu/energyecon/lng/LNG_introduction_08.php, Accessed on Dec. 20, 2012.

[138] Bernatik, A., Zimmerman, W., Pitt, M., Strizik, M., Nevrly, V., Zelinger, Z. Modelling accidental releases of dangerous gases into the lower troposphere from mobile sources. *Process Safety and Environmental Protection*, 86(3):198-207, 2008. DOI: 10.1016/j.psep.2007.12.002

[139] Horn, A. J. V., and Wilson, R. The potential risks of liquefied natural gas. *Energy*, 2(4):375-389, 1977. DOI: 10.1016/0360-5442(77)90003-2

[140] Huang, S., Chiu, C., and Elliot, D. *LNG: Basics of Liquefied Natural Gas*. USA: University of Texas, 2007.

Appendix A

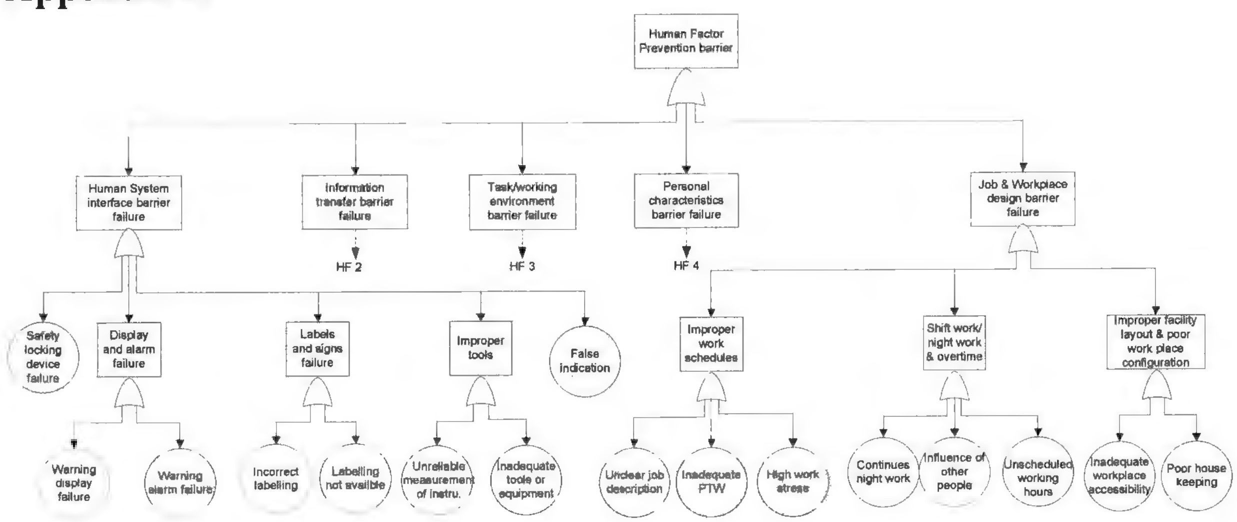

Figure A1: Fault tree analysis of Human Factor Barrier (HFB) failure [1, 66]

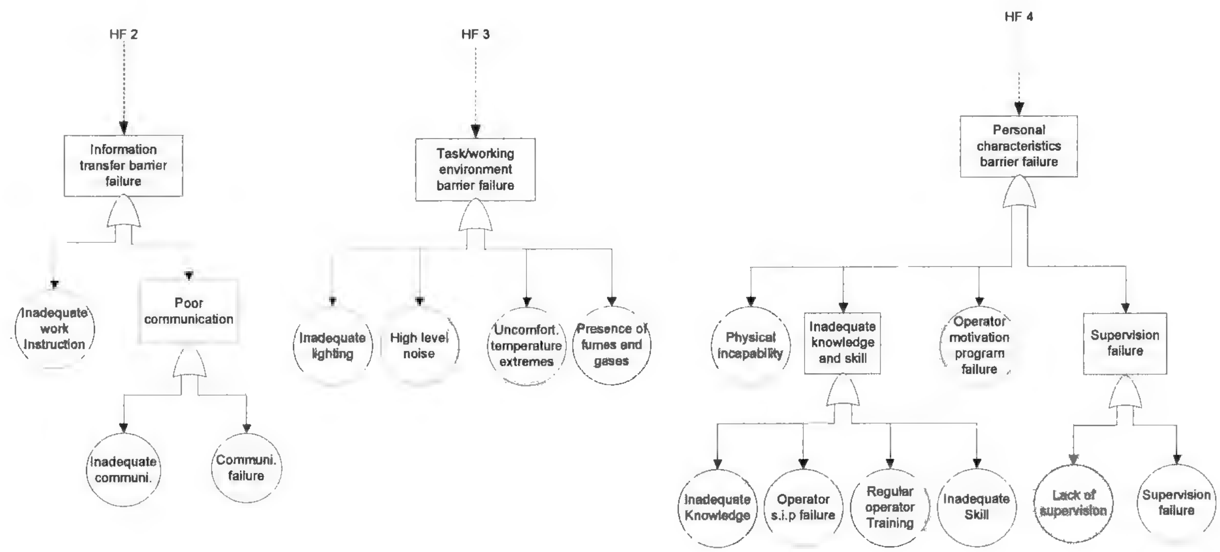

Figure A1: (Continued) Fault tree analysis of Human Factor Barrier (HFB) failure [1, 66]

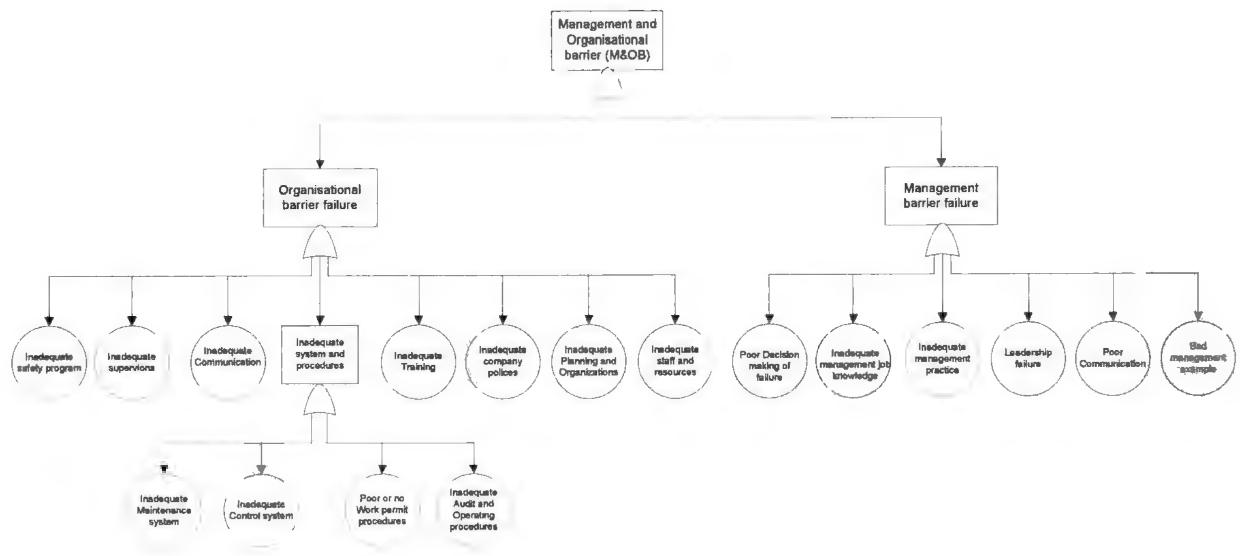

Figure A2: Fault tree analysis of Management and Organizational barrier (M&OB) failure [1, 66]

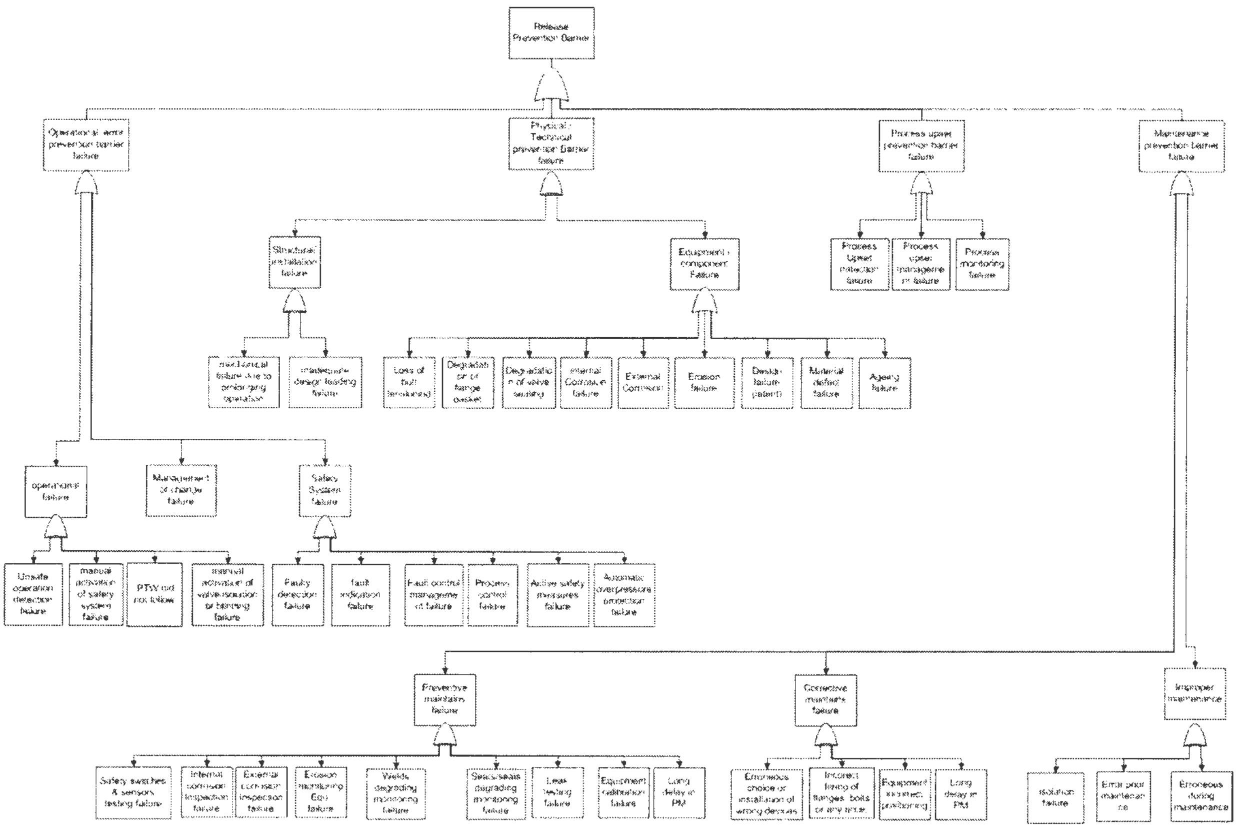

Figure A3: Fault tree analysis of Release Prevention Barrier (RPB) failure [1, 2]

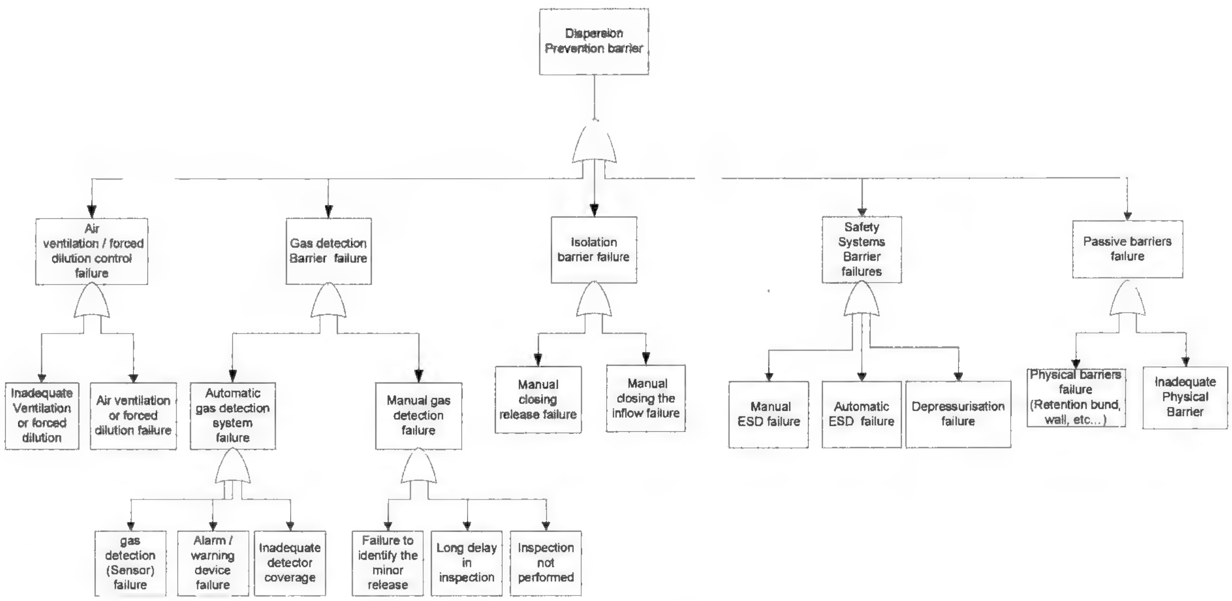

Figure A4: Fault tree analysis of Dispersion Prevention Barrier (DPB) failure [1, 2]

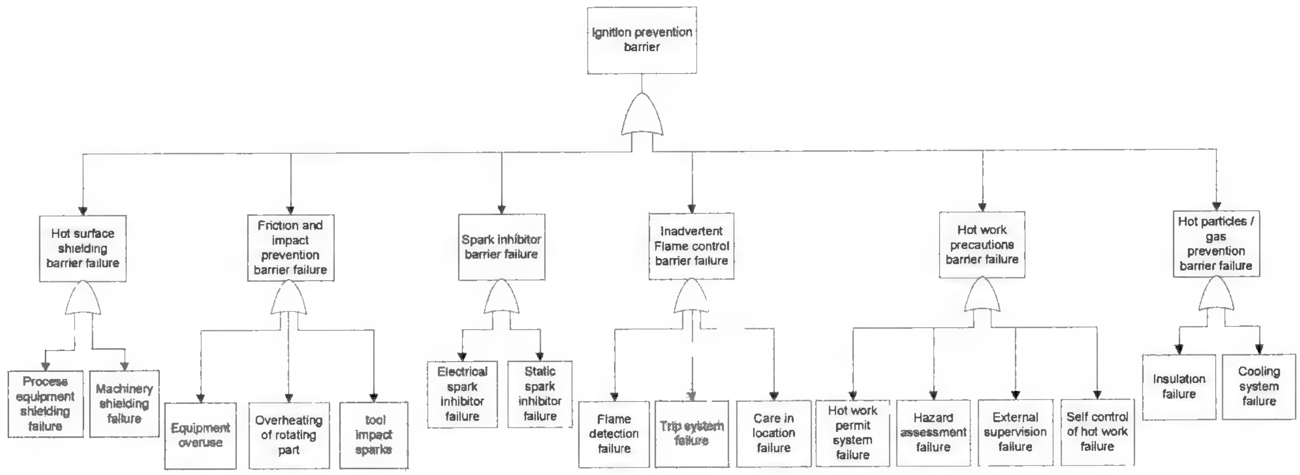

Figure A5: Fault tree analysis of Ignition Prevention Barrier (IPB) failure [1, 2]

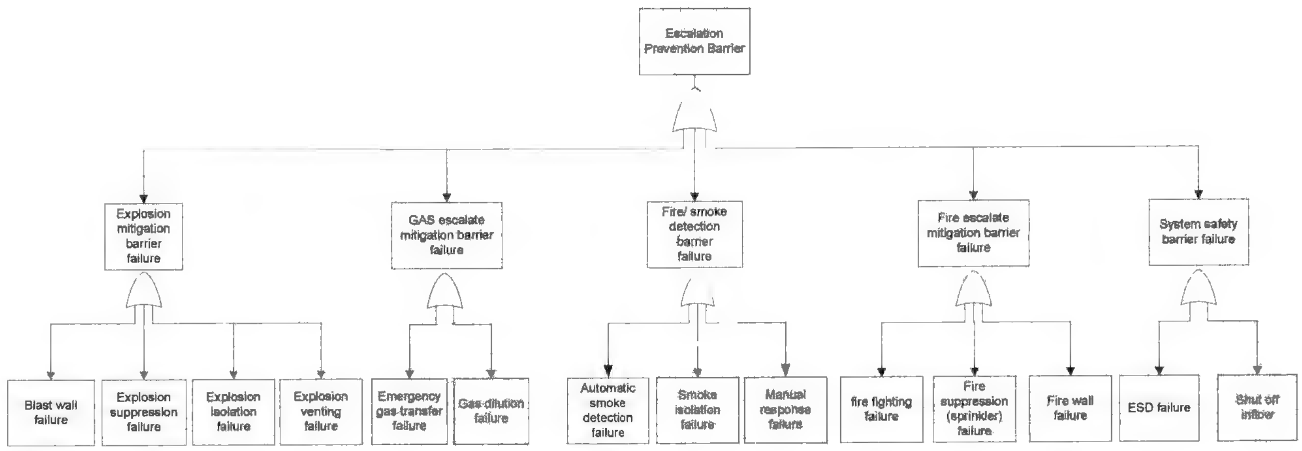

Figure A6: Fault tree analysis of Escalation Prevention Barrier (EPB) failure [1, 2]

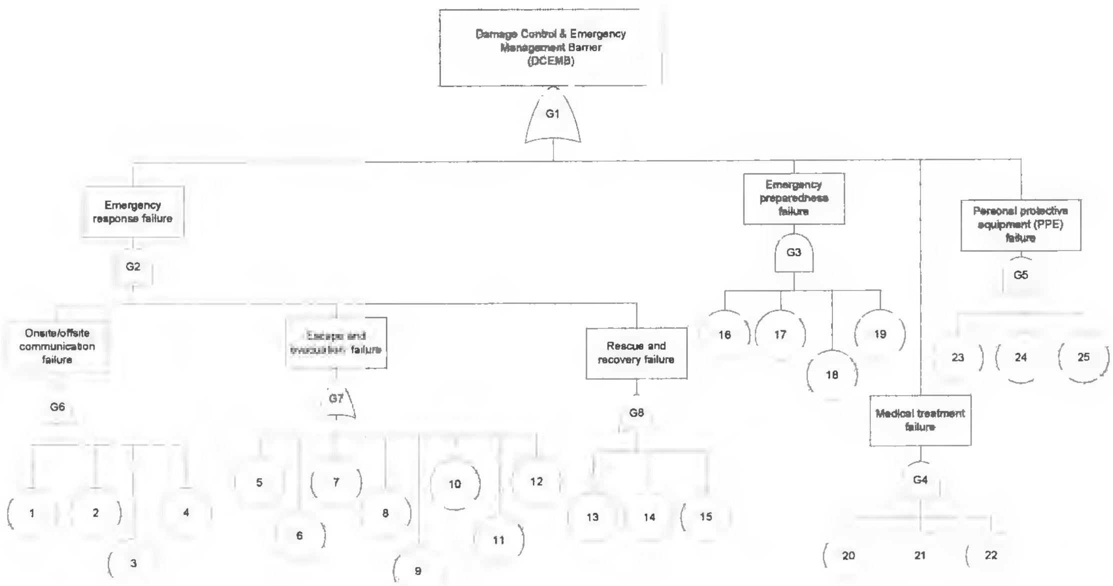

Figure A7: Fault tree analysis of Damage Control and Emergency Management Barrier (DCEMB) failure [135]

Table A1: Basic event failure probability for Human Factor Barrier (HFB) [66]

Event	Event Description	Assigned Probability
1	Safety locking device (safety interlock)failure	0.050
2	Warning display failure	0.050
3	Warning alarm failure	0.020
4	Incorrect labeling	0.100
5	Labeling not available	0.100
6	Unreliable measurement of instrumentation	0.001
7	Inadequate tools or equipment	0.020
8	False indication	0.020
9	Inadequate work instruction or procedures	0.025
10	Inadequate communication	0.050
11	Communication failure	0.025
12	Inadequate lighting	0.034
13	High level noise or mechanical vibration	0.050
14	Uncomfortable temperature extremes	0.100
15	Presence of fumes or gases or lack of oxygen	0.034
16	Physical incapability	0.050
17	Inadequate knowledge	0.100
18	Operator skill improvement program failure	0.020
19	Regular operator training and awareness failure	0.034
20	Inadequate skill	0.050
21	Operator motivation program failure	0.020
22	Lack of supervision	0.050
23	Supervision failure	0.020
24	Unclear job description	0.034
25	Inadequate permit-to-work	0.050
26	High work stress	0.067
27	Continuous night work	0.050
28	Influence of other people (colleague, management, senior workers, etc.)	0.020
29	Unscheduled working hours	0.034
30	Inadequate workplace accessibility	0.020
31	Poor housekeeping	0.050

Table A2: Basic event failure probability for Management & Organizational Factor Barrier (M&OB) [66]

Event	Event Description	Assigned Probability
1	Inadequate safety program	0.010
2	Inadequate supervision	0.034
3	Inadequate communication	0.050
4	Inadequate maintenance system	0.020
5	Inadequate control system	0.025
6	Poor or no work permit procedures	0.050
7	Inadequate audit and operating procedures	0.034
8	Inadequate training	0.025
9	Inadequate company polices	0.020
10	Inadequate staff resources	0.020
11	Inadequate planning and organization	0.025
12	Poor decision making or failure	0.040
13	Inadequate management job knowledge	0.020
14	Inadequate management polices	0.025
15	Leadership failure	0.010
16	Poor communication	0.050
17	Incompetent or insufficient management behaviors	0.020

Table A3: Basic event failure probability for Release Prevention Barrier (RPB) [2]

Event	Event Description	Assigned probability
1	Locking of manual actuator / valve / blinding failure	0.050
2	Labeling of valve / blinding failure	0.008
3	Automatic activation of blinding failure	0.071
4	Check list for control operation failed to perform	0.010
5	Adequate safety operations are not specified	0.040
6	Operating without Permit to Work (PTW)	0.010
7	Sensors failed to initiate the safety system	0.024
8	Redundant indicators failed to initiate manual safety system	0.020
9	Valve positioning sensor failure (function on demand)	0.090
10	Valve positioning control system failure	0.0147
11	Inspection of valve positioning performed but failed to detect	0.150
12	Inspection specified but not performed	0.015
13	Inspection is not specified in program	0.050
14	Regular inspection for mechanical failure did not perform	0.010
15	Regular inspection perform but did not identified the fault	0.050
16	Construction deficiency	0.010
17	Instruments (bolt) failure due to corrosion	0.0138
18	Compressor failure due to material deficiency	0.0198
19	Physical barriers are not available	0.010
20	High external load	0.010
21	Inadequate corrosion inspection program or method	0.090
22	Poor inspection	0.100
23	Long delay in inspection schedule	0.050
24	Area based leak search specified but did not perform	0.050
25	Area based leak search is not specified in program	0.070
26	Failed to detect minor release by area based leak search	0.050
27	Regular leak inspection specified but did not perform	0.050
28	Regular leak inspection is not specified in program	0.010
29	Failed to detect minor release by Regular inspection	0.050
30	Welding degrading monitoring performed but failed to detect	0.066
31	Welding degrading monitoring specified but did not perform	0.050

Table A4: Basic event failure probability for Dispersion Prevention Barrier (DPB) [2]

Event	Event Description	Assigned probability
1	Automatic gas detection sensor failure	0.128
2	Automatic gas detection controller failure	0.001
3	Automatic gas detection Alarm failure	0.020
4	Inadequate detector coverage	0.050
5	Long delay in Inspection	0.010
6	Manual detection of minor release failure	0.050
7	Manual inspection did not perform	0.050
8	Inadequate Ventilation or forced dilution	0.067
9	Ventilation or forced dilution failure	0.040
10	Manual closing of release failure (Clamping, Remediation, etc...)	0.025
11	Wrong Inflow valve selection or valve not accessible	0.050
12	Long delay in response	0.010
13	Operator awareness failure	0.040
14	Operator response failure	0.050
15	Long delay in manual response	0.010
16	ESD sensor failure	0.024
17	ESD controller Failure	0.250
18	ESD valve delayed operation	0.050
19	ESD valve failure to close on demand	0.130
20	Physical barrier not available	0.001
21	Inadequate barrier performance	0.010
22	Inerting not available	0.050
23	Inerting failure	0.080
24	Drainage not available	0.001
25	Inadequate functioning	0.001

Table A5: Basic event failure probability for Ignition Prevention Barrier (IPB) [2]

Event	Event Description	Assigned probability
1	Hot work permit has not been issued	0.033
2	Inadequate procedures or instruction in work permit	0.067
3	Risk assessment not performed prior to issue work permit	0.100
4	External supervision failure	0.083
5	Inadequate trained operator	0.100
6	Operation with wrong work permit	0.040
7	Failure to follow work permit	0.045
8	Operation without work permit	0.010
9	Hot surface shielding not available	0.067
10	Burner shielding failure	0.010
11	Inadvertent burner flare trip failure	0.044
12	Flame detector failure	0.056
13	Flame detector not available	0.050
14	Inadequate detector coverage	0.070
15	Manual inspection of ignition source failure	0.050
16	Insulation of fuel line failure	0.010
17	Insulation of burner failure	0.010

Table A6: Basic event failure probability for Escalation Prevention Barrier (EPB) [2]

Event	Event Description	Assigned probability
1	Inadequate flaring	0.001
2	Inadequate blow down	0.001
3	Inadequate chemical scrubbers	0.008
4	Inadequate air ventilation	0.067
5	Air ventilation failure	0.030
6	Inadequate water spraying	0.067
7	Water spraying failure	0.045
8	Fire detection Sensor failure	0.080
9	Fire detection Controller failure	0.001
10	Fire Alarm failure	0.021
11	Inadequate detector coverage	0.200
12	Operator did not detect the fire	0.050
13	Operator unable to activate the manual fire alarm	0.001
14	Manual fire alarm activator failure	0.001
15	Smoke detection sensor failure	0.080
16	Smoke detection Controller failure	0.001
17	Smoke Alarm failure	0.021
18	Inadequate detector coverage	0.070
19	Inadequate smoke isolation or venting	0.060
20	Smoke isolation failure	0.005
21	Inadequate fire resistant barrier	0.003
22	Fire resistant failure	0.030
23	Sprinkler not available	0.010
24	Inadequate sprinkling	0.040
25	Sprinkler failure	0.045
26	Inadequate Firefighting in given duration	0.020
27	long delay Fire fighting	0.080
28	Firefighting did not perform	0.0001
29	Closing release failure	0.013
30	Inflow valve not accessible or wrong valve	0.050
31	Long delay in manual operation	0.010
32	Operator awareness failure	0.040
33	Operator response to activate manual ESD failure	0.050
34	Long delay in response	0.010
35	ESD sensor failure	0.024
36	ESD Controller Failure	0.100
37	ESD valve delayed operation	0.050
38	ESD valve failure to close on demand	0.070

Table A7: Basic event failure probability for Damage Control and Emergency Management Barrier (DCEMB) [135]

Event	Event Description	Assigned Probability
1	Long delay activating alarm for mustering	0.15
2	Onsite and offsite communication failure	0.20
3	Crew did not detect or hear alarm	0.144
4	Crew did not identify alarm	0.139
5	Poor access quality of egress roots (obstructed or impaired)	0.175
6	Evacuation time too short	0.189
7	Failure to follow path leading to temporary refuge areas	0.161
8	Unable to obtain successful personnel on board (POB) count	0.15
9	No or inadequate evacuation mode available (helicopters, lifeboats, and crafts)	0.01
10	Craft function and preparation failure	0.13
11	Failure during transferring and launching process	0.20
12	Insufficient means to escape to sea	0.25
13	Adverse weather and visibility	0.10
14	Inadequate external support for evacuation	0.20
15	Inadequate support facility on rescue vessel	0.01
16	Insufficient offshore survival and safety training	0.01
17	Insufficient emergency drill and exercises	0.10
18	Inadequate or untrained emergency response personnel	0.11
19	Inadequate emergency preparedness plan	0.0788
20	Long delay for medical treatment	0.05
21	Onsite medical treatment not available or inadequate	0.20
22	Inadequate training of emergency medical response personnel	0.10
23	Inadequate or unavailable emergency shelter-in-place	0.02
24	Inadequate personal protective equipment	0.001
25	Personal protective equipment failure (lifejackets, survival suits, etc.)	0.01

Appendix B

Case Study: Macondo Well Blowout Accident

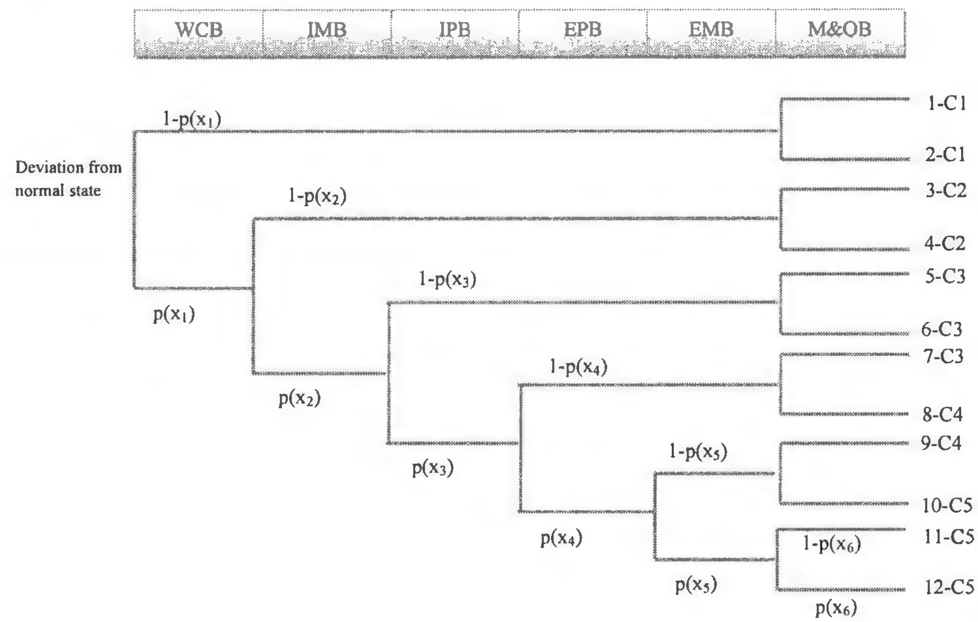

Figure B1: Event tree diagram of the Macondo well blowout accident [135]

X1 – Management & Organizational Barrier (M&OB)
X2 – Well Control Barrier (WCB)
X3 – Influx Mitigation Barrier (IMB)
X4 – Ignition Prevention Barrier (IPB)
X5 – Escalation Prevention Barrier (EPB)
X6 – Emergency Management Barrier (EMB)

C1 – Safe
C2 – Kick
C3 – Blowout
C4 – Fire and explosion
C5 – Catastrophic Accident

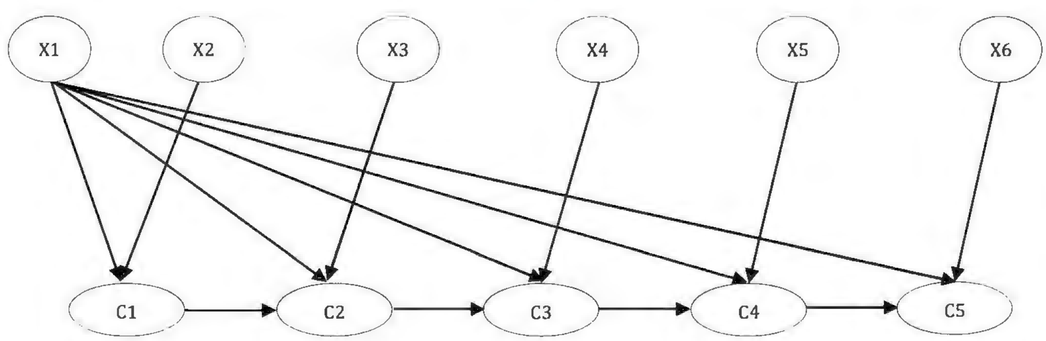

Figure B2: Bayesian network diagram of the Macondo well blowout accident

Table B1: Prior Occurrence Probability for Each Primary Safety Barrier [135]

Safety barrier(X_i)	Failure Probability, P(X_i)
Well control barrier (WCB)	7.13×10^{-2}
Influx mitigation barrier (IMB)	6.43×10^{-2}
Ignition prevention barrier (IPB)	13.77×10^{-2}
Escalation prevention barrier (EPB)	11.10×10^{-2}
Emergency management barrier (EMB)	10.88×10^{-2}
Management and organizational barrier (M&OB)	10.27×10^{-2}

Table B2: Prior Occurrence Probabilities of End Events Using SHIPP and Bayesian Model

End Events(E)	Event Tree Occurrence Probability, P(E_k)	Conditional Event Occurrence Probability, P(E_k)
Safe (E_1)	9.29×10^{-1}	9.29×10^{-1}
Kick (E_2)	6.67×10^{-2}	6.67×10^{-2}
Blowout (E_3)	4.45×10^{-3}	3.95×10^{-3}
Fire and explosion (E_4)	1.23×10^{-4}	5.61×10^{-4}
Catastrophe (E_5)	1.52×10^{-5}	6.25×10^{-5}

Safe state:

	End Events	Safety Barrier	State	Success Probability
1	**Safe**	Management Barrier	S	0.8793
		Well control Barrier	S	0.9287
2	**Safe**	Management Barrier	F	0.9579
		Well control Barrier	S	0.9287

Kick state:

	End Events	Safety Barrier	State	Success Probability
1	**Kick**	Management Barrier	S	0.8793
		Not Safe	S	7.1300e-2
		Influx Mitigation Barrier	S	0.9357
2	**Kick**	Management Barrier	F	0.1207
		Not Safe	S	7.1300e-2
		Influx Mitigation Barrier	S	0.9357

Blowout state:

	End Events	Safety Barrier	State	Success Probability
1	**Blowout**	Management Barrier	S	0.8793
		Not Kick	S	4.5850e-3
		Ignition Prevention Barrier	S	0.8623
2	**Blowout**	Management Barrier	F	0.1207
		Not Kick	S	4.5850e-3
		Ignition Prevention Barrier	S	0.8623

Fire and explosion state:

	End Events	Safety Barrier	State	Success Probability
1	**Fire and explosion**	Management Barrier	S	0.8793
		Not Blowout	S	6.3140e-4
		Escalation Prevention Barrier	S	0.8890
2	**Fire and explosion**	Management Barrier	F	0.1207
		Not Blowout	S	6.3140e-4
		Escalation Prevention Barrier	S	0.8890

Catastrophe state:

	End Events	Safety Barrier	State	Success Probability
1	**Catastrophe**	Management Barrier	S	0.8793
		Not Fire and explosion	S	7.0090e-5
		Emergency Management Barrier	S	0.8912
2	**Catastrophe**	Management Barrier	F	0.1207
		Not Fire and explosion	S	7.0090e-5
		Emergency Management Barrier	S	0.8912

Ns = Not Safe, NKick = Not Kick, Blowout = Bt, Not Blowout = NBt, Fire = Fi, Not Fire = NFi, Catastrophe = Cat

P(Safe) = P(Safe|X1,X2)P(X1) P(X2) + P(Safe|Ẍ1,X2) P(Ẍ1) P(X2)
= (1*0.8793*0.9287) + (1*0.1207*0.9287)
= 0.81661 + 0.11209
= **9.2870e-1**

P(Ns) = 1 – P(Safe)
= 1 – 9.2870e-1
= **7.1300e-2**

P(Kick) = P(Kick | X1,X3,Ns)P(X1) P(X3)P(Ns) + P(Kick | Ẍ1,X3,Ns)P(Ẍ1) P(X3)P(Ns)
= (1*0.8793*0.9357*7.1300e-2) + (1*0.1207*0.9357*7.1300e-2)
= 5.8663e-2 + 8.0525e-3
= **6.6715e-2**

P(Not Kick) = 1 – P(Safe) – P(Kick)
= 1 – 9.2870e-1 – 6.6715e-2
= **4.5850e-3**

P(Blowout) = P(Bt | X1,X4,NKick)P(X1)P(X4)P(NKick)
+ P(Bt | Ẍ1,X4,NKick)P(Ẍ1)P(X4)P(NKick)
= (1*0.8793*0.8623*4.5850e-3) + (1*0.1207*0.8623*4.5850e-3)
= 3.4764e-3 + 4.7721e-4
= **3.9536e-3**

P(Not Blowout) = 1 – P(Safe) – P(Kick) – P(Blowout)
= 1 - 9.2870e-1 - 6.6715e-2 - 3.9536e-3
= **6.3140e-4**

P(Fire) = P(Fi | X1,X5,NBt)P(X1) P(X5)P(NBt) + P(Fi | Ẍ1,X5,NBt)P(Ẍ1) P(X5)P(NBt)
= (1*0.8793*0.8890*6.3140e-4) + (1*0.1207*0.8890*6.3140e-4)
= 4.9356e-4 + 6.7751e-5
= **5.6131e-4**

P(Not Fire) = 1 – P(Safe) – P(Kick) – P(Blowout) – P(Fire)
= 1 - 9.2870e-1 - 6.6715e-2 - 3.9536e-3 - 5.6131e-4
= **7.0090e-5**

$$\begin{aligned}
\textbf{P(Catastrophe)} &= P(Cat \mid X1,X6,NFi)P(X1)P(X6)P(NFi) \\
&+ P(Cat \mid \ddot{X}1,X6,NFi)P(\ddot{X}1)P(X6)P(NFi) \\
&= (1*0.8793*0.8912*7.0090e\text{-}5) + (1*0.1207*0.8912*7.0090e\text{-}5) \\
&= 5.4925e\text{-}5 + 7.5394e\text{-}6 \\
&= \mathbf{6.2464e\text{-}5}
\end{aligned}$$

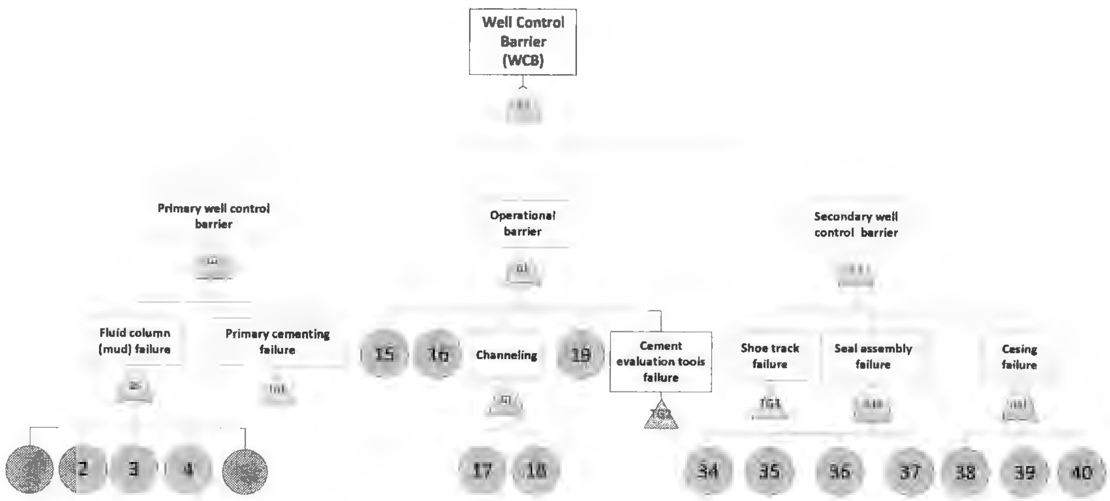

Figure B3: Fault tree diagram of the Well Control Barrier (WCB)

Detailed descriptions and failure probabilities of basic events of Well Control Barrier (WCB) are listed in Table B3.

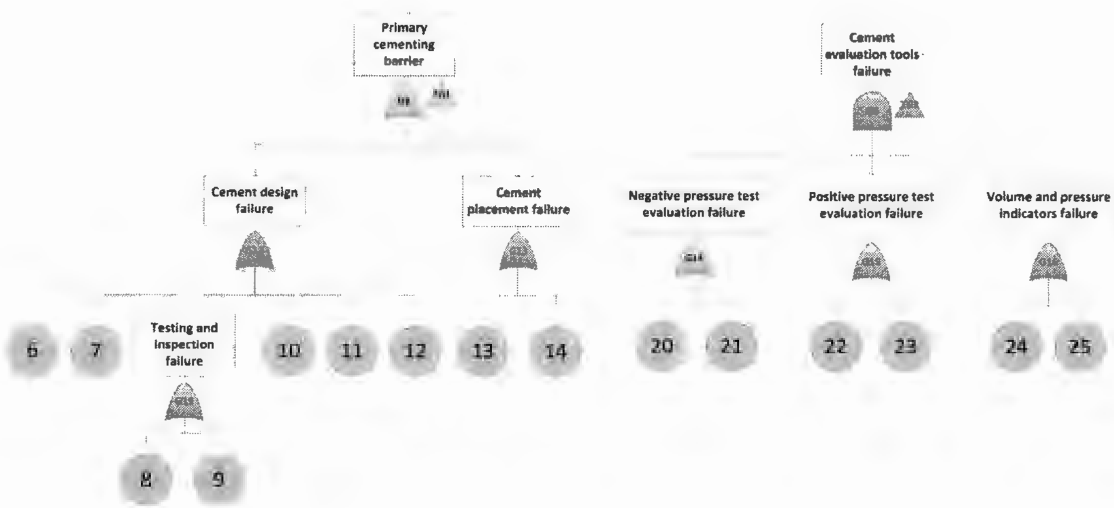

Figure B3: (Continued) Fault tree diagram of the Well Control Barrier (WCB)

Detailed descriptions and failure probabilities of basic events of the Well Control Barrier (WCB) are listed in Table B3.

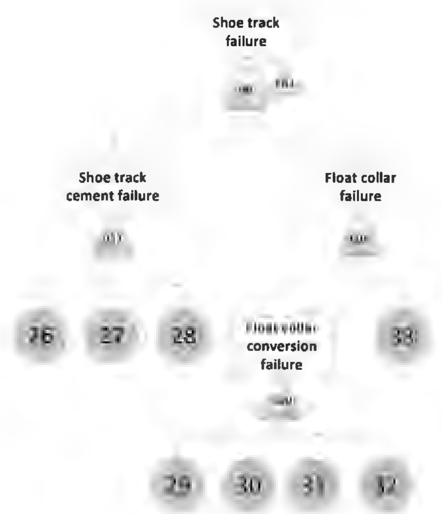

Figure B3: (Continued) Fault tree diagram of the Well Control Barrier (WCB)

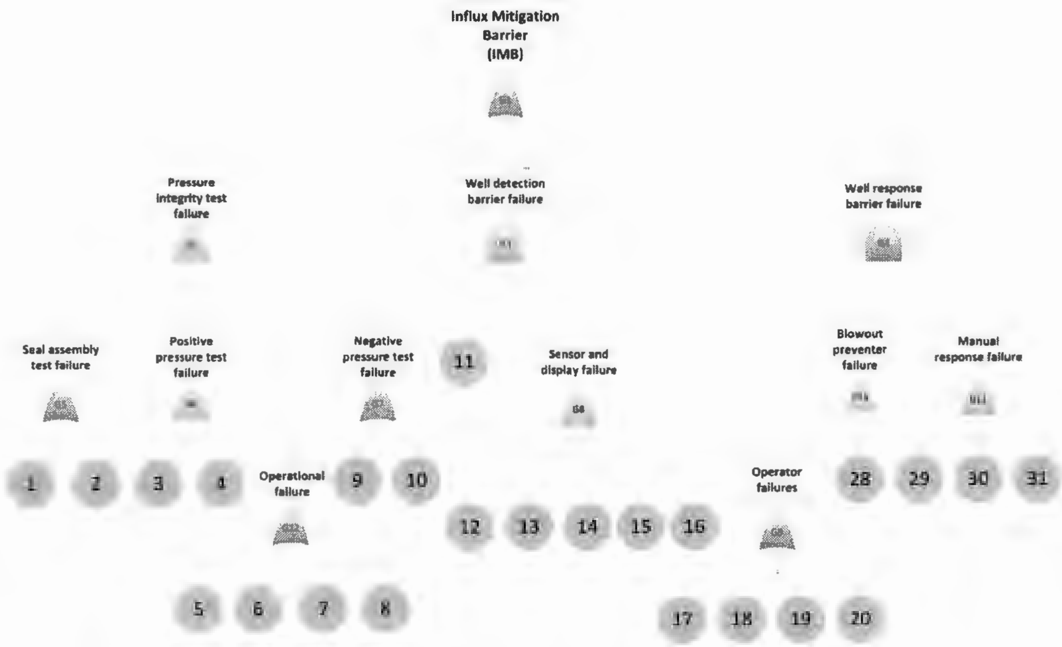

Figure B4: Fault tree diagram of the Influx Mitigation Barrier (IMB)

Detailed description and failure probabilities of basic events of Influx Mitigation Barrier (IMB) are listed in Table B4.

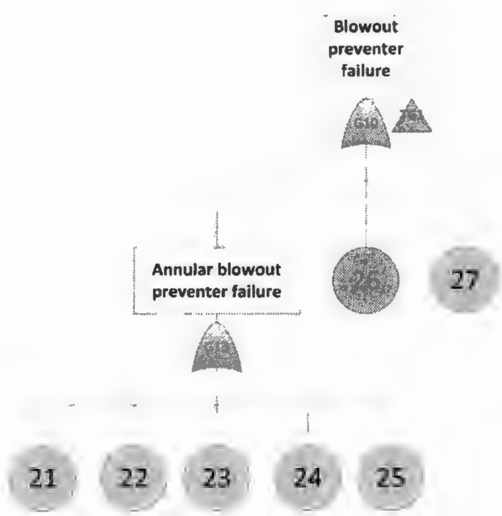

Figure B4: (Continued) Fault tree diagram for Influx Mitigation Barrier (IMB)

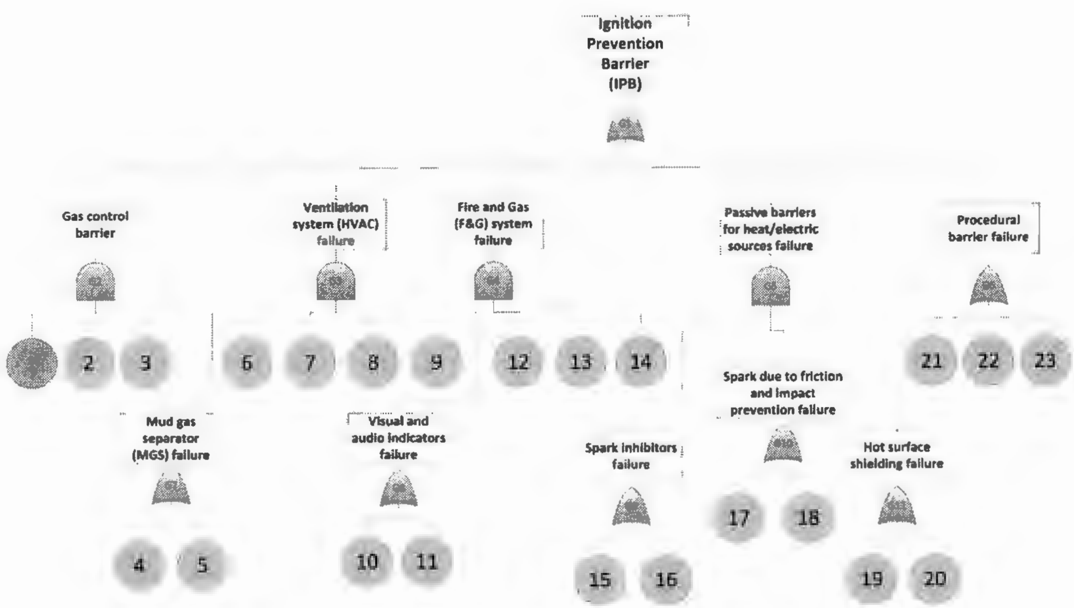

Figure B5: Fault tree diagram of the Ignition Prevention Barrier (IPB)

Detailed descriptions and failure probabilities of basic events of Ignition Prevention Barrier (IPB) are listed in Table B5.

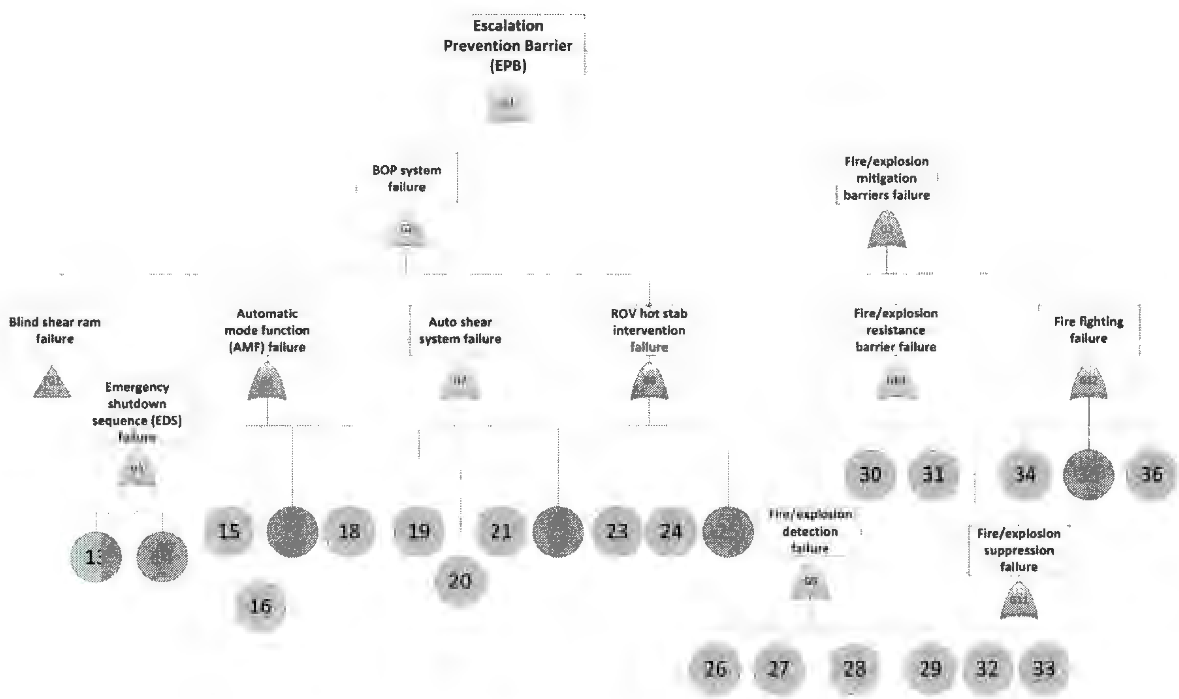

Figure B6: Fault tree diagram of the Escalation Prevention Barrier (EPB)

Detailed descriptions and failure probabilities of basic events of Escalation Prevention Barrier (EPB) are listed in Table B6.

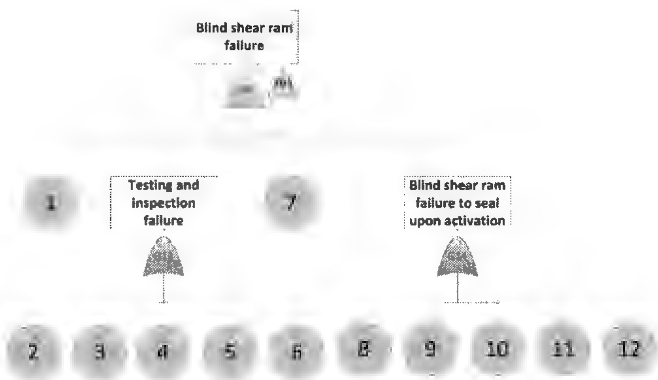

Figure B6: (Continued) Fault tree diagram of the Escalation Prevention Barrier (EPB)

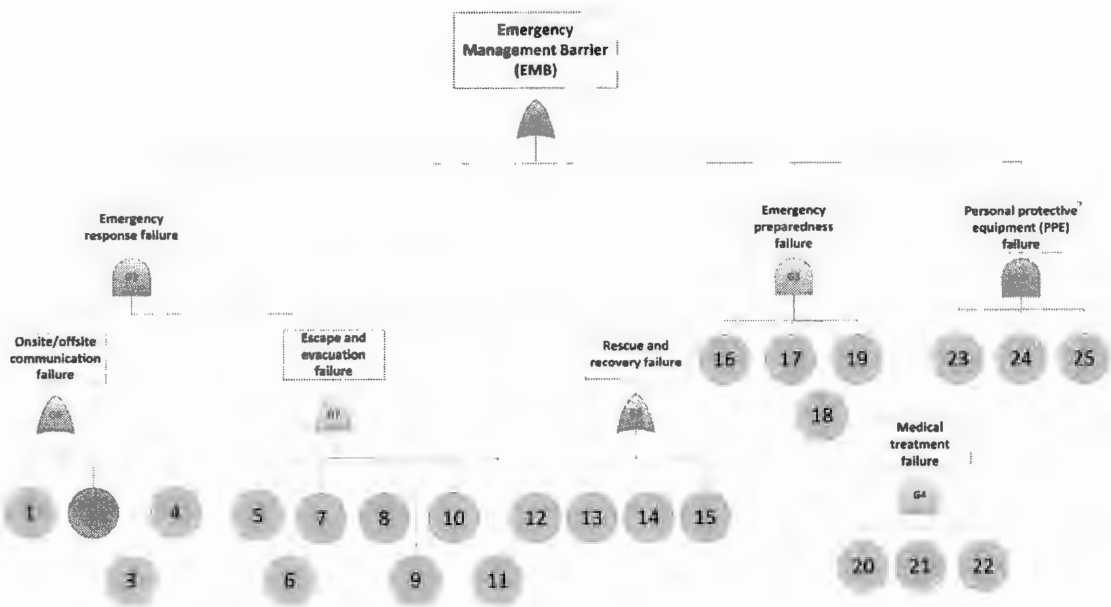

Figure B7: Fault tree diagram of the Emergency Management Barrier (EMB)

Detailed descriptions and failure probabilities of basic events of Emergency Management Barrier (EMB) are listed in Table B7.

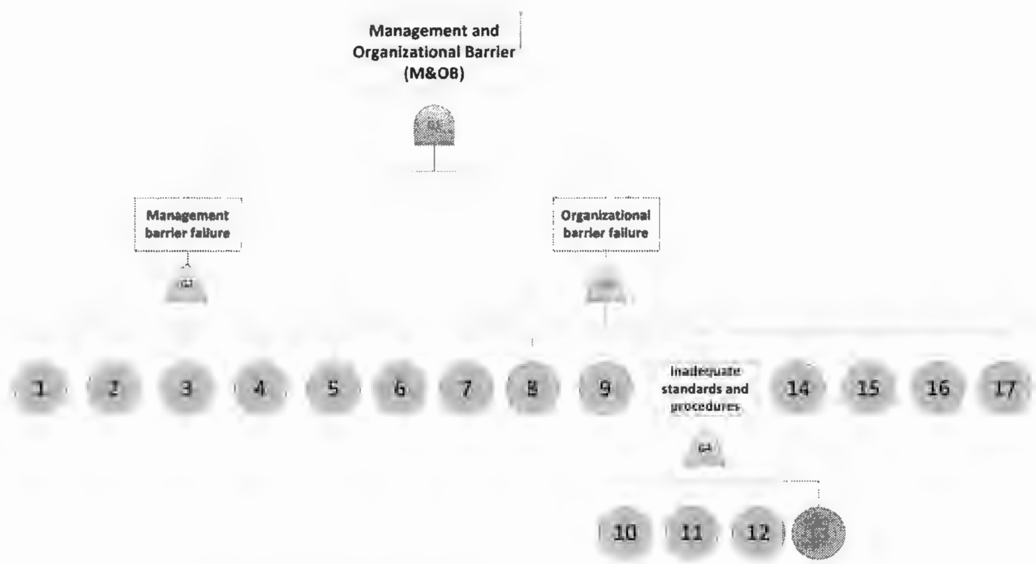

Figure B8: Fault tree diagram of the Management and Organizational Barrier (M&OB)

Detailed descriptions and failure probabilities of basic events of Management and Organizational Barrier (M&OB) are listed in Table B8.

Table B3: Basic event failure probability of the Well Control Barrier (WCB) [135]

Event	Event Description	Assigned Probability
1	Inadequate mud weight design or too low mud weight	5.00×10^{-2}
2	Loss of circulation	2.70×10^{-2}
3	Unexpected pore pressure	1.50×10^{-1}
4	Ballooning (mud loss when pumps are on)	2.00×10^{-2}
5	Swabbing during casing	5.40×10^{-2}
6	Unstable foam cement slurry design	2.00×10^{-2}
7	Low pump rate of cement flow	1.00×10^{-2}
8	Incorrect laboratory testing	2.00×10^{-3}
9	Operator unable to follow laboratory result	1.00×10^{-4}
10	Low/inadequate cement volume	1.00×10^{-2}
11	Inaccurate slurry composition	2.00×10^{-2}
12	Contamination of spacer and cement	5.00×10^{-3}
13	Poor displacement efficiency	2.00×10^{-2}
14	Failure to place cement according to cement program	3.30×10^{-2}
15	Incorrect production casing selection	1.00×10^{-2}
16	Unable to obtain bottoms-up circulation	2.00×10^{-3}
17	Inadequate number of centralizers	1.00×10^{-3}
18	Inaccurate centralizer placement	1.00×10^{-3}
19	Failure to perform adequate risk assessment	1.00×10^{-1}
20	Deficiencies in conducting negative pressure test	2.50×10^{-2}
21	Wrong interpretation of negative pressure test results	1.00×10^{-2}
22	Cement bond logging (CBL) not performed	1.00×10^{-3}
23	CBL performed but failed to provide adequate information	1.00×10^{-3}
24	Volume and pressure test unable to obtain full return	1.00×10^{-3}
25	Inaccurate lift pressure indicator	1.00×10^{-3}
26	Contamination of tail cement with spacer	5.00×10^{-3}
27	Swapping of mud through rat hole	1.00×10^{-3}
28	Inadequate tail cement design	2.00×10^{-2}
29	Failure to convert due to low flow rate	5.00×10^{-2}
30	Clogging reamer shoe or float collar	2.00×10^{-2}
31	Check valve failed to seal properly	3.12×10^{-2}
32	Rig personnel may not have converted float valve	1.00×10^{-4}
33	Float valve damage due to high load	1.00×10^{-3}
34	Design and installation failure	2.00×10^{-3}
35	Annular seal assembly (pack off) failure	1.30×10^{-3}
36	Lift-off the casing and casing hanger (casing hanger failure)	1.50×10^{-3}
37	Subsea well head failure	2.20×10^{-3}
38	Poor design of production casing	3.00×10^{-3}
39	Casing crossover breaching and leak through casing threads	6.40×10^{-3}
40	Fracture or hole in casing	6.40×10^{-3}

Table B4: Basic event failure probability of the Influx Mitigation Barrier (IMB) [135]

Event	Event Description	Assigned Probability
1	Failure to perform seal assembly test according to standard and industrial best practice	2.00×10^{-3}
2	Wrong interpretation of seal assembly test results	1.00×10^{-2}
3	Failure to perform positive pressure test	2.00×10^{-3}
4	Wrong interpretation of positive pressure test results	1.00×10^{-2}
5	Wrong interpretation of negative pressure test results	5.00×10^{-2}
6	Unable to follow procedures and standards	1.00×10^{-3}
7	Inadequate procedures and methods	2.00×10^{-3}
8	Inaccuracy of mathematical and simulation models	1.00×10^{-3}
9	Spacer fails to function as designed or required	2.50×10^{-2}
10	Annular preventer did not isolate completely	1.72×10^{-3}
11	Kick detection indicators fail (pit gain, drill pipe pressure, etc.)	2.00×10^{-3}
12	Inaccurate sensor readings	2.50×10^{-2}
13	No advance real-time monitoring system	2.00×10^{-2}
14	Unable to provide automation of simple well control calculation	2.00×10^{-2}
15	Inadequate alarms and warning systems or coverage	5.00×10^{-2}
16	Video feeds failure or inadequate video coverage	5.00×10^{-2}
17	Failure to recognize sign of kick	1.00×10^{-2}
18	Misinterpretation of feedback from well control	7.25×10^{-2}
19	Underestimated risk assessment	2.00×10^{-2}
20	Communication between BOP and rig personal failure (control systems failure)	2.60×10^{-3}
21	Design and manufacturing failure	2.00×10^{-3}
22	Fail-safe valves failure	1.30×10^{-4}
23	Hydraulic control system failure	7.58×10^{-4}
24	Internal leakage or failure to close	2.50×10^{-2}
25	Kill and/or choke lines failure	3.60×10^{-3}
26	Late response to activate BOP or did not activate	1.00×10^{-2}
27	Emergency Disconnect System (EDS) failure	3.12×10^{-4}
28	Kick detected but failure to respond timely	1.00×10^{-2}
29	Unable to take kick mitigation actions	1.00×10^{-3}
30	Kick not detected	1.00×10^{-3}
31	Inadequate procedures to respond to the kick	2.00×10^{-2}

Table B5: Basic event failure probability of the Ignition Prevention Barrier (IPB) [135]

Event	Event Description	Assigned Probability
1	Failure to activate overboard diversion lines	1.00×10^{-2}
2	Leakage through diverter packing due to high pressure	8.00×10^{-3}
3	Overboard diverter lines failure due to erosion, corrosion and mechanical causes	2.00×10^{-3}
4	Mechanical failure of mud gas separator equipment	2.00×10^{-3}
5	Mud gas separator (MGS) fails due to overpressure	5.00×10^{-1}
6	Fire/smoke damper systems not activated upon combustible gas detection	3.10×10^{-3}
7	No automated action to activate fire/smoke dampers	1.00×10^{-3}
8	Smoke or combustible gas detection malfunctioning	1.98×10^{-1}
9	Inadequate exhaust venting	6.70×10^{-2}
10	Alarms and visual display failure	2.10×10^{-2}
11	Alarms unable to trigger human attention	2.50×10^{-2}
12	Fire and gas detector failure	1.23×10^{-1}
13	Manual response failure	5.00×10^{-2}
14	Inadequate detector coverage	2.00×10^{-1}
15	Electric spark inhibitors failure	2.00×10^{-2}
16	Static spark inhibitors failure	2.00×10^{-2}
17	Equipment over-speed detection and control failure or not installed	2.50×10^{-2}
18	Cooling system for overheating of rotating part failure or not installed	2.50×10^{-2}
19	Hot surface shielding not installed	6.70×10^{-2}
20	Hot surfaces shielding installed but failed to perform as designed	1.00×10^{-2}
21	Inadequate electrical area classification	5.00×10^{-2}
22	Inadequate hazard and risk assessment prior to design	1.00×10^{-2}
23	External supervision failure	8.30×10^{-2}

Table B6: Basic event failure probability of the Escalation Prevention Barrier (EPB) [135]

Event	Event Description	Assigned Probability
1	Inadequate operator knowledge about performance of ram under high pressure	5.00×10^{-2}
2	Failure to perform testing prior to installation	1.50×10^{-2}
3	Testing standards and procedures compromised	2.00×10^{-2}
4	Leaks unidentified prior to incident	1.00×10^{-2}
5	Unable to perform pressure test	5.00×10^{-3}
6	Unable to perform function test	5.00×10^{-3}
7	Long delay of activation	1.00×10^{-2}
8	Erosion of shear ram due to high flow rate and pressure	2.50×10^{-2}
9	Unable to cut off the drill pipe due to design failure (blind shear ram coincide with tool joint)	3.40×10^{-2}
10	Insufficient hydraulic power of accumulators	1.00×10^{-2}
11	Internal hydraulic leakages	7.22×10^{-3}
12	Communication (multiplex lines) between rig & BOP failure	2.20×10^{-3}
13	Rig personnel did not arm or delay activation of EDS	1.00×10^{-2}
14	Damage of multiplex (MUX) lines (connector failure)	2.20×10^{-3}
15	Rig personnel did not arm or delay activation of automatic mode function (AMF)	1.00×10^{-2}
16	Both control pods and acoustic system fail to activate function	2.20×10^{-3}
17	Insufficient hydraulic power of accumulators	1.00×10^{-3}
18	Remotely operated vehicle (ROV) intervention failure to activate AMF	5.00×10^{-2}
19	Rig personnel did not arm or delay activation of auto shear	1.00×10^{-2}
20	Both control pods and acoustic system failure to activate function	2.20×10^{-3}
21	ROV intervention failure to activate auto shear system	5.00×10^{-2}
22	Insufficient hydraulic power of accumulators	1.00×10^{-2}
23	Internal hydraulic fluid leakages	7.22×10^{-3}
24	ROV failure to pump hydraulic fluid as required speed	2.00×10^{-2}
25	Delay in ROV intervention	2.00×10^{-2}
26	Fire alarm and indicators failure	2.10×10^{-2}
27	Inadequate coverage of fire detection	5.00×10^{-2}
28	Fire detectors or sensor failure	8.00×10^{-2}
29	Manual fire detection failure	5.00×10^{-2}
30	Inadequate fire and explosion resistance	3.00×10^{-3}
31	Barriers installed but failure to control escalation	3.00×10^{-2}
32	Sprinklers not available or inadequate	1.00×10^{-2}
33	Sprinklers not activated or do not respond to fire or smoke	4.50×10^{-2}
34	Inadequate firefighting in given time duration	2.00×10^{-2}
35	Long delay in fire fighting	9.00×10^{-2}
36	Firefighting not performed	1.00×10^{-4}

Table B7: Basic event failure probability of the Emergency Management Barrier (EMB)[135]

Event	Event Description	Assigned Probability
1	Long delay activating alarm for mustering	1.50×10^{-1}
2	Onsite and offsite communication failure	2.00×10^{-1}
3	Crew did not detect or hear alarm	1.44×10^{-1}
4	Crew did not identify alarm	1.39×10^{-1}
5	Poor access quality of egress roots (obstructed or impaired)	1.75×10^{-1}
6	Evacuation time too short	1.89×10^{-1}
7	Failure to follow path leading to temporary refuge areas	1.61×10^{-1}
8	Unable to obtain successful personnel on board (POB) count	1.50×10^{-1}
9	No or inadequate evacuation mode available (helicopters, lifeboats, and crafts)	1.00×10^{-2}
10	Craft function and preparation failure	1.30×10^{-1}
11	Failure during transferring and launching process	2.00×10^{-1}
12	Insufficient means to escape to sea	2.50×10^{-1}
13	Adverse weather and visibility	1.00×10^{-1}
14	Inadequate external support for evacuation	2.00×10^{-1}
15	Inadequate support facility on rescue vessel	1.00×10^{-2}
16	Insufficient offshore survival and safety training	1.00×10^{-2}
17	Insufficient emergency drill and exercises	1.00×10^{-1}
18	Inadequate or untrained emergency response personnel	1.10×10^{-1}
19	Inadequate emergency preparedness plan	7.88×10^{-2}
20	Long delay for medical treatment	5.00×10^{-2}
21	Onsite medical treatment not available or inadequate	2.00×10^{-1}
22	Inadequate training of emergency medical response personnel	1.00×10^{-1}
23	Inadequate or unavailable emergency shelter-in-place	2.00×10^{-2}
24	Inadequate personal protective equipment	1.00×10^{-3}
25	Personal protective equipment failure (lifejackets, survival suits, etc.)	1.00×10^{-2}

Table B8: Basic event failure probability of the Management and Organizational Barrier (M&OB)[135]

Event	Event Description	Assigned Probability
1	Inadequate leadership at critical time	1.00×10^{-1}
2	Poor organizing and reporting structure	1.00×10^{-1}
3	Inadequate communication and compartmentalization of information	5.00×10^{-2}
4	Inadequate onsite technical expertise or did not use effectively	3.40×10^{-2}
5	Inadequate management job knowledge	2.00×10^{-2}
6	Inadequate management practices	2.50×10^{-2}
7	Inadequate supervision	3.40×10^{-2}
8	Inadequate staff resources or poor management of staff	2.00×10^{-2}
9	Inadequate training	2.50×10^{-2}
10	Inadequate well design and operation guidance	1.00×10^{-2}
11	Inadequate control systems	5.00×10^{-2}
12	Inadequate maintenance procedures	5.00×10^{-2}
13	Inadequate inspection and testing procedures	2.00×10^{-2}
14	Lack of clarity about operator, contractor and subcontractor expertise and responsibility	1.00×10^{-1}
15	Inadequate technology and safety programs	1.00×10^{-1}
16	Poor documentation of important information	1.00×10^{-2}
17	Poor risk assessment and risk based decision making	1.00×10^{-1}

Appendix C

Matlab Code

```
%% Safe = Sf; Near miss = Nm; Mishap = Mh;
%% Incident = In; Accident = Acc; Catastrophe = Cat;

%%--------------------Prior barrier probabilities(success)-----------

px1=0.9971; px2=0.9579; px3=0.9473; px4=0.9384; px5=0.894;
px6=0.9729;
px7=0.8912;
%%-----------------Prior occurrence probability estimation-----------

Sf1 = (px1*px2*px3);
Sf2 = ((1-px1)*px2*px3);
Sf = Sf1 + Sf2;
Ns = 1-Sf;

Nm1 = (px1*px2*px4*Ns);
Nm2 = ((1-px1)*px2*px4*Ns);
Nm3 = (px1*(1-px2)*px4*Ns);
Nm4 = ((1-px1)*(1-px2)*px4*Ns);
Nm = Nm1+Nm2+Nm3+Nm4;
NNm = 1-Sf-Nm;

Mh1 = (px1*px2*px5*NNm);
Mh2 = ((1-px1)*px2*px5*NNm);
Mh3 = (px1*(1-px2)*px5*NNm);
Mh4 = ((1-px1)*(1-px2)*px5*NNm);
Mh = Mh1+Mh2+Mh3+Mh4;
NMh = 1-Sf-Nm-Mh;

In1 = (px1*px2*px6*NMh);
In2 = ((1-px1)*px2*px6*NMh);
In3 = (px1*(1-px2)*px6*NMh);
In4 = ((1-px1)*(1-px2)*px6*NMh);
In = In1+In2+In3+In4;
NIn = 1-Sf-Nm-Mh-In;

Ac1 = (px1*px2*px7*NIn);
Ac2 = ((1-px1)*px2*px7*NIn);
Ac3 = (px1*(1-px2)*px7*NIn);
Ac4 = ((1-px1)*(1-px2)*px7*NIn);
Ac = Ac1+Ac2+Ac3+Ac4;
NAc = 1-Sf-Nm-Mh-In-Ac;

Cat1 = (px1*px2*NAc);
Cat2 = ((1-px1)*px2*NAc);
Cat3 = (px1*(1-px2)*NAc);
Cat4 = ((1-px1)*(1-px2)*NAc);
Cat = Cat1+Cat2+Cat3+Cat4;

Prior = [Sf Nm Mh In Ac Cat];
```

```
%%---------------Likelihood calculation(improved methodology)------%%
%%--------------------Cumulative data 10 months--------------------

Safe =        [5 9 14 32 37 40 44 48 51 53]';
NearMiss =    [4 10 17 61 79 88 94 101 111 114]';
Mishap =      [2 4 6 18 23 24 24 27 30 32]';
Incident =    [1 1 2 10 12 13 14 15 16 18]';
Accident =    [0 0 0 1 1 1 2 2 2 2]';
Catastrophe = [0 0 0 0 0 0 0 0 0 0]';
Events = [Safe NearMiss Mishap Incident Accident Catastrophe];

%%----------10 months Cumulative Data Conversion to Real Data--------

m = 10;

SafeN = zeros(10,1); NearMissN = zeros(10,1);
MishapN = zeros(10,1); IncidentN = zeros(10,1);
AccidentN = zeros(10,1); CatastropheN = zeros(10,1);

UpdatedRealData = zeros(m,6);

SafeN(1,1) = Safe(1,1);
NearMissN(1,1) = NearMiss(1,1);
MishapN(1,1) = Mishap(1,1);
IncidentN(1,1) = Incident(1,1);
AccidentN(1,1) = Accident(1,1);
CatastropheN(1,1) = Catastrophe(1,1);

for i = 1:m-1
   SafeN(i+1,1) = Safe(i+1,1) - Safe(i,1);
   NearMissN(i+1,1) = NearMiss(i+1,1) - NearMiss(i,1);
   MishapN(i+1,1) = Mishap(i+1,1) - Mishap(i,1);
   IncidentN(i+1,1) = Incident(i+1,1) - Incident(i,1);
   AccidentN(i+1,1) = Accident(i+1,1) - Accident(i,1);
   CatastropheN(i+1,1) = Catastrophe(i+1,1) - Catastrophe(i,1);
end

disp('    Safe       Near miss      Mishap      Incident      Accident
Catastrophe ')
disp('------------------------------------------------------------
-')
UpdatedRealData = [SafeN NearMissN MishapN IncidentN AccidentN
CatastropheN]
```

```
%%-----------------Likelihood estimation 10 months data--------------

m = 10;

SafeL = zeros(10,1); NearMissL = zeros(10,1);
MishapL = zeros(10,1); IncidentL = zeros(10,1);
AccidentL = zeros(10,1); CatastropheL = zeros(10,1);
LikelihoodData = zeros(m,6);

for i = 1:m
   SafeL(i,1) = SafeN(i,1)/sum(UpdatedRealData(i,:));
   NearMissL(i,1) = NearMissN(i,1)/sum(UpdatedRealData(i,:));
   MishapL(i,1) = MishapN(i,1)/sum(UpdatedRealData(i,:));
   IncidentL(i,1) = IncidentN(i,1)/sum(UpdatedRealData(i,:));
   AccidentL(i,1) = AccidentN(i,1)/sum(UpdatedRealData(i,:));
   CatastropheL(i,1) = CatastropheN(i,1)/sum(UpdatedRealData(i,:));
end

disp('    Safe       Near miss      Mishap     Incident      Accident
Catastrophe ')
disp('------------------------------------------------------------
')
LikelihoodData = [SafeL NearMissL MishapL IncidentL AccidentL
CatastropheL]

%%---------------Posterior probability estimation 10 months----------

m = 10;

SafeP = zeros(10,1); NearMissP = zeros(10,1);
MishapP = zeros(10,1); IncidentP = zeros(10,1);
AccidentP = zeros(10,1); CatastropheP = zeros(10,1);
PosteriorData = zeros(m,6);
TotalProb = zeros(m,1);

for i = 1:m
   TotalProb(i,1)=(SafeL(i,1)*Sf)+(NearMissL(i,1)*Nm)+(MishapL(i,1)*M
   h)+
   (IncidentL(i,1)*In)+(AccidentL(i,1)*Ac)+(CatastropheL(i,1)*Cat);
end

for i = 1:m
   SafeP(i,1) = (SafeL(i,1)*Sf)/TotalProb(i,1);
   NearMissP(i,1) = (NearMissL(i,1)*Nm)/TotalProb(i,1);
   MishapP(i,1) = (MishapL(i,1)*Mh)/TotalProb(i,1);
   IncidentP(i,1) = (IncidentL(i,1)*In)/TotalProb(i,1);
   AccidentP(i,1) = (AccidentL(i,1)*Ac)/TotalProb(i,1);
   CatastropheP(i,1) = (CatastropheL(i,1)*Cat)/TotalProb(i,1);
end

disp('    Safe       Near miss      Mishap     Incident      Accident
Catastrophe ')
disp('------------------------------------------------------------
')
PosteriorData = [SafeP NearMissP MishapP IncidentP AccidentP
CatastropheP]
```

```
%%-------------------------10 months data plot----------------------
%%-----------------------------Safe plot-----------------------------

E = PosteriorData;
et1 = E(1:10,1);
plot(et1,'.-g')
% Labels are erased, so generate them manually:
title('Occurrence probability of Safe events over 10 months')
xlabel('Month')
ylabel('Posterior probability (Safe)')
% Add a legend in the upper left:
legend('Safe')

%%----------------------------Near miss plot-------------------------

et2 = E(1:10,2);
plot(et2,'.-b')
% Labels are erased, so generate them manually:
title('Occurrence probability of Near miss events over 10 months')
xlabel('Month')
ylabel('Posterior probability (Near miss)')
% Add a legend in the upper left:
legend('Near miss')

%%-------------------------------Mishap plot-------------------------

et3 = E(1:10,3);
plot(et3,'.-m')
% Labels are erased, so generate them manually:
title('Occurrence probability of Mishap events over 10 months')
xlabel('Month')
ylabel('Posterior probability (Mishap)')
% Add a legend in the upper left:
legend('Mishap')

%%-----------------------------Incident plot-------------------------

et4 = E(1:10,4);
plot(et4,'.-b')
% Labels are erased, so generate them manually:
title('Occurrence probability of Incident events over 10 months')
xlabel('Month')
ylabel('Posterior probability (Incident)')
% Add a legend in the upper left:
legend('Incident')

%%-----------------------------Accident plot-------------------------

et5 = E(1:10,5);
plot(et5,'.-m')
% Labels are erased, so generate them manually:
title('Occurrence probability of Accident events over 10 months')
xlabel('Month')
ylabel('Posterior probability (Accident)')
% Add a legend in the upper left:
legend('Accident')
```

```
%%--------------------------Catastrophe plot-------------------------

et6 = E(1:10,6);
plot(et6,'.-r')
% Labels are erased, so generate them manually:
title('Occurrence probability of Catastrophe events over 10 months')
xlabel('Month')
ylabel('Posterior probability (Catastrophe)')
% Add a legend in the upper left:
legend('Catastrophe')

%%-------------------------Subplot end events-----------------------
subplot(2,3,1)
plot(et1,'.-b')
subplot(2,3,2)
plot(et2,'.-b')
subplot(2,3,3)
plot(et3,'.-b')
subplot(2,3,4)
plot(et4,'.-b')
subplot(2,3,5)
plot(et5,'.-b')
subplot(2,3,6)
plot(et6,'.-b')
```

```
%%-------------Likelihood calculation(improved methodology)-------%%
%%---------------------Cumulative data 24 months-------------------

Safe = [3 5 10 21 24 26 30 31 33 35 36 40 45 49 54 64 67 70 74 78 81
83 90 94]';
NearMiss = [4 6 8 34 39 42 44 46 47 50 54 56 60 66 73 100 115 122 128
135 145 148 158 162]';
Mishap = [0 2 2 10 11 11 12 12 12 13 15 15 17 19 21 27 33 34 34 37 40
42 44 46]';
Incident = [0 1 1 2 2 2 3 6 6 6 6 6 7 7 8 11 13 14 15 16 17 19 19
19]';
Accident = [0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 2 2 2 3 3 3 3 3 3]';
Catastrophe = [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]';
Events = [Safe NearMiss Mishap Incident Accident Catastrophe];

%%---------24 months cumulative data conversion to real data---------

m = 24;

SafeN = zeros(24,1); NearMissN = zeros(24,1);
MishapN = zeros(24,1); IncidentN = zeros(24,1);
AccidentN = zeros(24,1); CatastropheN = zeros(24,1);

UpdatedRealData = zeros(m,6);

SafeN(1,1) = Safe(1,1);
NearMissN(1,1) = NearMiss(1,1);
MishapN(1,1) = Mishap(1,1);
IncidentN(1,1) = Incident(1,1);
AccidentN(1,1) = Accident(1,1);
CatastropheN(1,1) = Catastrophe(1,1);

for i = 1:m-1
   SafeN(i+1,1) = Safe(i+1,1) - Safe(i,1);
   NearMissN(i+1,1) = NearMiss(i+1,1) - NearMiss(i,1);
   MishapN(i+1,1) = Mishap(i+1,1) - Mishap(i,1);
   IncidentN(i+1,1) = Incident(i+1,1) - Incident(i,1);
   AccidentN(i+1,1) = Accident(i+1,1) - Accident(i,1);
   CatastropheN(i+1,1) = Catastrophe(i+1,1) - Catastrophe(i,1);
End

disp('    Safe       Near miss      Mishap     Incident      Accident
Catastrophe ')
disp('-------------------------------------------------------------')
UpdatedRealData = [SafeN NearMissN MishapN IncidentN AccidentN
CatastropheN]
```

```
%%----------------------Likelihood estimation----------------------
m = 24;
SafeL = zeros(24,1); NearMissL = zeros(24,1);
MishapL = zeros(24,1); IncidentL = zeros(24,1);
AccidentL = zeros(24,1); CatastropheL = zeros(24,1);
LikelihoodData = zeros(m,6);

for i = 1:m
   SafeL(i,1) = SafeN(i,1)/sum(UpdatedRealData(i,:));
   NearMissL(i,1) = NearMissN(i,1)/sum(UpdatedRealData(i,:));
   MishapL(i,1) = MishapN(i,1)/sum(UpdatedRealData(i,:));
   IncidentL(i,1) = IncidentN(i,1)/sum(UpdatedRealData(i,:));
   AccidentL(i,1) = AccidentN(i,1)/sum(UpdatedRealData(i,:));
   CatastropheL(i,1) = CatastropheN(i,1)/sum(UpdatedRealData(i,:));
End

disp('    Safe       Near miss      Mishap     Incident     Accident
Catastrophe ')
disp('------------------------------------------------------------')
LikelihoodData = [SafeL NearMissL MishapL IncidentL AccidentL
CatastropheL]

%%------------Posterior probability estimation 24 months data--------
m = 24;
SafeP = zeros(24,1); NearMissP = zeros(24,1);
MishapP = zeros(24,1); IncidentP = zeros(24,1);
AccidentP = zeros(24,1); CatastropheP = zeros(24,1);
PosteriorData = zeros(m,6);
TotalProb = zeros(m,1);

for i = 1:m
   TotalProb(i,1) = (SafeL(i,1)*Sf)+(NearMissL(i,1)*Nm)+
   (MishapL(i,1)*Mh)+(IncidentL(i,1)*In)+(AccidentL(i,1)*Ac)
   +(CatastropheL(i,1)*Cat);
end

for i = 1:m
   SafeP(i,1) = (SafeL(i,1)*Sf)/TotalProb(i,1);
   NearMissP(i,1) = (NearMissL(i,1)*Nm)/TotalProb(i,1);
   MishapP(i,1) = (MishapL(i,1)*Mh)/TotalProb(i,1);
   IncidentP(i,1) = (IncidentL(i,1)*In)/TotalProb(i,1);
   AccidentP(i,1) = (AccidentL(i,1)*Ac)/TotalProb(i,1);
   CatastropheP(i,1) = (CatastropheL(i,1)*Cat)/TotalProb(i,1);
end

disp('    Safe       Near miss      Mishap     Incident     Accident
Catastrophe ')
disp('------------------------------------------------------------')
PosteriorData = [SafeP NearMissP MishapP IncidentP AccidentP
CatastropheP]
```

```
%%-------------------------24 months Data Plot---------------------
%%------------------------------Safe plot--------------------------

E = PosteriorData;
et1 = E(1:24,1);
plot(et1,'.-g')
% Labels are erased, so generate them manually:
title('Occurrence probability of Safe events over 24 months')
xlabel('Month')
ylabel('Posterior probability (Safe)')
% Add a legend in the upper left:
legend('Safe')

%%---------------------------Near miss plot------------------------

et2 = E(1:24,2);
plot(et2,'.-b')
% Labels are erased, so generate them manually:
title('Occurrence probability of Near miss events over 24 months')
xlabel('Month')
ylabel('Posterior probability (Near miss)')
% Add a legend in the upper left:
legend('Near miss')

%%---------------------------Mishap plot---------------------------

et3 = E(1:24,3);
plot(et3,'.-m')
% Labels are erased, so generate them manually:
title('Occurrence probability of Mishap events over 24 months')
xlabel('Month')
ylabel('Posterior probability (Mishap)')
% Add a legend in the upper left:
legend('Mishap')

%%----------------------------Incident plot------------------------

et4 = E(1:24,4);
plot(et4,'.-b')
% Labels are erased, so generate them manually:
title('Occurrence probability of Incident events over 24 months')
xlabel('Month')
ylabel('Posterior probability (Incident)')
% Add a legend in the upper left:
legend('Incident')

%%----------------------------Accident plot------------------------

et5 = E(1:24,5);
plot(et5,'.-m')
% Labels are erased, so generate them manually:
title('Occurrence probability of Accident events over 24 months')
xlabel('Month')
ylabel('Posterior probability (Accident)')
% Add a legend in the upper left:
legend('Accident')
```

```
%%--------------------------Catastrophe plot------------------------

et6 = E(1:24,6);
plot(et6,'.-r')
% Labels are erased, so generate them manually:
title('Occurrence probability of Catastrophe events over 24 months')
xlabel('Month')
ylabel('Posterior probability (Catastrophe)')
% Add a legend in the upper left:
legend('Catastrophe')

%%----------------Subplot of 24 months end events' data--------------

subplot(2,3,1)
plot(et1,'.-b')
subplot(2,3,2)
plot(et2,'.-b')
subplot(2,3,3)
plot(et3,'.-b')
subplot(2,3,4)
plot(et4,'.-b')
subplot(2,3,5)
plot(et5,'.-b')
subplot(2,3,6)
plot(et6,'.-b')
```

```
%%-- Safe=S; Not safe=nS; Near miss=N; Not near miss=nN; Mishap=M;
%%-- Not mishap=nM; Incident=I; Not incident=nI; Accident=A;
%%-- Not accident=nA; Catastrophe=C; Not Catastrophe=nC;

%%-----------------Posterior data from 19th month-------------------

PSafe19 = 0.87429;
PNmiss19 = 0.12556;
PMishap19 = 0.0;
PIncident19 = 1.4167e-4;
PAccident19 = 3.5168e-6;
PCatastrophe19 = 0.0;

Posterior = [PSafe19 PNmiss19 PMishap19 PIncident19 PAccident19
PCatastrophe19]

%%---------------------Prior Occurrence Probability----------------

fx1 = 0.9971; fx2 = 0.9579; fx3 = 0.9473; fx4 = 0.9384; fx5 = 0.894;
fx6 = 0.9729; fx7 = 0.8912;

S1 = (fx1*fx2*fx3);
S2 = ((1-fx1)*fx2*fx3);
S = S1 + S2;
nS = 1 - S;

N1 = (fx1*fx2*fx4*nS);
N2 = ((1-fx1)*fx2*fx4*nS);
N3 = (fx1*(1-fx2)*fx4*nS);
N4 = ((1-fx1)*(1-fx2)*fx4*nS);
N = N1 + N2 + N3 + N4;
nN = 1 - S - N;

M1 = (fx1*fx2*fx5*nN);
M2 = ((1-fx1)*fx2*fx5*nN);
M3 = (fx1*(1-fx2)*fx5*nN);
M4 = ((1-fx1)*(1-fx2)*fx5*nN);
M = M1 + M2 + M3 + M4;
nM = 1 - S - N - M;

I1 = (fx1*fx2*fx6*nM);
I2 = ((1-fx1)*fx2*fx6*nM);
I3 = (fx1*(1-fx2)*fx6*nM);
I4 = ((1-fx1)*(1-fx2)*fx6*nM);
I = I1 + I2 + I3 + I4;
nI = 1 - S - N - M - I;

A1 = (fx1*fx2*fx7*nI);
A2 = ((1-fx1)*fx2*fx7*nI);
A3 = (fx1*(1-fx2)*fx7*nI);
A4 = ((1-fx1)*(1-fx2)*fx7*nI);
A = A1 + A2 + A3 + A4;
nA = 1 - S - N - M - I - A;
```

```
%%---------------X1, X2, X3 contributions on Safe events-------------

X1_S = (S1*fx1*fx2*fx3)/PSafe19;

X2_S = ((S1*fx1*fx2*fx3)+(S2*(1-fx1)*fx2*fx3))/PSafe19;

X3_S = ((S1*fx1*fx2*fx3)+(S2*(1-fx1)*fx2*fx3))/PSafe19;

Step1 = [X1_S X2_S X3_S]

%%------------X1, X2, X4 contributions on Near miss events-----------

PN1 = fx1*fx2*fx4*nS;
PN2 = (1-fx1)*fx2*fx4*nS;
PN3 = fx1*(1-fx2)*fx4*nS;
PN4 = (1-fx1)*(1-fx2)*fx4*nS;

PnS1 = fx1*(1-fx2)*fx3;
PnS2 = (1-fx1)*(1-fx2)*fx3;
PnS3 = fx1*fx2*(1-fx3);
PnS4 = (1-fx1)*fx2*(1-fx3);
PnS5 = fx1*(1-fx2)*(1-fx3);
PnS6 = (1-fx1)*(1-fx2)*(1-fx3);

X1_N = ((PN1*PnS3*fx1*fx2*fx4) + (PN3*(PnS1+PnS5)*fx1*(1-
fx2)*fx4))/PNmiss19;

X2_N = ((PN1*PnS3*fx1*fx2*fx4) + (PN2*PnS4*(1-
fx1)*fx2*fx4))/PNmiss19;

X4_N = ((PN1*PnS3*fx1*fx2*fx4) + (PN2*PnS4*(1-fx1)*fx2*fx4) +
(PN3*(PnS1+PnS5)*fx1*(1-fx2)*fx4) + (PN4*(PnS2+PnS6)*(1-fx1)*(1-
fx2)*fx4))/PNmiss19;

Step2 = [X1_N X2_N X3_S X4_N]

%%------------X1, X2, X5 contributions on Mishap events-------------

PM1 = fx1*fx2*fx5*nN;
PM2 = (1-fx1)*fx2*fx5*nN;
PM3 = fx1*(1-fx2)*fx5*nN;
PM4 = (1-fx1)*(1-fx2)*fx5*nN;

PnN1 = fx1*fx2*(1-fx4)*nS;
PnN2 = (1-fx1)*fx2*(1-fx4)*nS;
PnN3 = fx1*(1-fx2)*(1-fx4)*nS;
PnN4 = (1-fx1)*(1-fx2)*(1-fx4)*nS;

PnS1 = fx1*(1-fx2)*fx3;
PnS2 = (1-fx1)*(1-fx2)*fx3;
PnS3 = fx1*fx2*(1-fx3);
PnS4 = (1-fx1)*fx2*(1-fx3);
PnS5 = fx1*(1-fx2)*(1-fx3);
PnS6 = (1-fx1)*(1-fx2)*(1-fx3);
```

```
X1_M = ((PM1*PnN1*PnS3*fx1*fx2*fx5) + (PM3*PnN3*(PnS1+PnS5)*fx1*(1-
fx2)*fx5))/PMishap19;

X2_M = ((PM1*PnN1*PnS3*fx1*fx2*fx5) + (PM2*PnN2*PnS4*(1-
fx1)*fx2*fx5))/PMishap19;

X5_M = ((PM1*PnN1*PnS3*fx1*fx2*fx5) + (PM2*PnN2*PnS4*(1-fx1)*fx2*fx5)
+ (PM3*PnN3*(PnS1+PnS5)*fx1*(1-fx2)*fx5) + (PM4*PnN4*(PnS2+PnS6)*(1-
fx1)*(1-fx2)*fx5))/PMishap19;

Step3 = [X1_M X2_M X3_S X4_N X5_M]

%%-------------X1, X2, X6 contributions on Incident events-----------

PI1 = fx1*fx2*fx6*nM;
PI2 = (1-fx1)*fx2*fx6*nM;
PI3 = fx1*(1-fx2)*fx6*nM;
PI4 = (1-fx1)*(1-fx2)*fx6*nM;

PnM1 = fx1*fx2*(1-fx5)*nN;
PnM2 = (1-fx1)*fx2*(1-fx5)*nN;
PnM3 = fx1*(1-fx2)*(1-fx5)*nN;
PnM4 = (1-fx1)*(1-fx2)*(1-fx5)*nN;

PnN1 = fx1*fx2*(1-fx4)*nS;
PnN2 = (1-fx1)*fx2*(1-fx4)*nS;
PnN3 = fx1*(1-fx2)*(1-fx4)*nS;
PnN4 = (1-fx1)*(1-fx2)*(1-fx4)*nS;

PnS1 = fx1*(1-fx2)*fx3;
PnS2 = (1-fx1)*(1-fx2)*fx3;
PnS3 = fx1*fx2*(1-fx3);
PnS4 = (1-fx1)*fx2*(1-fx3);
PnS5 = fx1*(1-fx2)*(1-fx3);
PnS6 = (1-fx1)*(1-fx2)*(1-fx3);

X1_I = ((PI1*PnM1*PnN1*PnS3*fx1*fx2*fx6) +
(PI3*PnM3*PnN3*(PnS1+PnS5)*fx1*(1-fx2)*fx6))/PIncident19;

X2_I = ((PI1*PnM1*PnN1*PnS3*fx1*fx2*fx6) + (PI2*PnM2*PnN2*PnS4*(1-
fx1)*fx2*fx6))/PIncident19;
X6_I = ((PI1*PnM1*PnN1*PnS3*fx1*fx2*fx6) + (PI2*PnM2*PnN2*PnS4*(1-
fx1)*fx2*fx6) + (PI3*PnM3*PnN3*(PnS1+PnS5)*fx1*(1-fx2)*fx6) +
(PI4*PnM4*PnN4*(PnS2+PnS6)*(1-fx1)*(1-fx2)*fx6))/PIncident19;

Step4 = [X1_I X2_I X3_S X4_N X5_M X6_I]
```

```
%%-------------X1, X2, X7 contributions on Accident events-----------

PA1 = fx1*fx2*fx7*nI;
PA2 = (1-fx1)*fx2*fx7*nI;
PA3 = fx1*(1-fx2)*fx7*nI;
PA4 = (1-fx1)*(1-fx2)*fx7*nI;

PnI1 = fx1*fx2*(1-fx6)*nM;
PnI2 = (1-fx1)*fx2*(1-fx6)*nM;
PnI3 = fx1*(1-fx2)*(1-fx6)*nM;
PnI4 = (1-fx1)*(1-fx2)*(1-fx6)*nM;

PnM1 = fx1*fx2*(1-fx5)*nN;
PnM2 = (1-fx1)*fx2*(1-fx5)*nN;
PnM3 = fx1*(1-fx2)*(1-fx5)*nN;
PnM4 = (1-fx1)*(1-fx2)*(1-fx5)*nN;

PnN1 = fx1*fx2*(1-fx4)*nS;
PnN2 = (1-fx1)*fx2*(1-fx4)*nS;
PnN3 = fx1*(1-fx2)*(1-fx4)*nS;
PnN4 = (1-fx1)*(1-fx2)*(1-fx4)*nS;

PnS1 = fx1*(1-fx2)*fx3;
PnS2 = (1-fx1)*(1-fx2)*fx3;
PnS3 = fx1*fx2*(1-fx3);
PnS4 = (1-fx1)*fx2*(1-fx3);
PnS5 = fx1*(1-fx2)*(1-fx3);
PnS6 = (1-fx1)*(1-fx2)*(1-fx3);

X1_A = ((PA1*PnI1*PnM1*PnN1*PnS3*fx1*fx2*fx7) +
(PA3*PnI3*PnM3*PnN3*(PnS1+PnS5)*fx1*(1-fx2)*fx7))/PAccident19;

X2_A = ((PA1*PnI1*PnM1*PnN1*PnS3*fx1*fx2*fx7) +
(PA2*PnI2*PnM2*PnN2*PnS4*(1-fx1)*fx2*fx7))/PAccident19;

X7_A = ((PA1*PnI1*PnM1*PnN1*PnS3*fx1*fx2*fx7) +
(PA2*PnI2*PnM2*PnN2*PnS4*(1-fx1)*fx2*fx7) +
(PA3*PnI3*PnM3*PnN3*(PnS1+PnS5)*fx1*(1-fx2)*fx7) +
(PA4*PnI4*PnM4*PnN4*(PnS2+PnS6)*(1-fx1)*(1-fx2)*fx7))/PAccident19;

Step5 = [X1_A X2_A X3_S X4_N X5_M X6_I X7_A]
```

```
%%------------X1, X2 contributions on Catastrophic events----------

PC1 = fx1*fx2*nA;
PC2 = (1-fx1)*fx2*nA;
PC3 = fx1*(1-fx2)*nA;

PnA1 = fx1*fx2*(1-fx7)*nI;
PnA2 = (1-fx1)*fx2*(1-fx7)*nI;
PnA3 = fx1*(1-fx2)*(1-fx7)*nI;

PnI1 = fx1*fx2*(1-fx6)*nM;
PnI2 = (1-fx1)*fx2*(1-fx6)*nM;
PnI3 = fx1*(1-fx2)*(1-fx6)*nM;

PnM1 = fx1*fx2*(1-fx5)*nN;
PnM2 = (1-fx1)*fx2*(1-fx5)*nN;
PnM3 = fx1*(1-fx2)*(1-fx5)*nN;

PnN1 = fx1*fx2*(1-fx4)*nS;
PnN2 = (1-fx1)*fx2*(1-fx4)*nS;
PnN3 = fx1*(1-fx2)*(1-fx4)*nS;

PnS1 = fx1*(1-fx2)*fx3;
PnS2 = (1-fx1)*(1-fx2)*fx3;
PnS3 = fx1*fx2*(1-fx3);
PnS4 = (1-fx1)*fx2*(1-fx3);
PnS5 = fx1*(1-fx2)*(1-fx3);
PnS6 = (1-fx1)*(1-fx2)*(1-fx3);

X1_C = ((PC1*PnA1*PnI1*PnM1*PnN1*PnS3*fx1*fx2) +
(PC3*PnA3*PnI3*PnM3*PnN3*(PnS1+PnS5)*fx1*(1-fx2)))/PCatastrophe19;

X2_C = ((PC1*PnA1*PnI1*PnM1*PnN1*PnS3*fx1*fx2) +
(PC2*PnA2*PnI2*PnM2*PnN2*PnS4*(1-fx1)*fx2))/PCatastrophe19;

Step6 = [X1_C X2_C X3_S X4_N X5_M X6_I X7_A]

X1Total = [X1_S + X1_N + X1_M + X1_I + X1_A]
X2Total = [X2_S + X2_N + X2_M + X2_I + X2_A]
X3Total = [X3_S]
X4Total = [1 - X4_N]
X5Total = [1 - X5_M]
X6Total = [1 - X6_I]
X7Total = [1 - X7_A]
```

```
%%-------Posterior data from 20th month as normalizing factor--------

PSafe20 = 0.8533;
PNmiss20 = 0.14297;
PMishap20 = 0.0035958;
PIncident20 = 0.00013826;
PAccident20 = 0.0;
PCatastrophe20 = 0.0;
Posterior =[PSafe20 PNmiss20 PMishap20 PIncident20 PAccident20
PCatastrophe20]

%%----------------Updated barrier success probabilities--------------

bx1 = 9.6621e-1;
bx2 = 9.6617e-1;
bx3 = 9.3636e-1;
bx4 = 9.7014e-1;
bx5 = 1.0;
bx6 = 1.0;
bx7 = 1.0;

%%---------------Prior Occurrence Probability Estimation-------------

S1 = (bx1*bx2*bx3);
S2 = ((1-bx1)*bx2*bx3);
S = S1 + S2;
nS = 1 - S;

N1 = (bx1*bx2*bx4*nS);
N2 = ((1-bx1)*bx2*bx4*nS);
N3 = (bx1*(1-bx2)*bx4*nS);
N4 = ((1-bx1)*(1-bx2)*bx4*nS);
N = N1 + N2 + N3 + N4;
nN = 1 - S - N;

M1 = (bx1*bx2*bx5*nN);
M2 = ((1-bx1)*bx2*bx5*nN);
M3 = (bx1*(1-bx2)*bx5*nN);
M4 = ((1-bx1)*(1-bx2)*bx5*nN);
M = M1 + M2 + M3 + M4;
nM = 1 - S - N - M;

I1 = (bx1*bx2*bx6*nM);
I2 = ((1-bx1)*bx2*bx6*nM);
I3 = (bx1*(1-bx2)*bx6*nM);
I4 = ((1-bx1)*(1-bx2)*bx6*nM);
I = I1 + I2 + I3 + I4;
nI = 1 - S - N - M - I;

A1 = (bx1*bx2*bx7*nI);
A2 = ((1-bx1)*bx2*bx7*nI);
A3 = (bx1*(1-bx2)*bx7*nI);
A4 = ((1-bx1)*(1-bx2)*bx7*nI);
A = A1 + A2 + A3 + A4;
nA = 1 - S - N - M - I - A;
```

```
%%---------------X1, X2, X3 contributions on Safe events-------------

X1_S = (S1*bx1*bx2*bx3)/PSafe20;

X2_S = ((S1*bx1*bx2*bx3)+(S2*(1-bx1)*bx2*bx3))/PSafe20;

X3_S = ((S1*bx1*bx2*bx3)+(S2*(1-bx1)*bx2*bx3))/PSafe20;

Step1 = [X1_S X2_S X3_S]

%%-----------X1, X2, X4 contributions on Near miss events------------

PN1 = bx1*bx2*bx4*nS;
PN2 = (1-bx1)*bx2*bx4*nS;
PN3 = bx1*(1-bx2)*bx4*nS;
PN4 = (1-bx1)*(1-bx2)*bx4*nS;

PnS1 = bx1*(1-bx2)*bx3;
PnS2 = (1-bx1)*(1-bx2)*bx3;
PnS3 = bx1*bx2*(1-bx3);
PnS4 = (1-bx1)*bx2*(1-bx3);
PnS5 = bx1*(1-bx2)*(1-bx3);
PnS6 = (1-bx1)*(1-bx2)*(1-bx3);

X1_N = ((PN1*PnS3*bx1*bx2*bx4) + (PN3*(PnS1+PnS5)*bx1*(1-
bx2)*bx4))/PNmiss20;

X2_N = ((PN1*PnS3*bx1*bx2*bx4) + (PN2*PnS4*(1-
bx1)*bx2*bx4))/PNmiss20;

X4_N = ((PN1*PnS3*bx1*bx2*bx4) + (PN2*PnS4*(1-bx1)*bx2*bx4) +
(PN3*(PnS1+PnS5)*bx1*(1-bx2)*bx4) + (PN4*(PnS2+PnS6)*(1-bx1)*(1-
bx2)*bx4))/PNmiss20;

Step2 = [X1_N X2_N X3_S X4_N]

%%-------------X1, X2, X5 contributions on Mishap events-------------

PM1 = bx1*bx2*bx5*nN;
PM2 = (1-bx1)*bx2*bx5*nN;
PM3 = bx1*(1-bx2)*bx5*nN;
PM4 = (1-bx1)*(1-bx2)*bx5*nN;

PnN1 = bx1*bx2*(1-bx4)*nS;
PnN2 = (1-bx1)*bx2*(1-bx4)*nS;
PnN3 = bx1*(1-bx2)*(1-bx4)*nS;
PnN4 = (1-bx1)*(1-bx2)*(1-bx4)*nS;

PnS1 = bx1*(1-bx2)*bx3;
PnS2 = (1-bx1)*(1-bx2)*bx3;
PnS3 = bx1*bx2*(1-bx3);
PnS4 = (1-bx1)*bx2*(1-bx3);
PnS5 = bx1*(1-bx2)*(1-bx3);
PnS6 = (1-bx1)*(1-bx2)*(1-bx3);
```

```
X1_M = ((PM1*PnN1*PnS3*bx1*bx2*bx5) + (PM3*PnN3*(PnS1+PnS5)*bx1*(1-
bx2)*bx5))/PMishap20;

X2_M = ((PM1*PnN1*PnS3*bx1*bx2*bx5) + (PM2*PnN2*PnS4*(1-
bx1)*bx2*bx5))/PMishap20;

X5_M = ((PM1*PnN1*PnS3*bx1*bx2*bx5) + (PM2*PnN2*PnS4*(1-bx1)*bx2*bx5)
+ (PM3*PnN3*(PnS1+PnS5)*bx1*(1-bx2)*bx5) + (PM4*PnN4*(PnS2+PnS6)*(1-
bx1)*(1-bx2)*bx5))/PMishap20;

Step3 = [X1_M X2_M X3_S X4_N X5_M]

%%-------------X1, X2, X6 contributions on Incident events-----------

PI1 = bx1*bx2*bx6*nM;
PI2 = (1-bx1)*bx2*bx6*nM;
PI3 = bx1*(1-bx2)*bx6*nM;
PI4 = (1-bx1)*(1-bx2)*bx6*nM;

PnM1 = bx1*bx2*(1-bx5)*nN;
PnM2 = (1-bx1)*bx2*(1-bx5)*nN;
PnM3 = bx1*(1-bx2)*(1-bx5)*nN;
PnM4 = (1-bx1)*(1-bx2)*(1-bx5)*nN;

PnN1 = bx1*bx2*(1-bx4)*nS;
PnN2 = (1-bx1)*bx2*(1-bx4)*nS;
PnN3 = bx1*(1-bx2)*(1-bx4)*nS;
PnN4 = (1-bx1)*(1-bx2)*(1-bx4)*nS;

PnS1 = bx1*(1-bx2)*bx3;
PnS2 = (1-bx1)*(1-bx2)*bx3;
PnS3 = bx1*bx2*(1-bx3);
PnS4 = (1-bx1)*bx2*(1-bx3);
PnS5 = bx1*(1-bx2)*(1-bx3);
PnS6 = (1-bx1)*(1-bx2)*(1-bx3);

X1_I = ((PI1*PnM1*PnN1*PnS3*bx1*bx2*bx6) +
(PI3*PnM3*PnN3*(PnS1+PnS5)*bx1*(1-bx2)*bx6))/PIncident20;

X2_I = ((PI1*PnM1*PnN1*PnS3*bx1*bx2*bx6) + (PI2*PnM2*PnN2*PnS4*(1-
bx1)*bx2*bx6))/PIncident20;

X6_I = ((PI1*PnM1*PnN1*PnS3*bx1*bx2*bx6) + (PI2*PnM2*PnN2*PnS4*(1-
bx1)*bx2*bx6) + (PI3*PnM3*PnN3*(PnS1+PnS5)*bx1*(1-bx2)*bx6) +
(PI4*PnM4*PnN4*(PnS2+PnS6)*(1-bx1)*(1-bx2)*bx6))/PIncident20;

Step4 = [X1_I X2_I X3_S X4_N X5_M X6_I]
```

```
%%-------------X1, X2, X7 contributions on Accident events-----------

PA1 = bx1*bx2*bx7*nI;
PA2 = (1-bx1)*bx2*bx7*nI;
PA3 = bx1*(1-bx2)*bx7*nI;
PA4 = (1-bx1)*(1-bx2)*bx7*nI;

PnI1 = bx1*bx2*(1-bx6)*nM;
PnI2 = (1-bx1)*bx2*(1-bx6)*nM;
PnI3 = bx1*(1-bx2)*(1-bx6)*nM;
PnI4 = (1-bx1)*(1-bx2)*(1-bx6)*nM;

PnM1 = bx1*bx2*(1-bx5)*nN;
PnM2 = (1-bx1)*bx2*(1-bx5)*nN;
PnM3 = bx1*(1-bx2)*(1-bx5)*nN;
PnM4 = (1-bx1)*(1-bx2)*(1-bx5)*nN;

PnN1 = bx1*bx2*(1-bx4)*nS;
PnN2 = (1-bx1)*bx2*(1-bx4)*nS;
PnN3 = bx1*(1-bx2)*(1-bx4)*nS;
PnN4 = (1-bx1)*(1-bx2)*(1-bx4)*nS;

PnS1 = bx1*(1-bx2)*bx3;
PnS2 = (1-bx1)*(1-bx2)*bx3;
PnS3 = bx1*bx2*(1-bx3);
PnS4 = (1-bx1)*bx2*(1-bx3);
PnS5 = bx1*(1-bx2)*(1-bx3);
PnS6 = (1-bx1)*(1-bx2)*(1-bx3);

X1_A = ((PA1*PnI1*PnM1*PnN1*PnS3*bx1*bx2*bx7) +
(PA3*PnI3*PnM3*PnN3*(PnS1+PnS5)*bx1*(1-bx2)*bx7))/PAccident20;

X2_A = ((PA1*PnI1*PnM1*PnN1*PnS3*bx1*bx2*bx7) +
(PA2*PnI2*PnM2*PnN2*PnS4*(1-bx1)*bx2*bx7))/PAccident20;

X7_A = ((PA1*PnI1*PnM1*PnN1*PnS3*bx1*bx2*bx7) +
(PA2*PnI2*PnM2*PnN2*PnS4*(1-bx1)*bx2*bx7) +
(PA3*PnI3*PnM3*PnN3*(PnS1+PnS5)*bx1*(1-bx2)*bx7) +
(PA4*PnI4*PnM4*PnN4*(PnS2+PnS6)*(1-bx1)*(1-bx2)*bx7))/PAccident20;

Step5 = [X1_A X2_A X3_S X4_N X5_M X6_I X7_A]
```

```
%%-------------X1, X2 contributions on Catastrophic events-----------

PC1 = bx1*bx2*nA;
PC2 = (1-bx1)*bx2*nA;
PC3 = bx1*(1-bx2)*nA;

PnA1 = bx1*bx2*(1-bx7)*nI;
PnA2 = (1-bx1)*bx2*(1-bx7)*nI;
PnA3 = bx1*(1-bx2)*(1-bx7)*nI;

PnI1 = bx1*bx2*(1-bx6)*nM;
PnI2 = (1-bx1)*bx2*(1-bx6)*nM;
PnI3 = bx1*(1-bx2)*(1-bx6)*nM;

PnM1 = bx1*bx2*(1-bx5)*nN;
PnM2 = (1-bx1)*bx2*(1-bx5)*nN;
PnM3 = bx1*(1-bx2)*(1-bx5)*nN;

PnN1 = bx1*bx2*(1-bx4)*nS;
PnN2 = (1-bx1)*bx2*(1-bx4)*nS;
PnN3 = bx1*(1-bx2)*(1-bx4)*nS;

PnS1 = bx1*(1-bx2)*bx3;
PnS2 = (1-bx1)*(1-bx2)*bx3;
PnS3 = bx1*bx2*(1-bx3);
PnS4 = (1-bx1)*bx2*(1-bx3);
PnS5 = bx1*(1-bx2)*(1-bx3);
PnS6 = (1-bx1)*(1-bx2)*(1-bx3);

X1_C = ((PC1*PnA1*PnI1*PnM1*PnN1*PnS3*bx1*bx2) +
(PC3*PnA3*PnI3*PnM3*PnN3*(PnS1+PnS5)*bx1*(1-bx2)))/PCatastrophe20;

X2_C = ((PC1*PnA1*PnI1*PnM1*PnN1*PnS3*bx1*bx2) +
(PC2*PnA2*PnI2*PnM2*PnN2*PnS4*(1-bx1)*bx2))/PCatastrophe20;

Step6 = [X1_C X2_C X3_S X4_N X5_M X6_I X7_A]

X1Total = [X1_S + X1_N + X1_M + X1_I + X1_A]
X2Total = [X2_S + X2_N + X2_M + X2_I + X2_A]
X3Total = [X3_S]
X4Total = [1 - X4_N]
X5Total = [1 - X5_M]
X6Total = [1 - X6_I]
X7Total = [1 - X7_A]
```

Appendix D

Calculation (forward and backward analysis)

Safe state:

	End Events	Safety Barrier	State	Success Probability
1	**Safe**	Human Factor	S	0.9971
		Management Factor	S	0.9579
		Release Prevention Factor	S	0.9473
2	**Safe**	Human Factor	F	0.0029
		Management Factor	S	0.9579
		Release Prevention Factor	S	0.9473

Near miss state:

	End Events	Safety Barrier	State	Success Probability
1	**Near miss**	Human Factor	S	0.9971
		Management Factor	S	0.9579
		Not Safe	S	9.2581e-2
		Dispersion Prevention Factor	S	0.9384
2	**Near miss**	Human Factor	S	0.9971
		Management Factor	F	0.0421
		Not Safe	S	9.2581e-2
		Dispersion Prevention Factor	S	0.9384
3	**Near miss**	Human Factor	F	0.0029
		Management Factor	S	0.9579
		Not Safe	S	9.2581e-2
		Dispersion Prevention Factor	S	0.9384
4	**Near miss**	Human Factor	F	0.0029
		Management Factor	F	0.0421
		Not Safe	S	9.2581e-2
		Dispersion Prevention Factor	S	0.9384

Mishap state:

	End Events	Safety Barrier	State	Success Probability
1	**Mishap**	Human Factor	S	0.9971
		Management Factor	S	0.9579
		Not Near Miss	S	5.7030e-3
		Ignition Prevention Factor	S	0.8940
2	**Mishap**	Human Factor	S	0.9971
		Management Factor	F	0.0421
		Not Near Miss	S	5.7030e-3
		Ignition Prevention Factor	S	0.8940
3	**Mishap**	Human Factor	F	0.0029
		Management Factor	S	0.9579
		Not Near Miss	S	5.7030e-3
		Ignition Prevention Factor	S	0.8940
4	**Mishap**	Human Factor	F	0.0029
		Management Factor	F	0.0421
		Not Near Miss	S	5.7030e-3
		Ignition Prevention Factor	S	0.8940

Incident state:

	End Events	Safety Barrier	State	Success Probability
1	**Incident**	Human Factor	S	0.9971
		Management Factor	S	0.9579
		Not Mishap	S	6.0452e-4
		Escalation Prevention Factor	S	0.9729
2	**Incident**	Human Factor	S	0.9971
		Management Factor	F	0.0421
		Not Mishap	S	6.0452e-4
		Escalation Prevention Factor	S	0.9729
3	**Incident**	Human Factor	F	0.0029
		Management Factor	S	0.9579
		Not Mishap	S	6.0452e-4
		Escalation Prevention Factor	S	0.9729
4	**Incident**	Human Factor	F	0.0029
		Management Factor	F	0.0421
		Not Mishap	S	6.0452e-4
		Escalation Prevention Factor	S	0.9729

Accident state:

	End Events	Safety Barrier	State	Success Probability
1	**Accident**	Human Factor	S	0.9971
		Management Factor	S	0.9579
		Not Incident	S	1.6382e-5
		Damage Control Emergency Factor	S	0.8912
2	**Accident**	Human Factor	S	0.9971
		Management Factor	F	0.0421
		Not Incident	S	1.6382e-5
		Damage Control Emergency Factor	S	0.8912
3	**Accident**	Human Factor	F	0.0029
		Management Factor	S	0.9579
		Not Incident	S	1.6382e-5
		Damage Control Emergency Factor	S	0.8912
4	**Accident**	Human Factor	F	0.0029
		Management Factor	F	0.0421
		Not Incident	S	1.6382e-5
		Damage Control Emergency Factor	S	0.8912

Catastrophic state:

	End Events	Safety Barrier	State	Success Probability
1	**Catastrophe**	Human Factor	S	0.9971
		Management Factor	S	0.9579
		Not Accident	S	1.7824e-6
2	**Catastrophe**	Human Factor	S	0.9971
		Management Factor	F	0.0421
		Not Accident	S	1.7824e-6
3	**Catastrophe**	Human Factor	F	0.0029
		Management Factor	S	0.9579
		Not Accident	S	1.7824e-6
4	**Catastrophe**	Human Factor	F	0.0029
		Management Factor	F	0.0421
		Not Accident	S	1.7824e-6

Nm = Near Miss, Mishap = Mh, Incident = In, Accident = Acc, Catastrophe = Cat

P(Safe) = P(Safe|X1,X2,X3) P(X1) P(X2) P(X3) + P(Safe|Ẍ1,X2,X3) P(Ẍ1) P(X2) P(X3)
= (1*0.9971*0.9579*0.9473) + (1*0.0029*0.9579*0.9473)
= 0.90479 + 0.0026315
= **9.0742e-1**

P(Not safe) = 1 - P(Safe)
= 1 - 9.0742e-1
= **9.258e-2**

P(Near Miss) = P(Nm | X1, X2, X4, Not safe) P(X1) P(X2) P(X4) P(Not safe)
+ P(Nm | X1, Ẍ2, X4, Not safe) P(X1) P(Ẍ2) P(X4) P(Not safe)
+ P(Nm | Ẍ1, X2, X4, Not safe) P(Ẍ1) P(X2) P(X4) P(Not safe)
+ P(Nm | Ẍ1, Ẍ2, X4, Not safe) P(Ẍ1) P(Ẍ2) P(X4) P(Not safe)
= (1*0.9971*0.9579*0.9384*9.258e-2) + (1*0.9971*0.0421*0.9384*9.258e-2)
+ (1*0.0029*0.9579*0.9384*9.258e-2) + (1*0.0029*0.0421*0.9384*9.258e-2)
= 8.2978e-2 + 3.6469e-3 + 2.4134e-4 + 1.0607e-5
= **8.6877e-2**

P(Not Near Miss) = 1 - P(Safe) - P(Near Miss)
= 1 - 9.0742e-1 - 8.6877e-2
= **5.703e-3**

P(Mishap) = P(Mh | X1, X2, X5, Not Near miss) P(X1) P(X2) P(X5) P(Not Near miss)
+ P(Mh | X1, Ẍ2, X5, Not Near miss) P(X1) P(Ẍ2) P(X5) P(Not Near miss)
+ P(Mh | Ẍ1, X2, X5, Not Near miss) P(Ẍ1) P(X2) P(X5) P(Not Near miss)
+ P(Mh | Ẍ1, Ẍ2, X5, Not Near miss) P(Ẍ1) P(Ẍ2) P(X5) P(Not Near miss)
= (1*0.9971*0.9579*0.894*5.703e-3) + (1*0.9971*0.0421*0.894*5.703e-3)
+ (1*0.0029*0.9579*0.894*5.703e-3) + (1*0.0029*0.0421*0.894*5.703e-3)
= 4.8697e-3 + 2.1402e-4 + 1.4163e-5 + 6.2247e-7
= **5.0985e-3**

P(Not Mishap) = 1 – P(Safe) – P(Near Miss) – P(Mishap)
= 1- 9.0742e-1- 8.6877e-2 - 5.0985e-3
= **6.045e-4**

P(Incident) = P(In | X1, X2, X6, Not Mishap) P(X1) P(X2) P(X6) P(Not Mishap)
+ P(In | X1, Ẍ2, X6, Not Mishap) P(X1) P(Ẍ2) P(X6) P(Not Mishap)
+ P(In | Ẍ1, X2, X6, Not Mishap) P(Ẍ1) P(X2) P(X6) P(Not Mishap)
+ P(In | Ẍ1, Ẍ2, X6, Not Mishap) P(Ẍ1) P(Ẍ2) P(X6) P(Not Mishap)
= (1*0.9971*0.9579*0.9729*6.045e-4) + (1*0.9971*0.0421*0.9729*6.045e-4)
+ (1*0.0029*0.9579*0.9729*6.045e-4) + (1*0.0029*0.0421*0.9729*6.045e-4)
= 5.6172e-4 + 2.4688e-5 + 1.6337e-6 + 7.1803e-8
= 5.8811e-4

P(Not Incident) = 1 – P(Safe) – P(Near Miss) – P(Mishap) – P(Incident)
= 1 - 9.0742e-1 - 8.6877e-2 - 5.0985e-3 - 5.8811e-4
= 1.639e-5

P(Accident) = P(Acc | X1, X2, X7, Not Incident) P(X1) P(X2) P(X7) P(Not Incident)
+ P(Acc | X1, Ẍ2, X7, Not Incident) P(X1) P(Ẍ2) P(X7) P(Not Incident)
+ P(Acc | Ẍ1, X2, X7, Not Incident) P(Ẍ1) P(X2) P(X7) P(Not Incident)
+ P(Acc | Ẍ1, Ẍ2, X7, Not Incident) P(Ẍ1) P(Ẍ2) P(X7) P(Not Incident)
= (1*0.9971*0.9579*0.8912*1.639e-5) + (1*0.9971*0.0421*0.8912*1.639e-5)
+ (1*0.0029*0.9579*0.8912*1.639e-5) + (1*0.0029*0.0421*0.8912*1.639e-5)
= 1.3951e-5 + 6.1316e-7 + 4.0576e-8 + 1.7833e-9
= 1.4607e-5

P(Not Accident) = 1 – P(Safe) – P(Near Miss) – P(Mishap) – P(Incident) – P(Accident)
= 1- 9.0742e-1 - 8.6877e-2 - 5.0985e-3 - 5.8811e-4 - 1.4607e-5
= 1.783e-6

P(Catastrophe) = P(Cat | X1, X2, Not Accident) P(X1) P(X2) P(Not Accident)
+ P(Cat | X1, Ẍ2, Not Accident) P(X1) P(Ẍ2) P(Not Accident)
+ P(Cat | Ẍ1, X2, Not Accident) P(Ẍ1) P(X2) P(Not Accident)
+ P(Cat | Ẍ1, Ẍ2, Not Accident) P(Ẍ1) P(Ẍ2) P(Not Accident)
= (1*0.9971*0.9579*1.783e-6) + (1*0.9971*0.0421*1.783e-6)
+ (1*0.0029*0.9579*1.783e-6) + (1*0.0029*0.0421*1.783e-6)
= 1.703e-6 + 7.4847e-8 + 4.953e-9 + 2.1769e-10
= 1.783e-6

PRIOR EVENTS' SUCCESS PROBABILITIES					
SAFE	N.MISS	MISHAP	INCIDENT	ACCIDENT	CATASTROPHE
9.0742e-1	8.6877e-2	5.0985e-3	5.8811e-4	1.4607e-5	1.7830e-6

Prior Barrier Success Probabilities					
P(X1)	P(X2)	P(X3)	P(X4)	P(X5)	P(X6)
0.9971	0.9579	0.9473	0.9384	0.8940	0.8912

Posterior Events' Success Probabilities						
Month	Safe	N.Miss	Mishap	Incident	Accident	Catastrophe
19	8.7429e-1	1.2556e-1	0.00	1.4167e-4	3.5168e-6	0.00

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

P(Safe | X1 = S, X2 = S, X3 = S) = 0.9971*0.9579*0.9473 = 0.90479

P(X1 | Safe = yes)

= P(X1 & Safe = yes) / P(Safe = yes)

$=\sum_{x2,x3} P(X1 = S, X2, X3, Safe = yes)$/ P(Safe=yes)

$$\sum_{x2,x3} P(X1 = S, X2, X3, Safe = yes)$$

= P(X1 = S, X2 = S, X3 = S, Safe = yes) + P(X1 = S, X2 = F, X3 = S, Safe = yes)

+ P(X1 = S, X2 = S, X3 = F, Safe = yes) + P(X1 = S, X2 = F, X3 = F, Safe = yes)

= P(Safe = yes | X1 = S, X2 = S, X3 = S) P(X1 = S) P(X2 = S) P(X3 = S)

+ P(Safe = yes | X1 = S, X2 = F, X3 = S) P(X1 = S) P(X2 = F) P(X3 = S)

+ P(Safe = yes | X1 = S, X2 = S, X3 = F) P(X1 = S) P(X2 = S) P(X3 = F)

+ P(Safe = yes | X1 = S, X2 = F, X3 = F) P(X1 = S) P(X2 = F) P(X3 = F)

= (0.90479*0.9971*0.9579*0.9473) + 0 + 0 + 0

= 0.81864

P(X1 | Safe = yes) = P(X1 & Safe = yes) / P(Safe = yes)

= 0.81864 / 0.87429

= **0.93635**

P(Safe | X1 = S, X2 = S, X3 = S) = 0.9971*0.9579*0.9473 = 0.90479

P(Safe | X1 = F, X2 = S, X3 = S) = 0.0029*0.9579*0.9473 = 2.6315e-3

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	**NOT SAFE**
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

P(X2 | Safe = yes)

=P(X2 & Safe = yes) / P(Safe = yes)

= $\sum_{x1,x3} \mathrm{P(X1, X2 = S, X3, Safe = yes)}$ / P(Safe = yes)

$\sum_{x1,x3} \mathrm{P(X1, X2 = S, X3, Safe = yes)}$

= P(X1 = S, X2 = S, X3 = S, Safe = yes) + P(X1 = F, X2 = S, X3 = S, Safe = yes)

+ P(X1 = S, X2 = S, X3 = F, Safe = yes) + P(X1 = F, X2 = S, X3 = F, Safe = yes)

= P(Safe = yes | X1 = S, X2 = S, X3 = S) P(X1 = S) P(X2 = S) P(X3 = S)

+ P(Safe = yes | X1 = F, X2 = S, X3 = S) P(X1 = F) P(X2 = S) P(X3 = S)

+ P(Safe = yes | X1 = S, X2 = S, X3 = F) P(X1 = S) P(X2 = S) P(X3 = F)

+ P(Safe = yes | X1 = F, X2 = S, X3 = F) P(X1 = F) P(X2 = S) P(X3 = F)

= (0.90479*0.9971*0.9579*0.9473) + (2.6315e-3*0.0029*0.9579*0.9473) + 0 + 0

= 8.1864e-1 + 6.9248e-6 + 0 + 0

= 0.81865

P(X2 | Safe = yes) = P(X2 & Safe = yes) / P(Safe = yes)

= 0.81865 / 0.87429

= **0.93636**

P(Safe | X1 = S, X2 = S, X3 = S) = 0.9971*0.9579*0.9473 = 0.90479

P(Safe | X1 = F, X2 = S, X3 = S) = 0.0029*0.9579*0.9473 = 2.6315e-3

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	**NOT SAFE**
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

P(X3 | Safe = yes)

=P(X3 & Safe = yes) / P(Safe = yes)

= $\sum_{x1,x2} P(X1, X2, X3 = S, Safe = yes)$ / P(Safe = yes)

$\sum_{x1,x2} P(X1, X2, X3 = S, Safe = yes)$

= P(X1 = S, X2 = S, X3 = S, Safe = yes) + P(X1 = F, X2 = S, X3 = S, Safe = yes)

+ P(X1 = S, X2 = F, X3 = S, Safe = yes) + P(X1 = F, X2 = F, X3 = S, Safe = yes)

= P(Safe = yes | X1 = S, X2 = S, X3 = S) P(X1 = S) P(X2 = S) P(X3 = S)

+ P(Safe = yes | X1 = F, X2 = S X3 = S) P(X1 = F) P(X2 = S) P(X3 = S)

+ P(Safe = yes | X1 = S, X2 = F, X3 = S) P(X1 = S) P(X2 = F) P(X3 = S)

+ P(Safe = yes | X1 = F, X2 = F, X3 = S) P(X1 = F) P(X2 = F) P(X3 = S)

= (0.90479*0.9971*0.9579*0.9473) + (2.6315e-3*0.0029*0.9579*0.9473) + 0 + 0

= 0.81864 + 6.9248e-6 + 0 + 0

= 0.81865

P(X3 | Safe = yes)

= P(X3 & Safe = yes) / P(Safe = yes)

= 0.81865 / 0.87429

= **0.93636**

Step 1: Updated X1, X2, X3

Barrier	X1		X2		X3
	0.9971	↓	0.9579	↓	0.9473
Step	Updating				
1	0.93635	↓	0.93636	↓	0.93636

P(Nm = yes | X1 = S, X2 = S, X4 = S, Ns = yes) = (0.9971*0.9579*0.9384*0.09258) = 8.2978e-2

P(Nm = yes | X1 = S, Ẍ2 = F, X4 = S, Ns = yes) = (0.9971*0.0421*0.9384*0.09258) = 3.6469e-3

P(Ns = yes | X1 = S, X2 = S, Ẍ3 = F) = (0.9971*0.9579*0.0527) = 5.0335e-2

P(Ns = yes | X1 = S, Ẍ2 = F, X3 = S) = (0.9971*0.0421*0.9473) = 3.9766e-2

P(Ns = yes | X1 = S, Ẍ2 = F, Ẍ3 = F) = (0.9971*0.0421*0.0527) = 2.2122e-3

So, P(Ns = yes | X1 = S, Ẍ2 = F, X3 = S) + P(Ns = yes | X1 = S, Ẍ2 = F, Ẍ3 = F)

= 3.9766e-2 + 2.2122e-3

= 4.1978e-2

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

P(X1 | Near miss = yes)

=P(X1 & Near miss = yes) / P(Near miss = yes)

= $\sum_{x2,x4} \mathrm{P(X1 = S, X2, X4, Ns = yes, Nm = yes)}$/ P(Near miss = yes)

$\sum_{x2,x4} \mathrm{P(X1 = S, X2, X4, Ns = yes, Nm = yes)}$

= P(X1 = S, X2 = S, X4 = S, Ns = yes, Nm = yes) + P(X1 = S, Ẍ2 = F, X4 = S, Ns = yes, Nm = yes)

+ P(X1 = S, X2 = S, Ẍ4 = F, Ns = yes, Nm = yes) + P(X1 = S, Ẍ2 = F, Ẍ4 = F, Ns = yes, Nm = yes)

= P(Nm = yes | X1=S, X2=S, X4=S, Ns=y) P(Ns = yes | X1=S, X2=S, X4=S) P(X1=S) P(X2=S) P(X4=S)

+ P(Nm = yes | X1=S, Ẍ2=F, X4=S, Ns=y) P(Ns = yes | X1=S, Ẍ2=F, X4=S) P(X1=S) P(Ẍ2=F) P(X4=S)

+ P(Nm = yes | X1=S, X2=S, Ẍ4=F, Ns=y) P(Ns = yes | X1=S, X2=S, Ẍ4=F) P(X1=S) P(X2=S) P(Ẍ4=F)

+ P(Nm = yes | X1=S, Ẍ2=F, Ẍ4=F, Ns=y) P(Ns = yes | X1=S, Ẍ2=F, Ẍ4=F) P(X1=S) P(Ẍ2=F) P(Ẍ4=F)

= (8.2978e-2*5.0335e-2*0.9971*0.9579*0.9384) + (3.6469e-3*4.1978e-2*0.9971*0.0421*0.9384) + 0+0

= 3.7435e-3 + 6.0305e-6 + 0 + 0

= 3.7495e-3

P(X1 | Near miss = yes)

= P(X1 & Near miss = yes) / P(Near miss = yes)

= 3.7495e-3 / 0.12556

= **2.9862e-2**

P(Nm = yes | X1 = S, X2 = S, X4 = S, Ns = yes) = (0.9971*0.9579*0.9384*0.09258) = 8.2978e-2

P(Nm = yes | Ẍ1 = F, X2 = S, X4 = S, Ns = yes) = (0.0029*0.9579*0.9384*0.09258) = 2.4134e-4

P(Ns = yes | X1 = S, X2 = S, Ẍ3 = F) = (0.9971*0.9579*0.0527) = 5.0335e-2

P(Ns = yes | Ẍ1 = F, X2 = S, X3 = S) = (0.0029*0.9579*0.9473) = 2.6315e-3

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

P(X2 | Near miss = yes)

= P(X2 & Near miss = yes) / P(Near miss = yes)

= $\sum_{x1,x4} P(X1, X2 = S, X4, Ns = yes, Nm = yes)$ / P(Near miss = yes)

$\sum_{x1,x4} P(X1, X2 = S, X4, Ns = yes, Nm = yes)$

= P(X1 = S, X2 = S, X4 = S, Ns = yes, Nm = yes) + P(Ẍ1 = F, X2 = S, X4 = S, Ns = yes, Nm = yes)

+ P(X1 = S, X2 = S, Ẍ4 = F, Ns = yes, Nm = yes) + P(Ẍ1 = F, X2 = S, Ẍ4 = F, Ns = yes, Nm = yes)

= P(Nm = yes | X1=S, X2=S, X4=S, Ns=y) P(Ns = yes | X1=S, X2=S, X4=S) P(X1=S) P(X2=S) P(X4=S)

+ P(Nm = yes | Ẍ1=F, X2=S, X4=S, Ns=y) P(Ns = yes | Ẍ1=F, X2=S, X4=S) P(Ẍ1=F) P(X2=S) P(X4=S)

+ P(Nm = yes | X1=S, X2=S, Ẍ4=F, Ns=y) P(Ns = yes | X1=S, X2=S, Ẍ4=F) P(X1=S) P(X2=S) P(Ẍ4=F)

+ P(Nm = yes | Ẍ1=F, X2=S, Ẍ4=F, Ns=y) P(Ns = yes | Ẍ1=F, X2=S, Ẍ4=F) P(Ẍ1=F) P(X2=S) P(Ẍ4=F)

= (8.2978e-2*5.0335e-2*0.9971*0.9579*0.9384) + (2.4134e-4*2.6315e-3*0.0029*0.9579*0.9384) + 0 + 0

= 3.7435e-3 + 1.6555e-9 + 0 + 0

= 3.7435e-3

P(X2 | Near miss = yes)

= P(X2 & Near miss = yes) / P(Near miss = yes)

= 3.7435e-3 / 0.12556

= **2.9814e-2**

P(Nm = yes | X1 = S, X2 = S, X4 = S, Ns = yes) = (0.9971*0.9579*0.9384*0.09258) = 8.2978e-2
P(Nm = yes | Ẍ1 = F, X2 = S, X4 = S, Ns = yes) = (0.0029*0.9579*0.9384*0.09258) = 2.4134e-4
P(Nm = yes | X1 = S, Ẍ2 = F, X4 = S, Ns = yes) = (0.9971*0.0421*0.9384*0.09258) = 3.6469e-3
P(Nm = yes | Ẍ1 = F, Ẍ2 = F, X4 = S, Ns = yes) = (0.0029*0.0421*0.9384*0.09258) = 1.0607e-5

P(Ns = yes | X1 = S, X2 = S, Ẍ3 = F) = (0.9971*0.9579*0.0527) = 5.0335e-2

P(Ns = yes | Ẍ1 = F, X2 = S, Ẍ3 = F) = (0.0029*0.9579*0.0527) = 1.4640e-4

P(Ns = yes | X1 = S, Ẍ2 = F, X3 = S) = (0.9971*0.0421*0.9473) = 3.9766e-2
P(Ns = yes | X1 = S, Ẍ2 = F, Ẍ3 = F) = (0.9971*0.0421*0.0527) = 2.2122e-3,
So, 3.9766e-2 + 2.2122e-3
= 4.1978e-2

P(Ns = yes | Ẍ1 = F, Ẍ2 = F, X3 = S) = (0.0029*0.0421*0.9473) = 1.1566e-4
P(Ns = yes | Ẍ1 = F, Ẍ2 = F, Ẍ3 = F) = (0.0029*0.0421*0.0527) = 6.4341e-6
So, 1.1566e-4 + 6.4341e-6
= 1.2209e-4

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
F	**F**	**S**	
S	S	F	
[illegible]	[illegible]	[illegible]	
S	F	F	
F	**F**	**F**	

P(X4 | Near miss = yes)
=P(X4 & Near miss = yes) / P(Near miss = yes)
= $\sum_{x1,x2} P(X1, X2, X4 = S, \text{Near miss} = \text{yes})$/ P(Near miss = yes)
$\sum_{x1,x2} P(X1, X2, X4 = S, \text{Near miss} = \text{yes})$
= P(X1 = S, X2 = S, X4 = S, Ns = yes, Nm = yes) + P(X1 = F, X2 = S, X4 = S, Ns = yes, Nm = yes)
+ P(X1 = S, X2 = F, X4 = S, Ns = yes, Nm = yes) + P(X1 = F, X2 = F, X4 = S, Ns = yes, Nm = yes)
= P(Nm = yes | X1=S, X2=S, X4=S, Ns=y) P(Ns = yes | X1=S, X2=S, X4=S) P(X1=S) P(X2=S) P(X4=S)
+ P(Nm = yes | X1=F, X2=S, X4=S, Ns=y) P(Ns = yes | X1=F, X2=S, X4=S) P(X1=F) P(X2=S) P(X4=S)
+ P(Nm = yes | X1=S, X2=F, X4=S, Ns=y) P(Ns = yes | X1=S, X2=F, X4=S) P(X1=S) P(X2=F) P(X4=S)
+ P(Nm = yes | X1=F, X2=F, X4=S, Ns=y) P(Ns = yes | X1=F, X2=F, X4=S) P(X1=F) P(X2=F) P(X4=S)
= (8.2978e-2*5.0335e-2*0.9971*0.9579*0.9384) + (2.4134e-4*1.4640e-4*0.0029*0.9579*0.9384)
+ (3.6469e-3*4.1978e-2*0.9971*0.0421*0.9384) + (1.0607e-5*1.2209e-4*0.0029*0.0421*0.9384)
= 3.7435e-3 + 9.2104e-11 + 6.0305e-6 + 1.4837e-13
= 3.7495e-3

P(X4 | Near miss = yes)

= P(X4 & Near miss = yes) / P(Near miss = yes)

= 3.7495e-3 / 0.12556

= **2.9862e-2**

Step 2: Updated X1, X2, X4

Barriers	X1		X2		X3		X4
	0.9971	↓	0.9579		0.9473	↓	0.9384
Step	Updating						
1	0.93635	↓	0.93636		0.93636	↓	-
2	2.9862e-2	↓	2.9814e-2		-	↓	2.9862e-2

X1	X2	X4	STATE
S	S	S	NEAR MISS
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT NEAR MISS
F	S	F	
S	F	F	
F	F	F	

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

P(Ns = yes | X = S, X2 = S X3 = F) = (0.9971*0.9579*0.0527) = 5.0335e-2

P(Ns = yes | X1 = S, X2 = F, X3 = S) = (0.9971*0.0421*0.9473) = 3.9766e-2

P(Ns = yes | X1 = S, X2 = F, X3 = F) = (0.9971*0.0421*0.0527) = 2.2122e-3

So, 3.9766e-2 + 2.2122e-3 = 4.1978e-2

P(NNm = yes | X1 S, X2 = S, X4 = F, Ns = yes) = (0.9971*0.9579*0.0616*0.09258) = 5.447e-3

P(NNm = yes | X1 = S, X2 = F X4 = F, Ns = yes) = (0.9971*0.0421*0.0616*0.09258) = 2.394e-4

P(Mishap = yes | X1 = S, X2 = S X5 = S, NNm = yes) = (0.9971*0.9579*0.894*0.005703) = 4.8697e-3

P(Mishap = yes | X1 = S, X2 = F, X5 = S, NNm = yes) = (0.9971*0.0421*0.894*0.005703) = 2.1402e-4

P(X1 | Mishap = yes)

=P(X1 & Mishap = yes) / P(Mishap = yes)

= $\sum_{x2,x5} P(X1 = S, X2, X5, Mishap = yes)$ / P(Mishap = yes)

= P(X1=S, X2=S, X5=S, NNm=yes, Mishap=yes) + P(X1=S, X2=F, X5=S, NNm=yes, Mishap=yes)

+ P(X1=S, X2=S, X5=F, NNm=yes, Mishap=yes) + P(X1=S, X2=F, X5=F, NNm=yes, Mishap=yes)

= P(Mishap = yes | X1 = S, X2 = S, X5 = S, NNm = yes) P(NNm = yes | X1 = S, X2 = S, X5 = S, Ns = y)

P(Ns = yes | X1 = S, X2 = S, X5 = S) P(X1 = S) P(X2 = S) P(X5 = S)

+ P(Mishap = yes | X1 = S, X2 = F, X5 = S NNm = yes) P(NNm = yes | X1 = S, X2 = F, X5 = S, Ns = y)

P(Ns = yes | X1 = S, X2 = F, X5 = S) P(X1 = S) P(X2 = F) P(X5 = S)

+ P(Mishap = yes | X1 = S, X2 = S, X5 = F, NNm = yes) P(NNm = yes | X1 = S, X2 = S, X5 = F, Ns = y)

P(Ns = yes | X1 = S, X2 = S, X5 = F) P(X1 = S) P(X2 = S) P(X5 = F)

+ P(Mishap = yes | X1 = S, X2 = F, X5 = F, NNm = yes) P(NNm = yes | X1 = S, X2 = F, X5 = F, Ns = y)

P(Ns = yes | X1 = S, X2 = F, X5 = F) P(X1 = S) P(X2 = F) P(X5 = F)

= (4.8697e-3*5.447e-3*5.0335e-2*0.9971*0.9579*0.894)

+ (2.1402e-4*2.394e-4*4.1978e-2*0.9971*0.0421*0.894) + 0 + 0

= 1.1401e-6 + 8.0716e-11

= 1.1402e-6

P(X1 | Mishap = yes)

= P(X1 & Mishap = yes) / P(Mishap = yes)

= 1.1402e-6 / 0.0

= **0.0**

X1	X2	X4	STATE		X1	X2	X3	STATE
S	S	S	**NEAR MISS**		S	S	S	**SAFE**
F	S	S			F	S	S	
S	F	S			S	F	S	NOT SAFE
F	F	S			F	F	S	
S	S	F	NOT NEAR MISS		S	S	F	
F	S	F						
S	F	F			S	F	F	
F	F	F			F	F	F	

P(Ns = yes | X1 = S, X2 = S, X3 = F) = (0.9971*0.9579*0.0527) = 5.0335e-2

P(Ns = yes | X1 = F, X2 = S, X3 = F) = (0.0029*0 9579*0.0527) = 1 464e-4

NNm yes 1 X2 = S X4 F Ns =) 99 *0 79*0 0616*0 09258) 5 447e-3

P(NNm = yes X1 F X2 = S, X4 = F, Ns = yes) = (0 0029*0 9579*0 0616 09258 = 1 5842e-5

P(Mishap = yes | X1 = S, X2 = S, X5 = S, NNm = yes) = (0.9971*0.9579*0.894*0.005703) = 4.8697e-3

P(Mishap = yes | X1 = F, X2 = S. X5 = S, NNm = yes) = (0.0029*0.9579*0.894*0.005703) = 1 4163e-5

P(X2 | Mishap = yes)

=P(X2 & Mishap = yes) / P(Mishap = yes)

$=\sum_{x1,x5} \mathrm{P(X1, X2 = S, X5, Mishap = yes)}$ / P(Mishap = yes)

= P(X1=S, X2=S, X5=S, NNm=yes, Mishap=yes) + P(X1=F, X2=S, X5=S, NNm=yes, Mishap=yes)

+ P(X1=S, X2=S, X5=F, NNm=yes, Mishap=yes) + P(X1=F, X2=S, X5=F, NNm=yes, Mishap=yes)

= P(Mishap = yes | X1=S, X2=S, X5=S, NNm=yes) P(NNm = yes | X1=S, X2=S, X5=S, Ns=y)

P(Ns = yes | X1=S, X2=S, X5=S) P(X1=S)P(X2=S)P(X5=S)

+ P(Mishap = yes | X1=F, X2=S, X5=S, NNm=yes) P(NNm = yes | X1=F, X2=S, X5=S, Ns=y)

P(Ns = yes | X1=F, X2=S, X5=S) P(X1=F)P(X2=S)P(X5=S)

+ P(Mishap = yes | X1=S, X2=S, X5=F, NNm=yes) P(NNm = yes | X1=S, X2=S, X5=F, Ns=y)

P(Ns = yes | X1=S, X2=S, X5=F) P(X1=S)P(X2=S)P(X5=F)

+ P(Mishap = yes | X1=F, X2=S, X5=F, NNm=yes) P(NNm = yes | X1=F, X2=S, X5=F, Ns=y)

P(Ns = yes | X1=F, X2=S, X5=F) P(X1=F)P(X2=S)P(X5=F)

= (4.8697e-3*5.447e-3*5.0335e-2*0.9971*0.9579*0.894)

+ (1.4163e-5*1 5842e-5*1 464e-4*0.0029*0.9579*0.894) + 0 + 0

= 1.1401e-6 + 8.1576e-17

= 1.1401e-6

P(X2 | Mishap = yes)

= P(X2 & Mishap = yes) / P(Mishap = yes)

=1.1401e-6 / 0.0

= ∞

X1	X2	X4	STATE	X1	X2	X3	STATE
S	S	S	NEAR MISS	S	S	S	SAFE
F	S	S		F	S	S	
S	F	S		S	F	S	NOT SAFE
F	F	S		F	F	S	
S	S	F	NOT NEAR MISS	S	S	F	
F	S	F		[illegible]	[illegible]	[illegible]	
S	F	F		S	F	F	
F	F	F		F	F	F	

P(Ns = yes | X1 = S, X2 = S, X3 = F) = (0.9971*0.9579*0.0527) = 5.0335e-2

P(Ns = yes | X1 = F, X2 = S, X3 = F) = (0.0029*0.9579*0.0527) = 1.464e-4

P(Ns = yes | X1 = S, X2 = F, X3 = S) = (0.9971*0.0421*0.9473) = 3.9766e-2
P(Ns = yes | X1 = S X2 = F, X3 = F) = (0.9971*0.0421*0.0527) = 2.2122e-3
So, 3.9766e-2 + 2.2122e-3 = 4.1978e-2

P(Ns = yes | X1 = F, X2 = F, X3 = S) = (0.0029*0.0421*0.9473) = 1.1566e-4
P(Ns = yes | X1 = F, X2 = F, X3 = F) = (0.0029*0.0421*0.0527) = 6.4341e-6

So, 1.1566e-4 + 6.4341e-6 = 1.2209e-4

P(NNm = yes | X1 [illegible] S, X2 = S X4 = F, Ns = yes) = (0.9971*0.9579*0.061 [illegible]*0 [illegible] = 5.4470e [illegible]
P(NNm = yes | X1 = F X2 = S, X4 [illegible] F, Ns = yes) = (0.0029*0.9579*0.0616*0.09258) = 1.5842e-5
P(NNm = yes | X1 = S X2 = F X4 = F, Ns = yes) = (0.9971*0.0421*0.0616*0.09258) [illegible] 2.3940e-4
P(NNm = yes | X1 = F X2 = F X4 = F, Ns = yes) = (0.0029*0.0421*0.0616*0.09258) [illegible] 6.9627e-7

P(Mishap = yes | X1 = S, X2 = S, X5 = S, NNm = yes) = (0.9971*0.9579*0.894*0.005703) = 4.8697e-3
P(Mishap = yes | X1 = F, X2 = S, X5 = S, NNm = yes) = (0.0029*0.9579*0.894*0.005703) = 1.4163e-5
P(Mishap = yes | X1 = S, X2 = F, X5 = S, NNm = yes) = (0.9971*0.0421*0.894*0.005703) = 2.1402e-4
P(Mishap = yes | X1 = F X2 = F X5 = S, NNm = yes) = (0.0029*0.0421*0.894*0.005703) = 6.2247e-7

P(X5 | Mishap = yes)

=P(X5 & Mishap = yes) / P(Mishap = yes)

=$\sum_{x1,x2} \mathrm{P}(\mathrm{X1}, \mathrm{X2}, \mathrm{X5} = \mathrm{S}, \mathrm{Mishap} = \mathrm{yes})$ / P(Mishap = yes)

= P(X1=S, X2=S, X5=S, NNm=yes, Mishap=yes) + P(X1=F, X2=S, X5=S, NNm=yes, Mishap=yes)

+ P(X1=S, X2=F, X5=S, NNm=yes, Mishap=yes) + P(X1=F, X2=F, X5=S, NNm=yes, Mishap=yes)

= P(Mishap = yes | X1=S, X2=S, X5=S, NNm=yes) P(NNm = yes | X1=S, X2=S, X5=S, Ns=yes)

P(Ns = yes | X1=S, X2=S, X5=S) P(X1=S) P(X2=S) P(X5=S)

+ P(Mishap = yes | X1=F, X2=S, X5=S, NNm=yes) P(NNm = yes | X1=F, X2=S, X5=S, Ns=yes)

P(Ns = yes | X1=F, X2=S, X5=S) P(X1=F) P(X2=S) P(X5=S)

+ P(Mishap = yes | X1=S, X2=F X5=S, NNm=yes) P(NNm = yes | X1=S X2=F, X5=S, Ns=yes)

P(Ns = yes | X1=S, X2=F, X5=S) P(X1=S) P(X2=F) P(X5=S)

+ P(Mishap = yes | X1=F, X2=F, X5=S, NNm=yes) P(NNm = yes | X1=F, X2=F, X5=S, Ns=yes)

P(Ns = yes | X1=F, X2=F, X5=S) P(X1=F) P(X2=F) P(X5=S)

= (4 8697e-3*5 44[illegible]*5.0335e-2*0.9971*0.9579*0.894)

+ (1.4163e-5*1 [illegible]*1 464e-4*0.0029*0.9579*0.894)

+ (2.1402e-4*2.[illegible]-4*4 1978e-2*0.9971*0.0421*0.894)

+ (6 2247e-7*6 [illegible]*1.2209e-4*0.0029*0.0421*0.894)

= 1.1401e-6 + 8.1576e-17 + 8.0716e-11 + 5.7756e-21

= 1.1402e-6

P(X5 | Mishap = yes)

= P(X5 & Mishap = yes) / P(Mishap = yes)

= 1.1402e-6 / 0.0

= ∞

Updated X1, X2, X5

Barrier	X1		X2		X3		X4		X5
	0.9971	↓	0.9579	↓	0.9473	↓	0.9384	↓	0.894
Step	Updating								
1	0.93635	↓	0.93636	↓	0 93636	↓	-	↓	-
2	2.9862e-2	↓	2.9814e-2	↓	-	↓	2.9862e-2	↓	-
3	0.0	↓	0.0	↓	-	↓	-	↓	0.0

X1	X2	X5	STATE
S	S	S	MISHAP
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT MISHAP
F	S	F	
S	F	F	
F	F	F	

X1	X2	X4	STATE
S	S	S	NEAR MISS
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT NEAR MISS
F	S	F	
S	F	F	
F	F	F	

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

P(Ns = yes | X1 = S, X2 = S, X3 = F) = (0.9971*0.9579*0.0527) = 5.0335e-2

P(Ns = yes | X1 = S X2 = F, X3 = S) = (0 9971*0.0421*0.9473) = 3.9766e-2
P(Ns = yes | X1 = S X2 = F X3 = F) = (0 9971*0.0421*0 0527) = 2.2122e-3
So 3.9766e-2 + 2.2122e-3 = 4 1978e-2

P(NNm = yes | X1 = S, X2 = S, X4 = F, Ns = yes) = (0.9971*0.9579*0.0616*0.09258) = 5.4470e-3
P(NNm = yes | X1 = S, X2 = F, X4 = F. Ns = yes) = (0 9971*0.0421*0 0616*0.09258) = 2.3940e-4

P(NMh = yes | X1 = S, X2 = S, X5 = F, NNm = yes) = (0 9971*0 9579*0.106*0.005703) = 5.7739e-4
P(NMh = yes | X1 = S, X2 = F, X5 = S NNm = yes) = (0 9971*0.0421*0.894*0 005703) = 2.1402e-4

P(Incident = yes | X1 = S, X2 = S, X6 = S. NMh = yes) = (0.9971*0.9579*0.9729*6.045e-4) = 5.6172e-4
P(Incident = yes | X1 = S, X2 = F X6 = S NMh = yes) = (0 9971*0 0421*0 9729*6.045e-4) = 2 4688e-5

P(X1 | Incident = yes)
=P(X1 & Incident = yes) / P(Incident = yes)
=$\sum_{x2,x6} P(X1 = S, X2, X6, \text{Incident} = \text{yes})$ / P(Incident = yes)
= P(X1=S, X2=S, X6=S, NMh=yes, Incident=yes) + P(X1=S, X2=F, X6=S, NMh=yes, Incident=yes)
+ P(X1=S, X2=S, X6=F, NMh=yes, Incident=yes) + P(X1=S, X2=F, X6=F, NMh=yes, Incident=yes)
= P(Incident = yes | X1=S, X2=S, X6=S, NMh=yes) P(NMh = yes | X1=S, X2=S, X6=S, NNm=yes)
P(NNm = yes | X1=S. X2=S X6=S, Ns=yes) P(Ns = yes | X1=S, X2=S, X6=S) P(X1=S)P(X2=S)P(X6=S)
+ P(Incident = yes | X1=S, X2=F, X6=S. NMh=yes) P(NMh = yes | X1=S, X2=F, X6=S, NNm=yes)
P(NNm = yes | X1=S. X2=F, X6=S, Ns=yes) P(Ns = yes | X1=S, X2=F, X6=S) P(X1=S)P(X2=F)P(X6=S)
+ P(Incident = yes | X1=S, X2=S, X6=F, NMh=yes) P(NMh = yes | X1=S, X2=S, X6=F, NNm=yes)
P(NNm = yes | X1=S, X2=S, X6=F, Ns=yes) P(Ns = yes | X1=S, X2=S, X6=F) P(X1=S)P(X2=S)P(X6=F)
+ P(Incident = yes | X1=S, X2=F, X6=F, NMh=yes) P(NMh = yes | X1=S, X2=F, X6=F, NNm=yes)
P(NNm = yes | X1=S, X2=F, X6=F, Ns=yes) P(Ns = yes | X1=S, X2=F, X6=F) P(X1=S)P(X2=F)P(X6=F)
= (5.6172e-4*5.7739e-4*5 4470e-3*5.0335e-2*0.9971*0.9579*0.9729)
+ (2.4688e-5*2 1402e-4*2 3940e-4*4 1978e-2*0.9971*0.0421*0.9729) + 0 + 0
= 8.2631e-11 + 2.1686e-15
= 8.2633e-11

P(X1 | Incident = yes)

= P(X1 & Incident = yes) / P(Incident = yes)

= 8.2633e-11 / 1.4167e-4

= **5.8328e-7**

X1	X2	X5	STATE
S	S	S	MISHAP
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT MISHAP
F	S	F	
S	F	F	
F	F	F	

X1	X2	X4	STATE
S	S	S	NEAR MISS
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT NEAR MISS
F	S	F	
S	F	F	
F	F	F	

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

P(Ns = yes | X1 = S, X2 = S, X3 = F) = (0.9971*0.9579*0.0527) = 5.0335e-2
P(Ns = yes | X1 = F, X2 = S, X3 = F) = (0.0029*0.9579*0.0527) = 1.464e-4

P(NNm = yes | X1 = S, X2 = S, X4 = F, Ns = yes) = (0.9971*0.9579*0.0616*0.09258) = 5.4470e-3
P(NNm = yes | X1 = F, X2 = S, X4 = F, Ns = yes) = (0.0029*0.9579*0.0616*0.09258) = 1.5842e-5

P(NMh = yes | X1 = S, X2 = S, X5 = F, NNm = yes) = (0.9971*0.9579*0.106*0.005703) = 5.7739e-4
P(NMh = yes | X1 = F, X2 = S, X5 = F, NNm = yes) = (0.0029*0.9579*0.106*0.005703) = 1.6793e-6
P(Incident = yes | X1 = S, X2 = S, X6 = S, NMh = yes) = (0.9971*0.9579*0.9729*6.045e-4) = 5.6172e-4
P(Incident = yes | X1 = F, X2 = S, X6 = S, NMh = yes) = (0.0029*0.9579*0.9729*6.045e-4) = 1.6337e-6

P(X2 | Incident = yes)
=P(X2 & Incident = yes) / P(Incident = yes)
=$\sum_{x1,x6} P(X1, X2 = S, X6, Incident = yes)$ / P(Incident = yes)
= P(X1=S, X2=S, X6=S, NMh=yes, Incident=yes) + P(X1=F, X2=S, X6=S, NMh=yes, Incident=yes)
+ P(X1=S, X2=S, X6=F, NMh=yes, Incident=yes) + P(X1=F, X2=S, X6=F, NMh=yes, Incident=yes)
= P(Incident = yes | X1=S, X2=S, X6=S, NMh=yes) P(NMh = yes | X1=S, X2=S, X6=S, NNm=yes)
P(NNm = yes | X1=S, X2=S, X6=S, Ns=yes) P(Ns = yes | X1=S, X2=S, X6=S) P(X1=S)P(X2=S)P(X6=S)
+ P(Incident = yes | X1=F, X2=S, X6=S, NMh=yes) P(NMh = yes | X1=F, X2=S, X6=S, NNm=yes)
P(NNm = yes | X1=F, X2=S, X6=S, Ns=yes) P(Ns = yes | X1=F, X2=S, X6=S)P(X1=F)P(X2=S)P(X6=S)
+ P(Incident = yes | X1=S, X2=S, X6=F, NMh=yes) P(NMh = yes | X1=S, X2=S, X6=F, NNm=yes)
P(NNm = yes | X1=S, X2=S, X6=F, Ns=yes) P(Ns = yes | X1=S, X2=S, X6=F)P(X1=S)P(X2=S)P(X6=F)
+ P(Incident = yes | X1=F, X2=S, X6=F, NMh=yes) P(NMh = yes | X1=F, X2=S, X6=F, NNm=yes)
P(NNm = yes | X1=F, X2=S, X6=F, Ns=yes) P(Ns = yes | X1=F, X2=S, X6=F)P(X1=F)P(X2=S)P(X6=F)
= (5.6172e-4*5.7739e-4*5.4470e-3*5.0335e-2*0.9971*0.9579*0.9729)
+ (1.6337e-6*1.6793e-6*1.5842e-5*1.464e-4*0.0029*0.9579*0.9729) + 0 + 0
= 8.2631e-11 + 1.7196e-23
= 8.2631e-11

P(X2 | Incident = yes)
= P(X2 & Incident = yes) / P(Incident = yes)
= 8.2631e-11 / 1.4167e-4
= **5.8326e-7**

X1	X2	X5	STATE
S	S	S	MISHAP
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT MISHAP
F	S	F	
S	F	F	
F	F	F	

X1	X2	X4	STATE
S	S	S	NEAR MISS
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT NEAR MISS
F	S	F	
S	F	F	
F	F	F	

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

P(Ns = yes | X1 = S, X2 = S, X3 = F) = (0.9971*0.9579*0.0527) = 5.0335e-2

P(Ns = yes | X1 = F, X2 = S X3 = F) = (0.0029*0 9579*0.0527) = 1 464e-4

P(Ns = yes | X1 = S, X2 = F, X3 = S) = (0.9971*0.0421*0.9473) = 3.9766e-2

P(Ns = yes | X1 = S, X2 = F, X3 = F) = (0.9971*0.0421*0.0527) = 2.2122e-3

So, 3.9766e-2 + 2.2122e-3 = 4.1978e-2

P(Ns = yes | X1 = F, X2 = F, X3 = S) = (0.0029*0.0421*0.9473) = 1.1566e-4

P(Ns = yes | X1 = F, X2 = F, X3 = F) = (0.0029*0.0421*0.0527) = 6.4341e-6

So, 1.1566e-4 + 6.4341e-6 = 1.2209e-4

P(NNm = yes | X1 = S, X2 = S, X4 = F, Ns = yes) = (0.9971*0.9579*0 0616*0.09258) = 5.4470e-3

P(NNm = yes | X1 = F X2 = S, X4 = F, Ns = yes) = (0.0029*0.9579*0 0616*0.09258) = 1.5842e-5

P(NNm = yes | X1 = S, X2 = F, X4 = F, Ns = yes) = (0.9971*0.0421*0.0616*0.09258) = 2.394e-4

P(NNm = yes | X1 = F, X2 = F, X4 = F, Ns = yes) = (0.0029*0.0421*0.0616*0.09258) = 6.9627e-7

P(NMh = yes | X1 = S, X2 = S, X5 = F, NNm = yes) = (0.9971*0.9579*0.106*0.005703) = 5.7739e-4

P(NMh = yes | X1 = F X2 = S, X5 = F, NNm = yes) = (0 0029*0.9579*0.106*0.005703) = 1.6793e-6

P(NMh = yes | X1 = S, X2 = F, X5 = F, NNm = yes) = (0.9971*0.0421*0.106*0.005703) = 2.5376e-5

P(NMh = yes | X1 = F, X2 = F, X5 = F, NNm = yes) = (0.0029*0.0421*0.106*0.005703) = 7.3806e-8

P(Incident = yes | X1 = S, X2 = S, X6 = S, NMh = yes) = (0.9971*0.9579*0.9729*6 045e-4) = 5.6172e-4

P(Incident = yes | X1 = F, X2 = S X6 = S, NMh = yes)   (0 0029*0 9579*0 9729*6 045e-4) = 1.6337e-6

P(Incident = yes | X1 = S, X2 = F, X6 = S, NMh = yes) = (0.9971*0.0421*0.9729*6.045e-4) = 2.4688e-5

P(Incident = yes | X1 = F, X2 = F, X6 = S, NMh = yes) = (0.0029*0.0421*0.9729*6.045e-4) = 7.1803e-8

P(X6 | Incident = yes)

=P(X6 & Incident = yes) / P(Incident = yes)

$=\sum_{x1,x2} P(X1, X2, X6 = S, \text{Incident} = \text{yes})$ / P(Incident = yes)

= P(X1=S, X2=S, X6=S, NMh=yes, Incident=yes) + P(X1=F, X2=S, X6=S, NMh=yes, Incident=yes)

+ P(X1=S, X2=F, X6=S, NMh=yes, Incident=yes) + P(X1=F, X2=F, X6=S, NMh=yes, Incident=yes)

= P(Incident = yes | X1=S, X2=S, X6=S, NMh=yes) P(NMh = yes | X1=S, X2=S, X6=S, NNm=yes)

P(NNm = yes | X1=S, X2=S, X6=S, Ns=yes) P(Ns = yes | X1=S, X2=S, X6=S) P(X1=S)P(X2=S)P(X6=S)

+ P(Incident = yes | X1=F, X2=S, X6=S, NMh=yes) P(NMh = yes | X1=F, X2=S, X6=S, NNm=yes)

P(NNm = yes | X1=F, X2=S, X6=S, Ns=yes) P(Ns = yes | X1=F, X2=S, X6=S) P(X1=F)P(X2=S)P(X6=S)

+ P(Incident = yes | X1=S, X2=F, X6=S, NMh=yes) P(NMh = yes | X1=S, X2=F, X6=S, NNm=yes)

P(NNm = yes | X1=S, X2=F, X6=S, Ns=yes) P(Ns = yes | X1=S, X2=F, X6=S) P(X1=S)P(X2=F)P(X6=S)

+ P(Incident = yes | X1=F, X2=F, X6=S, NMh=yes) P(NMh = yes | X1=F, X2=F, X6=S, NNm=yes)

P(NNm = yes | X1=F, X2=F, X6=S, Ns=yes) P(Ns = yes | X1=F, X2=F, X6=S) P(X1=F)P(X2=F)P(X6=S)

= (5.6172e-4*5.7739e-4*5.4470e-3*5.0335e-2*0.9971*0.9579*0.9729)

+ ([illegible]*0.0029*0.9579*0.9729)

+ (2.4688e-5*2.5376e-5*2.394e-4*4.1978e-2*0.9971*0.0421*0.9729)

+ (7.1803e-8*7.3806e-8*6.9627e-7*1.2209e-4*0.0029*0.0421*0.9729)

= 8.2631e-11 + 1.7196e-23 + 2.5712e-16 + 5.3511e-29

= 8.2631e-11

P(X6 | Incident = yes)

= P(X2 & Incident =yes) / P(Incident = yes)

= 8.2631e-11 / 1.4167e-4

= **5.8326e-7**

Updated X1, X2, X6

Barrier	X1	X2	X3	X4	X5	X6
	0.9971	0.9579	0.9473	0.9384	0.894	0.9729
Step	Updating					
1	0.93636	0.93636	0.93636	-	-	-
2	2.9862e-2	2.9814e-2	-	2.9862e-2	-	-
3	0.0	0.0	-	-	0.0	-
4	5.8326e-7	5.5326e-7	-	-	-	5.8326e-7

X1	X2	X6	STATE
S	S	S	INCIDENT
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT INCIDENT
F	S	F	
S	F	F	
F	F	F	

X1	X2	X5	STATE
S	S	S	MISHAP
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT MISHAP
F	S	F	
S	F	F	
F	F	F	

X1	X2	X4	STATE
S	S	S	NEAR MISS
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT NEAR MISS
F	S	F	
S	F	F	
F	F	F	

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

P(Ns = yes | X1 = S, X2 = S, X3 = F) = (0 9971*0.9579*0 0527) = 5.0335e-2

P(Ns = yes | X1 = S, X2 = F, X3 = S) = (0.9971*0 0421*0.9473) = 3.9766e-2
P(Ns = yes | X1 = S, X2 = F, X3 = F) = (0.9971*0.0421*0.0527) = 2.2122e-3
4 1978e-2

P(NNm = yes | X1 = S, X2 = S, X4 = F, Ns = yes) = (0.9971*0.9579*0.0616*0.09258) = 5.4470e-3

P(NNm = yes | X1 = S X2 = F X4 = F, Ns = yes) = (0.9971*0.0421*0.0616*0.09258) = 2.394e-4

P(NMh = yes | X1 = S, X2 = S, X5 = F NNm = yes) = (0 9971*0 9579*0.106*0.005703) = 5.7739e-4

P(NMh = yes | X1 = S X2 = F, X5 = F, NNm = yes) = (0.9971*0 0421*0.106*0.005703) = 2.5376e-5

P(NIn = yes | X1 = S, X2 = S, X6 = F, NMh = yes) = (0.9971*0.9579*0.0271*6.045e-4) = 1.5647e-5

P(NIn = yes | X1 = S, X2 = F, X6 = F, NMh = yes) = (0.9971*0.0421*0.0271*6.045e-4) = 6.8768e-7

P(Accident = yes | X1 = S, X2 = S, X7 = S, NIn = yes) = (0.9971*0.9579*0.8912*1.639e-5) = 1.3951e-5

P(Accident = Y X1 = S X2 = F X7 = S, NIn = yes) = (0.9971*0.0421*0.8912*1.639e-5) = 6 1316e-7

P(X1 | Accident = yes)

=P(X1 & Accident = yes) / P(Accident = yes)

=$\sum_{x2,x7} P(X1 = S, X2, X7, Accident = yes)$ / P(Accident = yes)

= P(X1=S, X2=S, X7=S, NIn=yes, Accident=yes) + P(X1=S, X2=F, X7=S, NIn=yes, Accident=yes)

+ P(X1=S, X2=S, X7=F, NIn=yes, Accident=yes) + P(X1=S, X2=F, X7=F, NIn=yes, Accident=yes)

= P(Accident = yes | X1=S, X2=S, X7=S, NIn=yes) P(NIn=yes | X1=S, X2=S, X7=S, NMh=yes)

P(NMh = yes | X1=S, X2=S, X7=S, NNm=yes) P(NNm = yes | X1=S, X2=S, X7=S, Ns=yes)

P(Ns = yes | X1=S, X2=S, X7=S) P(X1=S) P(X2=S) P(X7=S)

+ P(Accident = yes | X1=S, X2=F, X7=S, NIn=yes) P(NIn = yes | X1=S, X2=F, X7=S, NMh=yes)

P(NMh = yes | X1=S, X2=F, X7=S NNm=yes) P(NNm = yes | X1=S, X2=F, X7=S, Ns=yes)

P(Ns = yes | X1=S, X2=F, X7=S) P(X1=S) P(X2=F) P(X7=S)

+ P(Accident = yes | X1=S, X2=S, X7=F, NIn=yes) P(NIn = yes | X1=S, X2=S, X7=F, NMh=yes)

P(NMh = yes | X1=S, X2=S, X7=F, NNm=yes) P(NNm = yes | X1=S, X2=S, X7=F, Ns=yes)

P(Ns = yes | X1=S, X2=S, X7=F) P(X1=S) P(X2=S) P(X7=F)

+ P(Accident = yes | X1=S, X2=F, X7=F, NIn=yes) P(NIn = yes | X1=S, X2=F, X7=F, NMh=yes)

P(NMh = yes | X1=S, X2=F, X7=F, NNm=yes) P(NNm = yes | X1=S, X2=F, X7=F, Ns=yes)

P(Ns = yes | X1=S, X2=F, X7=F) P(X1=S) P(X2=F) P(X7=F)

= (1.3951e-5*1.5647e-5*5.7739e-4*5.4470e-3*5.0335e-2*0.9971*0.9579*0.8912)

+ (6.1316e-7*6.8768e-7*2.5376e-5*2.394e-4*4.1978e-2*0.9971*0.0421*0.8912) + 0 + 0

= 2.9415e-17 + 4.0228e-24

= 2.9415e-17

P(X1 | Accident = yes)

= P(X1 & Accident = yes) / P(Accident = yes)

= 2.9415e-17 / 3.5168e-6

= **8.3641e-12**

X1	X2	X6	STATE
S	S	S	INCIDENT
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT INCIDENT
F	S	F	
S	F	F	
F	F	F	

X1	X2	X5	STATE
S	S	S	MISHAP
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT MISHAP
F	S	F	
S	F	F	
F	F	F	

X1	X2	X4	STATE
S	S	S	NEAR MISS
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT NEAR MISS
F	S	F	
S	F	F	
F	F	F	

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

P(Ns = yes | X1 = S X2 = S, X3 = F) = (0 9971*0.9579*0 0527) = 5.0335e-2

P(Ns = yes | X1 = F X2 = S, X3 = F) = (0 0029*0 9579*0 0527) = 1.464e-4

P(NNm = yes | X1 = S X2 = S, X4 = F, Ns = yes) = (0.9971*0.9579*0 0616*0.09258) = 5.4470e-3

P(NNm = yes | X1 = F X2 = S, X4 = F, Ns = yes) = (0 0029*0.9579*0 0616*0.09258) = 1 5842e-5

P(NMh = yes | X1 = S, X2 = S, X5 = F, NNm = yes) = (0.9971*0 9579*0.106*0.005703) = 5.7739e-4

P(NMh = yes | X1 = F, X2 = S X5 = F NNm = yes) = (0 0029*0 9579*0.106*0.005703) = 1.6793e-6

P(NIn = yes | X1 = S, X2 = S, X6 = F, NMh = yes) = (0.9971*0 9579*0.0271*6 045e-4) = 1.5647e-5

P(NIn = yes | X1 = F, X2 = S, X6 = F NMh = yes) = (0.0029*0 9579*0.0271*6 045e-4) = 4.5508e-8

P(Accident = yes | X1 = S, X2 = S, X7 = S, NIn = yes) = (0 9971*0.9579*0.8912*1.639e-5) = 1 3951e-5

P(Accident = yes | X1 = F, X2 = S, X7 = S, NIn = yes) = (0.0029*0.9579*0.8912*1.639e-5) = 4.0576e-8

P(X2 | Accident = yes)

= P(X2 & Accident = yes) / P(Accident = yes)

=$\sum_{x1,x7} \mathrm{P}(\mathrm{X1}, \mathrm{X2} = \mathrm{S}, \mathrm{X7}, \mathrm{Accident} = \mathrm{yes})$ / P(Accident = yes)

= P(X1=S, X2=S, X7=S, NIn=yes, Accident=yes) + P(X1=F, X2=S, X7=S, NIn=yes, Accident=yes)

+ P(X1=S, X2=S, X7=F, NIn=yes, Accident=yes) + P(X1=F, X2=S, X7=F, NIn=yes, Accident= yes)

= P(Accident = yes | X1=S, X2=S, X7=S, NIn=yes) P(NIn = yes | X1=S X2=S, X7=S, NMh=yes)

P(NMh = yes | X1=S, X2=S, X7=S, NNm=yes) P(NNm = yes | X1=S, X2=S, X7=S, Ns=yes)

P(Ns = yes | X1=S, X2=S, X7=S) P(X1=S) P(X2=S) P(X7=S)

+ P(Accident = yes | X1=F, X2=S, X7=S, NIn=yes) P(NIn = yes | X1=F, X2=S, X7=S, NMh=yes)

P(NMh = yes | X1=F, X2=S, X7=S, NNm=yes) P(NNm = yes | X1=F, X2=S, X7=S Ns=yes)

P(Ns = yes | X1=F, X2=S, X7=S) P(X1=F) P(X2=S) P(X7=S)

+ P(Accident = yes | X1=S, X2=S, X7=F, NIn=yes) P(NIn = yes | X1=S, X2=S, X7=F, NMh=yes)

P(NMh = yes | X1=S, X2=S, X7=F, NNm=yes) P(NNm = yes | X1=S, X2=S, X7=F, Ns=yes)

P(Ns = yes | X1=S, X2=S, X7=F) P(X1=S) P(X2=S) P(X7=F)

+ P(Accident = yes | X1=F, X2=S, X7=F, NIn=yes) P(NIn = yes | X1=F, X2=S, X7=F, NMh=yes)

P(NMh = yes | X1=F, X2=S, X7=F, NNm=yes) P(NNm = yes | X1=F, X2=S, X7=F, Ns=yes)

P(Ns = yes | X1=F, X2=S, X7=F) P(X1=F) P(X2=S) P(X7=F)

= (1 3951e-5*1.5647e-5*5.7739e-4*5.4470e-3*5.0335e-2*0.9971*0.9579*0.8912)

+ (4.0576e-8*4.5508e-8*1 6793e-6*1 5842e-5*1 464e-4*0.0029*0.9579*0.8912) + 0 + 0

= 2.9415e-17 + 1.7804e-32

= 2.9415e-17

P(X2 | Accident = yes)

= P(X2 & Accident = yes) / P(Accident = yes)

= 2.9415e-17 / 3.5168e-6

= **8.3641e-12**

X1	X2	X6	STATE
S	S	S	INCIDENT
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT INCIDENT
F	S	F	
S	F	F	

X1	X2	X5	STATE
S	S	S	MISHAP
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT MISHAP
F	S	F	
S	F	F	

X1	X2	X4	STATE
S	S	S	NEAR MISS
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT NEAR MISS
F	S	F	
S	F	F	

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
S	S	F	
F	S	F	
S	F	F	

P(Ns = yes | X1 = S, X2 = S, X3 = F) = (0 9971*0.9579*0.0527) = 5.0335e-2
P(Ns = yes | X1 = F, X2 = S, X3 = F) = (0 0029*0.9579*0 0527) = 1.464e-4

P(Ns = yes | X1 = S, X2 = F, X3 = S) = (0.9971*0.0421*0.9473) = 3.9766e-2
P(Ns = yes | X1 = S, X2 = F, X3 = F) = (0.9971*0.0421*0.0527) = 2.2122e-3
4.1978e-2

P(NNm = yes | X1 = S, X2 = S, X4 = F, Ns = yes) = (0.9971*0 9579*0.0616*0 09258) = 5.4470e-3
P(NNm = yes | X1 = F X2 = S, X4 = F Ns = yes) = (0 0029*0.9579*0.0616*0 09258) = 1 5842e-5
P(NNm = yes | X1 = S, X2 = F, X4 = F, Ns = yes) = (0.9971*0.0421*0.0616*0.09258) = 2.394e-4

P(NMh = yes | X1 = S, X2 = S, X5 = F, NNm = yes) = (0.9971*0.9579*0.106*0.005703) = 5.7739e-4
P(NMh = yes | X1 = F X2 = S, X5 = F NNm = yes) = (0 0029*0.9579*0 106*0 005703) = 1 6793e-6
P(NMh = yes | X1 = S, X2 = F, X5 = F, NNm = yes) = (0.9971*0.0421*0.106*0.005703) = 2.5376e-5

P(NIn = yes | X1 = S, X2 = S, X6 = F, NMh = yes) = (0.9971*0.9579*0.0271*6 045e-4) = 1.5647e-5
P(NIn = yes | X1 = F X2 = S, X6 = F NMh = yes) = (0.0029*0 9579*0 0271*6.045e-4) = 4 5508e-8
P(NIn = yes | X1 = S, X2 = F, X6 = F, NMh = yes) = (0.9971*0.0421*0.0271*6 045e-4) = 6.8768e-7

P(Accident = yes | X1 = S, X2 = S, X7 = S, NIn = yes) = (0.9971*0.9579*0.8912*1.639e-5) = 1.3951e-5

P(Accident = yes | X1 = F, X2 = S, X7 = S, NIn = yes) = (0.0029*0.9579*0.8912*1.639e-5) = 4.0576e-8

P(Accident = yes | X1 = S, X2 = F, X7 = S, NIn = yes) = (0.9971*0.0421*0.8912*1.639e-5) = 6.1316e-7

[illegible]

P(X7 | Accident = yes)

= P(X7 & Accident = yes) / P(Accident = yes)

$=\sum_{x1,x2} P(X1, X2, X7 = S, \text{Accident} = \text{yes})$ / P(Accident = yes)

= P(X1=S, X2=S, X7=S, NIn=yes, Accident=yes) + P(X1=F, X2=S, X7=S, NIn=yes, Accident=yes)

+ P(X1=S, X2=F, X7=S, NIn=yes, Accident=yes) [illegible]

= P(Accident = yes | X1=S, X2=S, X7=S, NIn=yes) P(NIn = yes | X1=S, X2=S, X7=S, NMh=yes)

P(NMh = yes | X1=S, X2=S, X7=S, NNm=yes) P(NNm = yes | X1=S, X2=S, X7=S, Ns=yes)

P(Ns = yes | X1=S, X2=S, X7=S) P(X1=S) P(X2=S) P(X7=S)

+ P(Accident = yes | X1=F, X2=S, X7=S, NIn=yes) P(NIn = yes | X1=F, X2=S, X7=S, NMh=yes)

P(NMh = yes | X1=F, X2=S, X7=S, NNm=yes) P(NNm = yes | X1=F, X2=S, X7=S, Ns=yes)

P(Ns = yes | X1=F, X2=S, X7=S) P(X1=F) P(X2=S) P(X7=S)

+ P(Accident = yes | X1=S, X2=F, X7=S, NIn=yes) P(NIn = yes | X1=S, X2=F, X7=S, NMh=yes)

P(NMh = yes | X1=S, X2=F, X7=S, NNm=yes) P(NNm = yes | X1=S, X2=F, X7=S, Ns=yes)

P(Ns = yes | X1=S, X2=F, X7=S) P(X1=S) P(X2=F) P(X7=S)

[illegible]

= (1.3951e-5*1.5647e-5*5.7739e-4*5.4470e-3*5.0335e-2*0.9971*0.9579*0.8912)

+ (4.0576e-8*4.5508e-8*1.6793e-6*1.5842e-5*1.464e-4*0.0029*0.9579*0.8912)

+ (6.1316e-7*6.8768e-7*2.5376e-5*2.394e-4*4.1978e-2*0.9971*0.0421*0.8912)

+ ([illegible]*0.0029*0.0421*0.8912)

= 2.9415e-17 + 1.7804e-32+ 4.0228e-24 + 2.4349e-39

= 2.9415e-17

P(X7 | Accident = yes)

= P(X7 & Accident = yes) / P(Accident = yes)

= 2.9415e-17 / 3.5168e-6

= **8.3641e-12**

Updated X1, X2, X7

Prior values							
Barrier	X1	X2	X3	X4	X5	X6	X7
	0.9971	0.9579	0.9473	0.9384	0.894	0.9729	0.8912
Updating							
Step	X1	X2	X3	X4	X5	X6	X7
1	0.95656	0.95636	0.93636				
2	2.9862e-2	2.9814e-2		2.9862e-2			
3	0.0	0.0			0.0		
4	5.8329e-7	5.8329e-7				5.8326e-7	
5	8.3641e-12	8.3641e-12					8.3641e-12

X1	X2	X7	STATE
S	S	S	ACCIDENT
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT ACCIDENT
F	S	F	
S	F	F	
F	F	F	

X1	X2	X6	STATE
S	S	S	INCIDENT
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT INCIDENT
F	S	F	
S	F	F	
F	F	F	

X1	X2	X5	STATE
S	S	S	MISHAP
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT MISHAP
F	S	F	
S	F	F	
F	F	F	

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

X1	X2	X4	STATE
S	S	S	NEAR MISS
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT NEAR MISS
F	S	F	
S	F	F	
F	F	F	

P(Ns = yes | X1 = S, X2 = S, X3 = F) = (0.9971*0.9579*0.0527) = 5.0335e-2

P(Ns = yes | X1 = S, X2 = F, X3 = S) = (0.9971*0.0421*0.9473) = 3.9766e-2

P(Ns = yes | X1 = S, X2 = F, X3 = F) = (0.9971*0.0421*0.0527) = 2.2122e-3

So, 3.9766e-2 + 2.2122e-3 = 4.1978e-2

P(NNm = yes | X1 = S, X2 = S, X4 = F, Ns = yes) = (0.9971*0.9579*0.0616*0.09258) = 5.4470e-3

P(NNm = yes | X1 = S, X2 = F, X4 = F, Ns = yes) = (0.9971*0.0421*0.0616*0.09258) = 2.394e-4

P(NMh = yes | X1 = S, X2 = S, X5 = F, NNm = yes) = (0.9971*0.9579*0.106*0.005703) = 5.7739e-4

P(NMh = yes | X1 = S, X2 = F, X5 = F, NNm = yes) = (0.9971*0.0421*0.106*0.005703) = 2.5376e-5

P(NIn = yes | X1 = S, X2 = S, X6 = F, NMh = yes) = (0.9971*0.9579*0.0271*6.045e-4) = 1.5647e-5

P(NIn = yes | X1 = S, X2 = F, X6 = F, NMh = yes) = (0.9971*0.0421*0.0271*6.045e-4) = 6.8768e-7

P(NAc = yes | X1 = S, X2 = S, X7 = F, Nin = yes) = (0.9971*0.9579*0.1088*1.639e-5) = 1.7032e-6

P(NAc = yes | X1 = S, X2 = F, X7 = F, Nin = yes) = (0.9971*0.0421*0.1088*1.639e-5) = 7.4856e-8

P(Catastrophe = yes | X1 = S, X2 = S, NAc = yes) = (0.9971*0.9579*1 7824e-6) = 1 7024e-6

P(Catastrophe = yes | X1 = S, X2 = F, NAc = yes) = (0.9971*0.0421*1.7824e-6) = 7.4821e-8

P(X1 | Catastrophe = yes)
= P(X1 & Catastrophe = yes) / P(Catastrophe = yes)
$=\sum_{x2} P(X1 = S, X2, \text{Catastrophe} = yes)$ / P(Catastrophe =yes)
= P(X1=S, X2=S, NAc=yes, Catastrophe=yes) + P(X1=S, X2=F, NAc=yes, Catastrophe=yes)
= P(Catastrophe = yes | X1=S X2=S, NAc=yes) P(NAc = yes | X1=S, X2=S, NIn=yes)
P(NIn = yes | X1=S, X2=S, NMh=yes) P(NMh = yes | X1=S, X2=S, NNm=yes)
P(NNm = yes | X1=S, X2=S, Ns=yes) P(Ns = yes | X1=S X2=S) P(X1=S) P(X2=S)
+ P(Catastrophe = yes | X1=S, X2=F, NIn=yes) P(NAc = yes | X1=S, X2=F, NIn=yes)
P(NIn = yes | X1=S, X2=F, NMh=yes) P(NMh = yes | X1=S, X2=F, NNm=yes)
P(NNm = yes | X1=S, X2=F, Ns=yes) P(Ns = yes | X1=S, X2=F) P(X1=S) P(X2=F)
= (1 7024e-6*1.7032e-6*1.5647e-5*5.7739e-4*5.4470e-3*5.0335e-2*0.9971*0.9579)
+ (7.4821e-8*7.4856e-8*6.8768e-7*2.5376e-5*2.394e-4*4.1978e-2*0.9971*0.0421)
= 6.8598e-24 + 4.1231e-32
= 6.8598e-24

P(X1 | Catastrophe = yes)
= P(X1 & Catastrophe = yes) / P(Catastrophe = yes)
= 6.8598e-24 / 0.0
= **0.0**

X1	X2	X7	STATE
S	S	S	ACCIDENT
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT ACCIDENT
F	S	F	
S	F	F	
F	F	F	

X1	X2	X6	STATE
S	S	S	INCIDENT
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT INCIDENT
F	S	F	
S	F	F	
F	F	F	

X1	X2	X5	STATE
S	S	S	MISHAP
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT MISHAP
F	S	F	
S	F	F	
F	F	F	

X1	X2	X4	STATE
S	S	S	NEAR MISS
F	S	S	
S	F	S	
F	F	S	
S	S	F	NOT NEAR MISS
F	S	F	
S	F	F	
F	F	F	

X1	X2	X3	STATE
S	S	S	SAFE
F	S	S	
S	F	S	NOT SAFE
F	F	S	
S	S	F	
F	S	F	
S	F	F	
F	F	F	

$P(Ns = yes \mid X1 = S, X2 = S, X3 = F) = (0.9971*0.9579*0.0527) = 5.0335e\text{-}2$

$P(Ns = yes \mid X1 = F, X2 = S, X3 = F) = (0.0029*0.9579*0.0527) = 1.464e\text{-}4$

$P(NNm = yes \mid X1 = S, X2 = S, X4 = F, Ns = yes) = (0.9971*0.9579*0.0616*0.09258) = 5.4470e\text{-}3$

$P(NNm = yes \mid X1 = F, X2 = S, X4 = F, Ns = yes) = (0.0029*0.9579*0.0616*0.09258) = 1.5842e\text{-}5$

$P(NMh = yes \mid X1 = S, X2 = S, X5 = F, NNm = yes) = (0.9971*0.9579*0.106*0.005703) = 5.7739e\text{-}4$

$P(NMh = yes \mid X1 = F, X2 = S, X5 = F, NNm = yes) = (0.0029*0.9579*0.106*0.005703) = 1.6793e\text{-}6$

$P(NIn = yes \mid X1 = S, X2 = S, X6 = F, NMh = yes) = (0.9971*0.9579*0.0271*6.045e\text{-}4) = 1.5647e\text{-}5$

$P(NIn = yes \mid X1 = F, X2 = S, X6 = F, NMh = yes) = (0.0029*0.9579*0.0271*6.045e\text{-}4) = 4.5508e\text{-}8$

$P(NAc = yes \mid X1 = S, X2 = S, X7 = F, NIn = yes) = (0.9971*0.9579*0.1088*1.639e\text{-}5) = 1.7032e\text{-}6$

$P(NAc = yes \mid X1 = F, X2 = S, X7 = F, NIn = yes) = (0.0029*0.9579*0.1088*1.639e\text{-}5) = 4.9537e\text{-}9$

$P(Catastrophe = yes \mid X1 = S, X2 = S, NAc = yes) = (0.9971*0.9579*1.7824e\text{-}6) = 1.7024e\text{-}6$

$P(Catastrophe = yes \mid X1 = F, X2 = S, NAc = yes) = (0.0029*0.9579*1.7824e\text{-}6) = 4.9513e\text{-}9$

P(X2 | Catastrophe = yes)

= P(X2 & Catastrophe = yes) / P(Catastrophe = yes)

$=\sum_{x1} P(X1, X2 = S, \text{Catastrophe} = \text{yes})$ / P(Catastrophe = yes)

= P(X1=S, X2=S, NAc=yes, Catastrophe=yes) + P(X1=F, X2=S, NAc=yes, Catastrophe=yes)

= P(Catastrophe = yes | X1=S, X2=S, NAc=yes) P(NAc = yes | X1=S, X2=S, NIn=yes)

P(NIn = yes | X1=S, X2=S, NMh=yes) P(NMh = yes | X1=S, X2=S, NNm=yes)

P(NNm = yes | X1=S, X2=S, Ns=yes) P(Ns = yes | X1=S X2=S) P(X1=S) P(X2=S)

+ P(Catastrophe = yes | X1=F, X2=S, NIn=yes) P(NAc = yes | X1=F, X2=S, NIn=yes)

P(NIn = yes | X1=F, X2=S, NMh=yes) P(NMh = yes | X1=F, X2=S, NNm=yes)

P(NNm = yes | X1=F, X2=S, Ns=yes) P(Ns = yes | X1=F, X2=S) P(X1=F) P(X2=S)

= (1 7024e-6*1.7032e-6*1.5647e-5*5.7739e-4*5.4470e-3*5.0335e-2*0.9971*0.9579)

+ (4.9513e-9*4.9537e-9*4.5508e-8*1.6793e-6*1.5842e-5*1.464e-4*0.0029*0.9579)

= 6.8598e-24 + 1.2076e-41

= 6.8598e-24

P(X2 | Catastrophe = yes)

= P(X2 & Catastrophe =yes) / P(Catastrophe = yes)

= 6.8598e-24 / 0.0

= **0.0**

Updated X1, X2, X7

Prior values													
Barrier	X1		X2		X3		X4		X5		X6		X7
	0 9971		0 9579		0 9473		0.9384		0.894		0.9729		0.8912
Updating													
Step	X1		X2		X3		X4		X5		X6		X7
1	[illegible]		[illegible]		[illegible]								
2	[illegible]		[illegible]				[illegible]						
3	0.0		0.0						0.0				
4	[illegible]		[illegible]								[illegible]		
5	[illegible]		[illegible]										[illegible]
6	0.0		0.0										
Total	**0.96621**		**0.96617**		**0.93636**		**0.97014**		**1**		**1**		**1**

Step 1: Updated X1, X2, X3

Prior values					
Barrier	X1		X2		X3
	0.9971	↓	0.9579	↓	0.9473
Updating					
Step	X1		X2		X3
1	0.93635	↓	0.93636	↓	0.93636

Step 2: Updated X1, X2, X4

Prior values							
Barrier	X1		X2		X3		X4
	0.9971	↓	0.9579	↓	0.9473	↓	0.9384
Updating							
Step	X1		X2		X3		X4
1	0.93635	↓	0.93636	↓	0.93636	↓	-
2	2.9862e-2	↓	2.9814e-2	↓	-	↓	2.9862e-2

Step 3: Updated X1, X2, X5

Prior values									
Barrier	X1		X2		X3		X4		X5
	0.9971	↓	0.9579	↓	0.9473	↓	0.9384	↓	0.894
Updating									
Step	X1		X2		X3		X4		X5
1	0.93635	↓	0.93636	↓	0.93636	↓		↓	-
2	2.9862e-2	↓	2.9814e-2	↓	-	↓	2.9862e-2	↓	-
3	0.0	↓	0.0	↓	-	↓	-	↓	0.0

Step 4: Updated X1, X2, X6

Prior values											
Barrier	X1		X2		X3		X4		X5		X6
	0.9971	↓	0.9579	↓	0.9473	↓	0.9384	↓	0.894	↓	0.9729
Updating											
Step	X1		X2		X3		X4		X5		X6
1	0.93635	↓	0.93636	↓	0.93636	↓	-	↓	-	↓	-
2	2.9862e-2	↓	2.9814e-2	↓	-	↓	2.9862e-2	↓	-	↓	-
3	0.0	↓	0.0	↓	-	↓	-	↓	0.0	↓	-
4	5.8328e-7	↓	5.8326e-7	↓	-	↓	-	↓	-	↓	5.8326e-7

Step 5: Updated X1, X2, X7

Prior values														
Barrier	X1		X2		X3		X4		X5		X6		X7
	0.9971	↓	0 9579	↓	0.9473	↓	0.9384	↓	0.894	↓	0 9729	↓	0 8912
Updating														
Step	X1		X2		X3		X4		X5		X6		X7
1	[illegible]		[illegible]		[illegible]								
2	[illegible]		[illegible]				[illegible]						
3	[illegible]		[illegible]						[illegible]				
4	[illegible]		[illegible]								[illegible]		
5	[illegible]		[illegible]										[illegible]

Step 6: Updated X1, X2

Prior values														
Barrier	X1		X2		X3		X4		X5		X6		X7
	0.9971	↓	0.9579	↓	0.9473	↓	0.9384	↓	0.894	↓	0 9729	↓	0 8912
Updating														
Step	X1		X2		X3		X4		X5		X6		X7
1	[illegible]		0.93636		[illegible]								
2	2.9862e-2		[illegible]				[illegible]						
3	[illegible]		[illegible]						[illegible]				
4	[illegible]		[illegible]								[illegible]		
5	[illegible]		[illegible]										[illegible]
6	[illegible]		[illegible]										

Updated Barrier Success Probabilities						
X1	X2	X3	X4	X5	X6	X7
0 96621	0 96617	0 93636	0 97014	1 0	1 0	1 0

Step 1: Updated X1, X2, X3

Prior values					
Barrier	X1		X2		X3
	0.96621	↓	0.96617	↓	0.93636
Updating					
Step	X1		X2		X3
1	0.89544	↓	0.89653	↓	0.89653

Step 2: Updated X1, X2, X4

Prior values							
Barrier	X1		X2		X3		X4
	0.96621	↓	0.96618	↓	0.93636	↓	0.97014
Updating							
Step	X1		X2		X3		X4
1	0.89544	↓	0.89653	↓	0.89653	↓	-
2	3.2508e-2	↓	3.2488e-2	↓	-	↓	3.2510e-2

Step 3: Updated X1, X2, X5

Prior values									
Barrier	X1		X2		X3		X4		X5
	0.96621	↓	0.96618	↓	0.93636	↓	0.97014	↓	1.0
Updating									
Step	X1		X2		X3		X4		X5
1	0.89544	↓	0.89653	↓	0.89653	↓	-	↓	-
2	3.2508e-2	↓	3.2488e-2	↓	-	↓	3.2510e-2	↓	-
3	1.0888e-4	↓	1.0888e-4	↓	-	↓	-	↓	1.0888e-4

Step 4: Updated X1, X2, X6

Prior values											
Barrier	X1		X2		X3		X4		X5		X6
	0.96621	↓	0.96618	↓	0.93636	↓	0.97014	↓	1.0	↓	1.0
Updating											
Step	X1		X2		X3		X4		X5		X6
1	0.89544	↓	0.89653	↓	0.89653	↓	-	↓		↓	-
2	3.2508e-2	↓	3.2488e-2	↓	-	↓	3.2510e-2	↓		↓	-
3	1.0888e-4	↓	1.0888e-4	↓	-	↓	-	↓	1.0888e-4	↓	-
4	0.0	↓	0.0	↓	-	↓	-	↓		↓	0.0

Step 5: Updated X1, X2, X7

Prior values													
Barrier	X1		X2		X3		X4		X5		X6		X7
	0.96621	↓	0.96618	↓	0.93636	↓	0.97014	↓	1.0	↓	1.0	↓	1.0
Updating													
Step	X1		X2		X3		X4		X5		X6		X7
1	0.89544	↓	0.89653		0.89653		-	↓	-		-		-
2	3.2508e-2		3.2488e-2		-		3.2510e-2		-		-		-
3	1.0535e-4		1.0885e-4				-		1.0888e-4		-		
4	0.0		0.0								0.0		
5	0.0		0.0						-		-		0.0

Step 6: Updated X1, X2

Prior values													
Barrier	X1		X2		X3		X4		X5		X6		X7
	0.96621	↓	0.96618	↓	0.93636	↓	0.97014	↓	1.0	↓	1.0	↓	1.0
Updating													
Step	X1		X2		X3		X4		X5		X6		X7
1	0.89544		0.89653		0.89653		-		-		-		-
2	3.2508e-2		3.2488e-2		-		3.2510e-2		-		-		-
3	1.0886e-4		1.0885e-4		-		-		1.0888e-4		-		-
4	0.0		0.0		-		-		-		0.0		-
5	0.0		0.0								-		0.0
6	0.0		0.0										

Updated Barrier Success Probabilities						
X1	X2	X3	X4	X5	X6	X7
0.92806	0.92913	0.89653	0.96749	0.99989	1.0	1.0