THE DEVELOPMENT OF DYNAMIC OPERATIONAL RISK ASSESSMENT IN OIL/GAS AND CHEMICAL INDUSTRIES

A Dissertation

by

XIAOLE YANG

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2010

Major Subject: Chemical Engineering

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Approved by:

Chair of Committee,	Mahboobul Mannan
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ABSTRACT

The Development of Dynamic Operational Risk Assessment in Oil/Gas and Chemical Industries. (May 2010)

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Chair of Advisory Committee: Dr. Mahboobul Mannan

In oil/gas and chemical industries, dynamics is one of the most essential characteristics of any process. Time-dependent response is involved in most steps of both the physical/engineering processes and the equipment performance. The conventional Quantitative Risk Assessment (QRA) is unable to address the time dependent effect in such dynamic processes. In this dissertation, a methodology of Dynamic Operational Risk Assessment (DORA) is developed for operational risk analysis in oil/gas and chemical industries. Given the assumption that the component performance state determines the value of parameters in process dynamics equations, the DORA probabilistic modeling integrates stochastic modeling and process dynamics modeling to evaluate operational risk. The stochastic system-state trajectory is modeled based on the abnormal behavior or failure of the components. For each of the possible system-state trajectories, a process dynamics evaluation is carried out to check whether process variables, *e.g.*, level, flow rate, temperature, pressure, or chemical concentration, remain in their desirable regions. Monte Carlo simulations are performed to calculate the probability of process variable exceeding the safety boundaries. Component testing/inspection intervals and repair time are critical parameters to define the system-state configuration; and play an important role for evaluating the probability of operational failure. Sensitivity analysis is suggested to assist selecting the DORA probabilistic modeling inputs. In this study, probabilistic approach to characterize uncertainty associated with QRA is proposed to analyze data and experiment results in order to enhance the understanding of uncertainty and improve the accuracy of the risk estimation. Different scenarios on an oil/gas separation system were used to demonstrate the application of DORA method, and approaches are proposed for sensitivity and uncertainty analysis. Case study on a knockout drum in the distillation unit of a refinery process shows that the epistemic uncertainty associated with the risk estimation is reduced through Bayesian updating of the generic reliability information using plant specific real time testing or reliability data. Case study on an oil/gas separator component inspection interval optimization illustrates the cost-benefit analysis in DORA framework and how DORA probabilistic modeling can be used as a tool for decision making. DORA not only provides a framework to evaluate the dynamic operational risk in oil/gas and chemical industries, but also guides the process design and optimization of the critical parameters such as component inspection intervals.

To

My parents,

Wenhui Long & Shunhua Yang

My sister,

Xiaoxiao Yang

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CHAPTER I

INTRODUCTION

A. Background

Offshore oil/gas operations and chemical process activities receive a great deal of public awareness and concern regarding their potential hazardous impact on people, environment and society. The offshore plants typically involve a number of stages of oil, gas and water separation, gas compression, and dehydration. Process operation, together with transportation and drilling operation, are the most hazardous activities on an offshore oil and gas platform[1]. A small mishap in the process operation might escalate to a catastrophic event due to the limited space, compact geometry of the process area, less ventilation, and difficult escape routes. The risk associated with a typical offshore installation may be categorized into: process risk, dropped object risk, structural failure risk, helicopter accident risk, and ship collision risk. Process risk, which is defined as the risk due to fire and explosion in the process facility, contributes more than 50% of the total risk of the offshore installation[2]. In chemical plants, processes involve activities including mixing, separation, high pressure and/or high temperature operation, reactive chemical reaction, etc. Mechanical hazards can cause worker injuries from tripping, falling, or moving equipment. Fire and explosion hazards, as well as reactivity hazards and toxic hazards are also significant in chemical plants.

Case histories show that incidents in oil/gas and chemical industries usually cause significant casualties and unbearable economic loss. For example, the Flixborough disaster, which occurred in a chemical plant that produced caprolactam, a precursor

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chemical used in the manufacture of nylon, in Flixborough, England, on June 1, 1974, killed 28 people and seriously injured 36[3]. The Bhopal disaster[3] took place at a Union Carbide pesticide plant in Bhopal, India, on December 3, 1984. The incident released methyl isocyanate (MIC) gas, exposing more than 500,000 people to MIC and other chemicals. It killed at least 3,800 people and caused significant morbidity and premature death for many thousands more. An explosion and resulting fire in the Piper Alpha disaster[4] destroyed the oil production platform on July 6, 1988, killing 167 people, and the total insured loss was $3.4 billion. A massive explosion in a high-density polyethylene plant in Pasadena, Texas, on October 23, 1989, killed 23 people, injured 314, and resulted in over $715 million capital losses[3]. In the recent past years, several offshore and refinery disasters have occurred. On March 23, 2005, a series of explosions occurred during the startup of the hydrocarbon isomerization unit at BP Texas City refinery killing 15 people, injuring 180 others and resulting in $1.5 billion losses[5]. On July 26, 2005, a fire at India's largest oil and gas platform Mumbai High North Platform, completely destroyed the platform and caused 22 fatalities[6].

All these accidents had a significant impact on public perceptions and the chemical engineering profession. Concerns to add new emphasis and standards in the practice of safety have been translated into federal or state regulations. For example, the Occupational Safety and Health Administration's (OSHA) Process Safety Management (PSM) standard, the Environmental Protection Agency's (EPA) Risk Management Program (RMP), Instrumentation, Systems, and Automation Society's (ISA) Safety Instrumented System (SIS) related standards: ISA-S84.01 and International Electrotechnical Commission's (IEC) IEC61508, and other federal regulations are dedicated to process safety[3].

The investigation on most of the major accidents shows that those tragedies could be avoided with effective risk analysis and safety management programs. Risk assessment approaches need to be consistently improved for better risk analysis and safety management. Development of Dynamic Operational Risk Assessment (DORA) methodology for oil/gas and chemical industries is the subject matter of this doctoral dissertation. Principal problems, research objectives, research contributions of the present work and the organization of the dissertation are presented in this Chapter together with the necessary introductory materials. In Section B, a brief description of the principal problem is presented. The dynamic concerns in Quantitative Risk Assessment (QRA) define the objectives of this work, which are presented in Section C. In the subsequent sections, the contributions of the work and the organization of the dissertation are described.

B. Problem Statement

The oil/gas and chemical process systems exhibit complicated and dynamic behavior. Various time-dependent effects such as season changes, aging of process equipment, physical processes, stochastic processes, operator response time, etc. are involved in such dynamic processes. With the accumulated experience of QRA and the progressive awareness of dynamic characteristics of reliability and safety, conventional approaches that are static reveal their weakness in nature when applied to dynamic processes[7, 8]. For instance, fault tree/event tree analysis (FTA/ETA)[9], initially applied in nuclear power plants, collects a set of logical expressions to represent static relationship between a component output event and component failure or another component output event in the process system. FTA is a good implementation tool using logic to identify output deviations due to input deviations or internal failures, but overlooks the system dynamic response to time, process variables, and human behavior[10]. FTA/ETA methods often used on a static basis consider only the major incidents or accidents but ignore minor incidents, abnormal events or near misses. Similarly, the conventional reliability assessment without profound understanding of the dynamics of both physical process and system performance is insufficient to help understand the operational risk that may trigger catastrophe when the critical process variables exceed their safety boundaries without being detected. Those conventional risk and reliability assessment methods fail to capture the variation of operational risks as time-dependent deviations or changes in the process take place.

In oil/gas and chemical processes, operation conditions, such as separation, high-pressure compression, storage, desulphurization, and blending, are vulnerable to escalate small mishaps into catastrophe. Abnormal events that are called accident precursors may result in incidents and near misses during the life of process. Protection systems are designed to monitor the process variables and take appropriate action if any or a combination of them exceed a predetermined desirable region. However, those protection systems may provide false or misleading information. The failure of this class of protection system becomes significant if it coincides with a deviation of the monitored parameters. For example, investigation on the BP Texas City incident found that the level transmitter indicated the level in the spliting tower was declining gradually but the level was actually rising during the startup. The level indicator read 7.9 feet in the tower; however, the tower level was actually 158 feet[5]. It is not experimentally practical to replicate such catastrophic events to evaluate the operational incident probability. Therefore, a new simulation tool for dynamic operational risk assessment is needed to assess the probability of operational incidents that potentially lead to a catastrophe.

C. Research Objective

The main objective is to develop a practical and systematic risk assessment method starting from conceptual design to mathematical modeling then to optimal resource allocation solutions. This methodology will improve understanding of the operational risk associated with dynamic processes in oil/gas and chemical industries. The objective is achieved through the following phases:

Phase I:

- Design the conceptual framework of DORA that can be generically applied to any dynamic process in oil/gas and chemical industries.
- Develop mathematical models for the dynamic risk assessment for oil/gas and chemical processes. Those models should be able to characterize the process dynamics governed by laws of physics and engineering and also the dynamics driven by the equipment performance and deterioration.

Phase II:

- Design algorithms to solve the mathematical models integrating discrete event simulation, process dynamics simulation and Monte Carlo simulation.
- Implement the algorithms and subsequent programming to a practical process.

Phase III:

- Establish a probabilistic approach to evaluate the quality of a QRA study. This approach should be able to characterize the uncertainty associated with risk analysis.

- Develop uncertainty reduction strategies to improve QRA study.

Phase IV:

- Optimize the resource allocation for risk reduction in the case study used in Phase II.

D. Research Contributions

Hazard identification, hazard assessment and risk estimation are key aspects in oil/gas and chemical process plant design and operation. One of the most important contributions of this research is to introduce a new simulation-base dynamic operational risk assessment approach to oil/gas and chemical industries and illustrated by case studies. Different from the conventional QRA approaches and other dynamic risk assessment tools, this research provides industries with:

- A systematic approach, DORA, for operational risk estimation.
- A prediction tool targeting the component/system abnormal events, also referred to as accident precursors. Accident precursors are considered so that this tool is able to prevent a failure from actually occurring. DORA methodology is applicable to scenarios with either system shutdown due to component failure or system remaining in process in the presence of component abnormal events.
- Monitoring on the simultaneous failure/abnormal events of multiple components using the stochastic simulation in DORA framework. The system-state trajectory is simulated upon Monte Carlo sampling from the distribution of stochastic variables.
- Characterization of the system state trajectory considering critical parameters in reliability and safety engineering, such as component inspection interval,

maintenance time, testing time, repair time, etc. Component states are not limited to only *up* and *down* to study the system stochastic behavior. Testing/inspection intervals and component repair times are important parameters to define the component states. It provides insights for testing/inspection interval optimization.

In the design phase of an oil/gas or chemical process or plant, DORA aids operational hazard identification and hazard assessment. Operational failure scenarios will be identified in order to recommend improvement in design for risk reduction. Meanwhile, DORA provides a risk measurement using a standard computational space storage and time consumption to assist evaluating the competing control system or safety system designs. In operation phase, implementing resource optimization proposed in DORA assists decision making on cost-effective inspection or test scheduling. This framework is implemented as an ongoing model to guide implementation and continual updating of safety program components such as risk-based and cost-effective monitoring, testing, maintenance, reliability assessment, component replacement timing, shutdown times, and timing of other operational decisions including selection of minimal reliability criteria during maintenance shutdowns.

E. Organization of This Dissertation

Following this introduction Chapter, three independent Chapters will explain the Dynamic Operational Risk Assessment (DORA) methodology, uncertainty characterization and reduction in QRA, and component inspection interval optimization. In Chapter II the author explains the development of DORA framework, including the steps of *Scope Identification and System Description*, *Hazard Identification*, *Scenario Identification*, *Component Failure Mode Identification*, *DORA Probabilistic Modeling*, *Incident Consequence Modeling*, *Risk Determination*, *Modification on the Design or Operation*, *Cost-Benefit Analysis*, and *Build and/or Operate the System*. The focus of the quantitative analysis is the development of *DORA Probabilistic Modeling* and the uncertainty characterization in *Incident Consequence Modeling*. Chapter III explores different types of uncertainty associated with a QRA, how to characterize the uncertainty in a fault tree analysis, and how to reduce epistemic uncertainty through Bayesian updating the reliability information of a system using real life reliability data or equipment testing data. Chapter IV extends the case study in Chapter II and optimizes the component inspection interval using multiobjective optimization approaches. Different multiobjective optimization techniques are introduced and two of them are applied in the case study. Chapters II through IV have their own introduction, literature review, body, and summary. The information in each chapter is relative but self-contained, Chapter V provides an overall summary of the conclusions and recommendations, followed by the Section of References. Other supplementary data are summarized in the Appendix.

CHAPTER II

DORA METHODOLOGY*

A. Introduction

A methodology of Dynamic Operational Risk Assessment (DORA) is proposed for operational risk analysis in oil/gas and chemical industries. In this Chapter, DORA methodology will be introduced comprehensively starting from the conceptual framework design to mathematical modeling and to decision making based on cost-benefit analysis. The probabilistic modeling part of DORA integrates stochastic modeling and process dynamics modeling to evaluate operational incident probability. The stochastic system-state trajectory is modeled according to the abnormal behavior or failure of each component in the system. For each of the possible system-state trajectories, a process dynamics evaluation is carried out to check whether process variables, e.g., level, flow rate, temperature, pressure, or chemical concentration, remain in their desirable regions. DORA methodology not only provides a framework to evaluate the dynamic operational risk in oil/gas and chemical industries, but also guides the process design and further optimization. Chapter II explores the literature on QRA in oil/gas and chemical industries as well as research in the dynamic risk assessment field, and explains the DORA framework development in detail. The main objective of this Chapter is to provide a general framework of DORA and the development of DORA probabilistic modeling. A case study on level control in an oil/gas separator will be used to illustrate the incident probabilistic modeling.

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Sensitivity analysis will be performed to evaluate the importance of selection of model input distribution type in the DORA case study.

B. Literature Review

Risk is a measure of the potential loss, such as loss of human life, adverse health effects, loss of property, environmental damage, and economic loss, etc, due to natural or human activities[11]. Risk analysis is the process that involves a series of activities including characterizing, managing, and informing others about the existence, nature, magnitude, prevalence, contributing factors, and uncertainties of the potential losses[11]. Risk analysis has three core elements: risk assessment, risk management, and risk communication[12]. In risk assessment, three basic questions posed by Kaplan and Garrick include[13]:

- What can go wrong?
- How likely is it?
- What are the losses (consequences)?

Both qualitative and quantitative techniques can be used to address those questions. Quantitative Risk Assessment (QRA) is preferred when adequate data and other evidences exist to estimate the probability and magnitude of the losses, and is required early in the project life cycle for major risk contributors identification and assessment[14].

QRA has been widely used in oil/gas and chemical industries; it dates back to the 1970s. The US 'Reactor Safety Study'[9], a project conducted for research and development purpose in 1975, investigated the availability of analysis methodologies and sufficient sophistication and robustness of data. Classical QRA approach such as Fault Tree Analysis(FTA) studied in this research is still widely used nowadays. FTA was first developed in 1961 at Bell Telephone Laboratories for a missile launch control reliability study during the Polaris project. It was extensively used in reliability studies in the nuclear and aerospace industries, and also adapted to chemical process industries. In 1981, the Norwegian Petroleum Directorate(NPD) issued their guidelines for safety evaluation of platform conceptual design[15]. QRA is required in these guidelines for all new offshore installations in the conceptual design phase in Norway. An efficient methodology was established and subsequently extended to application on existing installations. Ten years later, these NPD guidelines were replaced by regulations for the use and execution of risk analysis in 1991[16]. QRA became an official requirement for offshore after the Piper Alpha platform disaster that took place in 1988. Lord Cullen in his report recommended QRA as a technique to provide a structured, objective and quantitative approach to understanding risks and of the means to control them[17].

More extensive studies have also emerged since 1992 UK Safety Case Legislation required the use of offshore risk analysis in industry in the UK to be a part of the safety cases for existing and new installations. Vinnem[18] summarized the development of QRA in the offshore oil and gas industry for the last 20 years, since the research activities in the North Sea. Crawley and Grant[19] proposed a screening tool for offshore risk assessment that permits the risk assessment of design options in a methodical, consistent and auditable manner. The goal of this tool is to reduce front-end design costs and target design efforts in a cost-effective and safety-oriented manner. The application of QRA in design on modern offshore platform was discussed by Falck et al.[20]. Work methodology, selection of tools and data, and organization of QRA with other activities were addressed in this study. Rettedal et al.[21] proposed a method integrating QRA and SRA(structural reliability analysis) in a Bayesian framework for risk measurement in marine operation. Two examples show that the integration of SRA with 'fully Bayesian approach' is better than the integration with 'classical Bayesian approach'. QRA models for oil tankers were developed by Cross and Ballesio[22]. QRA is used in this study as a tool to evaluate competing designs, the relative benefits of redundancy, and the impact of equipment unavailability during operations. QRA study for loading and uploading facilities in marine hydrocarbon terminals sited in ports was published by Ronza et al.[23]. A number of studies on consequence analysis for offshore and chemical processes have been published. De León and Ortega presented an indirect losses calculation for an offshore oil complex in Mexico[24]. Explosion recurrence modeling has been studied by Yasseri and Prager[25]. A revised fire consequence model for offshore was developed by Pula et al.[26].

The review by Siu regarding the research on reliability and safety assessment of dynamic process systems is an important summary of the work already performed in this field of study[27]. The first Dynamic Probabilistic Risk Assessment (DPRA) approach was DYLAM, proposed by Amendola[28] to study the likelihood of accident sequences in a nuclear reactor. The DYLAM method couples the probabilistic and physical behavior of a system for a reliability analysis. Numerical simulation is conducted to study the physical system where the components are modeled in different working states: nominal, failed on, failed off, stuck, etc. DYLAM is designed to follow all the paths resulting from different component working state transitions and to drive the corresponding physical process simulation. The probability of occurrence of a certain top event is obtained by adding the probability of the corresponding sequences. The applications of DYLAM, DYLAM-3, and DYLAM-TRETA have been published[29, 30, 31, 32, 33].

Upgrades in the conventional event tree analysis for dynamics concern have resulted in two alternate groups of methods: Continuous Dynamic Event Tree (C-DET)[34] and Discrete Dynamic Event Tree (D-DET)[35]. Which method is used is dependent on how the branching times are selected. Monte Carlo sampling from the distribution of stochastic variables is the basis for event time selection in the C-DET approach, whereas branching time selection in the D-DET approach follows a set of rules, such as a discrete approximation of the corresponding C-DET[36]. Computer code, MSAS (Monte Carlo Simulation for Accident Sequences)[37], is designed to implement C-DET; and codes DYLAM[28], DETAM[38], as well as ADS[36], are designed for D-DET. In some of the approaches above, Monte Carlo techniques have been applied as an important tool in reliability assessment for dynamic process systems. A simulation-based approach proposed by Deoss [39] uses Monte Carlo techniques for introducing failures in time. A general theory to describe the deterministic and stochastic nature of incident events proposed by Smidts and Devooght[40] employs Monte Carlo techniques to study a fast reactor transit. A Monte Carlo dynamic approach to reliability was proposed by Marseguerra and Zio[41] and compared to classic static analysis.

Markov theory[42] is applicable to describe the stochastic behavior of a chemical process if it has Markov property:

- The system can be specified at any time by defining its process state at the time being; the system can be in any of a finite number of states.
- The conditional distribution of any future state given the past states and the present state, is independent of the past states and only depends on the present state.
- The individual Markov transition diagrams are mutually exclusive.

- Time at the transition from one state to another is independent and an exponentially distributed random variable. In a semi-Markov process, the restriction of exponential distribution type is removed.

- Transition probability from the instant state to itself is zero.

Let $X_n \in \Re$ denote a finite number of possible instant states of the process. When $X_n = i$, it says the component is the process in state i at time n. At the state of i, the probability of the process will next be in state j, P_{ij} is given by:

$$P_{ij} = P\left\{X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, \ldots, X_1 = i_1, X_0 = i_0\right\} \tag{2.1}$$

for all states i_0, i_1,..., i_{n-1}, i, j and all $n \geq 0$. This process is known as Markov chain. For a Markov chain, given the past states and the present state, the future states are only dependent on the present state, but independent of the past states, regardless of the whole state evolution process. An important assumption of its application is that the time at the transition from one state to another is an exponentially distributed random variable. Semi-Markov process is a generalization of the Markov and renewal process, which is not restricted to exponential distribution on the sojourn time. The evolution of the semi-Markovian process in time is an increasing sequence of random variables:

$$0 = T_0 \leq T_1 \leq T_2 \leq \ldots \leq T_n \leq \ldots \tag{2.2}$$

with value in $[0, \infty)$ and this random variable T_n is the time that the nth transit occurs when $n \geq 1$. So if $X_n = j$, $T_{n+1} - T_n$ is the random length of the episode in state j. The state (X_n, T_n) has the semi-Markov property if

$$P\left[X_{n+1}=j, T_{n+1}-T_n \leq t \middle| \left(X_k, T_k, k=0,1,\ldots,n\right)\right] \tag{2.3}$$

$$= P\left[X_{n+1}=j, T_{n+1}-T_n \leq t | X_n = i\right] \tag{2.4}$$

for all $n = 0, 1, 2, \ldots$, and $t \geq 0$.

Furthermore, the right side of equation 2.4 can be written in terms of the distribution function of the episode time $F_{ij}\left(x\right)$:

$$P\left[X_{n+1}=j, T_{n+1}-T_n \leq t | X_n = i\right] = p_{ij} F_{ij}\left(x\right) \tag{2.5}$$

where $p_{ij} = P\left[X_{n+1}=j | X_n = i\right]$.

Unlike the forward Kolmogorov differential equations in continuous time Markov jump processes, Markov renewal integral equations play a fundamental role in semi-Markov process analysis. Markov renewal equation is defined as:

$$P_{ij}\left(t\right) = D_{ij}\left(t\right) \sum_{k \neq j} \int_0^t Q_{ik}\left(s\right) P_{kj}\left(t-s\right) ds \tag{2.6}$$

where P_{ij} is an unknown matrix-valued function, and D_{ij} is a known matrix-value function. The process enters state k at some point $s \in (0, t]$ before entering state j. This equation can be written in the following form by using convolution $*$:

$$P = D + Q * P \tag{2.7}$$

Blin et al.[43] discussed the use of Markov processes for reliability problems. Papazoglou presented the elements of Markovian reliability analysis [44] and discussed the need of Markovian reliability analysis[8]. Aldemir[45] proposed a computer assisted Markov failure modeling for process control systems with control loops and continuous state dynamic variables. Markov models were used to describe the probabilistic evolution of the controlled variables in discrete time and discretized controlled variable state space in a data base oriented method for closed loop control systems by Hassan and Aldemir[46]. A mathematical formulation of probabilistic dynamics was adapted to dynamic process analysis[47]. The mixed probabilistic and deterministic dynamics formulation involves process variables, semi-Markovian process of the system transition, and human error modeling. Papazoglou and Gyftopoulos applied Markovian reliability analysis on a shutdown system of the clinch river breeder reactor[48]. Other approximate application of the Markovian method can be found in several publications[49, 50, 51].

C. DORA Framework

The conceptual framework of DORA is shown in Figure 1. The detailed approach of each step and the algorithm associated if any will be discussed in rest of the section.

1. Scope Identification and System Description

Scope Identification and System Description plays an important role in DORA as a foundation and starting point for further hazard identification and mathematical model development. The scope of a DORA project has to be defined for the study to be better managed, controlled, verified, and communicated to the stakeholders or customers. According to the demand of the stakeholders/customers, the analysis scope varies from a small scale of system, for instance a liquid storage tank, to a middle size of system, say, a cracker unit, to a large scale of system (perhaps the whole refinery plant) and so forth. Regardless of the size of the study scope, the system will be broken down into several subsystems, further components. Each component or a group of components within the same subsystem has its own fashion of failure mode.

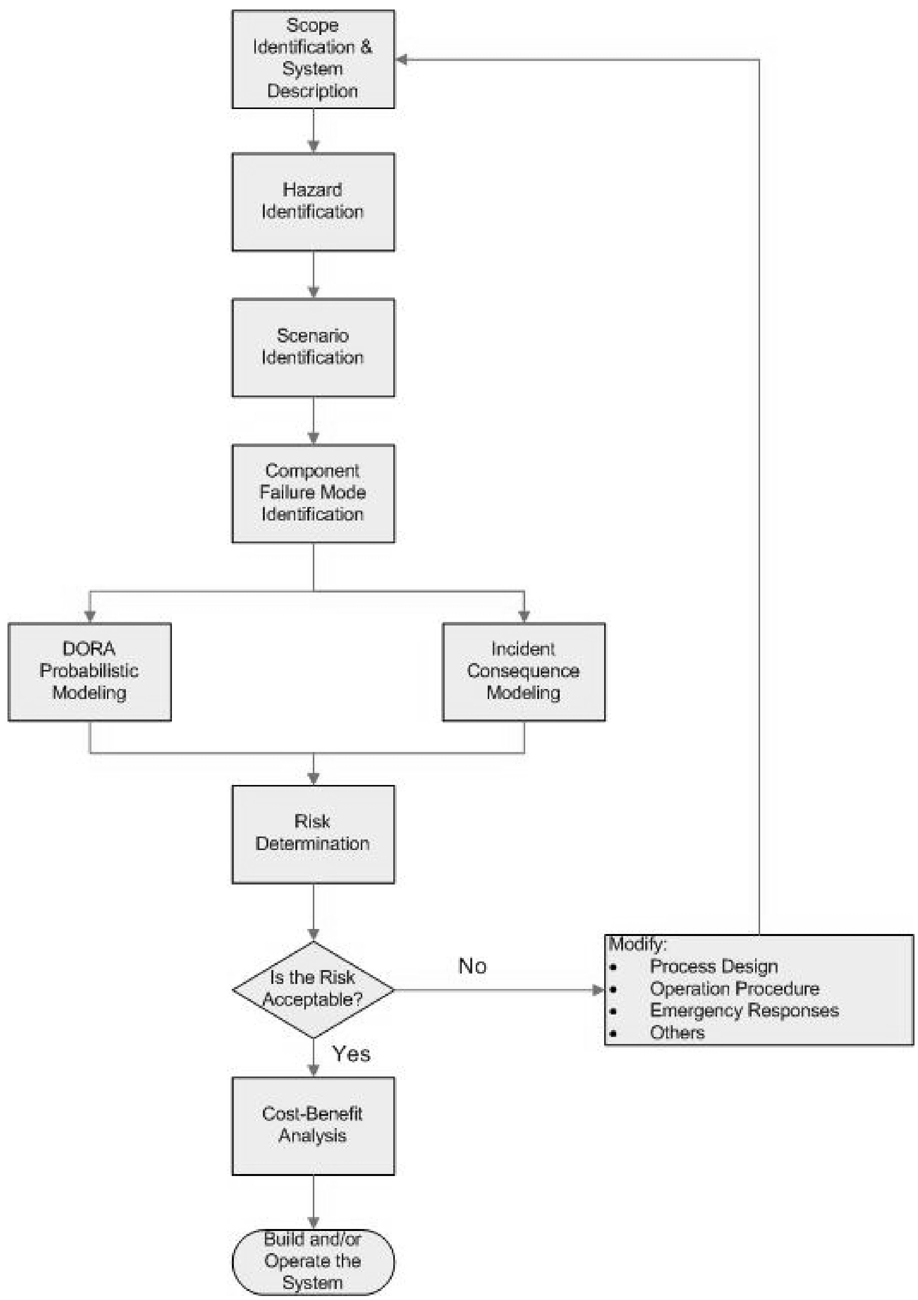

Fig. 1. DORA methodology scheme.

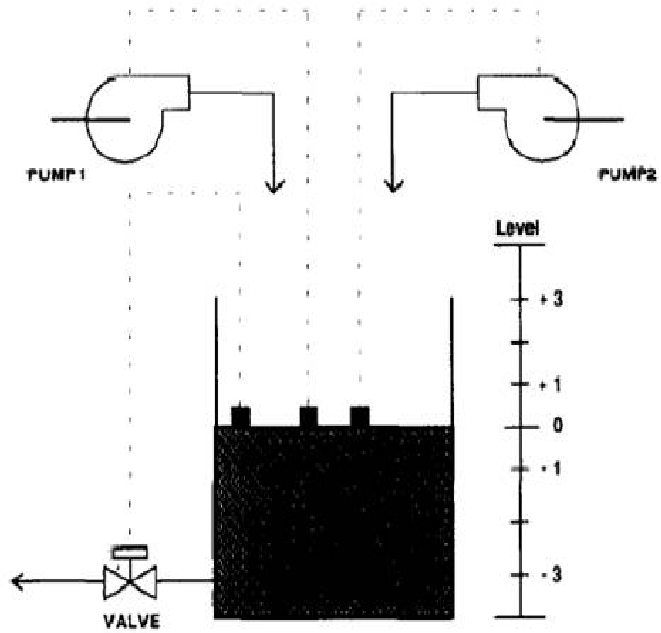

Fig. 2. A liquid storage tank.

For example, a liquid storage tank as shown in Figure 2[52] can be separated into two components as pump system and valve. The distribution of failure probability of this storage tank system can be used as a subsystem input when the study scope is enlarged.

2. Hazard Identification

Generally, hazard identification by itself can be performed at any stage during the initial design or ongoing operation of a process. However, it is required to be performed before the mathematical modeling for probabilistic safety analysis in the DORA framework. The DORA mathematical modeling is scenario and failure mode specific. And Hazard Identification is the step directing to the discovery of the scenario and component failure mode. Therefore, Hazard Identification and the subsequent Scenario Identification and Component Failure Mode Identification steps are necessary in the early stage of the operational risk assessment in a DORA study. The hazard identification methods for DORA are adapted from general hazard identification.

- **Hazards Checklists**

  A hazards checklist is simply a list of all the possible problems to be checked. This list reminds the operator, reviewer, or risk analyst of the potential hazardous areas. Checklists are suggested to be applied only during the preliminary stages of hazard identification and should not be used as a replacement for a more complete hazard identification procedure. A typical process safety checklist might contain the following items[53]:

  - Consequences of exposure to adjacent operations considered?
  - Special fume or dust hoods required?
  - Process laboratory checked for runaway explosive conditions?
  - Provisions for protection from explosions?
  - Hazardous reactions possible due to mistakes or contaminations?
  - Provisions for rapid disposal of reactants in an emergency?
  - Failure of mechanical equipment possible cause of hazards?
  - Hazards possible from gradual or sudden blockages in piping or equipment?

- **Hazards Surveys**

  A hazard survey can be one of the two popular forms: the Dow Fire and Explosion Index (F&EI)[54] and the Dow-Chemical Exposure Index (CEI)[55]. It also could be simple as an inventory of hazardous materials in a facility. F&EI and CEI are two formal systematic approaches using a rating form to provide a relative ranking of the hazard. The steps and application of F&EI and CEI forms can be found in AIChE's publications[54, 55]. Hazards survey approach is suitable for hazard identification associated with equipment design, layout, material storage, etc., but improper for operation or upset conditions.

- **Hazard and Operability Studies**

  A Hazard and Operability (HAZOP) study is a formal procedure of hazard identification in a chemical process facility. A multi-disciplinary HAZOP team is required to be led by a faciliator who is experienced with the HAZOP procedure and the chemical process under review. It is a qualitative technique based on guide-words. The HAZOP procedure includes the following steps[56, 3]:

  1. Break a detailed flow sheet into a number of process units. Select one for study.
  2. Identify a study node.
  3. Describe the design intent of the study node.
  4. Choose a process parameter, e.g., temperature, pressure, pH, level, flow, viscosity, and so forth.
  5. Apply a guide word to the process parameter to suggest possible deviations.
  6. Determine the possible causes and note any protective systems if the deviation is applicable.

7. Evaluate the consequences of the deviation if any.
8. Recommend action.
9. Record information.
10. Repeat steps 5 through 9 until all applicable guide words have been applied to the chosen process parameter.
11. Repeat steps 4 through 10 until all applicable process parameters have been considered for the predetermined study node.
12. Repeat steps 2 through 11 until all study nodes have been considered for the given section and proceed to the next one on the flow sheet.

- **Safety Reviews**

  A safety review is used to identify safety problems in laboratory and process areas. Solutions are then developed in the review for significant improvement. Usually, a formal safety review is for new processes, substantial changes in existing processes, and processes that need an updated review. However, an informal safety review is for small changes to existing processes and small bench scale or laboratory processes.

- **What-If**

  This is a structured brainstorming method of determining what can go wrong in an operation process by asking questions starting from 'what-if...'. Those questions could be relative to human errors, process upsets, and equipment failures. The errors and failures considered can be in the situation of normal operations, under construction, during maintenance activities, etc.

3. Scenario Identification

There could be several scenarios that lead to the same consequence in a process. For example, for fire hazard in a fuel storage tank system, multiple scenarios might be identified as the direct causes coincided with an ignition source: overflow of the storage tank, leakage at the tank bottom, leakage at piping, etc. The process dynamics modeling and incident consequence analysis are scenario specific. In each scenario, a unique dynamics model is developed to characterize the physical features of the process. Probabilities of hazardous scenarios are the outputs of DORA Probabilistic Modeling that will be discussed in subsection 6.

4. Component Failure Mode Identification

It is important to identify the component failure mode in a DORA study. The reasons are:

Firstly, any scenario identified in the third step has resulted from certain component failures or abnormal events. In this study, we will use the term 'failure mode' for both actual equipment failure mode and abnormal event mode. An explicit DORA study is dependent on identifying all the possible hazards, scenarios and component failure mode combinations. There are usually multiple components in the same system. Different component failure mode combinations could lead to the same scenario. The relationship among *Scope Identification and System Description*, *Hazard Identification*, *Scenario Identification*, and *Component Failure Mode Identification* is shown in Figure 3. For any one of the a hazards identified, there are b scenarios needing to be analyzed. In each of the b scenarios, there could be c possible component failure mode combinations driving the scenario. Therefore, in the system under review, there

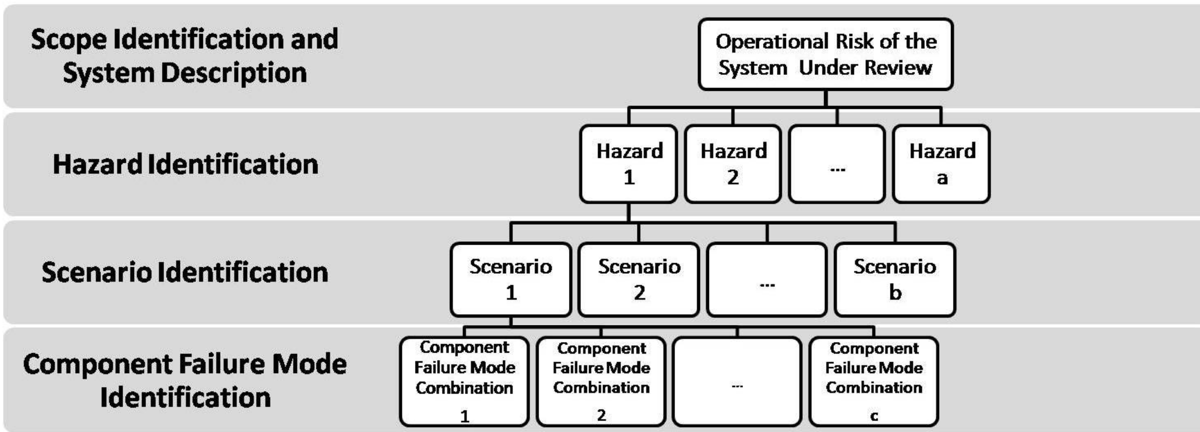

Fig. 3. The relationship among Scope Identification and System Description, Hazard Identification, Scenario Identification, and Component Failure Mode Identification.

will be total number of U system performance modelings and the associated DORA probabilistic modelings required:

$$U = c * b * a \tag{2.8}$$

Secondly, this step is the tunnel between the previous qualitative steps and the following quantitative assessment steps. The reliability data needed for further system performance analysis is failure mode specific. For the same piece of equipment, reliability data for different failure modes are totally different. The component failure mode identification will determine what component reliability data to be used as the input of the quantitative analysis steps(Figure 4).

5. DORA Probabilistic Modeling

DORA probabilistic modeling integrates process dynamics modeling and stochastic modeling to analyze the behavior of process variables in the presence of component failure/abnormal event. The evolution of incidental sequences in a process system is a

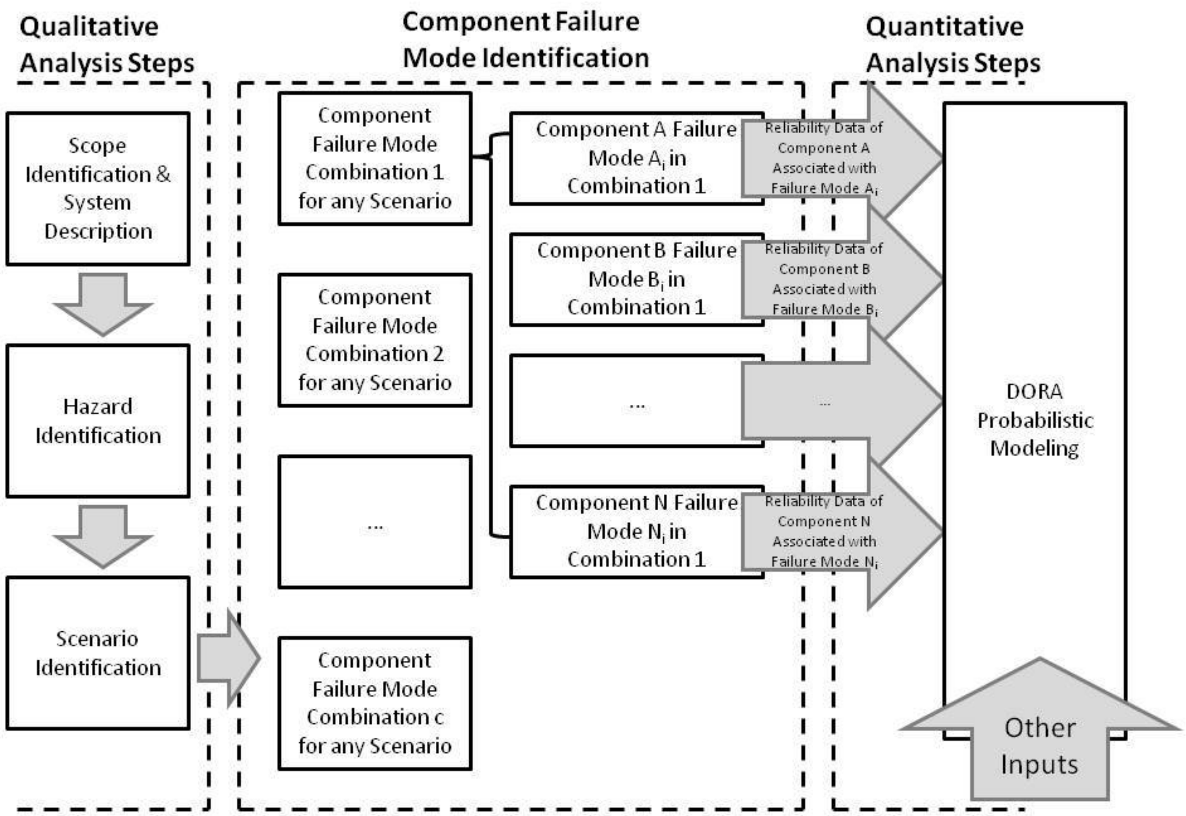

Fig. 4. The connection between qualitative steps and quantitative steps in a DORA study through Component Failure Mode Identification.

combination of deterministic and stochastic events. The physical behavior of a process is a set of deterministic events; and the system component performance determines the stochastic events. The linkage between the two is that the stochastic system-state trajectory is the driven force of the process physical variable trajectory. In this subsection, attention is confined to developing a systematic DORA probabilistic modeling for computing the probability of process variables exceeding the operational safety boundaries using considerable computational space storage and time consumption.

a. System-state Trajectory Modeling

The system-state trajectory modeling is designed to model the system performance. Discrete event simulation is the foundation of developing the system-state trajectory modeling. In discrete-event simulation, a chronological sequence of events represent the operation of a system in which each event occurs at an instant in time and marks a change of system-state[57]. Terminologies are stated as the following for the discrete event simulation:

Component: Any equipment, instrument, hardware or software, etc., composing the system that is under assessment. For example, a pump, a valve, a vessel, an alarm, etc. They are the smallest physical units in the DORA modeling construction.

Component-state: Each of the components can be specified at any time by defining its performance behavior state at that time. A component can be in any of a finite number of states. In this study, a component visits one of the three states indicating their instantaneous performance status, which are *Normal Operating*, *Abnormal Event Undetected*, and *Abnormal Event Detected and Under Repair*. The transition of component states follows a certain direction(Figure 5). Prior to each assessment, the component failure mode has to be defined to locate the corresponding failure rate or abnormal event rate data. At any instant, any component is only able to remain

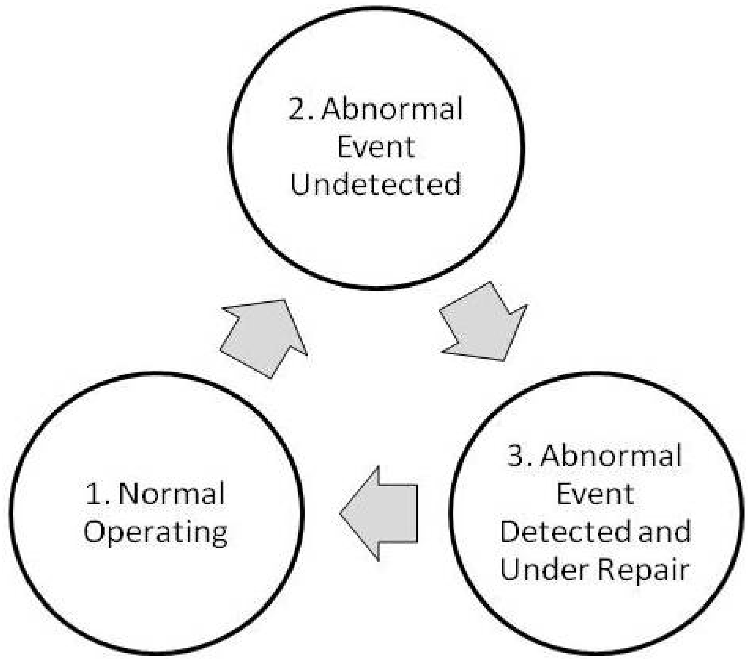

Fig. 5. Component states flow diagram.

in a unique state.

System-state: a combination of component states to describe the system behavior at the time being. If there are N components within a system, through A, B, $\ldots$, to N, the total number of possible system state, M, is given by:

$$M = 3^N \tag{2.9}$$

The system-state trajectory is a sequence of part or all of the M system states.

Sojourn time: a random variable to represent the time a component or system spends in a state. By probabilistic law, the sojourn time follows a certain type of distribution. The parameters of those distributions are specific in each case.

Process variable: variables that are used to describe the physical dynamics of the system process, for instance, temperature in the reactor, pressure in the vessel, level in the storage tank, etc. We use a vector $\bar{x}$ to denote a set of process variables of interest.

The first step in system-state trajectory simulation is to characterize the component state sojourn time distribution. The component-state sojourn time is the time a component spends in a specific state. For State 1 of a component, *Normal Operating*, the sojourn time is defined as the time between failures or abnormal event occurrences. Let random variable, X, denote the length of an episode between failures or abnormal event occurrences. In reliability engineering, a common assumption is that the time between failures is an exponentially distributed random variable. The exponential distribution assumption is also applicable in this study. Therefore, X follows an exponential distribution. The parameter(s) for the distribution of X depend on the failure rate or abnormal event rate. The probability density function of State 1 sojourn time distribution is given by:

$$f(x;\lambda) = \lambda e^{-\lambda x} \tag{2.10}$$

The time a component remains in State 2, *Abnormal Event Undetected*, is defined as the time between an abnormal event occurs without being detected and the abnormal event detected through testing or inspection. The sojourn time at this state is determined by both the failure rate or abnormal event rate and the component testing/inspection interval. Let random variable, Y, denote the length of an episode in component State 2. The relationship among X, Y, and the testing/inspection interval T is demonstrated in Figure 6. An important assumption for the problem formulation is that the testing/inspection interval T is a constant. The probability distribution function of Y is given by:

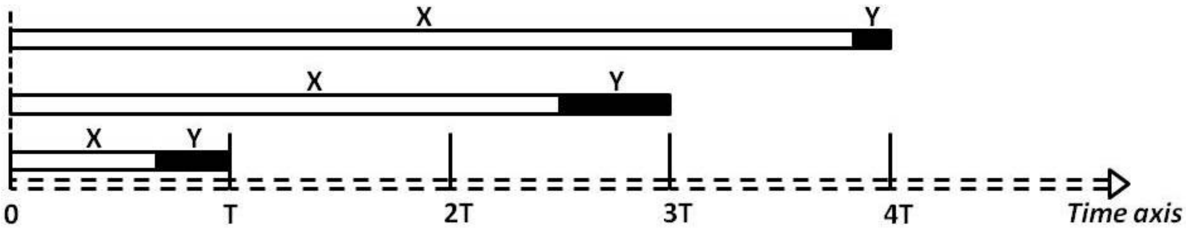

Fig. 6. The relationship among component State 1 sojourn time(X, the empty bars), component State 2 sojourn time(Y, the bold bars), and the testing/inspection interval(T) along time axis.

$$
\begin{aligned}
P\left(Y<y\right) &= P\left(T-X<y|X<T\right)P\left(X<T\right) \\
&+P\left(2T-X<y|T<X<2T\right)P\left(T<X<2T\right) \\
&+P\left(3T-X<y|2T<X<3T\right)P\left(2T<X<3T\right)+\cdots
\end{aligned}
\tag{2.11}
$$

This is equivalent to:

$$
\begin{aligned}
P\left(Y<y\right) &= P\left(X>T-y|X<T\right)P\left(X<T\right) \\
&+P\left(X>2T-y|T<X<2T\right)P\left(T<X<2T\right) \\
&+P\left(X>2T-y|2T<X<3T\right)P\left(2T<X<3T\right)+\cdots
\end{aligned}
\tag{2.12}
$$

Using conditional probability law:

$$
P\left(A\bigcap B\right)=P\left(B\right)P\left(A|B\right) \tag{2.13}
$$

Equation 2.12 is simplified as:

$$P\left(Y<y\right)=P\left(T-y<X<T\right)+P\left(2T-y<X<2T\right)+P\left(3T-y<X<3T\right)+\cdots \tag{2.14}$$

According to the equation of distribution probability density function of X (equation 2.10), and equation 2.14, the probability distribution function of Y is given by:

$$P\left(Y<y\right)=\frac{e^{-\lambda(T-y)}-e^{-\lambda T}}{1-e^{-\lambda T}} \tag{2.15}$$

The sojourn time distribution of component State 3, *Abnormal Event Detected and Under Repair*, is obtained by fitting appropriate distributions to industry data. The industry data is in the form of recorded labor hours to repair the components. Exponential distribution, gamma distribution, lognormal distribution and Weibull distribution are suggested for the fitting as they are the four widely used distribution types to describe the time to repair in reliability engineering.

The system-state trajectory depends on how long the system remains in each state before transiting to the next one, and which component(s) changes state at the transition time. The component state transition is a deterministic process as shown in Figure 5. If any of the components in the system changes its state, the system transits to the next state subsequently. According to this principle, random numbers are generated by Monte Carlo sampling from the current state sojourn time distribution of each component; and in each simulation run, the minimum value of those random numbers decides the point of time when system transits to next state.

Algorithm for the system-state trajectory is designed as the following(Algorithm 1). The total number of components in a system under review is N. The total number of transition steps is J. If total number of K simulations will be performed for the system-state trajectory prediction, the following items are defined for the algorithm:

1. A 3-D array $S(I, N, K)$ to record the system-state trajectory.
2. A matrix $time(I-1, K)$ to record the transition time.
3. A vector $container(1, N)$ to temporarily hold the random numbers generated at each step.
4. $State1 == 0$, $State2 == 1$, $State3 == 2$.
5. $S(1, :, k) = zeros(1, N)$.
6. $time(0, k) = 0$.
7. Random Generator 1 - random generate a number from exponential distribution equation 2.10 with the component specific failure rate.
8. Random Generator 2 - random generate a number from probability distribution function equation 2.15 with the component specific failure rate and inspection interval.
9. Random Generator 3 - random generate a number from probability distribution function equation fitted using industrial repair time data.

There are two options to call i to stop the kth discrete event simulation. The first one is when:

$$\begin{aligned} time(i-1, k) &\leq \psi \\ time(i, k) &\geq \psi \end{aligned} \tag{2.16}$$

where ψ is a predetermined number in the unit of time. For example, it could be a plant lifetime, or it could be a number of years the analyst decides will be considered for the risk assessment.

Algorithm 1: The pseudocode of system-state trajectory.

for *each simulation run* k **do**
for *each transition run* i **do**
for *each component* n **do**
if $S(i, n, k) = 0$ **then**
call Random Generator 1 to get t_i;
end
else if $S(i, n, k) = 1$ **then**
call Random Generator 2 to get t_i;
end
else if $S(i, n, k) = 2$ **then**
call Random Generator 3 to get t_i;
end
$container(1, n) = t_i$;
end
$min(container(1, :))$; $q =$ component index of $min(container(1, :))$;
$time(i, k) = time(i - 1, k) + min(container(1, :))$;
if $S(i, q, k) = 0$ **then**
$S(i + 1, q, k) = 1$, and the rest of the $q - 1$ component remain at the same state as at i
end
else if $S(i, q, k) = 1$ **then**
$S(i + 1, q, k) = 2$, and the rest of the $q - 1$ component remain at the same state as at i
end
else if $S(i, q, k) = 2$ **then**
$S(i + 1, q, k) = 0$, and the rest of the $q - 1$ component remain at the same state as at i
end
end
call Eliminator 1 $equation 2.16$ or Eliminator 2 $equation 2.17$
end

The other way to eliminate the kth simulation is when:

$$i = \omega \tag{2.17}$$

where ω is an integer that represents the number of discrete transition steps. In this case, analyst decides the number of transition steps prior to the modeling.

b. Process Dynamics Modeling

The subject of oil/gas and chemical process dynamics is the evolution over time of physics and engineering variables such as temperature, pressure, liquid level, reactivity, flow rate, heat transfer, mass transfer, energy transfer, etc. The process dynamics is essentially governed by the laws of physics and engineering, such as kinetic theory, chemical reaction, statistical mechanics, thermodynamics, and transportation theory, etc. The process units either must be maintained closed to their steady states for continuous operation or follow optimal trajectories for batch operation. Once the study scope is defined, interests of process variables are determined. Mathematical equations will be developed to characterize the process dynamics. We define the process vector $\bar{x}$ whose elements include all process variables of interest under the DORA study. Ordinary differential or partial differential equations are used in this section to illustrate process description:

$$\begin{gathered} \frac{d^m \bar{x}}{dt} = f_i(\bar{x}) \\ or \\ \frac{\partial^m \bar{x}}{\partial t} = f_i(\bar{x}) \end{gathered} \tag{2.18}$$

with initial condition $\bar{x}(0) = \bar{x}_0$ and where i is the index of system-state.

Safety criteria are needed for any risk assessment. From a safety point of view, the criteria in DORA are defined as upper/lower boundary conditions $\bar{x}_u = (x_{u1}, x_{u2}, x_{u3}, \ldots, x_{un})$ and $\bar{x}_l = (x_{l1}, x_{l2}, x_{l3}, \ldots, x_{ln})$. Those values generate a surface or sphere to define the safe domain of the system. These boundary conditions will be used as cutoff values for the probabilistic simulation.

In Markovian method for dynamic risk assessment, a Markovian state in a system is described by three elements: process variable, system-state, and time. The history of state transition in a system is a succession of states $(\bar{x}_1, i_1, t_1)$, $(\bar{x}_2, i_2, t_2)$, ..., $(\bar{x}_n, i_n, t_n)$. A transition at time t_n is in process variable state $\bar{x}_n$ and has just entered discrete system-state i_n. Discretization is not merely needed for system-state trajectory. The evolution of process variables are also needed to be discretized to characterize the state of a system. The characterization of process variables in a Markovian approach requires explicit discretization to model the real process variable trajectory. On the other hand, a definitive discretization required in both system-state trajectory and process variable evolution will increase the numerical computation difficulties.

In this DORA study, discretization of process variables is not necessarily driven by Markovian properties. Process variable is not integrated into the state characterization in the discrete system-state trajectory simulation. In fact, the system-state trajectory determines where and when to discretize the process variable evolution(Figure 7). The system state configuration decides the parameters in function f_i for system-state i in equation 2.18; whereas the sojourn time of the system on certain state quantified how long the process variable evolution will follow the rule determined by function f_i(Algorithm 2).

In an overview, the structure of discrete event simulation could be broken down at system-state transition level and component state transition level. The discrete event simulation simulator is connected to process dynamics simulator at system-state transition level. Discrete event simulation starts from component state transition,

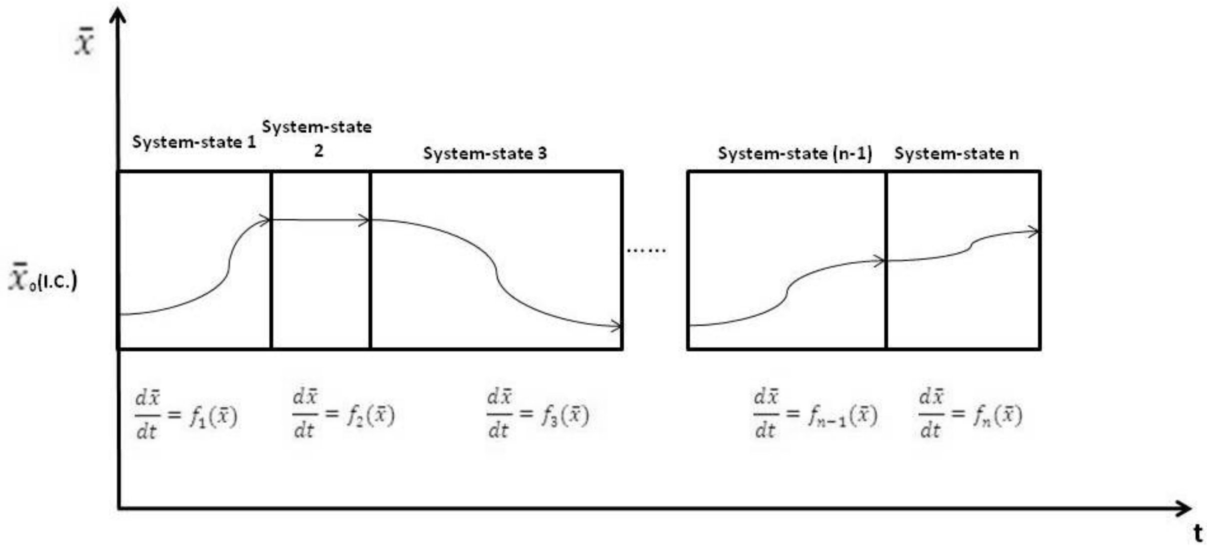

Fig. 7. The relationship between system-state trajectory and process variable evolution.

Algorithm 2: The pseudocode of DORA probabilistic computation.

$count_u = 0$;
$count_l = 0$;
for *each discrete event simulation run k* **do**
    the process variable initial conditions are $\bar{x}_0$
    for *each transition run i* **do**
        connect to algorithm1 to get the system-state identity;
        f_i is determined immediately according to this identity;
        solve f_i with initial condition of $x_{time(i-1,k)}$, and the integration upper limit of $time(i, k)$;
    end
    $u = find(\bar{x} > \bar{x}_u)$;
    $l = find(\bar{x} < \bar{x}_l)$;
    if $length(u) > 0$ **then**
        $count_u = count_u + 1$;
    end
    and;
    if $length(l) > 0$ **then**
        $count_l = count_l + 1$;
    end
end
the probability of process variable exceeding upper safety boundary $= count_u/K$;
the probability of process variable exceeding lower safety boundary $= count_l/K$;

---

and transfers the data to process dynamics simulator after finishing a system-state trajectory simulation. Reliability information, inspection interval, and repair rate are the information needed to initiate the discrete event simulation according to Algorithm 1. Information exchange occurs between the two simulators once a full system-state trajectory is determined in each loop.

c. Computation Reduction

In different system states, the parameters in equation 2.18 are different to characterize the evolution of process variables in phases. The system-state trajectory needs to be determined to specify those parameters in each state. The discrete event simulation on system-state trajectory demonstrates when and what component becomes abnormal, how long the state sojourn time is, and how long it will take to restore the system to normal operating conditions. However, it is not true that the process variable would go beyond the desirable region whenever an abnormal event occurs. To study operational risk, the Monte Carlo simulation needs to be performed on the process variable evolution upon every single system-state trajectory. Therefore, it ends up with the total number of continuous simulations on the entire process variable evolution needed as:

$$n = n_k \tag{2.19}$$

where:

n - total number of simulations on the whole process variable evolution needed

n_k - number of simulations needed on system-state trajectory

Even though the number of simulation runs is equal to the system-state trajectory simulation number, the numerical simulation on the whole evolution of process variable is still a great deal of work. Therefore, problem decomposition should be considered to save computational storage space. A reasonable argument is that the process variable evolution at steady state does not necessarily need to be simulated. The process variable should remain in the steady state region as long as all the components are under normal operation no matter in which system-state trajectory configuration. It saves computational storage space to have a pre-Monte Carlo simulation on the probability of process variables exceeding safety boundaries given that each individual component becomes into an abnormal state(Algorithm 3). The pre-Monte Carlo simulation calculates the probability of process variables exceeding safety boundary only when the components become abnormal. The probability of the system process variable exceeding the desirable operating region is determined using the probability of component abnormal event and the probability of the process variable exceeding the desirable operating region when the individual component goes into abnormal state:

$$P = \Sigma_{n=1}^{N} q_n p_n \tag{2.20}$$

where:

P - probability of a process variable exceeding safety boundary in the system

n - index of the component in the system

N - total number of the components in the system

q_n - probability of process variable exceeding the safety boundary when the component n goes into abnormal state

p_n - probability of component n goes into abnormal state

Algorithm 3: The pseudocode of pre-Monte Carlo simulation in DORA.

for *each simulation run* k **do**
    the process variable initial conditions are $\bar{x}_0$;
    for *each component* n **do**
        parameters for f_i is determined immediately according to component abnormal status;
        solve f_i with initial condition of x_0, and eliminate the integration until the integration time is long enough for any test/inspection interval to be applied.
    end
    Random generate a number r from an uniform distribution between $[0, 1]$;
    $cuttime = f^{-1}$ of equation 2.15 with r and an inspection interval T;
    $cuttime = ceil(cuttime)$; and $v\bar{a}r = \bar{x}(1 : cuttime)$;
    $above = find(v\bar{a}r > \bar{x}_u)$; and $below = find(v\bar{a}r < \bar{x}_l)$;
    if $length(above) == 0$ $(length(below) == 0)$ **then**
        $count_{above}(k, 1) = 0$ $(count_{below}(k, 1) = 0)$
    end
    else
        $count_{above}(k, 1) = 1$ $(count_{below}(k, 1) = 1)$
    end
end
the probability of process variable exceeding upper safety boundary $= length(find(count_{above} == 1))/K$;
the probability of process variable exceeding lower safety boundary $= length(find(count_{below} == 1))/K$;

q_n can be gained by pre-Monte Carlo simulations(Algorithm 3), whereas $p_n s$ can be obtained by the Monte Carlo simulation on system-state trajectory(Algorithm 1). The total number of simulations needed in this decomposed strategy is $n^{'}$:

$$n^{'} = N \times n_d + n_k \tag{2.21}$$

where

$n^{'}$ - total number of simulations needed

N - total number of the components in the system

n_d - number of simulations needed on process dynamics upon each component abnormal event

n_k - number of simulations needed on system-state trajectory

$n^{'}$ is a larger number than n, however, in the decomposed strategy, simulation on the process variable evolution given all the components operate in normal state is omitted. The process dynamics differential equations are not required to be solved at the whole time span but only when component goes into abnormal state.

6. Incident Consequence Modeling

The consequence analysis in DORA is nothing different from general consequence modeling except the uncertainty characterization. DORA incident consequence modeling includes toxic release models, source models, dispersion models, fires and explosions, etc. In many cases, parameters in those models are uncertain and usually need to be determined by expert judgment. In DORA, a probabilistic approach is proposed to characterize this epistemic uncertainty in the consequence modeling. Assuming $\bar{Z}$

in consequence modeling O is a vector of uncertain variables, algorithm 4 is designed for the uncertainty characterization in DORA consequence modeling.

7. Risk Determination

Risk is defined as:

$$risk = probability \times consequence \tag{2.22}$$

After DORA probabilistic analysis and incident consequence analysis, risk profiles should be generated considering both the aspects of probability and consequence of potential incidents in the system.

8. Is the Risk Acceptable?

A zero risk level is not attainable. After risk profiles are generated in DORA, an argument should be made not merely whether the risks are acceptable or not, but also how low a risk level can be achieved by feasible risk reduction if it is already in a tolerable region. These two questions need to be addressed in sequence. In this step, the question of "whether a risk is in totally unacceptable region or not" will be addressed. The decision is made according to health and safety guidelines, international standards and laws, and suggestion from advisory bodies, etc. If the risk level is higher than the minimum acceptance criteria, the assessed risk is in the totally unacceptable region. In this case, modifications on the process design, operation procedure or emergency strategy have to be made and the risk assessment will start over again from the very beginning at Step 1 through Step 7. This process will be eliminated until the risk level is below the totally unacceptable criteria.

Algorithm 4: The pseudocode of uncertainty characterization for consequence modeling in DORA.

Define $\bar{Z}_{min}$ and $\bar{Z}_{max}$;
for *each Monte Carlo simulation run i* **do**
  Random generate a number η from uniform distribution between $(0, 1)$;
  $\bar{Z}' = \eta \times (\bar{Z}_{max} - \bar{Z}_{min}) + \bar{Z}_{min}$;
  solve modeling U using $\bar{Z}'$ and results are saved in $\bar{re}(1, i)$;
end
$\bar{u1} = min(\bar{re})$;
$\bar{u2} = max(\bar{re})$;
Define a bin number $nbin$ to calculate u-population;
% width of bins
$\bar{du} = (\bar{u2} - \bar{u1})/nbin$;
% values at center of bins
$\bar{uc} = \bar{u1} + \bar{du}/2 : \bar{du} : \bar{u2} - \bar{du}/2$;
% calculates populations in bins
$\bar{upop} = zeros(1, nbin)$;
for $i = 1 : length(re)$ **do**
  % falls in to the idx'th bin
  $idx = ceil((\bar{re}(i) - \bar{u1})/\bar{du})$;
  if $idx == 0$ **then**
    $idx = 1$;
  end
  $\bar{upop}(idx) = \bar{upop}(idx) + 1$;
end
% renormalizes so that sum(upop) = 1
$\bar{upop} = \frac{\bar{upop} * 100}{totalnumberofsimulationrun}$;
plot $\bar{upop}$ vs. $\bar{re}$.

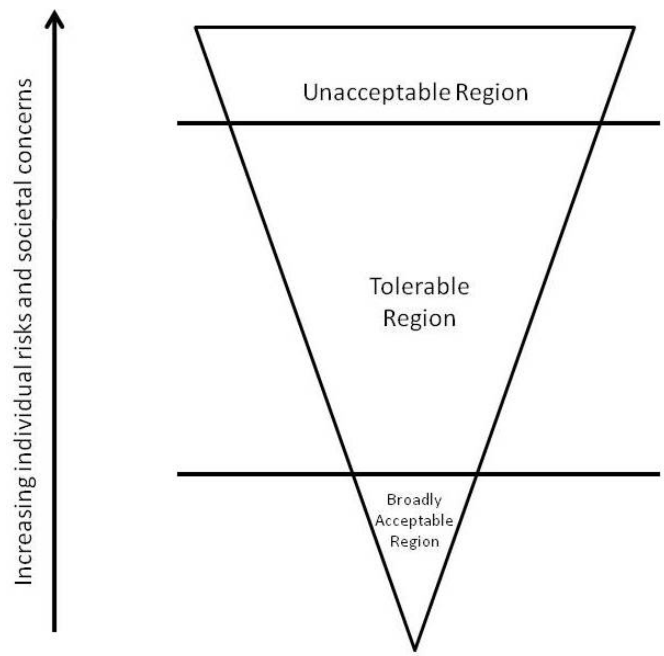

Fig. 8. ALARP(As Low As Reasonably Practicable).

9. Cost-Benefit Analysis

Determining that a risk has been reduced to ALARP (As Low As Reasonably Practicable)(Figure 8)(HSE) involves a cost-benefit analysis. When the risk remains in the tolerable region, the question of "how low a risk level can be achieved by feasible risk reduction efforts" needs to be addressed. Usually, the region of 'risk is totally unacceptable' is much smaller than 'risk is tolerable' region. In most cases, risk is not only expected to be in the tolerable region but expected to be reduced to ALARP. This practice must work within the real world constraints of feasibility, practicality and cost. DORA will provide efficient cost-benefit analysis to decision makers. An optimization on component inspection interval in an oil/gas separation system will be illustrated in Chapter VI.

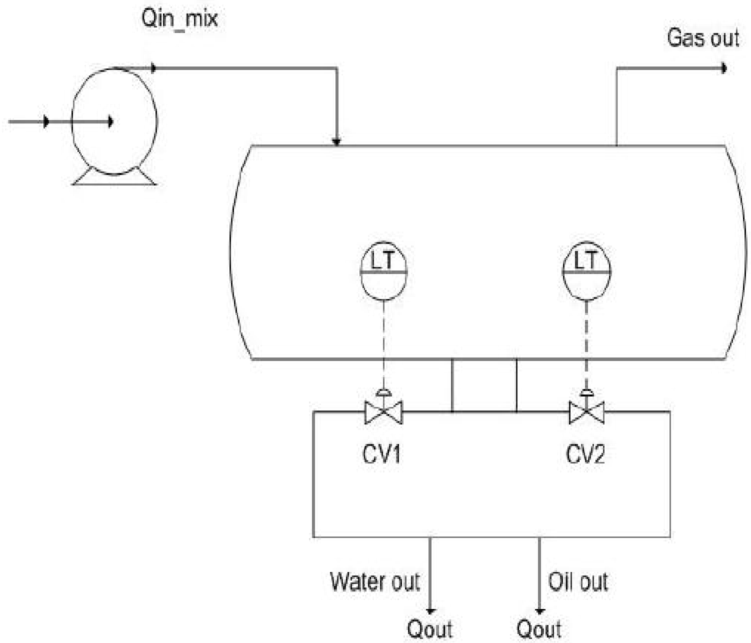

Fig. 9. A simplified PFD of an oil/gas and water separator.

10. Build and/or Operate the System

With the completion of the previous steps, the system is ready to be built or operated.

D. Case Study I - Level Control in an Oil/Gas Separator

1. Process Description

In offshore plants, gravity separators are used to separate oil, gas and water for exportation. A simplified PFD of this separation is shown in Figure 9.

Consider the material balance of liquids in separators, and assume a linear relationship between the height H and the volume, then:

$$\frac{dH(t)}{dt} = \frac{Q_{in}(t) - Q_{out}(t)}{A} \tag{2.23}$$

where $Q_{in}(t)$ is the inlet volumetric flow rate, and $Q_{out}(t)$ is the outlet volumetric flow rate. For simplicity, the outlet water flow and the outlet oil flow are assumed to be equal. The openness dynamic of the control valve is considered fast. A factor μ is related to the valve openness. Then, the outlet flow rate is given by:

$$Q_{out} = 2\mu\sqrt{H} \tag{2.24}$$

PI controller is one of the most used controllers for level and flow control in industry. Given that PI controller is applied in this case study, μ is governed by:

$$\mu = \mu_0 + K_c[e(t) + \frac{1}{\tau_I \int_0^t e(t^*)dt^*}] \tag{2.25}$$

where $e(t) = H_{set} - H(t)$. The inlet flow rate is given by:

$$Q_{in} = \varepsilon Q_{in\_nor} \tag{2.26}$$

where Q_{in_nor} is the inlet flow rate in normal operation state. ε is a factor between $(0, 1)$ to quantify the inlet flow abnormal situation. When the pump normally operates, $\varepsilon = 1$. Substituting equation 2.24, equation 2.25, and equation 2.26 into equation 2.23, we can obtain the following equation after linearization:

$$A\frac{dH}{dt} = \varepsilon Q_{in_nor} + \frac{\mu_0\sqrt{H_0}}{2} - \frac{\mu_0}{2\sqrt{H_0}}H - \sqrt{H_0}\mu \tag{2.27}$$

with initial values $\mu(0) = \mu_0$ and $H(0) = H_0$. Therefore, the process transfer function is given by:

$$G(s) = \frac{H(s)}{\mu(s)} = \frac{-\sqrt{H_0}}{As + \frac{\mu_0}{2\sqrt{H_0}}} \tag{2.28}$$

Table I. Process parameters of the separator system.

Process parameters	
Q_{in_nor}	$310m^3/h$
H	$1.5m$
A	$1.766m^2$
H_{set}	$0.7m$
Q_{out_nor}	$155m^3/h$

PI controller model A is selected according to IMC method[58], which is:

$$G(s) = \frac{K}{\tau s + 1} \tag{2.29}$$

$$K_c K = \frac{\tau}{\tau_c} \tag{2.30}$$

$$\tau_I = \tau \tag{2.31}$$

In our case:

$$\tau_c = 1 \tag{2.32}$$

$$K = -\frac{2H_0}{\mu_0} \tag{2.33}$$

$$\tau = \frac{2A\sqrt{H_0}}{\mu_0} \tag{2.34}$$

All the process parameters and control parameters are summarized in Table I. The following DORA probabilistic modeling is specific for the hazard, scenario and failure mode of f*ire hazard → overflow/dryout scenario → failure mode combination: pump - low output; CV - random valve opening; LT - random level reading error.*

2. Component Sojourn Time Distribution Characterization

The system-state trajectory simulation inputs are the component state sojourn time distribution parameters. To formulate the sojourn time distribution of component State 1, the failure rates for the components in this study are collected from the OREDA database[59]. *Low output* is selected as the failure mode for the pump; *spurious operation* is selected as the failure mode for the CV; *abnormal instrument reading* is selected as the failure mode for the LT. The reliability data are specific to those failure modes respectively. All of the three failure modes are not necessarily leading to a system shutdown, but may cause an operational failure. The parameters in the process equations and control equations vary as the component state transits(Table II).

With exponential distribution assumption discussed before, the probability density functions of the sojourn time of component State 1 are summarized as the following equations:

for pump:

$$f_A(x;\lambda_A) = 2.5 \times 10^{-6} e^{-2.5\times 10^{-6} x} \tag{2.35}$$

for CV:

$$f_B(x;\lambda_B) = 6.1 \times 10^{-7} e^{-6.1\times 10^{-7} x} \tag{2.36}$$

for LT:

$$f_C(x;\lambda_C) = 2.4 \times 10^{-7} e^{-2.4\times 10^{-7} x} \tag{2.37}$$

where λ_A, λ_B, and λ_C are the failure rates of pump, CV and LT in the failure mode of

Table II. Control parameters upon component performance in the separator.

Component index	Component	Component state	Parameter setting
		1, normal operation	$\varepsilon = 1$
A	pump	2, abnormal as low output	$\varepsilon = random$
		3, under repair	$\varepsilon = 0$
		1, normal operation	$\mu = 185.26$ with valve opening 60%
B	CV	2, abnormal as random valve opening	$\mu = 308.77 * random$
		3, under repair	$\mu = 0$
		1, normal operation	$e = H_{set} - H$
C	LT	2, abnormal as random level reading error	$e = H_{set} - rand * H$
		3, under repair	$Q_{out} = 0$

abnormal as low output, *abnormal as random valve opening*, and *abnormal as random level reading error* respectively.

The sojourn time distribution functions of component State 2 are summarized as follows according to equation 2.15, with the assumption of constant inspection interval T_A, T_B, and T_C for pump, CV and LT respectively:

$$P_A(y;\lambda_A) = \frac{e^{-2.5\times10^{-6}(T_A-y)} - e^{-2.5\times10^{-6}T_A}}{1-e^{-2.5\times10^{-6}T_A}} \tag{2.38}$$

$$P_B(y;\lambda_B) = \frac{e^{-6.1\times10^{-7}(T_B-y)} - e^{-6.1\times10^{-7}T_B}}{1-e^{-6.1\times10^{-7}T_B}} \tag{2.39}$$

$$P_C(y;\lambda_C) = \frac{e^{-2.4\times10^{-7}(T_C-y)} - e^{-2.4\times10^{-7}T_C}}{1-e^{-2.4\times10^{-7}T_C}} \tag{2.40}$$

The sojourn time distributions of component State 3 are obtained by distribution fitting. The repair labor hour data of each component is collected from industry. The repair time for the pump and CV fits to Weibull distribution, and the repair time for LT fits to exponential distribution:

$$f_A(z;\lambda_A^{'},k_A) = \frac{0.73}{8.13}(\frac{z}{8.13})^{-0.27}e^{-(\frac{z}{8.13})^{0.73}} \tag{2.41}$$

$$f_B(z;\lambda_B^{'},k_B) = \frac{1.25}{5.83}(\frac{z}{5.83})^{0.25}e^{-(\frac{z}{5.83})^{1.25}} \tag{2.42}$$

$$f_C(z;\lambda_C^{'}) = \frac{1}{2.92}e^{-\frac{1}{2.92}z} \tag{2.43}$$

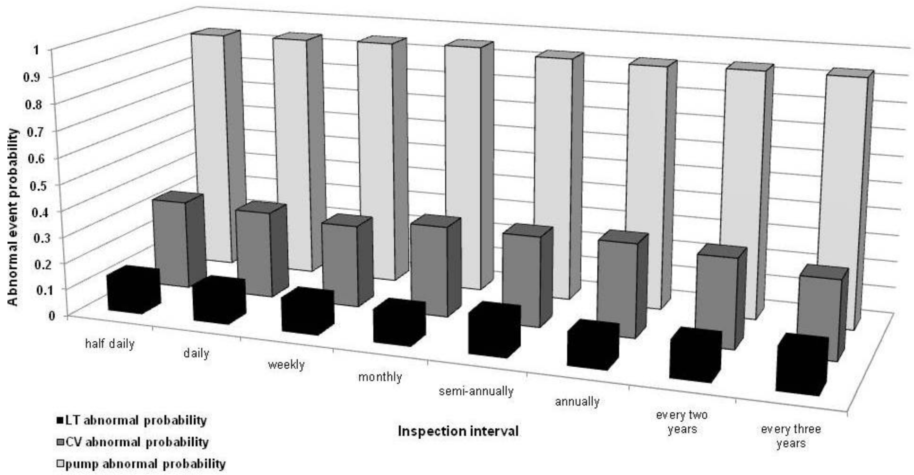

Fig. 10. Pump, CV, and LT abnormal event probabilities using different inspection intervals: half daily, daily, weekly, monthly, semi-annually, annually, every two years, and every three years.

3. System-state Trajectory Simulation

Given the assumption that the plant has a 30-year lifetime, Monte Carlo simulations on the system-trajectory are performed to study the probabilities of pump abnormal event, CV abnormal event and LT abnormal event. Since the inspection interval is considered as an important parameter in this study, different inspection intervals for pump, CV and LT are tested to research their impact on component abnormal event probability. Half day, daily, weekly, monthly, semi-annually, annually, two years, and three years are tested in the simulations. When the inspection interval of one component is varied, the inspection intervals for all other components are fixed at $12h$. The abnormal event probabilities of each component given eight different inspection intervals are shown in Figure 10. It is found that the inspection interval has no impact on component abnormal event probability. This is because the sequence of component behavior is defined as: *normal operation* $\rightarrow$ *failure or abnormal event occurs without being detected* $\rightarrow$ *failure or abnormal event is detected* $\rightarrow$ *repair and* *restore the component to normal operation.* Abnormal event always occurs before being detected through inspection. However, the inspection interval has impact on overflow/dryout probability as it determines how fast the system can be restored to normal operating conditions. An optimal inspection interval will find the component abnormal situation and corrective action will always be taken to restore the system before the process parameters exceed the desirable regions. In this study, mean value of component abnormal event probabilities with eight different inspection intervals will be used in the future calculation:

$$\begin{aligned} p_{pump} &= 0.93 \\ p_{CV} &= 0.33 \\ p_{LT} &= 0.14 \end{aligned} \tag{2.44}$$

The frequencies of pump abnormal event, CV abnormal event and LT abnormal event are also simulated in a prolonged time period and the results are summarized in Figure 11. The mean values of component abnormal event frequencies turn out to be the same as the frequency data we collected in the OREDA database and used as input. The results of the frequencies simulation confirm the conclusion that the inspection interval in this study has no impact on the frequency of component abnormal event. In addition, it validates the algorithm for system-state trajectory. It cannot be emphasized more that inspection interval does affect the frequency of component fatal failure, but not abnormal event as inspection detects abnormal situation and corrective action must be taken before the fatal failure actually occurs.

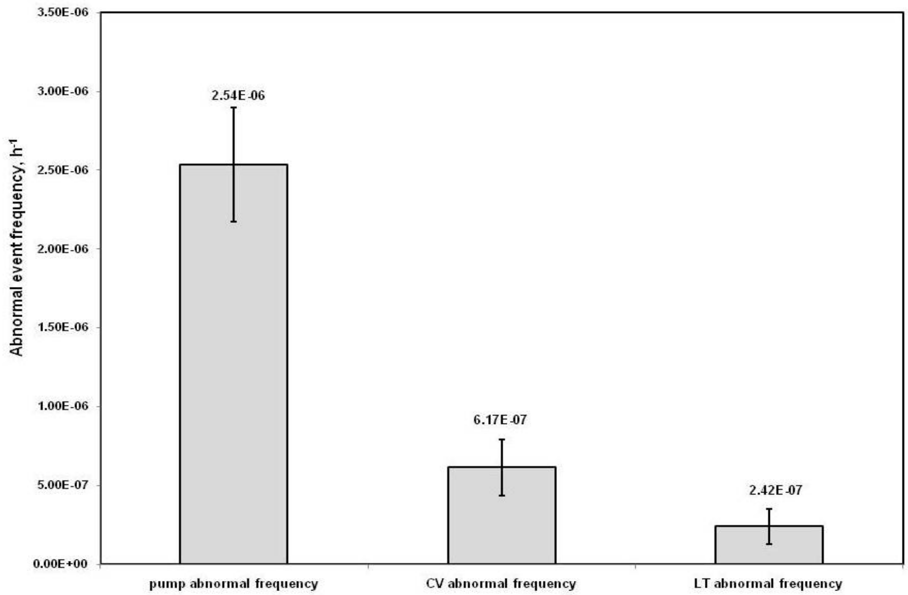

Fig. 11. Mean values and standard deviations of Pump, CV, and LT abnormal event frequencies using different inspection intervals: half daily, daily, weekly, monthly, semi-annually, annually, every two years, and every three years.

4. Probability of Incident Due to Individual Component Precursor

In this case study, the safe boundaries are defined as:

$$
\begin{aligned}
H_u &= 1.5m \\
H_l &= 0.1m
\end{aligned}
\tag{2.45}
$$

Therefore, Monte Carlo simulation based on Algorithm 3 is performed to study the probability of separator overflow ($H > 1.5m$) and dryout ($H < 0.1m$) when each of the components, pump, CV, and LT, individually goes from normal operation to abnormal situation until the abnormal situation is detected. The simulation time span is sufficiently long to study the impact of testing/inspection interval on the probabilistic simulation results. Different inspection intervals, 12 hours, one day, one week, one month, semi-annual, annual, two years, and three years, are tested in the

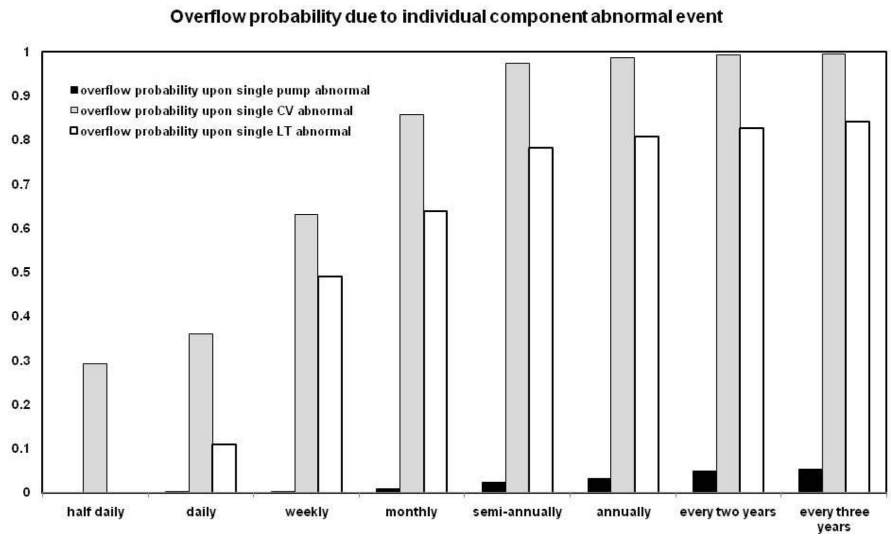

Fig. 12. Overflow probability due to individual pump abnormal event, CV abnormal event and LT abnormal event respectively using different inspection intervals: half daily, daily, weekly, monthly, semi-annually, annually every two years and every three years.

study. As the inspection interval increases, the probability of overflow and dryout due to pump abnormal event, CV abnormal event, and LT abnormal event increases except probability of dryout due to CV abnormal event(Figures 12 and 13).

The probability of separator dryout due to CV abnormal event is zero no matter what inspection interval among the tested eight applies. The overflow probability due to CV abnormal is 17.4 $\sim$ 359 times greater than that due to pump abnormal event; the overflow probability due to LT abnormal event is 14.6 $\sim$ 244.5 times greater than that due to pump abnormal event; and the dryout probability due to LT abnormal event is 5.1 $\sim$ 29.7 times greater than that due to pump abnormal event. Therefore, the CV abnormal event is the most critical reason for overflow scenario, whereas the LT abnormal event is the most critical reason for dryout scenario.

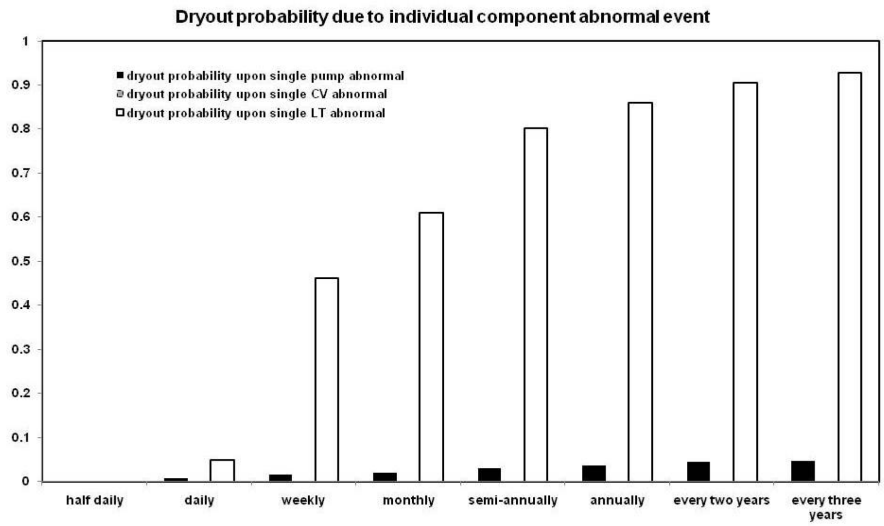

Fig. 13. Dryout probability due to individual pump abnormal event, CV abnormal event and LT abnormal event respectively using different inspection intervals: half daily, daily, weekly, monthly, semi-annually, annually every two years and every three years.

5. Separator Overflow/Dryout Probability

The probability data of separator overflow and dryout upon pump, CV, and LT abnormal event individually by the pre-Monte Carlo simulation are summarized in Table III and Table IV. They will be used to calculate probability of separator overflow/dryout in the plant lifetime and frequency of separator overflow/dryout. Results are plotted in Figures 14, 15, 16, and 17. Each point in the figures carries the information on annual total inspection cost, separator overflow/dryout probability or frequency, and the corresponding component inspection intervals. Inspection interval less than one day for LT keeps the dryout frequency at least around 10 times lower than that when the interval is more than one day. The probability of dryout will be kept less than 0.1 if LT inspection interval is less than one month. However, the objective of this step in DORA is to provide industry a tool to assess dynamic operational risk. Further inspection interval optimization study is needed and will

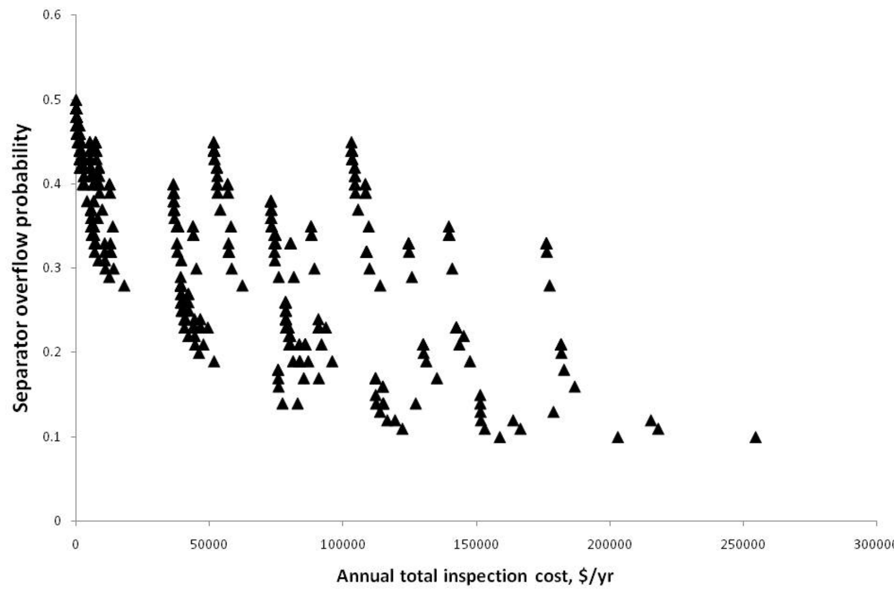

Fig. 14. Separator overflow probability vs. annual total component inspection cost.

be demonstrated in Chapter V in this dissertation. The decision on the component testing/inspection interval is left to decision makers according to the cost-benefit analysis.

6. Sensitivity Analysis on Model Inputs

For DORA probabilistic modeling, component state sojourn time distributions are the inputs for system-state trajectory simulation. Among the three component states, *normal operating*, *abnormal event undetected*, and *abnormal event detected and under repair*, the third state sojourn time distribution is obtained by fitting distribution to industry component repair time data. In the case that the collected data is sufficient enough, distribution fitting is statistically satisfied with accepted uncertainty. However, it is not always possible to find enough data. In a highly reliable system, a single failure may occur at a frequency in order of 10^{-6} and repair

Table III. Probability of separator overflow due to individual abnormal event of pump, CV, or LT using different testing/inspection intervals: half daily, daily, weekly, monthly, semi-annually, annually, every two years, and every three years.

Overflow probability	Half daily	Daily	Weekly	Monthly	Semi-annually	Annually	Every two years	Every three years
pump	0	0.001	0.002	0.01	0.025	0.033	0.049	0.054
CV	0.292	0.36	0.631	0.859	0.975	0.987	0.994	0.996
LT	0	0.11	0.491	0.639	0.783	0.809	0.828	0.842

Table IV. Probability of separator dryout due to individual abnormal event of pump, CV, or LT using different testing/inspection intervals: half daily, daily, weekly, monthly, semi-annually, annually, every two years, and every three years.

Dryout probability	Half daily	Daily	Weekly	Monthly	Semi-annually	Annually	Every two years	Every three years
pump	0.001	0.008	0.015	0.02	0.03	0.037	0.045	0.046
CV	0	0	0	0	0	0	0	0
LT	0	0.049	0.461	0.611	0.802	0.859	0.905	0.928

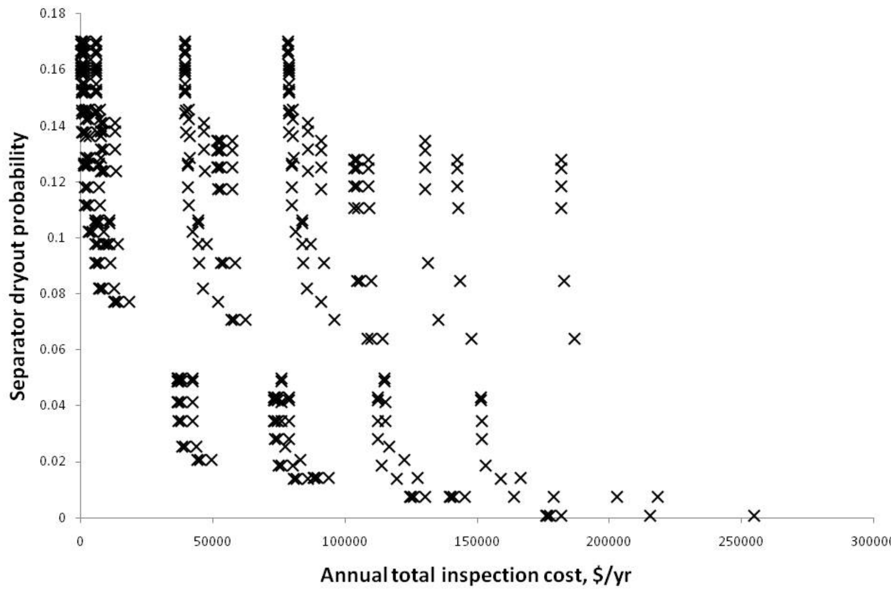

Fig. 15. Separator dryout probability vs. annual total component inspection cost.

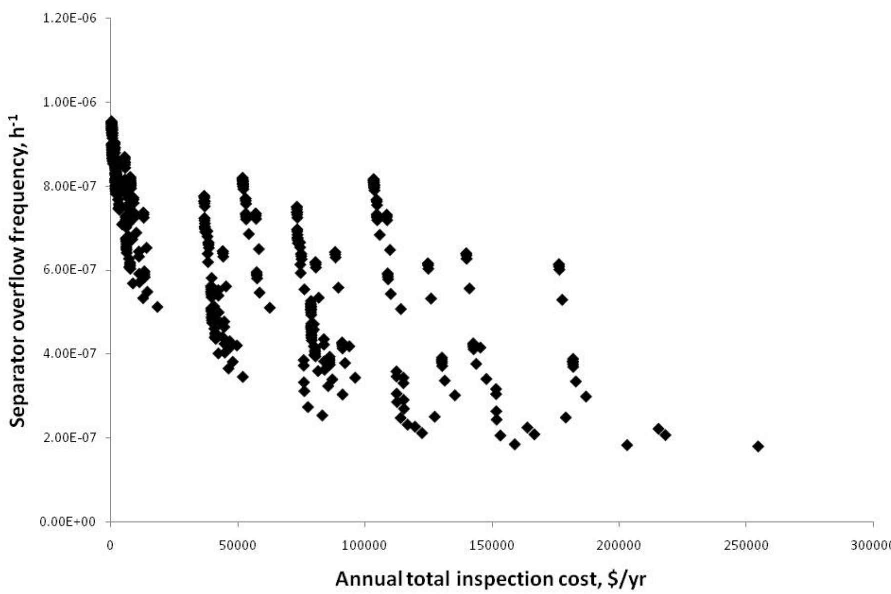

Fig. 16. Separator overflow frequency vs. annual total component inspection cost.

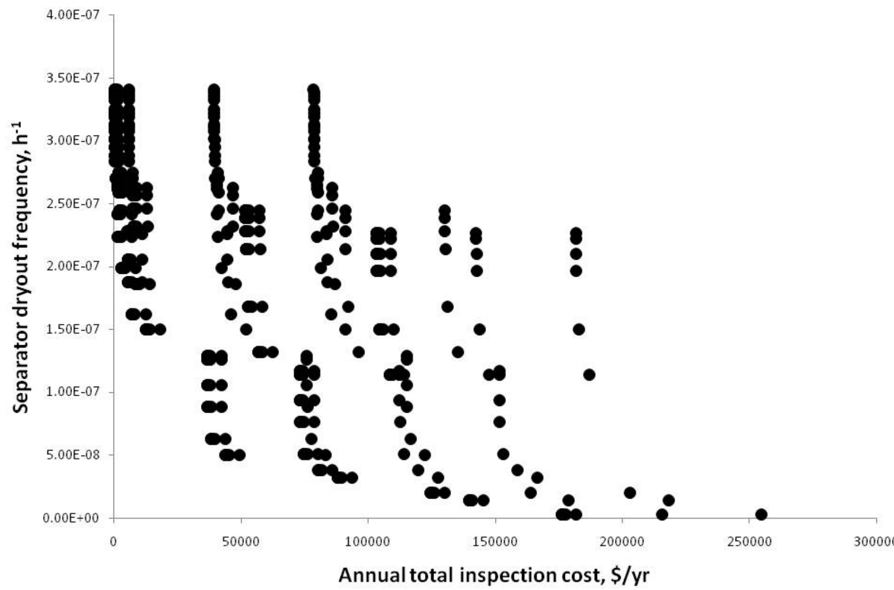

Fig. 17. Separator dryout frequency vs. annual total component inspection cost.

happens at a corresponding low frequency so that the repair data is usually not enough for a good distribution fitting. Given the limited repair time data points, the major concern on this probabilistic modeling uncertainty includes:

- what distribution type should be selected for component repair time distribution fitting;
- whether the distribution type is a sensitive factor for DORA probabilistic modeling results.

When a failure occurs to a component, the component must be repaired and it is then unavailable for processing during a certain amount of time called the repair time[60]. In reliability engineering, random variables from exponential distribution, gamma distribution, log-normal distribution or Weibull distribution are usually assumed to characterize the time-to-repair distribution in most of the models. By selecting candidates from those distribution families, epistemic uncertainty is reduced by engineering expert judgment. The uncertainty is further reduced by selecting the distribution model according to the rank of goodness-of-fit. The objective of this subsection is to propose and apply statistical techniques to characterize the uncertainty and sensitivity on the distribution model selection and the associated parameters determination, in order to study how the DORA probabilistic modeling output can be apportioned by the distribution model selection.

There are several techniques to examine how well a sample of data agrees with a given distribution as its population. In those goodness-of-fit techniques, hypothesis test is based on measuring the discrepancy or consistency of the sample data to the hypothesized distribution. Chi-square test is used to measure how well the fit matches the data if the data are represented by discrete points with Gaussian uncertainties[61]. However, the value of the chi-square test statistic depends on how the data is binned. Another disadvantage of chi-square is that it requires an adequate sample size for the approximations to be valid. Pearson's chi-square test is distinguished from the case with Gaussian errors, and is applied if the data are represented by integer numbers of events in discrete bins, following Poisson statistics rule[62]. Kolmogorov-Smirnov (K-S) test is a goodness-of-fit measurement technique for one-dimensional data samples. It is used to test whether the data sample comes from a population with a specific distribution[63]. Anderson-Darling test[64] is a modification of K-S test and gives more weight to the tails than does the K-S test. There are several others, such as the Shapiro-Wilk test[65] and the probability plot[66] for goodness-of-fit measurement. Chi-square test, Kolmogorove-Smirnov test, and Anderson- Darling test are proposed in this subsection to measure the goodness-of-fit to rank the distribution models for characterizing the component repair time distribution.

a. The Chi-square Test

The null hypothesis in a chi-square test is:

H_0: The data follow a specified distribution.

H_a: The data do not follow the specified distribution.

The data are divided into k bins and the test statistic is defined as:

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{2.46}$$

where O_i is the observed frequency for bin i and E_i is the expected frequency for bin i, which is given by:

$$E_i = F(Y_u) - F(Y_l) \tag{2.47}$$

where F is the cumulative distribution function (CDF) for the distribution being tested, Y_u is the upper limit for class i, and Y_l is the lower limit for class i. The test statistic approximately follows a chi-square distribution with $(k - c - 1)$ degrees of freedom where k is the number of non-empty cells and c is the number of estimated parameters for the distribution. Therefore, the hypothesis that the data are from a population with the specified distribution is rejected if

$$\chi^2 > \chi^2_{(1-\alpha,k-1)} \tag{2.48}$$

where $\chi^2_{(1-\alpha,k-1)}$ is the chi-square inverse CDF with $(k-1)$ degrees of freedom and a significance level of α. Though the number of degrees of freedom is $(k - c - 1)$, it is calculated as $(k - 1)$ since this kind of test is least likely to reject the fit in error.

b. The Kolmogorov-Smirnov Test

The null hypothesis in a Kolmogorov-Smirnov test is:

H_0: The data follow a specified distribution.

H_a: The data do not follow the specified distribution.

The K-S test statistic is defined as:

$$D = max_{1 \leq i \leq N}(F(Y_i) - \frac{(i-1)}{N}, \frac{i}{N} - F(Y_i)) \tag{2.49}$$

where i is the index of the total N ordered data points Y_1,Y_2,...,Y_N. F is the cumulative distribution function of the distribution being tested which must be a continuous distribution. The hypothesis is rejected at significance level α if the test statistic, D, is greater than the critical value obtained from a table. There are variations of these tables in different literatures that use different scaling for the K-S test statistic and critical regions. The software programs that perform a K-S test provide the relevant critical values.

c. The Anderson-Darling Test

The null hypothesis in an Anderson-Darling test is:

H_0: The data follow a specified distribution.

H_a: The data do not follow the specified distribution.

The Anderson-Darling test statistic is defined as:

$$A^2 = -N - S \tag{2.50}$$

where

$$S = \sum_{i=1}^{N} \frac{(2i-1)}{N}[\ln F(Y_i) + \ln(1 - F(Y_{N+1-i}))] \tag{2.51}$$

F is the cumulative distribution function of the specified distribution and Y_i are the ordered data points. The critical values for the Anderson-Darling test depend on the specific distribution that is being tested. The hypothesis that the data follow a specified distribution is rejected if the test statistic, A, is greater than the critical value. The software programs that were used to perform an Anderson-Darling test provide the relevant critical values.

d. Graphical Goodness-of-fit Measurement

To illustrate the goodness-of-fit measurement graphically, probability-probability (P-P) plot, quantile-quantile (Q-Q) plot and probability difference graph are created. The P-P plot is a graph of the empirical CDF values plotted against the theoretical CDF values. The Q-Q plot is a graph of the input data points plotted against the theoretical distribution quantiles. The reference diagonal line in the Q-Q plot is the line along which the graph points should fall. Both P-P plot and Q-Q plot will be approximately linear if the specified theoretical distribution is the correct model to represent the input data. The probability difference graph is a plot of the difference between the empirical CDF and the theoretical CDF.

Four widely used distribution types in reliability engineering modeling: exponential, gamma, lognormal, and Weibull are used to fit the collected repair time data. Each type has two distributions with different number of parameters. They are exponential with single parameter (exponential), exponential with two parameters (exponential (2P)), gamma with two parameters (gamma), gamma with three parameters (gamma (3P)), lognormal with two parameters (lognormal), lognormal with three parameters (lognormal (3P), Weibull with two parameters (Weibull), and Weibull with three parameters (Weibull (3P)). The fitting distribution parameters are summarized in Table V.

Table V. Distribution parameters of the eight distributions fitted to the pump, CV and LT repair time data.

Distribution	Pump - Parameters	CV - Parameters	LT - Parameters
Exponential	$\lambda = 0.11744$	$\lambda = 0.16901$	$\lambda = 0.32258$
Exponential (2P)	$\lambda = 0.13307$, $\gamma = 1.0$	$\lambda = 0.29268$, $\gamma = 2.5$	$\lambda = 0.90909$, $\gamma = 2.0$
Gamma	$\alpha = 0.23273$, $\beta = 36.586$	$\alpha = 0.98773$, $\beta = 5.9901$	$\alpha = 7.3923$, $\beta = 0.41935$
Gamma (3P)	$\alpha = 0.33912$, $\beta = 24.11$, $\gamma = 1.0$	$\alpha = 0.51275$, $\beta = 6.7362$, $\gamma = 2.5$	$\alpha = 0.46567$, $\beta = 1.754$, $\gamma = 2.0$
Lognormal	$\sigma = 0.99585$, $\mu = 1.4947$	$\sigma = 0.64201$, $\mu = 1.5107$	$\sigma = 0.30246$, $\mu = 1.0832$
Lognormal (3P)	$\sigma = 1.3804$, $\mu = 1.0937$, $\gamma = 0.82505$	$\sigma = 6.7709$, $\mu = -0.46155$, $\gamma = 2.5$	$\sigma = 0.78934$, $\mu = 0.04695$, $\gamma = 1.7088$
Weibull	$\alpha = 1.1698$, $\beta = 7.0744$	$\alpha = 3.7703$, $\beta = 3.8824$	$\alpha = 4.2115$, $\beta = 2.8792$
Weibull (3P)	$\alpha = 0.54255$, $\beta = 5.7422$, $\gamma = 1.0$	$\alpha = 0.61366$, $\beta = 2.5638$, $\gamma = 2.5$	$\alpha = 0.88087$, $\beta = 1.1366$, $\gamma = 2.0$

The goodness-of-fit measurement results in chi-square test are summarized in Table VI. K-S test results are shown in Tables VII, VIII, and IX. A-D test results can be found in Table X, XI, and XII. P-P plots of pump, CV, and LT repair time fitting to lognormal distribution are shown in Figures 18, 19, and 20 respectively. Q-Q plots of pump, CV, and LT repair time fitting to lognormal distribution are shown in Figures 21, 22, and 23 respectively. Probability different graphs of pump, CV, and LT repair time fitting to lognormal distribution are shown in Figures 24, 25, and 26 respectively.

The Chi-square test and K-S test results for pump repair time fitting show that all the distribution fitting hypotheses are rejected. In A-D test, lognormal and lognormal (3P) fitting for pump repair time are not rejected at low α values. In K-S test, result for CV repair time fitting shows that all the distribution fitting hypotheses are accepted but the fittings in A-D test reject the hypotheses on exponential (2P), gamma (3P), lognormal (3P), and Weibull (3P). All the LT repair time distribution fitting hypotheses are accepted in K-S test, but the fittings to exponential (2P), gamma (3P), and Weibull (3P) are rejected. Therefore, the distribution fitting selection and ranking results are: ”lognormal (3P), lognormal” for pump repair time distribution fitting, ”lognormal, exponential, gamma, Weibull” for CV repair time distribution fitting and ”lognormal (3P), lognormal, gamma, exponential, Weibull” for LT repair time distribution fitting. Those selected distributions with associated parameters will be used in the following sensitivity analysis.

The sensitivity of the component repair time distribution type is measured in this case study on the level control system of an oil/gas separator. Overflow is defined as the scenario when the level in the separator is greater than $1.5m$. Dryout is defined as the scenario when the level in the separator is less than $0.1m$. The probability of overflow and dryout will be the output of the DORA probabilistic modeling(Figure27).

Table VI. The Chi-square test results of measuring goodness of pump repair time distribution fitting.

<table>
<tr><th>Pump Chi-Square</th><th>Exponential</th><th>Gamma</th><th>Lognormal</th><th>Weibull</th></tr>
<tr><td>Deg. of freedom</td><td>7</td><td>7</td><td>7</td><td>7</td></tr>
<tr><td>Statistic</td><td>22.49</td><td>244.66</td><td>34.69</td><td>31.27</td></tr>
<tr><td>P-Value</td><td>2.09E-03</td><td>0.00E+00</td><td>1.28E-05</td><td>5.56E-05</td></tr>
<tr><td>Rank</td><td>1</td><td>6</td><td>4</td><td>3</td></tr>
<tr><td>α</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td></tr>
<tr><td>Critical Value</td><td>9.80|12.02|14.07|16.62|18.48</td><td>9.80|12.02|14.07|16.62|18.48</td><td>9.80|12.02|14.07|16.62|18.48</td><td>9.80|12.02|14.07|16.62|18.48</td></tr>
<tr><td>Reject?</td><td>$Yes|Yes|Yes|Yes|Yes$</td><td>$Yes|Yes|Yes|Yes|Yes$</td><td>$Yes|Yes|Yes|Yes|Yes$</td><td>$Yes|Yes|Yes|Yes|Yes$</td></tr>
<tr><th>Pump Chi-Square</th><th>Exponential(2P)</th><th>Gamma(3P)</th><th>Lognormal(3P)</th><th>Weibull(3P)</th></tr>
<tr><td>Deg. of freedom</td><td>7</td><td>–</td><td>6</td><td>–</td></tr>
<tr><td>Statistic</td><td>76.444</td><td>–</td><td>30.49</td><td>–</td></tr>
<tr><td>P-Value</td><td>7.29E-14</td><td>–</td><td>3.17E-05</td><td>–</td></tr>
<tr><td>Rank</td><td>5</td><td>–</td><td>2</td><td>–</td></tr>
<tr><td>α</td><td>0.20|0.10|0.05|0.02|0.01</td><td>– – – – –</td><td>0.20|0.10|0.05|0.02|0.01</td><td>– – – – –</td></tr>
<tr><td>Critical Value</td><td>9.80|12.02|14.07|16.62|18.48</td><td>– – – – –</td><td>8.56|10.65|12.59|15.03|16.81</td><td>– – – – –</td></tr>
<tr><td>Reject?</td><td>$Yes|Yes|Yes|Yes|Yes$</td><td>– – – – –</td><td>$Yes|Yes|Yes|Yes|Yes$</td><td>– – – – –</td></tr>
</table>

Table VII. The Kolmogorov-Smirnov test results of measuring goodness of pump repair time distribution fitting.

<table>
<tr><th>Pump K-S</th><th>Exponential</th><th>Gamma</th><th>Lognormal</th><th>Weibull</th></tr>
<tr><td>Sample size</td><td>169</td><td>169</td><td>169</td><td>169</td></tr>
<tr><td>Statistic</td><td>0.1932</td><td>0.4730</td><td>0.1339</td><td>0.1724</td></tr>
<tr><td>P-Value</td><td>5.36E − 06</td><td>0.00E + 00</td><td>4.21E − 03</td><td>7.33E − 05</td></tr>
<tr><td>Rank</td><td>4</td><td>8</td><td>1</td><td>3</td></tr>
<tr><td>α</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td></tr>
<tr><td>Critical Value</td><td>0.08|0.09|0.10|0.12|0.13</td><td>0.08|0.09|0.10|0.12|0.13</td><td>0.08|0.09|0.10|0.12|0.13</td><td>0.08|0.09|0.10|0.12|0.13</td></tr>
<tr><td>Reject?</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|Yes|Yes</td></tr>
<tr><th>Pump K-S</th><th>Exponential(2P)</th><th>Gamma(3P)</th><th>Lognormal(3P)</th><th>Weibull(3P)</th></tr>
<tr><td>Sample size</td><td>169</td><td>169</td><td>169</td><td>169</td></tr>
<tr><td>Statistic</td><td>0.2456</td><td>0.2822</td><td>0.155</td><td>0.2265</td></tr>
<tr><td>P-Value</td><td>1.97E − 9</td><td>2.58E − 12</td><td>5.18E − 4</td><td>4.39E − 8</td></tr>
<tr><td>Rank</td><td>6</td><td>7</td><td>2</td><td>5</td></tr>
<tr><td>α</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td></tr>
<tr><td>Critical Value</td><td>0.08|0.09|0.10|0.12|0.13</td><td>0.08|0.09|0.10|0.12|0.13</td><td>0.08|0.09|0.10|0.12|0.13</td><td>0.08|0.09|0.10|0.12|0.13</td></tr>
<tr><td>Reject?</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|Yes|Yes</td></tr>
</table>

Table VIII. The Kolmogorov-Smirnov test results of measuring goodness of CV repair time distribution fitting.

CV K-S	Exponential	Gamma	Lognormal	Weibull
Sample size	6	6	6	6
Statistic	0.3446	0.3471	0.4102	0.3401
P-Value	3.85E-01	3.76E-01	2.00E-01	4.00E-01
Rank	4	5	7	3
α	0.20|0.10|0.05|0.02|0.01	0.20|0.10|0.05|0.02|0.01	0.20|0.10|0.05|0.02|0.01	0.20|0.10|0.05|0.02|0.01
Critical Value	0.41|0.47|0.52|0.58|0.62	0.41|0.47|0.52|0.58|0.62	0.41|0.47|0.52|0.58|0.62	0.41|0.47|0.52|0.58|0.62
Reject?	*No|No|No|No|No*	*No|No|No|No|No*	*No|No|No|No|No*	*No|No|No|No|No*
CV K-S	Exponential(2P)	Gamma(3P)	Lognormal(3P)	Weibull(3P)
Sample size	6	6	6	6
Statistic	0.478	0.3482	0.3197	0.3202
P-Value	8.79E-02	3.73E-01	4.74E-01	4.72E-01
Rank	8	6	1	2
α	0.20|0.10|0.05|0.02|0.01	0.20|0.10|0.05|0.02|0.01	0.20|0.10|0.05|0.02|0.01	0.20|0.10|0.05|0.02|0.01
Critical Value	0.41|0.47|0.52|0.58|0.62	0.41|0.47|0.52|0.58|0.62	0.41|0.47|0.52|0.58|0.62	0.41|0.47|0.52|0.58|0.62
Reject?	*Yes|Yes|No|No|No*	*No|No|No|No|No*	*No|No|No|No|No*	*No|No|No|No|No*

Table IX. The Kolmogorov-Smirnov test results of measuring goodness of LT repair time distribution fitting.

<table>
<tr><th>LT K-S</th><th>Exponential</th><th>Gamma</th><th>Lognormal</th><th>Weibull</th></tr>
<tr><td>Sample size</td><td>5</td><td>5</td><td>5</td><td>5</td></tr>
<tr><td>Statistic</td><td>0.4754</td><td>0.2862</td><td>0.2797</td><td>0.2955</td></tr>
<tr><td>P-Value</td><td>1.48E-01</td><td>7.18E-01</td><td>7.42E-01</td><td>6.82E-01</td></tr>
<tr><td>Rank</td><td>8</td><td>5</td><td>4</td><td>6</td></tr>
<tr><td>α</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td></tr>
<tr><td>Critical Value</td><td>0.45|0.51|0.56|0.63|0.67</td><td>0.45|0.51|0.56|0.63|0.67</td><td>0.45|0.51|0.56|0.63|0.67</td><td>0.45|0.51|0.56|0.63|0.67</td></tr>
<tr><td>Reject?</td><td>$Yes|No|No|No|No$</td><td>$No|No|No|No|No$</td><td>$No|No|No|No|No$</td><td>$No|No|No|No|No$</td></tr>
<tr><td>LT K-S</td><td>Exponential(2P)</td><td>Gamma(3P)</td><td>Lognormal(3P)</td><td>Weibull(3P)</td></tr>
<tr><td>Sample size</td><td>5</td><td>5</td><td>5</td><td>5</td></tr>
<tr><td>Statistic</td><td>0.2029</td><td>0.3769</td><td>0.2042</td><td>0.2093</td></tr>
<tr><td>P-Value</td><td>9.57E-01</td><td>3.76E-01</td><td>9.55E-01</td><td>9.46E-01</td></tr>
<tr><td>Rank</td><td>1</td><td>7</td><td>2</td><td>3</td></tr>
<tr><td>α</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td></tr>
<tr><td>Critical Value</td><td>0.45|0.51|0.56|0.63|0.67</td><td>0.45|0.51|0.56|0.63|0.67</td><td>0.45|0.51|0.56|0.63|0.67</td><td>0.45|0.51|0.56|0.63|0.67</td></tr>
<tr><td>Reject?</td><td>$No|No|No|No|No$</td><td>$No|No|No|No|No$</td><td>$No|No|No|No|No$</td><td>$No|No|No|No|No$</td></tr>
</table>

Table X. The Anderson-Darling test results of measuring goodness of pump repair time distribution fitting.

<table>
<tr><th>Pump A-D</th><th>Exponential</th><th>Gamma</th><th>Lognormal</th><th>Weibull</th></tr>
<tr><td>Sample size</td><td>169</td><td>169</td><td>169</td><td>169</td></tr>
<tr><td>Statistic</td><td>9.2076</td><td>41.487</td><td>2.8531</td><td>9.0128</td></tr>
<tr><td>Rank</td><td>4</td><td>5</td><td>2</td><td>3</td></tr>
<tr><td>α</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td></tr>
<tr><td>Critical Value</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td></tr>
<tr><td>Reject?</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|No|No</td><td>Yes|Yes|Yes|Yes|Yes</td></tr>
<tr><td>Pump A-D</td><td>Exponential(2P)</td><td>Gamma(3P)</td><td>Lognormal(3P)</td><td>Weibull(3P)</td></tr>
<tr><td>Sample size</td><td>169</td><td>169</td><td>169</td><td>169</td></tr>
<tr><td>Statistic</td><td>60.719</td><td>66.423</td><td>2.5438</td><td>63.26</td></tr>
<tr><td>Rank</td><td>6</td><td>8</td><td>1</td><td>7</td></tr>
<tr><td>α</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td></tr>
<tr><td>Critical Value</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td></tr>
<tr><td>Reject?</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|No|No</td><td>Yes|Yes|Yes|Yes|Yes</td></tr>
</table>

Table XI. The Anderson-Darling test results of measuring goodness of CV repair time distribution fitting.

<table>
<tr><th>CV A-D</th><th>Exponential</th><th>Gamma</th><th>Lognormal</th><th>Weibull</th></tr>
<tr><td>Sample size</td><td>6</td><td>6</td><td>6</td><td>6</td></tr>
<tr><td>Statistic</td><td>0.9475</td><td>0.9513</td><td>0.8771</td><td>1.8105</td></tr>
<tr><td>Rank</td><td>2</td><td>3</td><td>1</td><td>4</td></tr>
<tr><td>α</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td></tr>
<tr><td>Critical Value</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td></tr>
<tr><td>Reject?</td><td>No|No|No|No|No</td><td>No|No|No|No|No</td><td>No|No|No|No|No</td><td>Yes|No|No|No|No</td></tr>
<tr><td>CV A-D</td><td>Exponential(2P)</td><td>Gamma(3P)</td><td>Lognormal(3P)</td><td>Weibull(3P)</td></tr>
<tr><td>Sample size</td><td>6</td><td>6</td><td>6</td><td>6</td></tr>
<tr><td>Statistic</td><td>6.2849</td><td>3.9857</td><td>4.1715</td><td>3.9129</td></tr>
<tr><td>Rank</td><td>8</td><td>6</td><td>7</td><td>5</td></tr>
<tr><td>α</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td></tr>
<tr><td>Critical Value</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td></tr>
<tr><td>Reject?</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|Yes|Yes</td><td>Yes|Yes|Yes|Yes|Yes</td></tr>
</table>

Table XII. The Anderson-Darling test results of measuring goodness of LT repair time distribution fitting.

<table>
<tr><th>LT A-D</th><th>Exponential</th><th>Gamma</th><th>Lognormal</th><th>Weibull</th></tr>
<tr><td>Sample size</td><td>5</td><td>5</td><td>5</td><td>5</td></tr>
<tr><td>Statistic</td><td>1.212</td><td>0.3307</td><td>0.3301</td><td>1.8213</td></tr>
<tr><td>Rank</td><td>4</td><td>3</td><td>2</td><td>5</td></tr>
<tr><td>α</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td></tr>
<tr><td>Critical Value</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td></tr>
<tr><td>Reject?</td><td>$No|No|No|No|No$</td><td>$No|No|No|No|No$</td><td>$No|No|No|No|No$</td><td>$No|No|No|No|No$</td></tr>
<tr><td>LT A-D</td><td>Exponential(2P)</td><td>Gamma(3P)</td><td>Lognormal(3P)</td><td>Weibull(3P)</td></tr>
<tr><td>Sample size</td><td>5</td><td>5</td><td>5</td><td>5</td></tr>
<tr><td>Statistic</td><td>6.066</td><td>4.331</td><td>0.2766</td><td>3.576</td></tr>
<tr><td>Rank</td><td>8</td><td>7</td><td>1</td><td>6</td></tr>
<tr><td>α</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td><td>0.20|0.10|0.05|0.02|0.01</td></tr>
<tr><td>Critical Value</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td><td>1.37|1.93|2.50|3.29|3.91</td></tr>
<tr><td>Reject?</td><td>$Yes|Yes|Yes|Yes|Yes$</td><td>$Yes|Yes|Yes|Yes|Yes$</td><td>$No|No|No|No|No$</td><td>$Yes|Yes|Yes|Yes|No$</td></tr>
</table>

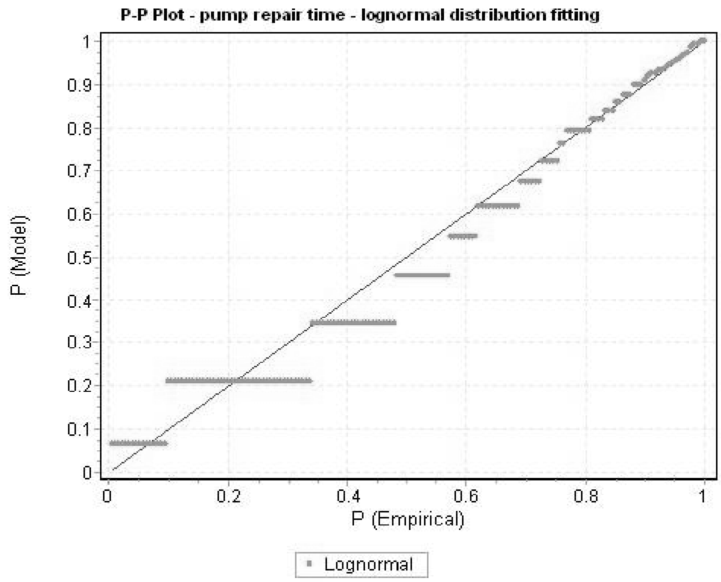

Fig. 18. Probability-probability (P-P) plot of pump repair time fitting to lognormal distribution.

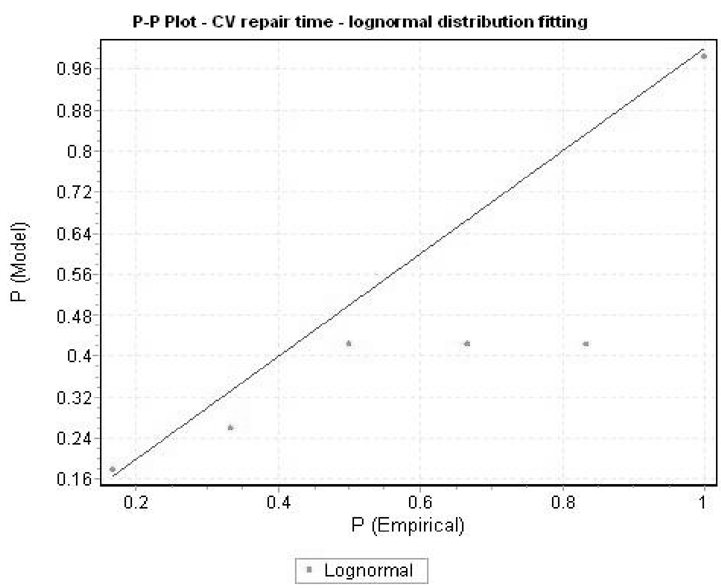

Fig. 19. Probability-probability (P-P) plot of CV repair time fitting to lognormal distribution.

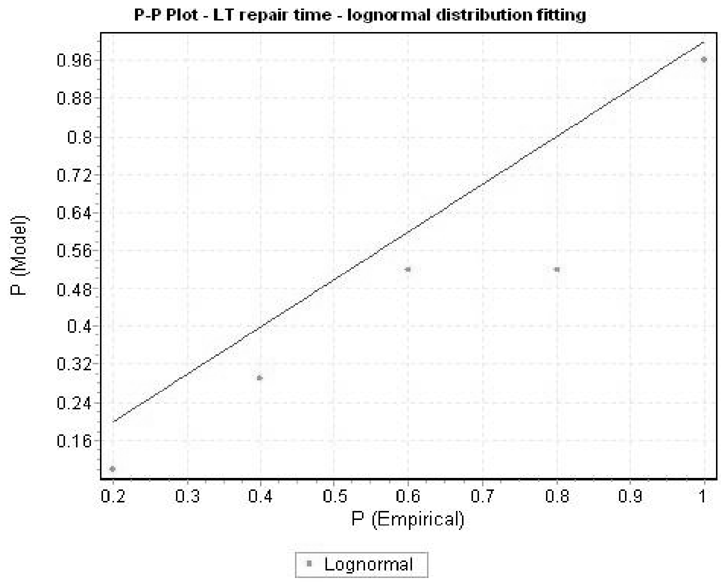

Fig. 20. Probability-probability (P-P) plot of LT repair time fitting to lognormal distribution.

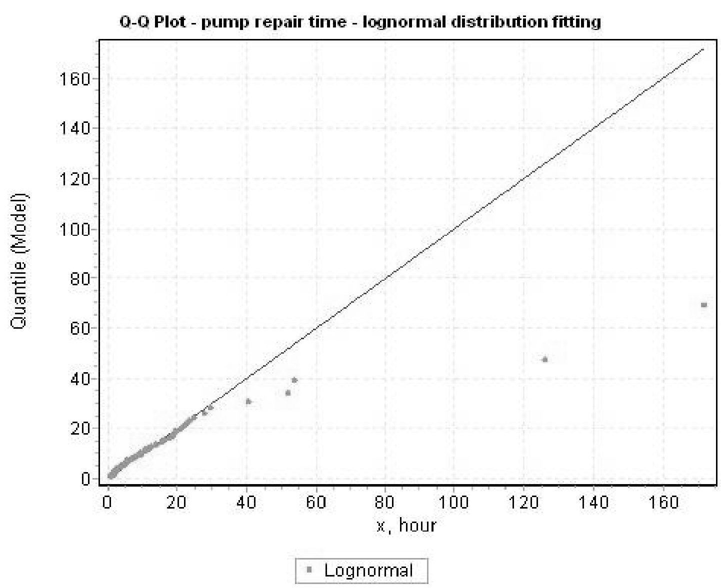

Fig. 21. Quantile-quantile (Q-Q) plot of pump repair time fitting to lognormal distribution.

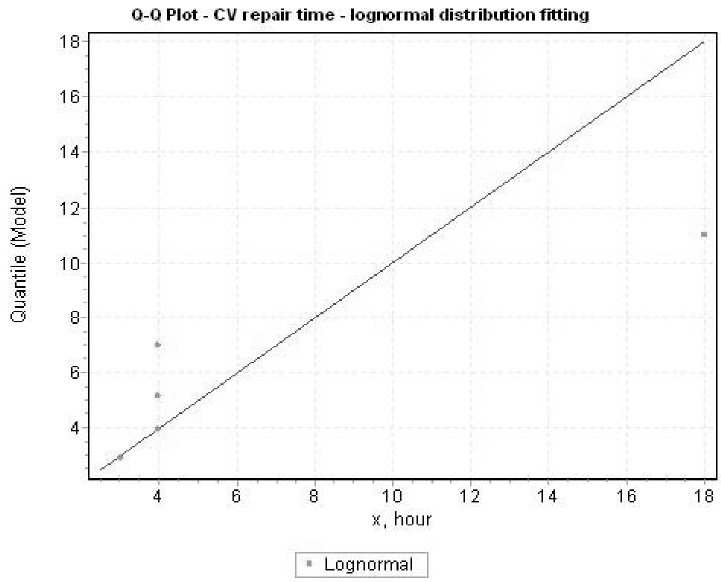

Fig. 22. Quantile-quantile (Q-Q) plot of CV repair time fitting to lognormal distribution.

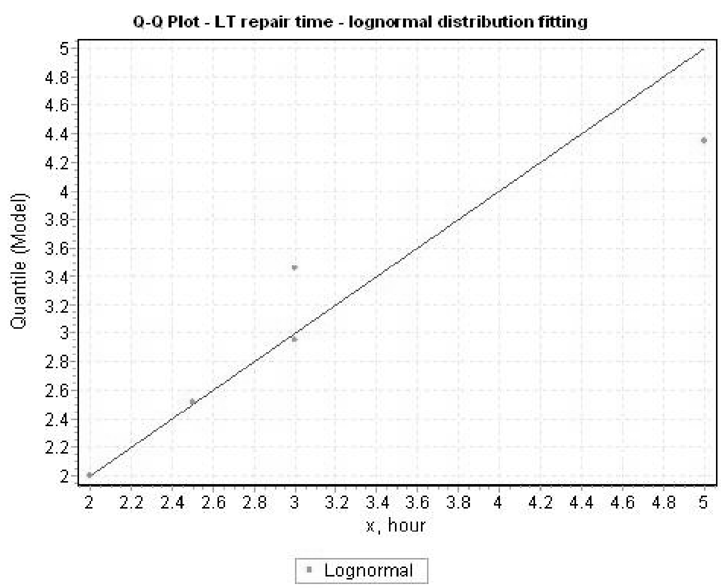

Fig. 23. Quantile-quantile (Q-Q) plot of LT repair time fitting to lognormal distribution.

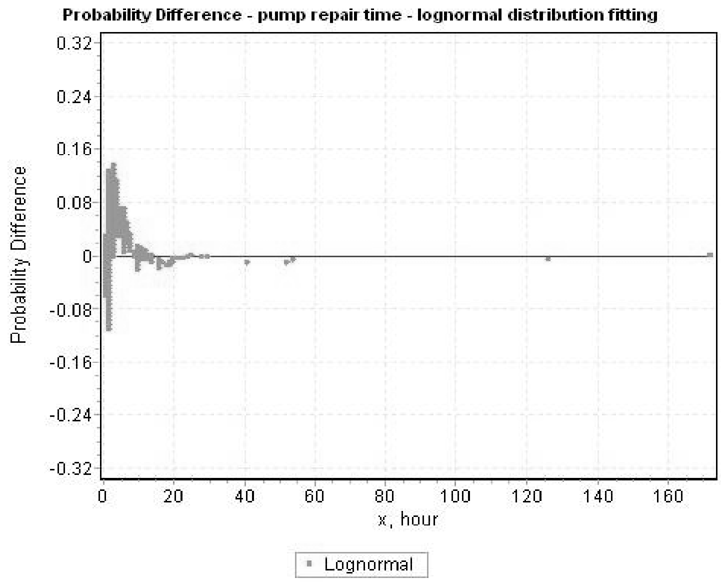

Fig. 24. Probability difference graph of pump repair time fitting to lognormal distribution.

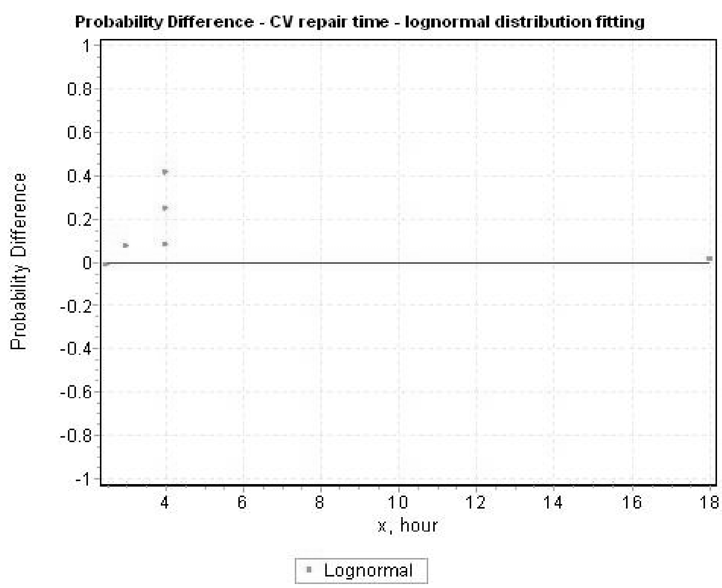

Fig. 25. Probability difference graph of CV repair time fitting to lognormal distribution.

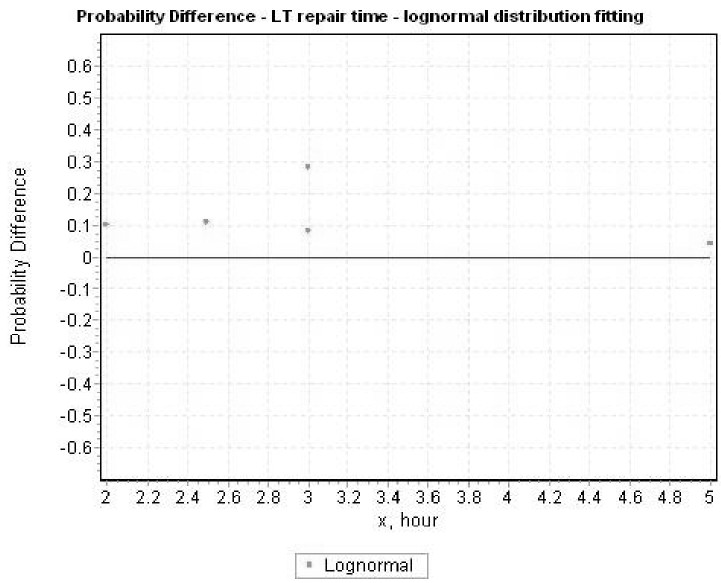

Fig. 26. Probability difference graph of LT repair time fitting to lognormal distribution.

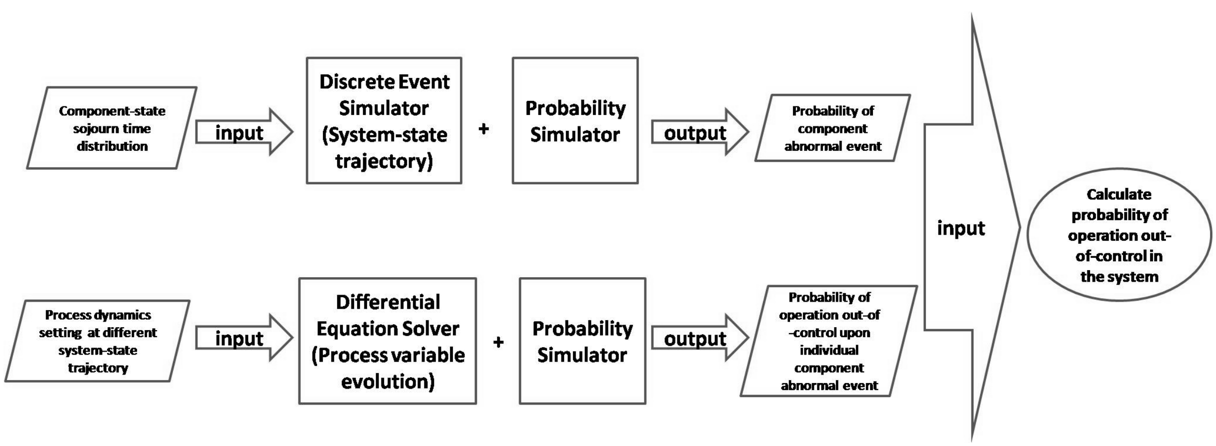

Fig. 27. Scheme of DORA probabilistic model.

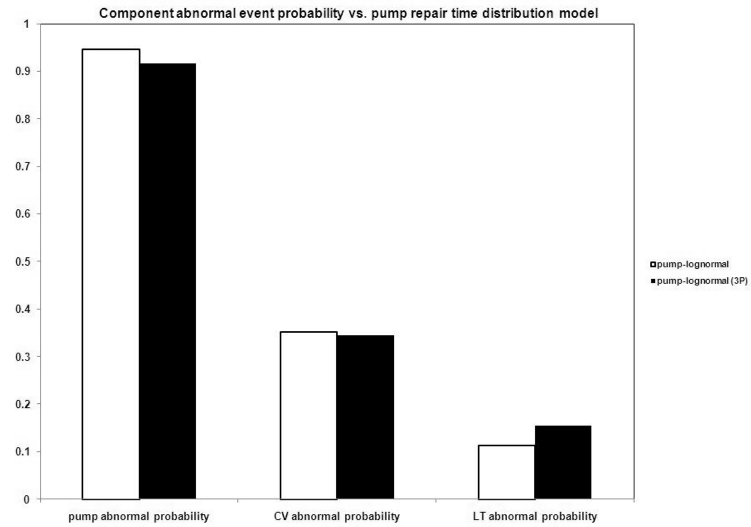

Fig. 28. Component abnormal event probability vs. different distribution types to characterize pump repair time as DORA probabilistic modeling input.

It is shown in Figure 27 that the paths to compute probability of component abnormal event and probability of operation out-of-control upon individual component abnormal event are independent of each other. The uncertainty on the component State 3 sojourn time distribution type would change the probability of operation out-of-control only by affecting the probability of component abnormal event.

Through Monte Carlo simulation, the probability of the pump, CV, and LT abnormal event are computed using different component State 3 sojourn time distribution as inputs as shown in Figures 28, 29, and 30.

As shown in the results, the selection among lognormal and lognormal (3P) for pump repair time distribution has no significant impact on studying the probability of overflow in the oil/gas separator in the case study. The same conclusion is made for the selection among exponential, gamma, lognormal and Weibull distributions for CV repair time, and the selection among exponential, gamma, lognormal, lognormal (3P) and Weibull distribution for LT repair time.

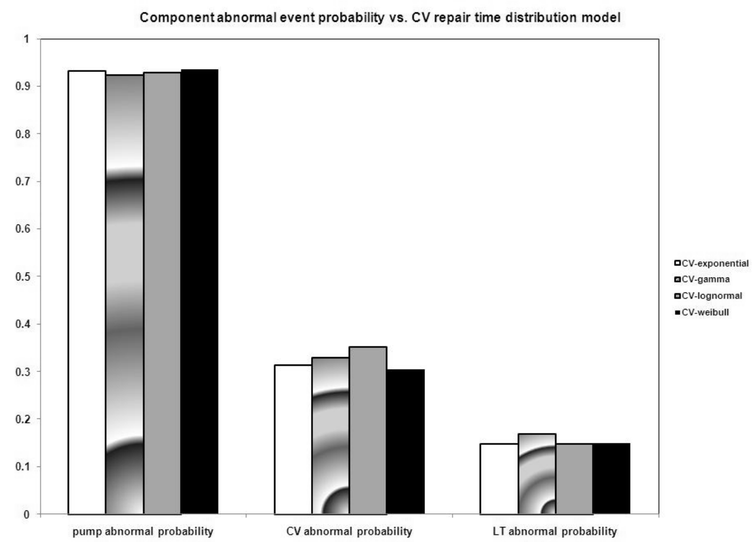

Fig. 29. Component abnormal event probability vs. different distribution types to characterize CV repair time as DORA probabilistic modeling input.

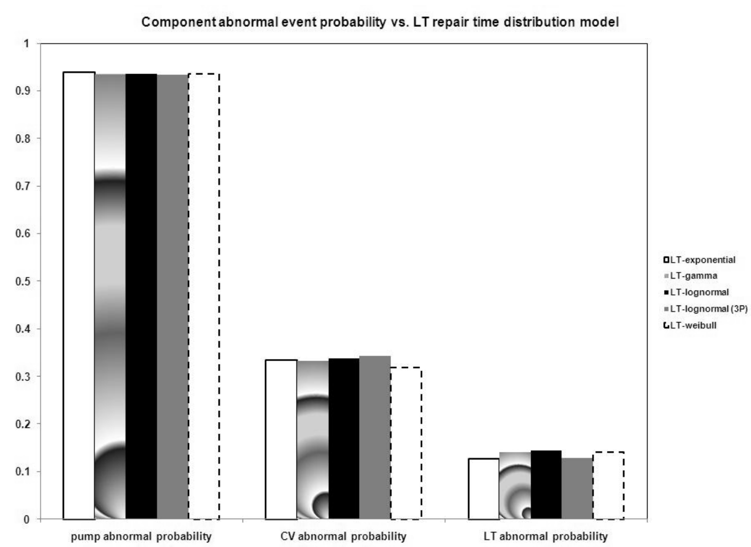

Fig. 30. Component abnormal event probability vs. different distribution types to characterize LT repair time as DORA probabilistic modeling input.

E. Summary

The DORA methodology presented in this Chapter provides a complete framework for dynamic operational risk assessment in oil/gas and chemical industries. The quantitative analysis development focuses on the DORA Probabilistic Modeling step and the uncertainty characterization in Incident Consequence Modeling step. Algorithms are designed for the specific goals. The probabilistic modeling uses stochastic process and process dynamics to study the operational risk of a dynamic process with standard computational space storage and time consumption. The objective is not to assess whether a sequence of component failures will cause the system to fail or not. This methodology aims to assess the probability of the operational failure of a system. The DORA methodology also aids in incident prevention as it studies the system degraded behavior due to component abnormal event before a failure actually occurs. The dynamic modeling provides us a simulation tool to study the process dynamics in the presence of the possibility that a protection system malfunctions.

The outcomes of DORA probabilistic modeling applied to the level control case study provide significant insight for further component inspection interval optimization. The control valve is preliminarily identified as the most critical component to the overflow scenario and level transmitter to dryout scenario. More industry inspection scheduling cost data is needed for further component inspection interval optimization study. The optimization will be discussed in Chapter IV. In the sensitivity analysis, the component State 3 sojourn time was characterized by fitting distributions to the limited industrial data. Four time-to-repair distribution types widely applied in reliability engineering and used in this study are exponential distribution, gamma distribution, lognormal distribution, and Weibull distribution. Two distributions with different number of parameters from each distribution type were selected as the fitting candidates. Goodness-of-fit measurement results show that pump and LT repair time data fit to lognormal distribution with three parameters the best and CV repair time data fit to lognormal distribution the best. Uncertainty associated with the component State 3 sojourn time distribution type was reduced by ranking the fitting hypothesis using chi-square test, K-S test, and A-D test. Sensitivity analysis results show that the probability of operation out-of-control has no significant response to the component repair time distribution model chosen as the DORA inputs in this level control system in the oil/gas separator case study. This conclusion does not mean that any distribution type could be selected as DORA input. On the contrary, the uncertainty and sensitivity analysis proposed in this paper should be performed for any other DORA probabilistic modeling to achieve a desirable quality of risk assessment.

CHAPTER III

UNCERTAINTY CHARACTERIZATION AND REDUCTION IN QRA*

A. Introduction

Quantitative risk assessment (QRA) in the oil/gas and chemical industries aims to quantify risk as a function of occurrence probabilities and consequences of major accident scenarios. System component failure rates used in point values from laboratory or generic data have generally been accepted in the past by industry to estimate the system failure occurrence probabilities in a QRA. However, this practice includes uncertainty and may mislead the QRA evaluation as well as the subsequent decision-making. As the results of QRA provide information to prevent losses in major accident hazards and aid in many decisions on risk management, it is important to increase accuracy of the results. Uncertainty is a broad and general term used to characterize a variety of various concepts including indeterminacy, judgment, approximation, linguistic imprecision, error, and significance[67]. A discussion of uncertainty is critical for the risk characterization in order to fully evaluate the implications and limitations of the risk assessment[68], evaluate how close the assessment is from reality and how the risk is reliably identified, in order to make critical chemical process safety design decisions.

In a simple and commonly used reliability model, the failure rate of a component is assumed to be constant. The variation of the failure rates of the same piece of equipment but from different reliability information resources belongs to aleatory

*Part of this chapter is reprinted with permission from "Uncertainty Reduction for Improved Mishap Probability Prediction: Application to Level Control of Distillation Unit" by Xiaole Yang, William J. Rogers, and M. Sam Mannan, 2009. *Journal of Loss Prevention in the Process Industries*, vol. 22, pp. 1-8, Copyright[2009] by Elsevier.

uncertainty category that is irreducible; however the epistemic uncertainty on the failure rates can be reduced using Bayesian theory by updating the parameter(s) of the reliability models. In Bayesian updating, the probability distribution represents our knowledge and uncertainty about the optimum value of parameter(s). Our prior knowledge about the failure rates is combined with observation and test evidence, which is the plant specific real life reliability data used in this study, to gain a posterior distribution. As our knowledge of the component reliability increases, the uncertainty of prediction on incident occurrence probability is reduced by continually updating the component failure rate distribution parameters.

In this Chapter, probabilistic approach will be proposed to characterize aleatory uncertainty. Bayesian approach will be used to reduce the epistemic uncertainty in a QRA study.

B. Literature Review

The risk assessment community distinguishes different types of uncertainty as either aleatory uncertainty or epistemic uncertainty[69]. Aleatory uncertainty is due to randomness and is irreducible in principle. Vagueness arises from natural randomness and unpredictable variation in the performance of the system components under assessment, such as the variation in atmosphere conditions and the variation in fatigue life of compressor and turbine blades. Aleatory uncertainty is typically incorporated into a QRA with an experimental design based on importance sampling[70]. On the other hand, epistemic uncertainty results from inadequate information or incomplete knowledge about the behavior of system components under assessment, such as unknown modeling parameters. Distinctive from aleatory uncertainty, epistemic uncertainty is reducible by increasing the information/knowledge of the system. In a different way for uncertainty categorization, it is also helpful to distinguish uncertainty according to where it originates. The sources of uncertainty include: statistical variation, subjective judgment, linguistic imprecision, variability, inherent randomness, disagreement, incomplete/imprecise data/information, approximation and so forth.

The importance of uncertainty characterization was earlier emphasized by the U.S. Nuclear Regulatory Commission: "The Commission is aware that uncertainties are not caused by the use of quantitative methodology in decision making but are merely highlighted through use of the quantification process. Confidence in the use of probabilistic and risk assessment techniques has steadily improved. In fact, through the quantitative techniques, important uncertainties have been and continue to be brought into better focus and may even be reduced compared with those that would remain with a sole reliance on deterministic decision making. To the extent practicable the Commission intends to ensure that the quantitative techniques used for regulatory decision making take into account the potential uncertainties that exist so that an estimate can be made on the confidence level to be ascribed to the quantitative results."[71]

The classical method, referring to the statistical method, is working with measurement uncertainty. This statistical method determines the randomness and systematic errors by calculating standard deviations, confidence intervals, and other statistical parameters. An elaborate discussion on measurement uncertainty analysis can be found in the U.S./ISO guide[72] and in the NIST (National Institute of Standards and Technology) guide[73]. In these guidelines, two types of uncertainty evaluation were discussed: uncertainty evaluation based on any valid statistical method for treating data and uncertainty evaluation based on scientific judgement. The valid statistical methods include: calculating the standard deviation of the mean of a series of independent observation, least squares method to fit a curve to data for model parameter estimation and standard deviation estimation, variance analysis to identify and quantify random effects in certain kinds of measurements, etc. However, scientific judgement includes previous measurement data, experience, manufacturers specifications, and calibration reports.

The application of modern probabilistic theories for the characterization of uncertainty was discussed in reliability engineering, risk analysis, and system safety analysis[74, 75]. Probabilistic approaches are applied in the case that we can assume the model structure is accurate[76]. The central limit theorem can be implemented for propagation of distributions. The theorem is stated as the distribution function of the sum of a sufficiently large number of independent variables approaches the normal distribution[77]. Approximation methods based on Taylor series expansion, such as statistical error propagation, are used to propagate the mean and other central moments of random variables through a model. However information regarding the tails of each input distribution is not considered in those approximation methods. In probabilistic risk assessment (PRA) field, methods for the propagation of the uncertainty on the basic events through the quantification process, to generate a characterization of uncertainty on the output of the assessment are established[78]. The uncertainties on parameters are generally characterized by probability distributions, and the most used technique is Monte Carlo method[79, 80, 81]. The acceptance and application of Bayesian theorem[82] has been increased for probabilistic estimation combining prior information about the system under analysis and likelihood function which usually could be testing or observation data. A Bayesian reliability assessment procedure for complex systems in binomial sampling proposed by Cole[83]. A Bayesian reliability analysis of series systems of binomial subsystems and components was presented by Martz et al.[84] Rubost Bayesian analysis was proposed by Berger for the application where sets of prior distributions and sets of likelihood functions are considered instead of single prior distribution and single likelihood function[85, ?]. Zhang and Mahadevan proposed a Bayesian procedure to quantify the modeling uncertainty and the uncertainty in distribution parameters[86]. Forest et al.[87] applied Bayes' theorem to quantify the uncertainties in climate system properties with the use of recent climate observation.

A number of alternative mathematical structures for the representation of uncertainty have been proposed, including fuzzy set theory, evidence theory and possibility theory. Fuzzy set theory was first introduced in 1965 by Zadeh[88]. Fuzzy sets imprecisely define classes of sets to describe the uncertainty or imprecision that are non-statistical in nature but play an important role in the processes and communication[89]. Vague concepts can be defined in a mathematical sense in fuzzy set theory. A membership function is assigned to a set. All the sets are mapped into the entire unit interval $[0, 1]$ and the value of the membership function of a set indicates the degree to which this objective satisfies the properties of the set. Fuzzy sets application is discussed in several texts[90, 91, 92, 93]. Evidence theory[94, 95, 96, 97, 98, 99] provides two specifications of the uncertainty associated with a set of possible analysis inputs or results: a belief and a plausibility. The belief provides a measure of the extent to which the available information implies that the true value is contained in the set under consideration, whereas the plausibility provides a measure of the extent to which the available information implies that the true value might be contained in the set under consideration[100]. The belief and plausibility interpret the smallest possible probability and largest possible probability for the set that is consistent with all available information. The plausibility of something being true plus the belief in it not being true is equal to one. Therefore, evidence theory is viewed as a logic independent of probability theory for reasoning under uncertainty[?]. While evidence theory is tied to probability theory, another alternative to probabilistic approach, possibility theory, is more closely tied to fuzzy set theory[101, 102]. Possibility theory[103] involves two specifications of likelihood for the representation of uncertainty: a necessity and a possibility. Like evidence theory, the sum of necessity and possibility equals to one.

C. Uncertainty Reduction by Bayesian Updating in Risk Prediction

In this Section, probabilistic approach is used to characterize uncertainty associated with a QRA. Bayesian theory is applied to reduce the risk prediction uncertainty by enhancing our knowledge on the reliability of the system. In the remainder of the Section, Bayesian updating method will be discussed and a case study on knockout drum in a distillation unit will be used to illustrate the method proposed.

1. Methodology

In probability theory, the Bayesian theorem relates the conditional and marginal probabilities of two random events. This theorem is often used to compute posterior probabilities given observations. The posterior probability density function (pdf) for a continuous random variable θ is given by:

$$f(\theta|t) = \frac{h(\theta)l(t|\theta)}{\int_{-\infty}^{\infty} h(\theta)l(t|\theta)d\theta} \tag{3.1}$$

where $h(\theta)$ is a continuous prior pdf of θ, and $l(\theta|t)$ is the likelihood information based on sample data. In order to keep reliability information updated by the increased knowledge on the system under assessment, we use the failure rates data from the OREDA database as prior information and onsite equipment real life reliability data as the likelihood information. As we keep updating the failure rates of equipment, we gain increased knowledge about the equipment reliability.

a. Prior Distribution

Reliability data are usually provided as component failure modes and rates and used as the input of risk assessment models, such as fault tree/event tree analysis. Instead of point values, the input reliability data for this study are all presented as distributions. Since the failure rates in the available databases or handbooks are from generic data or similar plants, they are not significantly representative for the specific case under assessment; but they are sound enough to be used as prior distribution for the further Bayesian updating.

OREDA2002[59] is one of the major resources of reliability data for offshore reliability analysis. OREDA2002 collects reliability data from multiple companies. The variation from multi-samples is described by a gamma distribution with parameters given in the OREDA2002 handbook. The gamma distribution of failure rates in OREDA is used as prior distribution in this study:

$$h(\lambda;\alpha,\beta) = \lambda^{\alpha-1}\frac{\beta^{-\alpha}e^{-\frac{1}{\beta}}}{\Gamma(\alpha)} \tag{3.2}$$

b. Likelihood Information

If in a test or field observation in which there are n exactly same items, r distinct times failure founded to or between $t_1 < t_2 < \cdots < t_r$, and $n-r$ times normal operating observation founded to censoring t_{c1}, t_{c2}, $\cdots$, $t_{c(n-r)}$. The total time T to detect r times failures of a single item is given by:

$$T = \sum_{i=1}^{r} t_i + \sum_{i=1}^{n-r} t_{ci} \tag{3.3}$$

The likelihood function can be written with the exponential distribution assumption on the time between failures:

$$l(t|\lambda) = \Pi_{i=1}^{n-r}\lambda e^{-\lambda t_i}\Pi_{i=1}^{n-r}e^{-\lambda t_{ci}} = \lambda^r e^{-\lambda T} \tag{3.4}$$

When plant testing data is available, the total testing time and component failure number will be used to develop likelihood function for each component. However, it is very common that this testing information is not available prior to a QRA. In the absence of testing data, the plant real life reliability data is a suitable alternative and can be used as likelihood information.

c. Posterior Distribution

Substituting equation 3.2 and equation 3.4 into Bayesian theory(equation 3.1), the posterior distribution of failure rates is given by:

$$f(\lambda|T) = \frac{e^{-\lambda(T+\frac{1}{\beta})}\lambda^{r+\alpha-1}}{\int_0^\infty e^{-\lambda(T+\frac{1}{\beta})}\lambda^{r+\alpha-1}d\lambda} \tag{3.5}$$

By the definition of gamma function:

$$\int_0^\infty \lambda^{r+\alpha-1}e^{\lambda(T+\frac{1}{\beta})}d\lambda = \frac{\Gamma(\alpha+r)}{(T+\frac{1}{\beta})^{\alpha+r}} \tag{3.6}$$

Finally, the posterior pdf of λ is rewritten as:

$$f(\lambda|T) = \frac{(T+\frac{1}{\beta})^{\alpha+r}}{\Gamma(\alpha+r)}\lambda^{\alpha+r-1}e^{-\lambda(T+\frac{1}{\beta})} \tag{3.7}$$

2. Case Study II - Flammable Liquid Overfilling from a Knockout Drum of the Distillation Unit

The objective of this subsection is to apply a probabilistic quantitative risk assessment on a knockout drum of the distillation unit, analyze the uncertainty associated with the risk evaluation, reduce the uncertainty through Bayesian updating on the component reliability data and guide process safety design.

In petroleum refineries, petrochemical and chemical plants, and natural gas processing plants, continuous and steady-state fractional distillation is widely used. Henry Kister, a distillation tower expert, analyzed recent trends in distillation tower malfunctions from 900 cases, and found that half of the tower base malfunctions involved high liquid levels[104]. The U. K. Health and Safety Executive reported that overflow was the second leading cause in analysis of 718 loss of containment incidents for vessels[105]. As part of a distillation unit, a knockout drum (KO drum) is an empty vessel where vapor-liquid separation takes place. Many of the accidents and unit upsets associated with KO drums negatively affect petroleum refineries. Liquid overfilling incidents in vapor-liquid separation vessels, which carried to high consequences, occurred in the past decades. For example, BPs Texas City Refinery incident on March 23, 2005 occurred during the start-up, following a temporary outage of the isomerization Unit (ISOM) and involved an explosion and fires which killed 15 workers and injured more than 170 others. The incident was investigated exhaustively in the final investigation report released on the CSB website. (http://www.csb.gov). Kister similarly concluded that faulty level measurement and control are the primary cause of tower high level events, as seen in BP ISOM incident[5, 106]. The case study in this subsection focuses on a fault tree analysis on liquid overfilling a KO drum in a distillation unit and uncertainty analysis associated with the probability estimation.

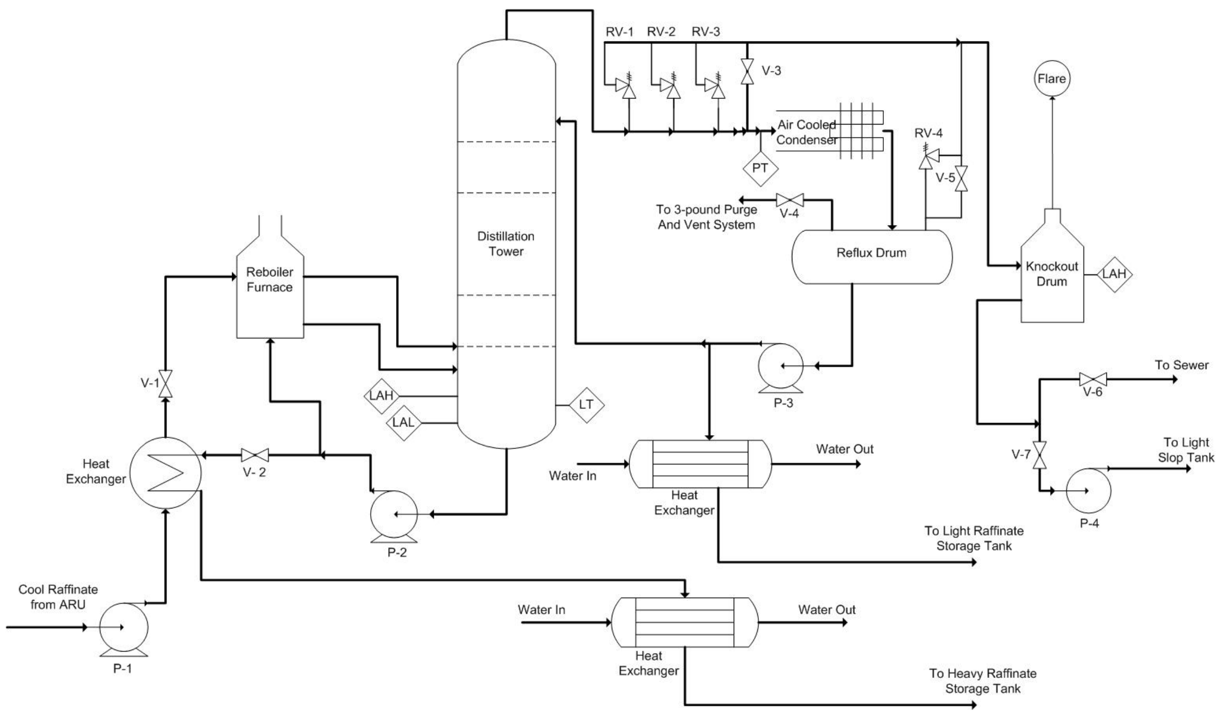

Fig. 31. Process flow diagram of the distillation unit with a knockout drum.

a. Fault Tree Development

A simplified process flow diagram in Figure 31 is used to demonstrate the process. A fault tree developed to analyze the overfilling of KO drum is shown in Figure 32 The Boolean logic expression of the top event is given by:

$$T = A \bigcap \{(F \bigcup C) \bigcup [(D \bigcup C \bigcup B) \bigcup (A1 \bigcap A2 \bigcap E)]\} \tag{3.8}$$

where: T - Flammable liquid overfilling from the KO drum

A - LAH(Level Alarm High) fails

A1 - LAH1(Level Alarm High) fails

A2 - LAH2(Level Alarm High) fails

B - V-4 fails to open

C - Piping blockage

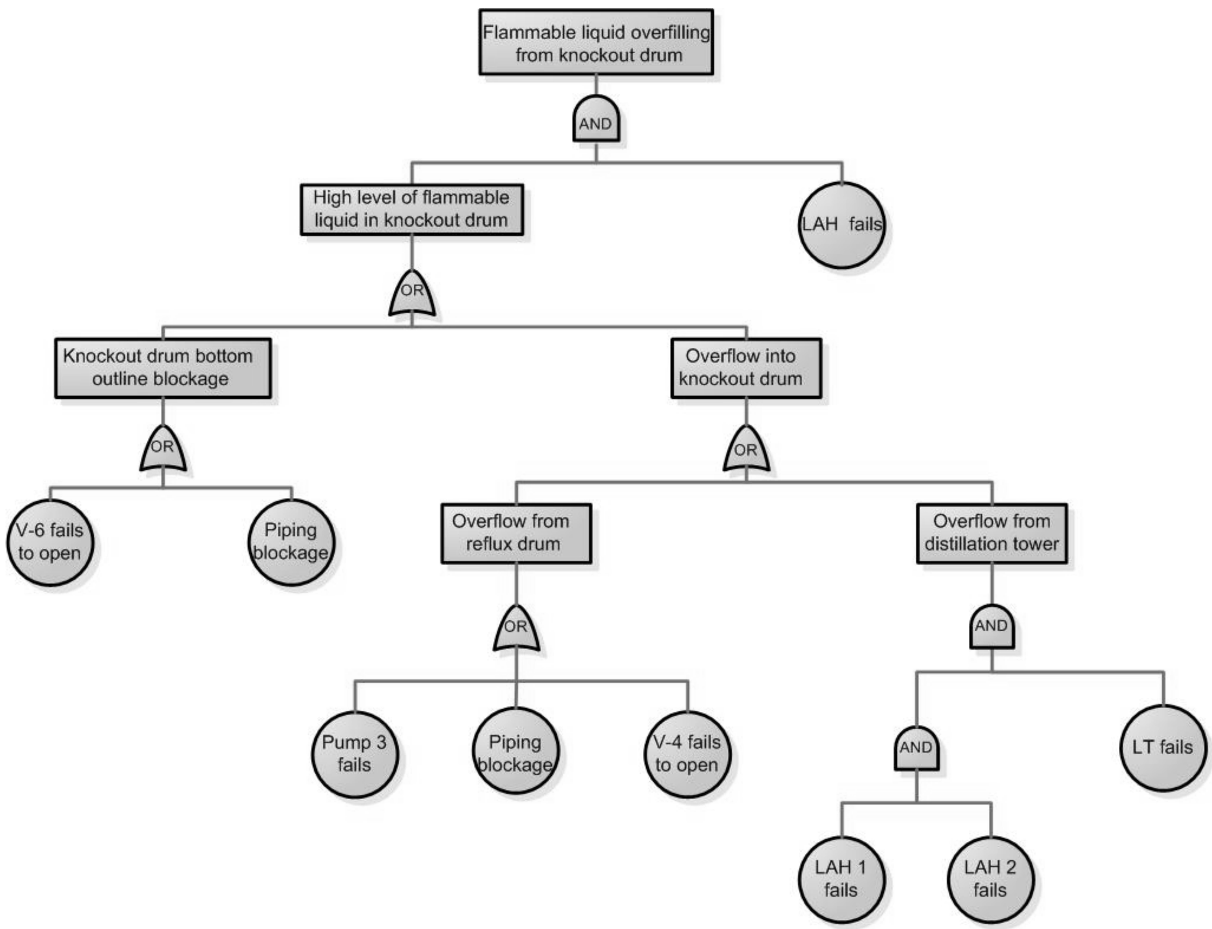

Fig. 32. Fault tree of flammable liquid overfilling from knockout drum in the distillation unit.

D - Pump 3 fails

E - LT(Level Transmitter) fails

F - F-6 fails to open

With the assumption that LAH, LAH1, and LAH2 share the same failure rate data, the probability of flammable liquid overfilling from the KO drum, is given by:

$$P_{top-event} = [(P_F + P_C) + (P_D + P_C + P_B) + P_A^2 \times P_E] \times P_A \tag{3.9}$$

b. Uncertainty Reduction through Bayesian Updating

OREDA2002 and CCPS(Center for Chemical Process of Safety)[107] handbook are the two major sources of the reliability data for this study. OREDA2002 data was introduced in the previous section. CCPS handbook obtains reliability data by conducting a literature search and an industry survey. The lognormal distribution is chosen in the CCPS handbook due to the general shape, popularity among data analysts, and ease of calculation[107]. The lognormal distribution parameter information is insufficient in CCPS handbook. Therefore, different failure rate lognormal distribution parameter σ values of *Piping blockage* and *LT fails* were assumed in a set of experiments to study the impact of input uncertainty on output uncertainty. Reliability data for all the basic events used as the first set of prior function in this study are shown in Table XIII.

We assume that the Bayesian updating interval is two years in this case study. Thus, the updating interval and component failure number detected within the two years are the likelihood information for Bayesian updating. For two basic events, *Piping blockage* and *LT fails*, the real life reliability data is not available. So their prior distributions will be directly used as the input without any Bayesian updating.

Table XIII. Reliability prior data collected from the OREDA database and the CCPS handbook for all components in the FTA.

				λ, Failure rate(per 10^6 h)				
Index	Component	Failure Mode	Distribution type	λ_{low}	λ_{mean}	λ_{up}	λ_{sd}	Data source
A	LAH fails	Spurious operation	Gamma	0.03	1.55	4.77	1.68	OREDA
B	V-4 fails to open	Fail to open on demand	Gamma	72.43	13.69	43.08	13.69	OREDA
C	Piping blockage	Catastrophic	Lognormal	0.000465	0.0268	0.104	C	CCPS
D	Pump fails	Fail to start on demand	Gamma	0.02	13.74	55.88	21.1	OREDA
E	LT fails	Level-capacitance probe	Lognormal	0.436	25.1	97.1	C	CCPS
F	V-6 fails to open	Fail to open on demand	Gamma	0	109.71	520.95	213.55	OREDA

All the likelihood information is summarized in Table XIV.

Three continual updatings were conducted in the case study. The posterior distribution after each updating is used as prior distribution for the next updating. In doing so, all the available information about the component reliability is included to update the failure rate distribution parameters. Through Bayesian updating, the uncertainty is reduced. The prior distribution parameters, likelihood information, and updated posterior distribution parameters of equipment used for this analysis can be also found in Table XIV. And the Bayesian updating distribution graphs are shown in Figure 33.

Table XIV. Prior gamma distribution parameters, likelihood information, and posterior gamma distribution parameters of basic events probabilities (LAH fails, V-4 fails to open, Pump fails, and V-6 fails to open) through each Bayesian updating.

	Prior		Likelihood						Posterior					
Basic events	β	α	1st r	1st T,h	2nd r	2nd T,h	3rd r	3rd T,h	1st β'	1st α'	2nd β'	2nd α'	3rd β'	3rd α'
LAH fails	1.82e-06	8.51e-01	3	17520	2	17520	1	17520	1.76e-06	3.85e+00	1.71e-06	5.85e+00	1.66e-06	6.85e+00
V-4 fails to open	1.37e-05	1.00e+00	2	17520	3	17520	1	17520	1.10e-05	3.00e+00	9.25e-06	6.00e+00	7.96e-06	7.00e+00
Pump fails	3.24e-05	4.24e-01	3	17520	2	17520	2	17520	2.07e-05	3.42e+00	1.52e-05	5.42e+00	1.20e-05	7.42e+00
V-6 fails to open	4.16e-04	2.64e-01	3	17520	2	17520	1	17520	5.02e-05	3.26e+00	2.67e-05	5.26e+00	1.82e-05	6.26e+00

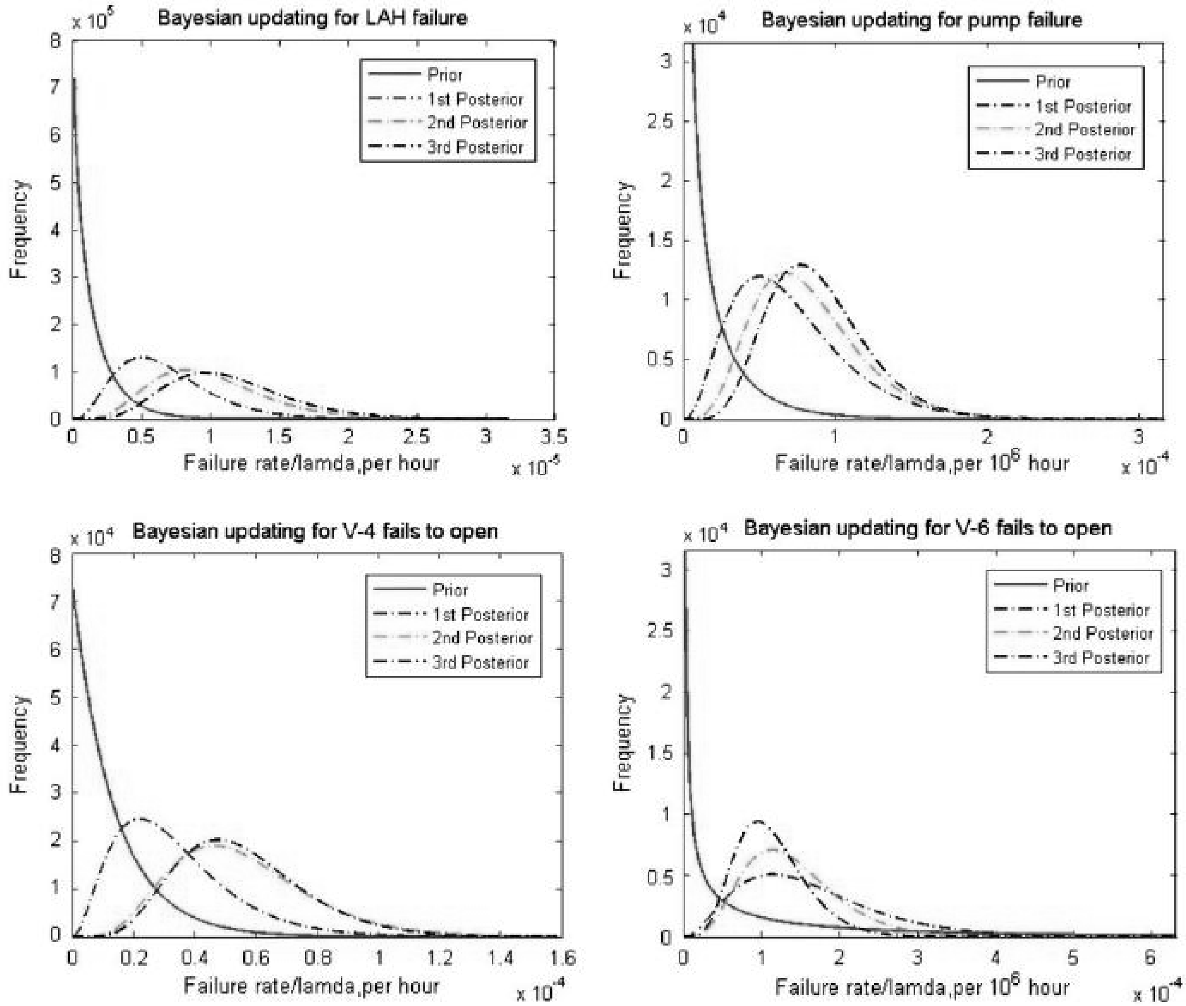

Fig. 33. Prior distribution and posterior distributions for failure rates of LAH, pump, V-4, and V-6.

Bayesian Updating on Basic Event Probability Distribution Parameters

The real life reliability data provided likelihood information to update the failure rate distributions (Figure 33). As shown in Figure 33, after being updated, component failure rate pdf curves changed their shape from the prior pdf curve and all the updated curves shifted upon each updating. Through the updating, all of the three new α' parameters of posterior gamma distributions of LAH failure rate, pump failure rate, and V-6 failure rate were one order of magnitude higher than the prior α; All the three new β' parameters of posterior gamma distributions of V-6 failure rate and the last two times updated β' parameters of V-4 failure rate were one order of magnitude lower than the prior β (Table XIV). Therefore, our knowledge on component failure rates is enhanced and more accurate QRA results are expected using renewed information.

Uncertainty in Top Event Probability Affected by Input Probability Uncertainty

Due to insufficient testing data or real life reliability data for piping and LT, their prior lognormal distributions were used directly as the inputs for the top event probability calculation. In order to study the effect of input (basic events of *piping blockage* and *LT fails*) uncertainty on the output (top event), different σ values of the input lognormal distribution were used. As shown in Figure 34, at the same time point, the 5th year since the prior evaluation, both mean value and standard deviation of the top event probability changed as the σ value changed. In Figure 35, a plot of upper, lower, mean and SD of top event probability distribution vs. different σ values of the lognormal distributions of input basic events illustrates: when $\sigma < 1$, the risk estimation is considered accurate as there is no significant difference between the upper value line and lower value line; and the SD is converged to zero; when $\sigma > 1$,

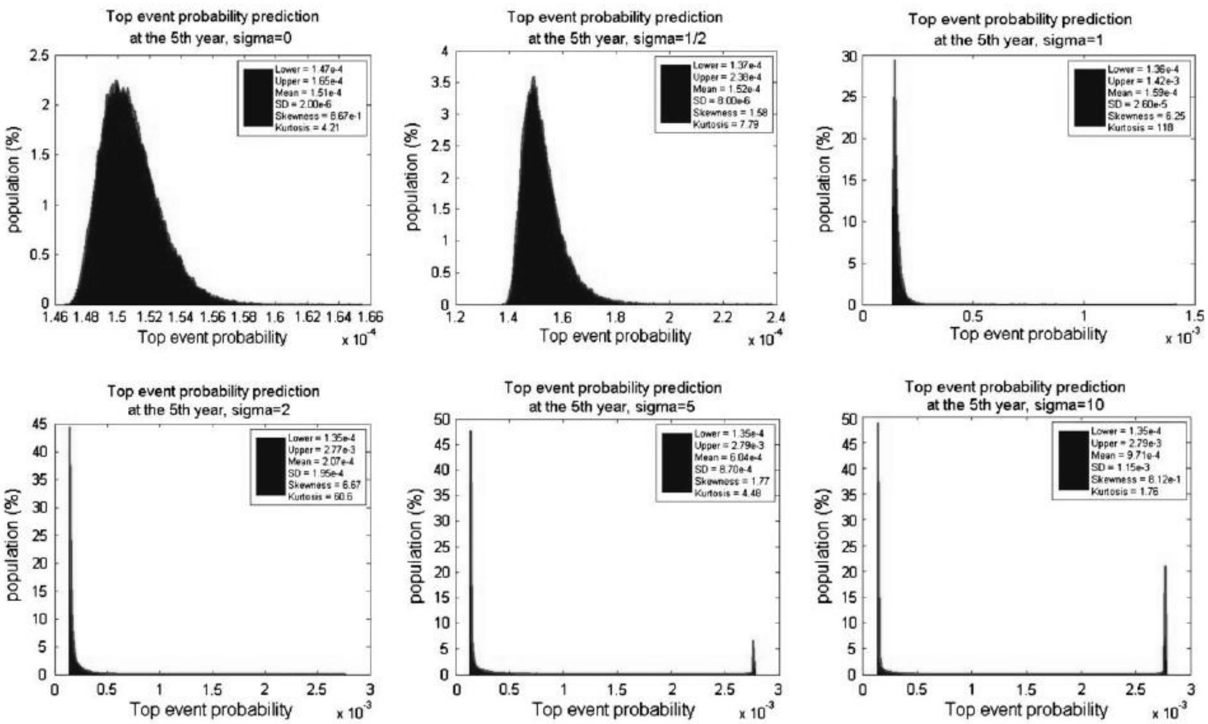

Fig. 34. Top event probabilities simulated using different σ values of failure rate distributions of piping blockage and LT fails. The basic event failure rate distributions used to generate the graphs are the second posterior distributions at the 5th year since the prior evaluation.

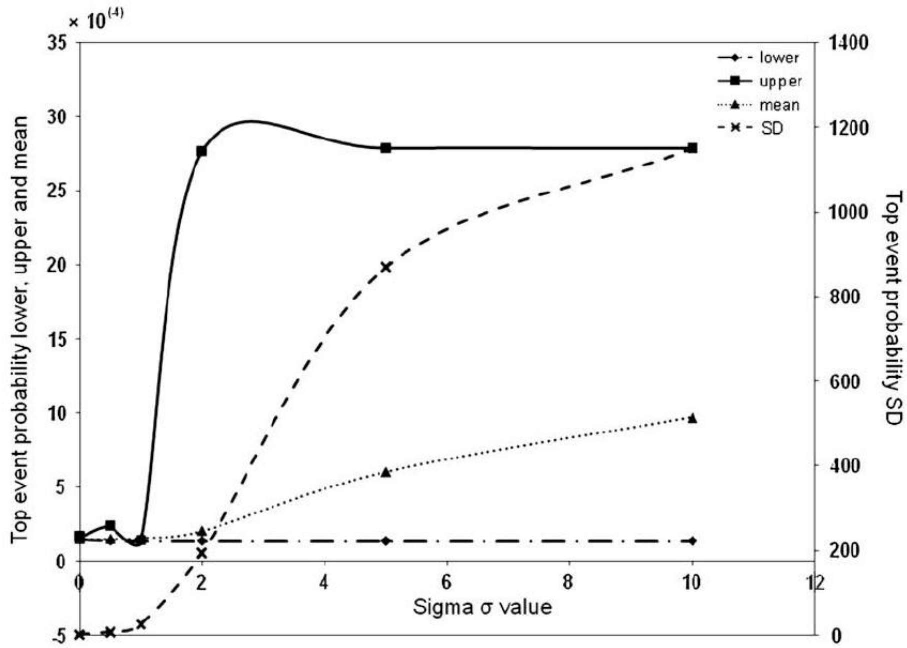

Fig. 35. Uncertainty of the top event probability distribution vs. parameter σ of the basic events (piping blockage and LT fails) probability distributions.

the upper-lower range increased, and the SD of the top event probability estimation was increased by the raising σ values of two input lognormal distributions (*piping blockage* and *LT fails*). Therefore, the uncertainty associated with the input of our QRA has a significant impact on the top event probability estimation accuracy.

Probability Prediction Uncertainty Reduction by Bayesian Updating

Assuming the lifetime of this process unit is about 25 years, the probability of flammable liquid release is changing over time due to the lifetime of equipment performance. We calculated four predictions on flammable liquid release probability throughout the system lifetime using the four sets of basic event probabilities distribution parameters. The four predictions were based on one prior information set, and the other three posterior distributions parameter sets upon Bayesian updating shown in Table XIV. Figure 36 shows the prediction on mean value of flammable liquid release probability distribution over time with $\sigma = 0$ for the lognormal proba-

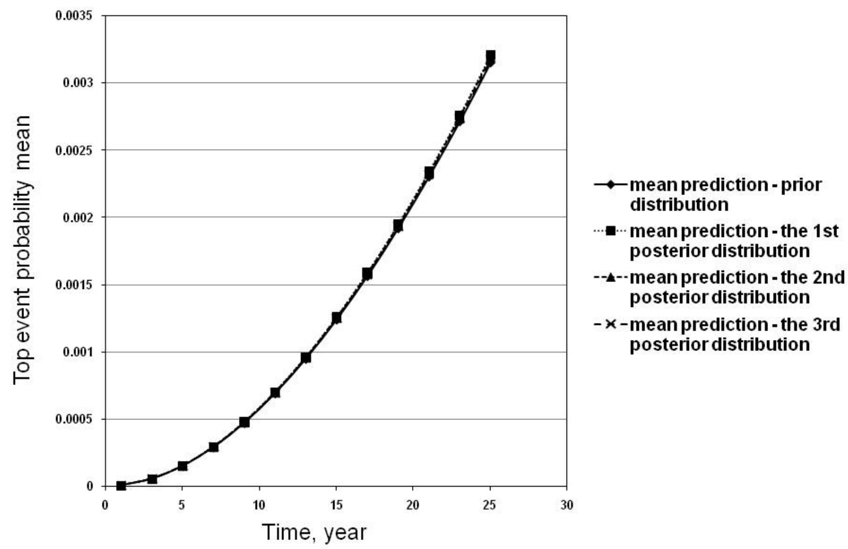

Fig. 36. Predictions on mean value of flammable liquid release probability using continually updating failure rates distribution.

bility distribution of *piping blockage* and *LT fails*. The mean values of the probability increased over time due to the deterioration of the equipment. Figure 37 shows the uncertainty of the four predictions. The four mean value prediction curves overlapped among each other (Figure 36), but the predictions based on updated failure rates information had lower uncertainty than the prediction based on the prior information (Figure 37). The conclusion is that the accumulated information about component failure rates increased our knowledge on the system performance and the uncertainty of the estimation has been reduced.

D. Summary

At all levels, the understanding of uncertainty associated with risk of major chemical industrial hazards should be enhanced. This Chapter aims to draw attention to

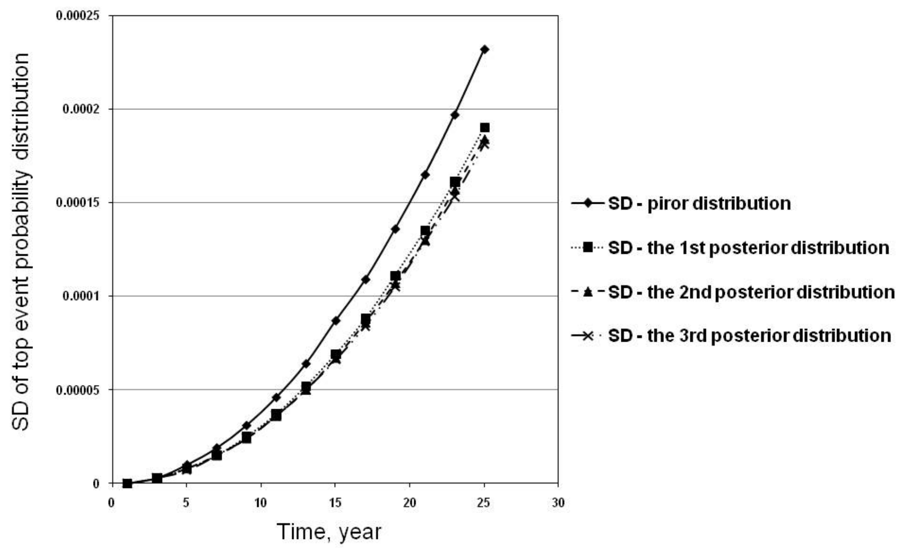

Fig. 37. Uncertainty profiles associated with the four top event probability predictions.

uncertainty characterization and reduction using probabilistic approaches. The fault tree analysis on case study II identified five minimum cut sets for the top event of flammable liquid overfilling from knockout drum in the distillation unit. They are: (LAH fails, V-6 fails to open), (LAH fails, piping blockage), (LAH fails, pump fails), (LAH fails, V-4 fails to open), and (LAH fails, LT fails). LAH fails was identified as the most critical issue to initiate a flammable liquid overfilling. This FTA conclusion confirms that level measurement and control is a primary cause for a high level incident. The FTA results showed that the probability of this top event increases over time. The uncertainty analysis revealed that: 1) the aleatory uncertainty of failure rates from various data resources can be efficiently characterized by probability distributions, and further used to propagate the output uncertainty through a fault tree analysis model. 2) uncertainty of inputs (basic event probabilities) has a significant impact on the uncertainty of output (top event probability) in a QRA. In this study, uncertainty analysis proves that more information on the piping blockage and level transmitter failure is needed to improve the accuracy of further QRA; 3) uncertainty of the top event probability prediction is reduced by Bayesian updating of the component failure rates using real life reliability data at the absence of component testing data.

The approaches presented in this Chapter, Monte Carlo simulations to get a probability distribution instead of point values and Bayesian updating using real life reliability data to enhance our knowledge on the system continually, provide industry a tool to characterize and reduce uncertainty for improving overall mishap probability prediction.

CHAPTER IV

COMPONENT INSPECTION INTERVAL OPTIMIZATION

A. Introduction

Preventive maintenance is undertaken regularly at predetermined intervals in order to reduce or eliminate accumulated deterioration of the system[108]. In most of the current maintenance practices, the frequency of testing, inspection, and repair is determined by the component maintenance history. Scheduled component inspections play an important role in maintenance program because they provide a means to discover dormant failures and/or degradation before it leads to catastrophe. As with other maintenance activities, it is crucial to determine the appropriate inspection schedule to meet certain performance expectations of the system. From an operational risk point of view, the inspection schedule should be able to detect system degradation before process variables, e.g., temperature, pressure, and level, exceed desired bounds and abnormal events occur.

It is widely recognized that the decision on inspection scheduling is a series of compromises among performance, risk, cost, and quality attributes, etc. In conventional approaches to inspection planning, various inspection criteria, such as fatigue lives, member criticality, stress levels, past inspection data, previous experience, etc., are combined qualitatively to produce the optimal inspection plan[109]. Reliability/risk-based inspection planning techniques were developed in a quantitative manner through the use of probabilistic functions which take into account the uncertainties associated with the parameters that determine component reliability[110, 111, 112, 113]. There are several industrial guidelines and techniques, such as API 580 - Risk-based Inspection in petroleum industry[114] and Reliability Centered Maintenance (RCM)[115], to help make decisions on the inspection intervals. Cost is usually treated as a constraint. However, in practical risk assessment, overall risk and inspection cost are conflicting objectives. It is more reasonable to perform a multiobjective optimization that rigorously considers these objectives.

This Chapter deals with component inspection interval optimization of the oil/ gas separation system in offshore plants described in Chapter II. In this Chapter, we propose a set of Pareto optimal solutions focusing on the inspection scheduling of pump, control valve, and level transmitter in the system. A numerical pareto optimization technique based on an evolutionary algorithm and scaler method in which a scaling factor is used to represent the weights of trade-off objectives are used in this Chapter. Pareto optimal curves were generated to represent the optimal inspection budget and scheduling. The results show that both methods are favorable to identify the pareto set of the problem prior to a final decision on what component inspection interval of the system should be selected.

B. Literature Review

As the name suggests, a multiobjective optimization problem (MOOP) deals with a vector of objective functions to be minimized or maximized. In single objective optimization, the goal is to find a solution or solutions that optimize the sole objective function. Decision space is the only search space when solving a single objective optimization problem. However, a multiobjective optimization problem deals with two search spaces, decision space and objective space. This is one of the striking differences between single objective and multiobjective optimization problems[116]. These two spaces are linked by a unique mapping that is often nonlinear. Figure 38 illustrates the two search spaces in a two objective functions optimization and a

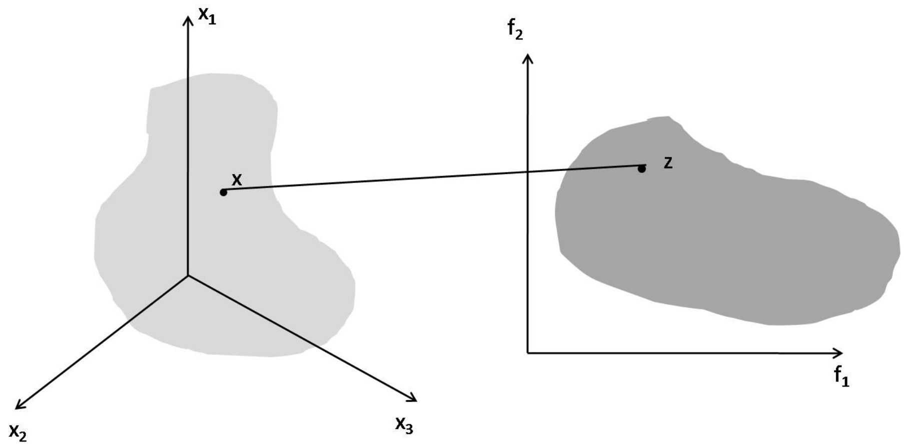

Fig. 38. Representation of the decision space and the corresponding objective space.

mapping between them. A multiobjective optimization problem can be stated as:

$$
\begin{aligned}
min\mathbf{J}(\mathbf{x},\mathbf{p}) \\
s.t.g(\mathbf{x},\mathbf{p}) \leq 0 \\
h(\mathbf{x},\mathbf{p}) = 0 \\
\mathbf{x}_{i,l} \leq \mathbf{x}_i \leq \mathbf{x}_{i,u}(i = 1, 2, 3, ..., n)
\end{aligned}
\tag{4.1}
$$

where $\mathbf{J}$ is the objective function vector. $\mathbf{x}$ is the decision vector and $\mathbf{p}$ is the fixed parameter vector. g and h are the inequality and equality constraints. $x_{i,l}$ and $x_{i,u}$ are the lower and upper boundaries of the ith design variable.

Pareto optimality was first introduced into engineering and sciences in 1970s by Stadler[117]. The Pareto-optimal set is a non-dominated set in which the members are not dominated by any member of a set of solutions[116]. If the non-dominated set is valid for the entire feasible search space, this non-dominated set is the global Pareto-optimal set. Otherwise, a local Pareto-optimal set is defined as:

If for every member x in a set $\underline{P}$ there exists no solution y (in the neighborhood of x such that $\|y - x\|_\infty \leq \epsilon$, where ϵ is a small positive number) dominating any member

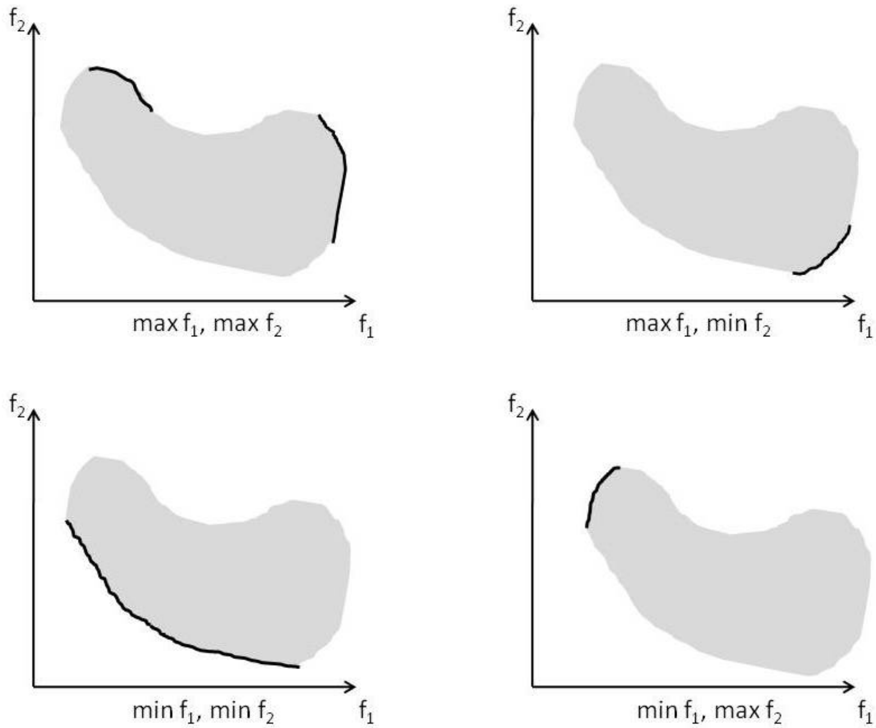

Fig. 39. Pareto-optimal sets are marked in the bold continuous curves for four different scenarios in a two objectives optimization problem.

of the set $\underline{P}$, then solutions belonging to the set $\underline{P}$ constitute a locally Pareto-optimal set[118, 119].

On many occasions, the Pareto-optimal set refers to the global Pareto-optimal set since solutions of this set are not dominated by any feasible member of the search space so that they are optimal solutions of the multiobjective optimization problem. Figure 39 illustrates the continuous Pareto curves in four different scenarios for a two objective optimization problem. The solutions in the Pareto-optimal set are all on a particular edge of the feasible search region.

In the past decades, classical methods for solving multiobjective functions have been developed. Cohon[120] classified those algorithms into two types:

- Generating methods: a few non-dominated solutions are generated without *a priori* knowledge of relative importance of each objective for the decision-makers.

- Preference-based methods: some known preference for each objective is used in this method.

The simplest and most widely used method for multiobjective optimization is the weighted sum method. This method belongs to Cohon's preference-based method category because it uses perference information in the optimization process. Weighted sum method transfers a multiobjective optimization problem into an aggregated single objective optimization problem weighting each individual objective. The aggregated objective function is given by:

$$J_{weightedsum} = w_1 J_1 + w_2 J_2 + w_3 J_3 ... + w_n J_n \tag{4.2}$$

where $w_i (i = 1, 2, 3, ..., n)$ is a weighting factor for the ith objective function J_i. For a single objective formulation, the weights are selected in proportion to the relative importance of each individual objective in the problem. Each point on the Pareto curve is an optimization solution corresponding to a particular set of values for the weights. The weighted sum method adjusts the weights systematically in order to traverse the Pareto curve.

Initial work on weighted sum method can be found in Zadeh's publication in 1963[121]. The advantage of this method is due to its simplicity. Its concept is intuitive and easy to implement. This method guarantees finding the entire Pareto-optimal solution set for problems having a convex Pareto-optimal front. However, the disadvantages were also discussed in a number of studies[122, 123, 124]. First of all, the Pareto-optimal solutions are not uniformly distributed. It is difficult to set the weight vectors to obtain a Pareto-optimal solution in a desired region in the objective space. Moreover, weighted sum method fails to find the Pareto-optimal solution in the case of an non-convex objective space. In AWS method, additional inequality constraints are imposed in the usual weighted sum method. The optimization is performed only in a newly-defined feasible region where more exploration is needed. The AWS method produces well-distributed solutions and finds Pareto-optimal solutions in non-convex regions. However, AWS method is only applied in the case of two objective functions which refers to bi-objective adapted weighted sum method. The same authors published adapted weighted sum method for multiobjective optimization in 2006[125]. Instead of inequality constraints in bi-objective problem, additional equality constraints are imposed to connect the pseudo-nadir point and the expected locations of Pareto-optimal solutions on the piecewise linearized plane in the objective space. Suboptimizations are performed for further refinement along equality constraint lines to determine solutions near desired positions, which leads to a well-distributed mesh representation of the Pareto.

The ϵ-Constraint method was proposed by Marglin[126] in 1967. Haimes et al.[127] in 1971 suggested reformulating MOOP in order to alleviate the difficulties in solving non-convex objective spaces in weighted sum method, by just keeping one of the objectives and restricting the rest of them within user-supplied values:

$$\begin{aligned} min J_{\mu}(x,p) \\ s.t. J_m(x,p) \leq \epsilon_m \\ g(x,p) \leq 0 \\ h(x,p) = 0 \\ x_{i,l} \leq x_i \leq x_{i,u} (i = 1,2,3,...,n) \end{aligned} \tag{4.3}$$

where ϵ_m represents an upper bound of the value of J_m but not necessarily a small value close to zero. The advantage of ϵ-Constraint method is that it can be applied for any arbitrary problem either having convex or non-convex objective spaces. On the other hand, the disadvantage of this method depends on how much information is obtained from the user. As the number of objectives increases, there are more elements in ϵ vector so that more information is required from users. In addition, elements in ϵ vector have to be chosen within the minimum or maximum values of the individual objective function. Otherwise, there exists no feasible solution to the optimization problem.

The goal programming methods were first introduced in single objective linear programming problem by Charnes et al. in 1955[128]. After the work of Lee[129], Ignizio[130, 131], and many others, goal programming methods became more popular. Romero[132] has presented a comprehensive overview of the goal programming techniques and their application in engineering[133, 134]. In goal programming method, the goal is to to find solutions which attain a predefined target for one or more objective functions. If there exists a solution with the desired target, the task of goal programming is to identify this particular solution. On the other hand, if there is no solution which achieves predetermined targets in all objective functions, the task is to find solutions which minimize the deviations from the predefined targets.

Interactive methods are another alternative. As some Pareto-optimal solutions are found, their location and interactions are analyzed. Some of the most popular interactive methods include: interactive surrogate worth trade-off (ISWT) method[135], step method[136], reference point method[137], guess method[138], nondifferentiable interactive multi-objective bundle-based optimization system (NIMBUS) approach[139], and light beam search method[140].

There are some other classical methods to solve multiobjective optimization problems. Weighted Tchebycheff metric methods[119], Benson's method[141, 142], the value function method[119], etc. All the classical methods described above are based on a similar premise, namely, converting a multiobjective optimization problem into a sequence of single objective optimization problem. However, difficulties are observed in those methods[116]:

- One simulation in the classical algorithm run can find only one Pareto-optimal solution.
- Some classical algorithms fail to find all Pareto-optimal solutions in non-convex multiobjective optimization problems.
- All classical algorithms require some prior knowledge.

Thinking on the disadvantages stated above, it would not be surprising that a number of non-classical, unorthodox and stochastic search and optimization algorithms have been developed over the past decades. Evolutionary algorithms (EAs) for MOOP are inspired by biological evolution such as inheritance, mutation, selection, and crossover, etc, and drives the search towards an optimal solution in a process which mimics nature's evolutionary principles. Over the last decade, genetic algorithms (GAs) have been extensively used in science, commerce and engineering. In GAs, a population of abstract representations (called chromosomes or the genotype) of candidate solutions (called phenotypes) to an optimization problem evolves toward better solutions. Genetic algorithm was first introduced by John Holland[143]. The genetic algorithms can be found in several textbooks[143, 144, 145, 146, 147, 148], and a more comprehensive description in a compiled handbook[149]. The major journals that are now dedicated to promote research on GA include: 'Evolutionary Computation Journal' published by MIT Press, 'Transactions on Evolutionary Computation' published by IEEE and 'Genetic Programming and Evolvable Machines' published by Kluwer Academic Publishers.

Several widely used evolutionary algorithms are listed here:

- Vector Evaluated Genetc Algorithm (VEGA)[150] is a straightforward extension of a single objective GA for multiobjective optimization. In a MOOP which has N objectives, VEGA divides GA populations into N equal subpopulations randomly at every generation. Fitness is assigned to each subpopulation based on different objective function. In doing so, each of the N objectives is used to evaluate some members in the population.

- Weighted-Based Genetic Algorithm (WBGA)[151] is a weighted-based algorithm. Each objective function is multiplied by a weighting factor. The fitness of a solution is calculated based on the weighted objective function values. However, each individual in a GA population is assigned a different weighting vector. In this way, one simulation run can find multiple Pareto-optimal solutions.

- Multiple Objective Genetic Algorithm (MOGA)[152] is the first algorithm to emphasize non-dominated solutions and meanwhile maintains diversity in the non-dominated solutions. The fitness value is assigned to each solution in the population. That is the difference of the MOGA from a classical GA, but the rest is the same.

- Non-dominated Sorting Genetic Algorithm (NSGA)[144, 153] is one of the first evolutionary algorithms. The fitness assignment procedure initiates from the first non-dominated set and successively proceeds to dominated sets. The main advantage of an NSGA is that fitness is assigned according to non-dominated sets. Therefore, the selection procedure in an NSGA progresses towards the

Pareto-optimal front. Moreover, performing sharing in the design space can find phenotypically diverse solutions when using NSGAs. However, criticisms on NSGA were stated by Deb et al.[154]: high computational complexity of non-dominated sorting, lack of elitism, and need for specifying the sharing parameter.

- Niched-Pareto Genetic Algorithm (NPGA)[155] was proposed based on the non-domination concept. VEGAs, NSGAs, and MOGAs use proportionate selection method for the selection operator, while NPGAs use binary tournament selection as they have better growth and convergence properties compared to proportionate selction.

- Elitist Non-Dominated Sorting Genetic Algorithm (NSGA-II)[154] uses an explicit diversity-preserving mechanism instead of using only an elite-preservation strategy as in algorithms described above. The crowded comparison selection operator in NSGA-II selects the best solutions in a mating pool created by combining the parent and child populations. NSGA-II becomes more popular due to its low computational requirements, elitist approach, and parameter-less sharing approach.

- Strength Pareto Evolutionary Algorithm (SPEA)[156] is also an elitist evolutionary algorithm which explicitly maintains a fixed size of external population. This population stores a set of non-dominated solutions and the solutions are compared to newly found non-dominated solutions at every generation. The resulting non-dominated solutions are preserved.

- Pareto-Archived Evolution Strategy (PAES)[157] is a (1+1) evolution algorithm which employs local search and uses a reference archive of previously found solutions for a place in an elite population. Elitism is ensured by the 'plus' strategy and the continuous update of an external archive with better solutions.

Comparison of multi-objective evolutionary algorithms can be found in Zitzler, Deb and Thiele's studies[158, 159], Veldhuizen's study[160], Knowles and Corne's study[157], Deb, Agrawal, Pratap and Meyarivan's study[154], etc.

C. Case Study III - Component Inspection Interval Optimization in the Oil/Gas Separator

In this Section, we perform an optimization study on component inspection interval determination focusing on level control in an oil/ gas separator system. As liquid overflow has been considered one of the major contributors to incidents involving the vapor-liquid separation system, component inspection interval should be optimized to reduce the risk of the oil/gas separator overflow. There are two objective functions in the inspection interval optimization problem in this study; one is the operational risk function in form of probability of separator overflow, and the other is the annual component inspection cost function. There are multiple components involved in the same system. Given the same total amount of annual inspection budget, multiple component inspection scheduling plans could be proposed but only one of them is on the Pareto curve.

1. Optimization Problem Formulation

As mentioned earlier, the objective functions in this multiobjective optimization problem include risk function that is essentially defined in equation 2.20 and cost function. The probability of a component becoming abnormal, p_n, can be obtained by simulation using component failure rate data and be used as a set of constant parameters in the optimization. The probability of overflow when the component n goes abnormal is function of component inspection interval. Variable I_n is defined as $I_n = \frac{365\times 24}{T_n}$, where T_n is the actual inspection interval. Eight different inspection intervals, half daily, daily, weekly, monthly, semi-annually, annually, every two years, and every three years, were used as the inputs for probability simulation to calculate the probability of overflow due to individual component abnormal events. Therefore, function q_{I_n} in equation 2.20 can be obtained by regress of those simulation results to obtain the relationship between q_{I_n} and I_n. Therefore, the risk function is given by:

$$f_1(I) = \sum_{n=1}^{3} p_n q_{I_n} \tag{4.4}$$

Denote component unit inspection cost as C_n, the cost function is given by:

$$f_2(I) = \sum_{n=1}^{3} C_n I_n \tag{4.5}$$

Generally speaking, inspection can be categorized as operator inspection and mechanical inspection. Operator inspection has no impact on failure rate; it is intended for detecting abnormal event. The cost for operator inspection is usually cheap; it does not include the cost for mechanical checks and repairs. However, mechanical inspection inspection does affect failure rate, and it is usually expensive. The cost function in this study refers to operator inspection only.

The operator inspection cost includes only the actual labor and material required to inspect plant equipment. It does not include the impact of inspection or maintenance on availability, production capacity, operating costs, product quality and the myriad of other factors that limit plant effectiveness. The component inspection unit cost are approximately given from cost history as:

$$C_{1:pump} = 141.5\$/task \tag{4.6}$$

$$C_{2:CV} = 107.5\$/task \tag{4.7}$$

$$C_{3:LT} = 100\$/task \tag{4.8}$$

The p_n is the probability of nth component becoming abnormal. The $p_n s$ for all components in the case study were computed using reliability data and listed here:

$$p_{1:pump} = 0.93 \tag{4.9}$$

$$p_{2:CV} = 0.33 \tag{4.10}$$

$$p_{3:LT} = 0.14 \tag{4.11}$$

In order to obtain the $q_n s$ through regression, eight different inspection intervals for each component in this separator system, pump, CV and LT, are tested: half day, one day, one week, one month, half year, one year, two years and three years. The simulation results are shown in Figures 40,41,42. The coefficients and r-square values of the exponential regression are summarized in Table XV. Therefore, the first objective function, the probability of separator overflow can be written as:

$$\begin{aligned} f_1(I) = 0.93(0.06211e^{-0.003565*141.5I_1}) + 0.33(0.5434e^{-0.0001924*107.5I_2} + \\ 0.4534e^{-5.674e-6*107.5I_2}) + 0.14(0.8047e^{-9.283e-5*100I_3}) \end{aligned} \tag{4.12}$$

The second objective function, the total annual component inspection cost is given by:

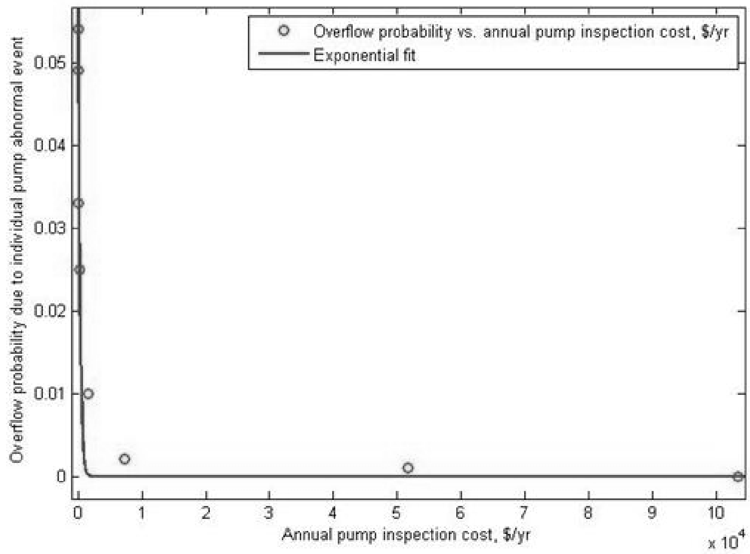

Fig. 40. Overflow probability due to individual pump abnormal event regression on annual individual pump inspection cost.

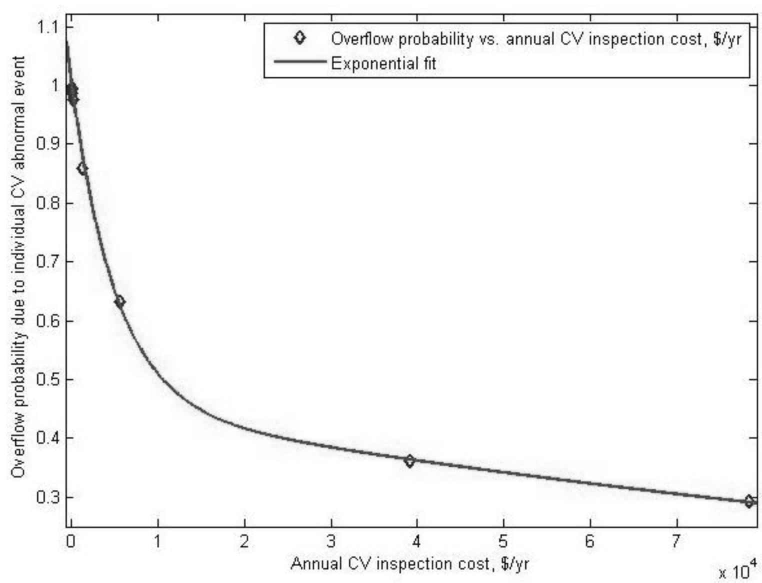

Fig. 41. Overflow probability due to individual CV abnormal event regression on annual individual CV inspection cost.

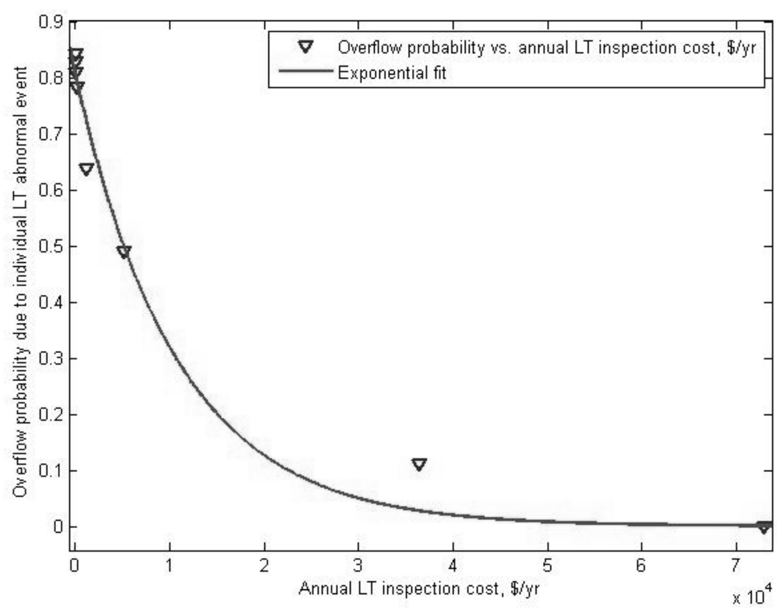

Fig. 42. Overflow probability due to individual LT abnormal event regression on annual individual LT inspection cost.

Table XV. The coefficients and r-square values of regression on the overflow probability as function of individual component inspection cost.

	Exponential fitting a*exp(b*x) + c*exp(d*x)				
	a	**b**	**c**	**d**	**r-square value**
pump	0.06211	-0.003565	0	0	0.9609
CV	0.5434	-0.0001924	0.4534	-5.67E-06	0.9996
LT	0.8047	-9.28E-05	0	0	0.9801

$$f_2(I) = 141.5I_1 + 107.5I_2 + 100I_3 \tag{4.13}$$

2. Optimization Results and Discussion

In the weighted sum method (WSM), a weighting factor, α, is introduced to describe the weights of objective functions under consideration in the optimization. Thus, this multiobjective optimization problem is transformed to a single objective problems:

$$\begin{aligned} f = \alpha(0.93(0.06211e^{-0.003565*141.5I_1}) + 0.33(0.5434e^{-0.0001924*107.5I_2} + \\ 0.4534e^{-5.674e-6*107.5I_2}) + 0.14(0.8047e^{-9.283e-5*100I_3})) + \\ (1-\alpha)(141.5I_1 + 107.5I_2 + 100I_3) \end{aligned} \tag{4.14}$$

The optimization problem is formulated in AMPL[161] and solved using IPOPT[162]. The α value starts from 0.001 and is adjusted at an increment of 0.001 up to 1, and thus 1000 data points were computed to generated the Pareto curve. This Pareto curve is presented in Figure 43.

Kanpur Genetic Algorithms Laboratory developed NSGA - II: an evolutionary algorithm for solving multiobjective optimization problem is used in this study. Pareto curves at different generations generated using NSGA -II in C language are shown in Figure 43. The simulation data points and a Pareto curve generated based on these points is also shown in Figure 43.

The shape of the curves represents the expected trade-off situation where the annual total component inspection cost is to be judged against operational risk. The Pareto curves by both NSGA-II at 500 generation and WSM show a smooth behavior.

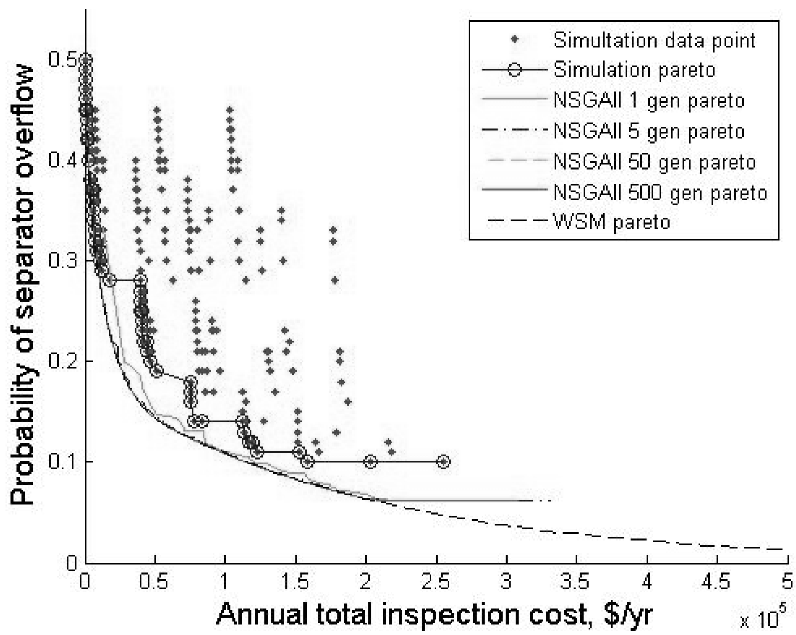

Fig. 43. Pareto curves generated using generic algorithm at different generations and using the WSM.

The lower generation Pareto curves by NSGA-II, as well as all the simulation results in Figure 43, are above the NSGA-II 500 gen and the WSM Pareto curves. However, NSGA-II only achieves the local optimal as it failed to find the optimal solutions in the entire feasible search space. The WSM Pareto curve and the 500 gen NSGA-II Pareto curve overlap with each other before the total annual inspection cost exceeds around $200,000\$/yr$. Beyond this budget, the WSM optimal solutions are below NSGA-II Pareto curve. The risk reduction rate before the overflow probability decreased to 0.1 is dramatically larger than that afterwards. Increase the inspection budget from $\sim 175\$/yr$ to $\sim 14,507\$/yr$ and the probability of separator overflow will be reduced by about 2 times from 0.48 to 0.25. A further decrease of the probability from 0.25 to 0.1 requires an increase in the budget of 10 times more to $\sim 114,924\$/yr$. However, the risk reduction as a function of increasing inspection budget is relatively slow after the overflow probability is reduced below 0.1. Doubling the inspection budget to $\sim 231,023\$/yr$ only reduces the overflow probability from 0.1 to 0.05. The total annual inspection has to be increased to $\sim 860,261\$/yr$ to further decrease the overflow probability to 0.002. The functions and design variables associated with each solution on the WSM Pareto curve were plotted in Figures 44, 45, 46, and 47. A single point in function space Figure 44 has a unique mapping to a single point in Figures 45,46,and 47 respectively. The risk is reduced while the inspection intervals of all three components are monotonically decreasing. However, the inspection intervals for three components have different sensitive zone. Decreasing pump inspection interval has a linear pattern impact on risk reduction. Inspection interval within $50hr \sim 10hr$ for CV is the most sensitive range for risk reduction as in this range risk reduction has sharper slope than the out of this range. Decreasing the LT inspection interval has larger impact on the risk reduction when the probability of overflow is above 0.25. Below 0.25, the probability of overflow is reduced at a slower pace as the LT inspection interval decreases. In order to keep probability of overflow around or below 0.1, the inspection intervals of all three components need to be tuned up simultaneously for better cost effective inspection scheduling.

D. Summary

This Chapter has presented mathematical modeling for assessing the operational risk, focusing on overflow scenario in oil/gas separation system, and optimizing the component inspection interval in the same system. The weighted sum method and evolutionary algorithms were utilized to solve the multiobjective optimization problem. WSM achieved better optimal solutions in an oil/gas separation system, whereas the evolutionary algorithm only found the local optimal solutions of the inspection

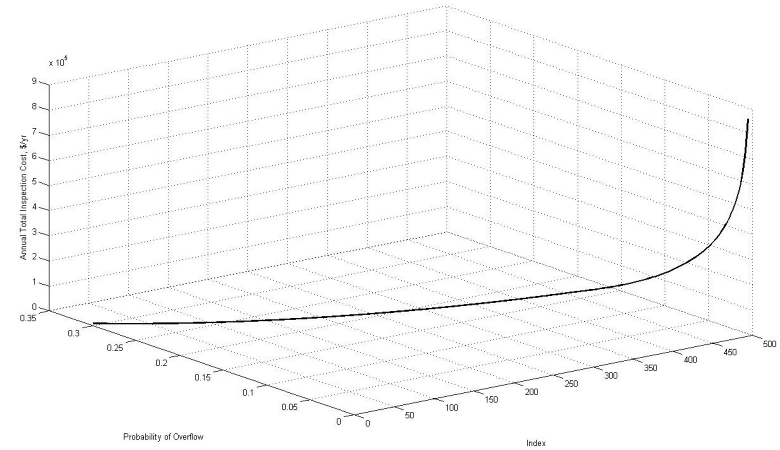

Fig. 44. The WSM Pareto-optimal solutions in function space.

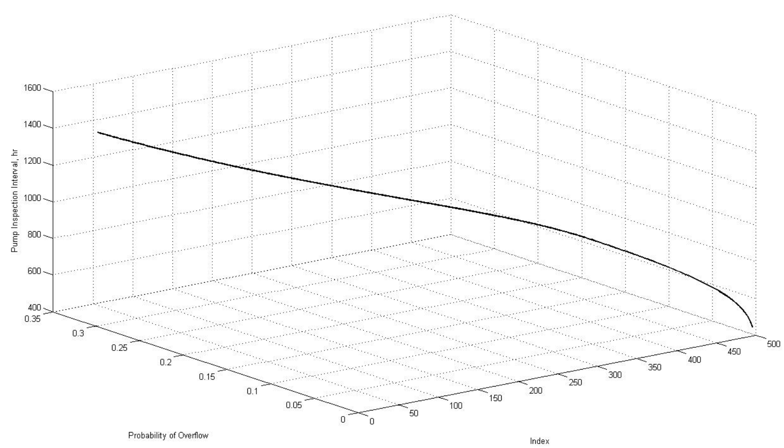

Fig. 45. Design variable I pump inspection interval associated with the WSM Pareto-optimal solutions.

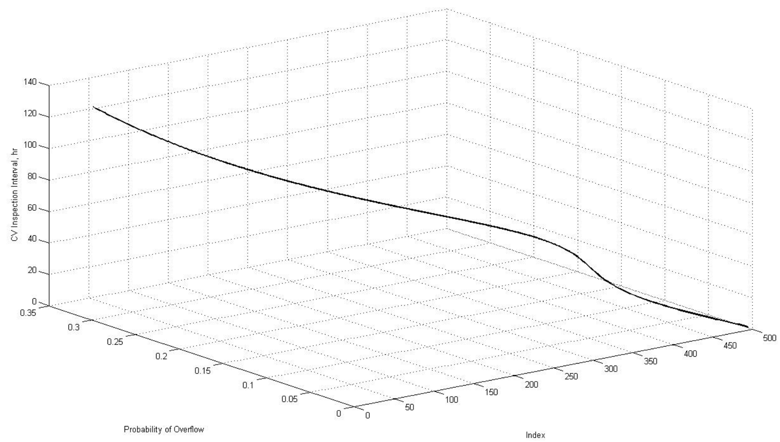

Fig. 46. Design variable II CV inspection interval associated with the WSM Pareto-optimal solutions.

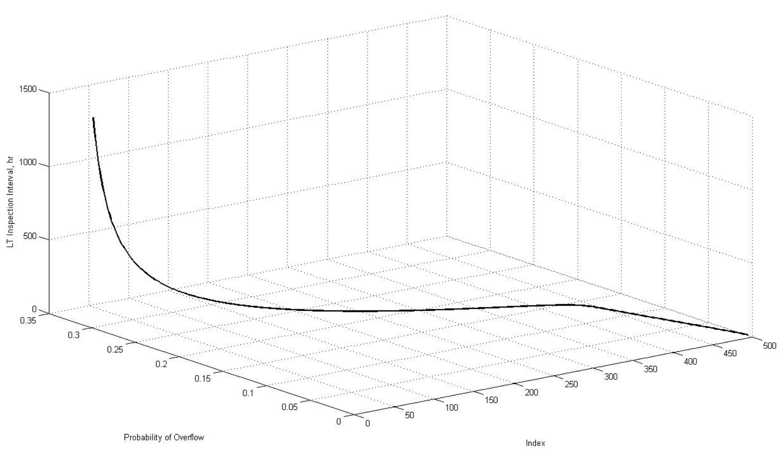

Fig. 47. Design variable III LT inspection interval associated with the WSM Pareto-optimal solutions.

interval optimization problem in this MOOP case study. The results of the optimization process yield an immediate choice of component inspection interval sets for whatever relative weighting is considered as the most appropriate one for the actual design problem by the final decision makers. The pump was identified as the highest priority component on the inspection interval management for risk reduction in the oil/gas separation system in the case study.

CHAPTER V

SUMMARY AND RECOMMENDATION

The main subject of this dissertation is to improve the current quantitative risk assessment approaches and develop a methodology for dynamic operational risk assessment in oil/gas and chemical industries. The previous three chapters following the introduction chapter are self-contained but relative in the same vein of the innovation in quantitative risk assessment research.

Chapter II is the main contribution of this dissertation. This chapter develops a complete conceptual DORA framework for quantitative risk assessment of dynamic processes in oil/gas and chemical industries. This methodology can be implemented as an ongoing model to guide implementation and continual updating of safety program components such as risk-based and cost-effective monitoring, testing, maintenance, reliability assessment, component replacement timing, shutdown times, and timing of other operational decisions including selection of minimal reliability criteria during maintenance shutdowns. The DORA framework emphasizes the importance to identify hazards, scenarios and component failure mode combinations in the system in a sequential order. This preliminary analysis on hazardous scenarios and component performance consists of the logic structure behind DORA probabilistic modeling. DORA probabilistic modeling design is the most novel contribution in this chapter. It well considers the time-dependent factors in a dynamic process, and models the process using a generic algorithm which is not limited to the currently used Markovian approaches. The component performance is not modeled by any stochastic models with many restrictions, such as a Markovian chain or a Semi-Markovian chain without the restriction on exponential distribution on sojourn time. On the contrary, any component performance process, including the ones carry Markovian properties, can be modeled using DORA probabilistic modeling proposed in this dissertation. Simultaneous component failures also can be detected using the stochastic simulation in DORA probabilistic modeling. Furthermore, even though the author is not the first one to propose the integration of stochastic modeling on component performance and dynamics modeling on the physical process, the way to achieve this integration is an innovation. At the steady state, the evolution of process variable is governed by the same dynamics equation set. However, when the component precursor exists, the trajectory of process variable does not follow the dynamics equations for steady state anymore. DORA probabilistic modeling monitors the component precursors and simulates the probability of operation out of control based on the information predicted when and only when component abnormal event occurs. In doing this, computational space is saved. This advantage will be more revealed when DORA is applies to a complex system. Matlab is the software used for programming in this dissertation for the level control in oil/gas separator case study. However, since the system in the case study is relatively small compared to what this method could be apply for, the programming needs to be improved to achieve faster computation speed for analysis on more complicated systems. Therefore, recommendations on the future work for the DORA probabilistic modeling include the application on a complex system and coding the algorithm using a more advanced computer language to save computation time.

Uncertainty is an emerging topic in quantitative risk assessment research area nowadays. Throughout the whole dissertation, uncertainty associated with a QRA is considered when developing any quantitative modeling in DORA framework. For example, the inputs of DORA probabilistic modeling are component reliability data in form of distributions instead of point values, the analysis on uncertainty associated with selecting distribution type for the DORA probabilistic modeling inputs, and the uncertainty treatment in the consequence modeling in DORA framework, etc. Algorithm was designed for uncertainty characterization when one applies incident consequence modeling during the implementation of DORA framework. It was discussed in Chapter II. A more comprehensive discussion on uncertainty characterization and reduction in quantitative risk assessment is discussed in Chapter III. The contribution of the author in this area is that a Bayesian approach for uncertainty reduction using plant specific real time reliability data for Bayesian updating is proposed to enhance our knowledge on the system continually, providing industry a practical tool to characterize and reduce uncertainty for improving overall mishap probability prediction.

Chapter IV is an extension of Chapter II. Cost-benefit analysis is one of the steps composing DORA framework and is illustrated in Chapter IV by a case study. The work in Chapter IV shows how one can implement DORA probabilistic modeling for practical decision making. The recommendation for further optimization work is to include the cost due to unavailability of the component, the potential profit loss on the shutdown time due to any repair activities, and the cost due to repair if any abnormal event is detected, etc. in order to better formulate the cost function. In this case, excessively more industrial data may needed for the future work.

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APPENDIX A

THE WSM PARETO CURVE

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.001	0.499	7.900E-04	4380000000	4380000000	2920000000
0.002	0.499	7.700E-04	4380000000	4380000000	2920000000
0.003	0.499	7.800E-04	4380000000	4380000000	2920000000
0.004	0.499	8.000E-04	4380000000	4380000000	2920000000
0.005	0.499	8.100E-04	4380000000	4380000000	2920000000
0.006	0.499	8.300E-04	4380000000	4380000000	2920000000
0.007	0.499	8.500E-04	4380000000	4380000000	2920000000
0.008	0.499	8.700E-04	4380000000	4380000000	2920000000
0.009	0.499	8.900E-04	2920000000	4380000000	2920000000
0.01	0.499	9.100E-04	2920000000	4380000000	2920000000
0.011	0.499	9.400E-04	2920000000	4380000000	2920000000
0.012	0.499	9.700E-04	2920000000	4380000000	2920000000
0.013	0.499	1.010E-03	2920000000	4380000000	2920000000
0.014	0.499	1.050E-03	2190000000	4380000000	2920000000
0.015	0.499	1.090E-03	2190000000	4380000000	2920000000
0.016	0.499	1.150E-03	2190000000	2920000000	2920000000
0.017	0.499	1.210E-03	1752000000	2920000000	2920000000
0.018	0.499	1.280E-03	1752000000	2920000000	2920000000

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.019	0.499	1.360E-03	1460000000	2920000000	2920000000
0.02	0.499	1.450E-03	1460000000	2920000000	2920000000
0.021	0.499	1.560E-03	1251428571	2920000000	2920000000
0.022	0.499	1.700E-03	1095000000	2920000000	2920000000
0.023	0.499	1.860E-03	973333333	2920000000	2920000000
0.024	0.499	2.040E-03	796363636	2920000000	2920000000
0.025	0.499	2.270E-03	730000000	2920000000	2920000000
0.026	0.499	2.550E-03	625714286	2920000000	2920000000
0.027	0.499	2.900E-03	515294118	2920000000	2920000000
0.028	0.499	4.300E-04	4380000000	8760000000	8760000000
0.029	0.499	4.400E-04	4380000000	8760000000	8760000000
0.03	0.499	4.600E-04	4380000000	8760000000	8760000000
0.031	0.499	4.700E-04	4380000000	8760000000	8760000000
0.032	0.499	4.900E-04	4380000000	8760000000	8760000000
0.033	0.499	5.200E-04	4380000000	8760000000	8760000000
0.034	0.499	5.400E-04	4380000000	8760000000	8760000000
0.035	0.499	1.590E-03	1251428571	2920000000	2920000000
0.036	0.499	1.690E-03	1095000000	2920000000	2920000000
0.037	0.499	1.820E-03	973333333	2920000000	2920000000
0.038	0.499	1.980E-03	876000000	2920000000	2920000000
0.039	0.499	2.190E-03	796363636	2920000000	2920000000
0.04	0.499	2.500E-03	625714286	2920000000	2920000000
0.041	0.499	3.010E-03	515294118	2920000000	2920000000
0.042	0.499	4.090E-03	350400000	2920000000	2920000000

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.043	0.499	7.410E-03	182500000	2920000000	2920000000
0.044	0.499	2.060E-03	673846154	8760000000	8760000000
0.045	0.499	1.112E-02	118378378	2920000000	2920000000
0.046	0.499	4.209E-02	29594595	8760000000	8760000000
0.047	0.498	4.343E+00	285444	8760000000	8760000000
0.048	0.497	1.054E+01	117587	2920000000	2920000000
0.049	0.496	1.661E+01	74610	8760000000	8760000000
0.05	0.495	2.259E+01	54883	2920000000	2920000000
0.051	0.494	2.843E+01	43601	2920000000	2920000000
0.052	0.493	3.417E+01	36276	2920000000	2920000000
0.053	0.492	3.981E+01	31138	2920000000	2920000000
0.054	0.491	4.535E+01	27334	2920000000	2920000000
0.055	0.490	5.079E+01	24405	2920000000	2920000000
0.056	0.489	5.614E+01	22079	2920000000	2920000000
0.057	0.488	6.140E+01	20187	2920000000	2920000000
0.058	0.487	6.658E+01	18617	2920000000	2920000000
0.059	0.486	7.167E+01	17294	2920000000	2920000000
0.06	0.486	7.669E+01	16164	2920000000	2920000000
0.061	0.485	8.162E+01	15187	2920000000	2920000000
0.062	0.484	8.648E+01	14333	2920000000	2920000000
0.063	0.483	9.127E+01	13581	2920000000	2920000000
0.064	0.483	9.599E+01	12914	2920000000	2920000000
0.065	0.482	1.006E+02	12317	2920000000	2920000000
0.066	0.481	1.052E+02	11781	2920000000	2920000000

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.067	0.481	1.097E+02	11296	2920000000	2920000000
0.068	0.480	1.142E+02	10855	2920000000	2920000000
0.069	0.479	1.186E+02	10453	2920000000	2920000000
0.07	0.479	1.229E+02	10084	2920000000	2920000000
0.071	0.478	1.272E+02	9744	2920000000	2920000000
0.072	0.478	1.314E+02	9431	2920000000	2920000000
0.073	0.477	1.356E+02	9141	2920000000	2920000000
0.074	0.477	1.397E+02	8871	2920000000	2920000000
0.075	0.476	1.438E+02	8620	2190000000	2920000000
0.076	0.476	1.478E+02	8386	2190000000	2920000000
0.077	0.475	1.518E+02	8167	2190000000	2920000000
0.078	0.475	1.557E+02	7961	2190000000	2920000000
0.079	0.474	1.596E+02	7767	2190000000	2920000000
0.08	0.474	1.634E+02	7585	2190000000	2920000000
0.081	0.473	1.672E+02	7413	2190000000	2920000000
0.082	0.473	1.710E+02	7251	8760000000	8760000000
0.083	0.473	1.747E+02	7097	8760000000	8760000000
0.084	0.472	1.783E+02	6951	8760000000	8760000000
0.085	0.472	1.819E+02	6813	8760000000	8760000000
0.086	0.471	1.855E+02	6681	8760000000	8760000000
0.087	0.471	1.891E+02	6555	8760000000	8760000000
0.088	0.471	1.926E+02	6436	8760000000	8760000000
0.089	0.470	1.961E+02	6322	8760000000	8760000000
0.09	0.470	1.995E+02	6213	8760000000	8760000000

alpha	**risk**	**cost, \$/yr**	**T1, h**	**T2, h**	**T3, h**
0.091	0.470	2.029E+02	6108	8760000000	8760000000
0.092	0.469	2.063E+02	6008	8760000000	8760000000
0.093	0.469	2.096E+02	5913	8760000000	8760000000
0.094	0.469	2.130E+02	5821	8760000000	8760000000
0.095	0.468	2.162E+02	5733	8760000000	8760000000
0.096	0.468	2.195E+02	5648	8760000000	8760000000
0.097	0.468	2.227E+02	5566	8760000000	8760000000
0.098	0.467	2.259E+02	5488	4380000000	8760000000
0.099	0.467	2.290E+02	5412	4380000000	8760000000
0.1	0.467	2.322E+02	5339	4380000000	8760000000
0.101	0.467	2.353E+02	5268	4380000000	8760000000
0.102	0.466	2.384E+02	5200	4380000000	8760000000
0.103	0.466	2.414E+02	5135	4380000000	8760000000
0.104	0.466	2.444E+02	5071	4380000000	8760000000
0.105	0.466	2.474E+02	5010	4380000000	8760000000
0.106	0.465	2.504E+02	4950	4380000000	8760000000
0.107	0.465	2.533E+02	4893	4380000000	8760000000
0.108	0.465	2.563E+02	4837	4380000000	8760000000
0.109	0.465	2.592E+02	4783	4380000000	8760000000
0.11	0.464	2.620E+02	4730	4380000000	8760000000
0.111	0.464	2.649E+02	4679	4380000000	8760000000
0.112	0.464	2.677E+02	4630	4380000000	8760000000
0.113	0.464	2.705E+02	4582	4380000000	8760000000
0.114	0.463	2.733E+02	4535	4380000000	8760000000

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.115	0.463	2.761E+02	4490	4380000000	8760000000
0.116	0.463	2.788E+02	4445	4380000000	8760000000
0.117	0.463	2.816E+02	4402	4380000000	8760000000
0.118	0.463	2.843E+02	4360	4380000000	8760000000
0.119	0.462	2.870E+02	4320	4380000000	8760000000
0.12	0.462	2.896E+02	4280	4380000000	8760000000
0.121	0.462	2.923E+02	4241	4380000000	8760000000
0.122	0.462	2.949E+02	4203	4380000000	8760000000
0.123	0.462	2.975E+02	4167	4380000000	8760000000
0.124	0.461	3.001E+02	4131	4380000000	8760000000
0.125	0.461	3.027E+02	4095	4380000000	8760000000
0.126	0.461	3.052E+02	4061	1460000000	2920000000
0.127	0.461	3.078E+02	4028	1460000000	2920000000
0.128	0.461	3.103E+02	3995	1460000000	2920000000
0.129	0.461	3.128E+02	3963	1460000000	2920000000
0.13	0.460	3.153E+02	3932	1460000000	2920000000
0.131	0.460	3.177E+02	3901	1460000000	2920000000
0.132	0.460	3.202E+02	3871	1460000000	2920000000
0.133	0.460	3.226E+02	3842	1460000000	2920000000
0.134	0.460	3.251E+02	3813	1460000000	2920000000
0.135	0.460	3.275E+02	3785	1251428571	2920000000
0.136	0.459	3.299E+02	3758	1251428571	2920000000
0.137	0.459	3.323E+02	3731	1251428571	2920000000
0.138	0.459	3.346E+02	3704	1251428571	2920000000

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.139	0.459	3.370E+02	3678	1251428571	2190000000
0.14	0.459	3.393E+02	3653	1251428571	2190000000
0.141	0.459	3.416E+02	3628	1251428571	2190000000
0.142	0.459	3.439E+02	3604	1251428571	2190000000
0.143	0.458	3.462E+02	3580	1251428571	2190000000
0.144	0.458	3.485E+02	3557	1095000000	2190000000
0.145	0.458	3.508E+02	3534	1095000000	2190000000
0.146	0.458	3.530E+02	3511	1095000000	2190000000
0.147	0.458	3.553E+02	3489	1095000000	2190000000
0.148	0.458	3.575E+02	3467	1095000000	2190000000
0.149	0.458	3.597E+02	3446	1095000000	2190000000
0.15	0.458	3.619E+02	3425	1095000000	2190000000
0.151	0.457	3.641E+02	3404	973333333	2190000000
0.152	0.457	3.663E+02	3384	973333333	2190000000
0.153	0.457	3.685E+02	3364	973333333	2190000000
0.154	0.457	3.706E+02	3344	973333333	2190000000
0.155	0.457	3.728E+02	3325	973333333	2190000000
0.156	0.457	3.749E+02	3306	876000000	2190000000
0.157	0.457	3.771E+02	3287	876000000	2190000000
0.158	0.457	3.792E+02	3269	876000000	2190000000
0.159	0.456	3.813E+02	3251	876000000	2190000000
0.16	0.456	3.834E+02	3233	876000000	2190000000
0.161	0.456	3.854E+02	3216	796363636	2190000000
0.162	0.456	3.875E+02	3199	796363636	2190000000

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.163	0.456	3.896E+02	3182	796363636	2190000000
0.164	0.456	3.916E+02	3165	730000000	2190000000
0.165	0.456	3.937E+02	3149	730000000	2190000000
0.166	0.456	3.957E+02	3133	730000000	2190000000
0.167	0.456	3.977E+02	3117	673846154	2190000000
0.168	0.455	3.997E+02	3101	673846154	2190000000
0.169	0.455	4.017E+02	3085	673846154	2190000000
0.17	0.455	4.037E+02	3070	625714286	2190000000
0.171	0.455	4.057E+02	3055	625714286	2190000000
0.172	0.455	4.077E+02	3040	584000000	2190000000
0.173	0.455	4.097E+02	3026	584000000	2190000000
0.174	0.455	4.116E+02	3011	547500000	2190000000
0.175	0.455	4.136E+02	2997	547500000	2190000000
0.176	0.455	4.155E+02	2983	515294118	2190000000
0.177	0.455	4.174E+02	2970	486666667	2190000000
0.178	0.455	4.193E+02	2956	486666667	2190000000
0.179	0.454	4.213E+02	2942	461052632	2190000000
0.18	0.454	4.232E+02	2929	438000000	2190000000
0.181	0.454	4.251E+02	2916	417142857	2190000000
0.182	0.454	4.269E+02	2903	398181818	2190000000
0.183	0.454	4.288E+02	2891	417142857	2190000000
0.184	0.454	4.307E+02	2878	380869565	2190000000
0.185	0.454	4.326E+02	2866	365000000	2190000000
0.186	0.454	4.344E+02	2853	350400000	2190000000

alpha	**risk**	**cost, $/yr**	**T1, h**	**T2, h**	**T3, h**
0.187	0.454	4.363E+02	2841	336923077	2190000000
0.188	0.454	4.381E+02	2829	312857143	2190000000
0.189	0.454	4.399E+02	2818	292000000	2190000000
0.19	0.454	4.418E+02	2806	273750000	2190000000
0.191	0.453	4.436E+02	2794	257647059	2190000000
0.192	0.453	4.454E+02	2783	236756757	2190000000
0.193	0.453	4.472E+02	2772	224615385	2190000000
0.194	0.453	4.490E+02	2761	203720930	2190000000
0.195	0.453	4.508E+02	2750	190434783	2190000000
0.196	0.453	4.526E+02	2739	171764706	2190000000
0.197	0.453	4.544E+02	2728	156428571	2190000000
0.198	0.453	4.561E+02	2718	141290323	2190000000
0.199	0.453	4.579E+02	2707	126956522	2190000000
0.2	0.453	4.597E+02	2697	113766234	2190000000
0.201	0.453	4.614E+02	2687	100689655	2190000000
0.202	0.453	4.631E+02	2676	88484848	2190000000
0.203	0.453	4.649E+02	2666	76842105	2190000000
0.204	0.453	4.666E+02	2657	796363636	4380000000
0.205	0.452	4.683E+02	2647	730000000	4380000000
0.206	0.452	4.700E+02	2637	673846154	4380000000
0.207	0.452	4.718E+02	2628	625714286	4380000000
0.208	0.452	4.735E+02	2618	584000000	4380000000
0.209	0.452	4.752E+02	2609	547500000	4380000000
0.21	0.452	4.769E+02	2599	486666667	4380000000

alpha	**risk**	**cost, $/yr**	**T1, h**	**T2, h**	**T3, h**
0.211	0.452	4.785E+02	2590	438000000	4380000000
0.212	0.452	4.802E+02	2581	143606557	2190000000
0.213	0.452	4.819E+02	2572	126956522	2190000000
0.214	0.452	4.836E+02	2563	109500000	2190000000
0.215	0.452	4.852E+02	2555	90309278	2190000000
0.216	0.452	4.869E+02	2546	67906977	2190000000
0.217	0.452	4.886E+02	2537	40183486	2190000000
0.218	0.452	4.903E+02	2529	13094170	1752000000
0.219	0.452	4.919E+02	2520	23485255	1752000000
0.22	0.452	4.935E+02	2512	15840868	4380000000
0.221	0.451	5.105E+02	2504	61218	4380000000
0.222	0.450	5.430E+02	2495	20371	1752000000
0.223	0.449	5.754E+02	2487	12226	1752000000
0.224	0.448	6.076E+02	2479	8747	1752000000
0.225	0.446	6.398E+02	2471	6813	1752000000
0.226	0.445	6.719E+02	2463	5582	1752000000
0.227	0.444	7.039E+02	2456	4729	1752000000
0.228	0.443	7.358E+02	2448	4105	1752000000
0.229	0.442	7.676E+02	2440	3627	1752000000
0.23	0.441	7.993E+02	2433	3250	1752000000
0.231	0.440	8.310E+02	2425	2945	4380000000
0.232	0.439	8.625E+02	2418	2692	4380000000
0.233	0.438	8.939E+02	2410	2481	4380000000
0.234	0.437	9.253E+02	2403	2300	4380000000

alpha	**risk**	**cost, $/yr**	**T1, h**	**T2, h**	**T3, h**
0.235	0.436	9.566E+02	2396	2144	4380000000
0.236	0.435	9.877E+02	2388	2009	4380000000
0.237	0.434	1.019E+03	2381	1890	4380000000
0.238	0.433	1.050E+03	2374	1784	4380000000
0.239	0.432	1.081E+03	2367	1690	4380000000
0.24	0.431	1.112E+03	2360	1606	1752000000
0.241	0.430	1.142E+03	2353	1530	1752000000
0.242	0.429	1.173E+03	2347	1461	1752000000
0.243	0.428	1.204E+03	2340	1398	1752000000
0.244	0.427	1.234E+03	2333	1340	1752000000
0.245	0.426	1.265E+03	2326	1287	1752000000
0.246	0.425	1.295E+03	2320	1238	1752000000
0.247	0.424	1.325E+03	2313	1193	1752000000
0.248	0.423	1.355E+03	2307	1151	1752000000
0.249	0.422	1.385E+03	2300	1112	1752000000
0.25	0.421	1.415E+03	2294	1076	1752000000
0.251	0.421	1.445E+03	2288	1042	1752000000
0.252	0.420	1.475E+03	2281	1010	1752000000
0.253	0.419	1.505E+03	2275	981	1752000000
0.254	0.418	1.535E+03	2269	953	1752000000
0.255	0.417	1.564E+03	2263	926	1752000000
0.256	0.416	1.594E+03	2257	901	1752000000
0.257	0.415	1.624E+03	2251	878	1752000000
0.258	0.415	1.653E+03	2245	855	1752000000

alpha	risk	cost, \$/yr	T1, h	T2, h	T3, h
0.259	0.414	1.682E+03	2239	834	1752000000
0.26	0.413	1.712E+03	2233	814	1752000000
0.261	0.412	1.741E+03	2227	795	1752000000
0.262	0.411	1.770E+03	2221	777	1752000000
0.263	0.410	1.799E+03	2216	760	1460000000
0.264	0.410	1.828E+03	2210	743	1460000000
0.265	0.409	1.857E+03	2204	727	1460000000
0.266	0.408	1.886E+03	2199	712	1460000000
0.267	0.407	1.915E+03	2193	698	1460000000
0.268	0.406	1.944E+03	2187	684	1460000000
0.269	0.406	1.972E+03	2182	671	1460000000
0.27	0.405	2.001E+03	2177	658	1460000000
0.271	0.404	2.030E+03	2171	646	1460000000
0.272	0.403	2.058E+03	2166	634	1460000000
0.273	0.403	2.087E+03	2160	622	1460000000
0.274	0.402	2.115E+03	2155	612	1460000000
0.275	0.401	2.143E+03	2150	601	1460000000
0.276	0.400	2.172E+03	2145	591	1460000000
0.277	0.400	2.200E+03	2139	581	1460000000
0.278	0.399	2.228E+03	2134	572	1460000000
0.279	0.398	2.256E+03	2129	563	1460000000
0.28	0.397	2.284E+03	2124	554	1460000000
0.281	0.397	2.312E+03	2119	545	1460000000
0.282	0.396	2.340E+03	2114	537	1460000000

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.283	0.395	2.368E+03	2109	529	1460000000
0.284	0.394	2.396E+03	2104	521	1460000000
0.285	0.394	2.424E+03	2099	514	1460000000
0.286	0.393	2.451E+03	2094	506	1460000000
0.287	0.392	2.479E+03	2089	499	1460000000
0.288	0.392	2.507E+03	2085	493	1460000000
0.289	0.391	2.534E+03	2080	486	1460000000
0.29	0.390	2.562E+03	2075	479	1460000000
0.291	0.390	2.589E+03	2070	473	1460000000
0.292	0.389	2.616E+03	2066	467	1460000000
0.293	0.388	2.644E+03	2061	461	1460000000
0.294	0.388	2.671E+03	2056	455	1460000000
0.295	0.387	2.698E+03	2052	450	1460000000
0.296	0.386	2.726E+03	2047	444	1251428571
0.297	0.386	2.753E+03	2043	439	1251428571
0.298	0.385	2.780E+03	2038	434	1251428571
0.299	0.385	2.807E+03	2034	429	1251428571
0.3	0.384	2.834E+03	2029	424	1251428571
0.301	0.383	2.861E+03	2025	419	1251428571
0.302	0.383	2.888E+03	2020	414	1251428571
0.303	0.382	2.915E+03	2016	409	1251428571
0.304	0.381	2.941E+03	2012	405	1251428571
0.305	0.381	2.968E+03	2007	401	1251428571
0.306	0.380	2.995E+03	2003	396	1251428571

alpha	risk	cost, \$/yr	T1, h	T2, h	T3, h
0.307	0.380	3.022E+03	1999	392	1251428571
0.308	0.379	3.048E+03	1995	388	1251428571
0.309	0.378	3.075E+03	1990	384	1251428571
0.31	0.378	3.101E+03	1986	380	1251428571
0.311	0.377	3.128E+03	1982	376	1251428571
0.312	0.377	3.154E+03	1978	373	1251428571
0.313	0.376	3.181E+03	1974	369	1251428571
0.314	0.375	3.207E+03	1970	365	1251428571
0.315	0.375	3.234E+03	1966	362	1251428571
0.316	0.374	3.260E+03	1962	358	1251428571
0.317	0.374	3.286E+03	1958	355	1251428571
0.318	0.373	3.312E+03	1954	352	1251428571
0.319	0.373	3.338E+03	1950	348	1251428571
0.32	0.372	3.365E+03	1946	345	1095000000
0.321	0.371	3.391E+03	1942	342	1095000000
0.322	0.371	3.417E+03	1938	339	1095000000
0.323	0.370	3.443E+03	1934	336	1095000000
0.324	0.370	3.469E+03	1930	333	1095000000
0.325	0.369	3.495E+03	1926	330	1095000000
0.326	0.369	3.521E+03	1922	327	1095000000
0.327	0.368	3.547E+03	1919	325	1095000000
0.328	0.368	3.572E+03	1915	322	1095000000
0.329	0.367	3.598E+03	1911	319	1095000000

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.33	0.367	3.624E+03	1907	317	1095000000
0.331	0.366	3.650E+03	1904	314	1095000000
0.332	0.366	3.675E+03	1900	312	1095000000
0.333	0.365	3.701E+03	1896	309	1095000000
0.334	0.365	3.727E+03	1893	307	1095000000
0.335	0.364	3.752E+03	1889	304	1095000000
0.336	0.364	3.778E+03	1885	302	1095000000
0.337	0.363	3.803E+03	1882	299	1095000000
0.338	0.363	3.829E+03	1878	297	1095000000
0.339	0.362	3.854E+03	1875	295	973333333
0.34	0.362	3.880E+03	1871	293	973333333
0.341	0.361	3.905E+03	1868	291	973333333
0.342	0.361	3.931E+03	1864	288	973333333
0.343	0.360	3.956E+03	1861	286	973333333
0.344	0.360	3.981E+03	1857	284	973333333
0.345	0.359	4.006E+03	1854	282	973333333
0.346	0.359	4.032E+03	1850	280	973333333
0.347	0.358	4.057E+03	1847	278	973333333
0.348	0.358	4.082E+03	1843	276	973333333
0.349	0.357	4.107E+03	1840	274	973333333
0.35	0.357	4.132E+03	1837	272	973333333
0.351	0.356	4.158E+03	1833	270	973333333
0.352	0.356	4.183E+03	1830	269	973333333

alpha	risk	cost, \$/yr	T1, h	T2, h	T3, h
0.353	0.355	4.208E+03	1827	267	876000000
0.354	0.355	4.233E+03	1823	265	876000000
0.355	0.354	4.258E+03	1820	263	876000000
0.356	0.354	4.283E+03	1817	262	876000000
0.357	0.354	4.308E+03	1814	260	876000000
0.358	0.353	4.333E+03	1810	258	876000000
0.359	0.353	4.357E+03	1807	256	876000000
0.36	0.352	4.382E+03	1804	255	876000000
0.361	0.352	4.407E+03	1801	253	876000000
0.362	0.351	4.432E+03	1798	252	876000000
0.363	0.351	4.457E+03	1794	250	876000000
0.364	0.350	4.481E+03	1791	249	796363636
0.365	0.350	4.506E+03	1788	247	796363636
0.366	0.350	4.531E+03	1785	245	796363636
0.367	0.349	4.556E+03	1782	244	796363636
0.368	0.349	4.580E+03	1779	242	796363636
0.369	0.348	4.605E+03	1776	241	796363636
0.37	0.348	4.630E+03	1773	240	796363636
0.371	0.348	4.654E+03	1770	238	796363636
0.372	0.347	4.679E+03	1767	237	796363636
0.373	0.347	4.703E+03	1764	235	796363636
0.374	0.346	4.728E+03	1761	234	730000000
0.375	0.346	4.752E+03	1758	233	730000000

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.376	0.345	4.777E+03	1755	231	730000000
0.377	0.345	4.801E+03	1752	230	730000000
0.378	0.345	4.826E+03	1749	229	730000000
0.379	0.344	4.850E+03	1746	227	730000000
0.38	0.344	4.875E+03	1743	226	730000000
0.381	0.343	4.899E+03	1740	225	673846154
0.382	0.343	4.923E+03	1737	224	673846154
0.383	0.343	4.948E+03	1734	222	673846154
0.384	0.342	4.972E+03	1731	221	673846154
0.385	0.342	4.996E+03	1728	220	673846154
0.386	0.342	5.021E+03	1726	219	673846154
0.387	0.341	5.045E+03	1723	218	673846154
0.388	0.341	5.069E+03	1720	217	625714286
0.389	0.340	5.093E+03	1717	215	625714286
0.39	0.340	5.118E+03	1714	214	625714286
0.391	0.340	5.142E+03	1712	213	625714286
0.392	0.339	5.166E+03	1709	212	625714286
0.393	0.339	5.190E+03	1706	211	584000000
0.394	0.338	5.214E+03	1703	210	584000000
0.395	0.338	5.238E+03	1701	209	584000000
0.396	0.338	5.262E+03	1698	208	584000000
0.397	0.337	5.287E+03	1695	207	584000000
0.398	0.337	5.311E+03	1692	206	547500000
0.399	0.337	5.335E+03	1690	205	547500000

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.4	0.336	5.359E+03	1687	204	547500000
0.401	0.336	5.383E+03	1684	203	547500000
0.402	0.336	5.407E+03	1682	202	547500000
0.403	0.335	5.431E+03	1679	201	515294118
0.404	0.335	5.455E+03	1676	200	515294118
0.405	0.334	5.479E+03	1674	199	515294118
0.406	0.334	5.503E+03	1671	198	486666667
0.407	0.334	5.527E+03	1668	197	486666667
0.408	0.333	5.551E+03	1666	196	486666667
0.409	0.333	5.575E+03	1663	195	486666667
0.41	0.333	5.599E+03	1661	194	461052632
0.411	0.332	5.623E+03	1658	193	461052632
0.412	0.332	5.646E+03	1656	192	547500000
0.413	0.332	5.670E+03	1653	191	547500000
0.414	0.331	5.694E+03	1650	191	547500000
0.415	0.331	5.718E+03	1648	190	515294118
0.416	0.331	5.742E+03	1645	189	1460000000
0.417	0.330	5.766E+03	1643	188	1460000000
0.418	0.330	5.790E+03	1640	187	1460000000
0.419	0.330	5.813E+03	1638	186	1460000000
0.42	0.329	5.837E+03	1635	185	1460000000
0.421	0.329	5.861E+03	1633	185	1251428571
0.422	0.329	5.885E+03	1630	184	1251428571
0.423	0.328	5.908E+03	1628	183	1251428571

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.424	0.328	5.932E+03	1625	182	1251428571
0.425	0.328	5.956E+03	1623	181	461052632
0.426	0.327	5.980E+03	1621	181	461052632
0.427	0.327	6.004E+03	1618	180	438000000
0.428	0.327	6.027E+03	1616	179	438000000
0.429	0.326	6.051E+03	1613	178	438000000
0.43	0.326	6.075E+03	1611	178	417142857
0.431	0.326	6.098E+03	1609	177	417142857
0.432	0.326	6.122E+03	1606	176	398181818
0.433	0.325	6.146E+03	1604	175	398181818
0.434	0.325	6.169E+03	1601	175	398181818
0.435	0.325	6.193E+03	1599	174	380869565
0.436	0.324	6.217E+03	1597	173	380869565
0.437	0.324	6.240E+03	1594	172	365000000
0.438	0.324	6.264E+03	1592	172	365000000
0.439	0.323	6.288E+03	1590	171	350400000
0.44	0.323	6.311E+03	1587	170	350400000
0.441	0.323	6.335E+03	1585	170	336923077
0.442	0.323	6.359E+03	1583	169	336923077
0.443	0.322	6.382E+03	1581	168	324444444
0.444	0.322	6.406E+03	1578	168	324444444
0.445	0.322	6.430E+03	1576	167	312857143
0.446	0.321	6.453E+03	1574	166	302068966
0.447	0.321	6.477E+03	1571	166	302068966

alpha	**risk**	**cost, \$/yr**	**T1, h**	**T2, h**	**T3, h**
0.448	0.321	6.500E+03	1569	165	292000000
0.449	0.320	6.524E+03	1567	164	282580645
0.45	0.320	6.548E+03	1565	164	273750000
0.451	0.320	6.571E+03	1562	163	265454545
0.452	0.320	6.595E+03	1560	162	257647059
0.453	0.319	6.618E+03	1558	162	250285714
0.454	0.319	6.642E+03	1556	161	243333333
0.455	0.319	6.666E+03	1554	160	236756757
0.456	0.318	6.689E+03	1551	160	230526316
0.457	0.318	6.713E+03	1549	159	219000000
0.458	0.318	6.736E+03	1547	159	213658537
0.459	0.318	6.760E+03	1545	158	203720930
0.46	0.317	6.784E+03	1543	157	194666667
0.461	0.317	6.807E+03	1540	157	182500000
0.462	0.317	6.831E+03	1538	156	171764706
0.463	0.317	6.854E+03	1536	156	159272727
0.464	0.316	6.878E+03	1534	155	148474576
0.465	0.316	6.901E+03	1532	155	134769231
0.466	0.316	6.925E+03	1530	154	120000000
0.467	0.315	6.949E+03	1528	153	105542169
0.468	0.315	6.972E+03	1525	153	91250000
0.469	0.315	6.996E+03	1523	152	76173913
0.47	0.315	7.019E+03	1521	152	62127660
0.471	0.314	7.043E+03	1519	151	48938547

alpha	risk	cost, \$/yr	T1, h	T2, h	T3, h
0.472	0.314	7.066E+03	1517	151	37435897
0.473	0.314	7.090E+03	1515	150	312857143
0.474	0.314	7.114E+03	1513	150	292000000
0.475	0.313	7.137E+03	1511	149	273750000
0.476	0.313	7.161E+03	1509	149	250285714
0.477	0.313	7.184E+03	1507	148	84230769
0.478	0.313	7.208E+03	1505	148	76842105
0.479	0.312	7.231E+03	1503	147	68976378
0.48	0.312	7.255E+03	1501	146	60000000
0.481	0.312	7.279E+03	1499	146	49772727
0.482	0.312	7.302E+03	1496	145	36500000
0.483	0.311	7.326E+03	1494	145	21736973
0.484	0.311	7.350E+03	1492	144	9711752
0.485	0.311	7.373E+03	1490	144	73000000
0.486	0.310	7.397E+03	1488	143	18061856
0.487	0.310	7.420E+03	1486	143	5622593
0.488	0.310	7.444E+03	1484	142	4143803
0.489	0.310	7.477E+03	1482	142	97538
0.49	0.309	7.543E+03	1480	142	16996
0.491	0.308	7.610E+03	1478	141	9253
0.492	0.308	7.676E+03	1476	141	6361
0.493	0.307	7.743E+03	1475	140	4842
0.494	0.306	7.810E+03	1473	140	3912
0.495	0.306	7.876E+03	1471	139	3281

alpha	**risk**	**cost, \$/yr**	**T1, h**	**T2, h**	**T3, h**
0.496	0.305	7.943E+03	1469	139	2825
0.497	0.304	8.010E+03	1467	138	2480
0.498	0.304	8.077E+03	1465	138	2211
0.499	0.303	8.144E+03	1463	137	1994
0.5	0.302	8.210E+03	1461	137	1816
0.501	0.301	8.277E+03	1459	136	1667
0.502	0.301	8.344E+03	1457	136	1541
0.503	0.300	8.411E+03	1455	136	1432
0.504	0.300	8.478E+03	1453	135	1338
0.505	0.299	8.544E+03	1451	135	1255
0.506	0.298	8.611E+03	1449	134	1182
0.507	0.298	8.678E+03	1447	134	1117
0.508	0.297	8.745E+03	1446	133	1059
0.509	0.296	8.812E+03	1444	133	1007
0.51	0.296	8.879E+03	1442	133	959
0.511	0.295	8.946E+03	1440	132	916
0.512	0.294	9.013E+03	1438	132	876
0.513	0.294	9.079E+03	1436	131	840
0.514	0.293	9.146E+03	1434	131	807
0.515	0.292	9.213E+03	1432	130	776
0.516	0.292	9.280E+03	1431	130	747
0.517	0.291	9.347E+03	1429	130	721
0.518	0.291	9.414E+03	1427	129	696
0.519	0.290	9.481E+03	1425	129	673

alpha	risk	cost, \$/yr	T1, h	T2, h	T3, h
0.52	0.289	9.548E+03	1423	128	651
0.521	0.289	9.615E+03	1421	128	631
0.522	0.288	9.683E+03	1420	128	612
0.523	0.287	9.750E+03	1418	127	594
0.524	0.287	9.817E+03	1416	127	577
0.525	0.286	9.884E+03	1414	126	561
0.526	0.286	9.951E+03	1412	126	546
0.527	0.285	1.002E+04	1410	126	532
0.528	0.284	1.009E+04	1409	125	518
0.529	0.284	1.015E+04	1407	125	505
0.53	0.283	1.022E+04	1405	125	493
0.531	0.283	1.029E+04	1403	124	481
0.532	0.282	1.035E+04	1401	124	470
0.533	0.281	1.042E+04	1400	123	459
0.534	0.281	1.049E+04	1398	123	449
0.535	0.280	1.056E+04	1396	123	440
0.536	0.280	1.062E+04	1394	122	430
0.537	0.279	1.069E+04	1393	122	421
0.538	0.279	1.076E+04	1391	122	413
0.539	0.278	1.083E+04	1389	121	404
0.54	0.277	1.089E+04	1387	121	396
0.541	0.277	1.096E+04	1386	121	389
0.542	0.276	1.103E+04	1384	120	381
0.543	0.276	1.110E+04	1382	120	374

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.544	0.275	1.116E+04	1380	119	368
0.545	0.275	1.123E+04	1379	119	361
0.546	0.274	1.130E+04	1377	119	355
0.547	0.273	1.137E+04	1375	118	348
0.548	0.273	1.144E+04	1373	118	343
0.549	0.272	1.150E+04	1372	118	337
0.55	0.272	1.157E+04	1370	117	331
0.551	0.271	1.164E+04	1368	117	326
0.552	0.271	1.171E+04	1367	117	321
0.553	0.270	1.178E+04	1365	116	316
0.554	0.270	1.184E+04	1363	116	311
0.555	0.269	1.191E+04	1361	116	306
0.556	0.268	1.198E+04	1360	115	301
0.557	0.268	1.205E+04	1358	115	297
0.558	0.267	1.212E+04	1356	115	293
0.559	0.267	1.218E+04	1355	114	288
0.56	0.266	1.225E+04	1353	114	284
0.561	0.266	1.232E+04	1351	114	280
0.562	0.265	1.239E+04	1350	113	277
0.563	0.265	1.246E+04	1348	113	273
0.564	0.264	1.253E+04	1346	113	269
0.565	0.264	1.259E+04	1345	112	266
0.566	0.263	1.266E+04	1343	112	262
0.567	0.263	1.273E+04	1341	112	259

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.568	0.262	1.280E+04	1340	112	255
0.569	0.261	1.287E+04	1338	111	252
0.57	0.261	1.294E+04	1336	111	249
0.571	0.260	1.301E+04	1335	111	246
0.572	0.260	1.308E+04	1333	110	243
0.573	0.259	1.314E+04	1331	110	240
0.574	0.259	1.321E+04	1330	110	237
0.575	0.258	1.328E+04	1328	109	234
0.576	0.258	1.335E+04	1327	109	232
0.577	0.257	1.342E+04	1325	109	229
0.578	0.257	1.349E+04	1323	108	226
0.579	0.256	1.356E+04	1322	108	224
0.58	0.256	1.363E+04	1320	108	221
0.581	0.255	1.370E+04	1318	108	219
0.582	0.255	1.377E+04	1317	107	216
0.583	0.254	1.384E+04	1315	107	214
0.584	0.254	1.391E+04	1314	107	212
0.585	0.253	1.397E+04	1312	106	210
0.586	0.253	1.404E+04	1310	106	207
0.587	0.252	1.411E+04	1309	106	205
0.588	0.252	1.418E+04	1307	106	203
0.589	0.251	1.425E+04	1306	105	201
0.59	0.251	1.432E+04	1304	105	199
0.591	0.250	1.439E+04	1302	105	197

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.592	0.250	1.446E+04	1301	104	195
0.593	0.249	1.453E+04	1299	104	193
0.594	0.249	1.460E+04	1298	104	191
0.595	0.249	1.467E+04	1296	104	189
0.596	0.248	1.474E+04	1294	103	188
0.597	0.248	1.481E+04	1293	103	186
0.598	0.247	1.489E+04	1291	103	184
0.599	0.247	1.496E+04	1290	102	182
0.6	0.246	1.503E+04	1288	102	181
0.601	0.246	1.510E+04	1287	102	179
0.602	0.245	1.517E+04	1285	102	177
0.603	0.245	1.524E+04	1284	101	176
0.604	0.244	1.531E+04	1282	101	174
0.605	0.244	1.538E+04	1280	101	173
0.606	0.243	1.545E+04	1279	101	171
0.607	0.243	1.552E+04	1277	100	170
0.608	0.242	1.559E+04	1276	100	168
0.609	0.242	1.566E+04	1274	100	167
0.61	0.242	1.574E+04	1273	100	165
0.611	0.241	1.581E+04	1271	99	164
0.612	0.241	1.588E+04	1270	99	162
0.613	0.240	1.595E+04	1268	99	161
0.614	0.240	1.602E+04	1267	98	160
0.615	0.239	1.609E+04	1265	98	158

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.616	0.239	1.617E+04	1263	98	157
0.617	0.238	1.624E+04	1262	98	156
0.618	0.238	1.631E+04	1260	97	155
0.619	0.237	1.638E+04	1259	97	153
0.62	0.237	1.645E+04	1257	97	152
0.621	0.237	1.653E+04	1256	97	151
0.622	0.236	1.660E+04	1254	96	150
0.623	0.236	1.667E+04	1253	96	149
0.624	0.235	1.674E+04	1251	96	147
0.625	0.235	1.682E+04	1250	96	146
0.626	0.234	1.689E+04	1248	95	145
0.627	0.234	1.696E+04	1247	95	144
0.628	0.234	1.703E+04	1245	95	143
0.629	0.233	1.711E+04	1244	95	142
0.63	0.233	1.718E+04	1242	94	141
0.631	0.232	1.725E+04	1241	94	140
0.632	0.232	1.733E+04	1239	94	139
0.633	0.231	1.740E+04	1238	94	138
0.634	0.231	1.747E+04	1236	94	137
0.635	0.231	1.755E+04	1235	93	136
0.636	0.230	1.762E+04	1233	93	135
0.637	0.230	1.769E+04	1232	93	134
0.638	0.229	1.777E+04	1230	93	133
0.639	0.229	1.784E+04	1229	92	132

alpha	risk	cost, \$/yr	T1, h	T2, h	T3, h
0.64	0.228	1.792E+04	1227	92	131
0.641	0.228	1.799E+04	1226	92	130
0.642	0.228	1.806E+04	1224	92	129
0.643	0.227	1.814E+04	1223	91	128
0.644	0.227	1.821E+04	1221	91	128
0.645	0.226	1.829E+04	1220	91	127
0.646	0.226	1.836E+04	1219	91	126
0.647	0.226	1.844E+04	1217	90	125
0.648	0.225	1.851E+04	1216	90	124
0.649	0.225	1.859E+04	1214	90	123
0.65	0.224	1.866E+04	1213	90	123
0.651	0.224	1.874E+04	1211	90	122
0.652	0.224	1.881E+04	1210	89	121
0.653	0.223	1.889E+04	1208	89	120
0.654	0.223	1.897E+04	1207	89	119
0.655	0.222	1.904E+04	1205	89	119
0.656	0.222	1.912E+04	1204	88	118
0.657	0.222	1.919E+04	1202	88	117
0.658	0.221	1.927E+04	1201	88	116
0.659	0.221	1.935E+04	1200	88	116
0.66	0.220	1.942E+04	1198	88	115
0.661	0.220	1.950E+04	1197	87	114
0.662	0.220	1.958E+04	1195	87	113
0.663	0.219	1.965E+04	1194	87	113

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.664	0.219	1.973E+04	1192	87	112
0.665	0.218	1.981E+04	1191	86	111
0.666	0.218	1.988E+04	1189	86	111
0.667	0.218	1.996E+04	1188	86	110
0.668	0.217	2.004E+04	1187	86	109
0.669	0.217	2.012E+04	1185	86	109
0.67	0.216	2.019E+04	1184	85	108
0.671	0.216	2.027E+04	1182	85	107
0.672	0.216	2.035E+04	1181	85	107
0.673	0.215	2.043E+04	1179	85	106
0.674	0.215	2.051E+04	1178	84	105
0.675	0.215	2.059E+04	1177	84	105
0.676	0.214	2.066E+04	1175	84	104
0.677	0.214	2.074E+04	1174	84	104
0.678	0.213	2.082E+04	1172	84	103
0.679	0.213	2.090E+04	1171	83	102
0.68	0.213	2.098E+04	1169	83	102
0.681	0.212	2.106E+04	1168	83	101
0.682	0.212	2.114E+04	1167	83	101
0.683	0.212	2.122E+04	1165	83	100
0.684	0.211	2.130E+04	1164	82	100
0.685	0.211	2.138E+04	1162	82	99
0.686	0.210	2.146E+04	1161	82	98
0.687	0.210	2.154E+04	1160	82	98

alpha	**risk**	**cost, $/yr**	**T1, h**	**T2, h**	**T3, h**
0.688	0.210	2.162E+04	1158	82	97
0.689	0.209	2.170E+04	1157	81	97
0.69	0.209	2.178E+04	1155	81	96
0.691	0.209	2.186E+04	1154	81	96
0.692	0.208	2.194E+04	1152	81	95
0.693	0.208	2.203E+04	1151	81	95
0.694	0.208	2.211E+04	1150	80	94
0.695	0.207	2.219E+04	1148	80	94
0.696	0.207	2.227E+04	1147	80	93
0.697	0.206	2.235E+04	1145	80	93
0.698	0.206	2.244E+04	1144	80	92
0.699	0.206	2.252E+04	1143	79	92
0.7	0.205	2.260E+04	1141	79	91
0.701	0.205	2.268E+04	1140	79	91
0.702	0.205	2.277E+04	1138	79	90
0.703	0.204	2.285E+04	1137	79	90
0.704	0.204	2.293E+04	1136	78	89
0.705	0.204	2.302E+04	1134	78	89
0.706	0.203	2.310E+04	1133	78	88
0.707	0.203	2.319E+04	1131	78	88
0.708	0.203	2.327E+04	1130	78	87
0.709	0.202	2.335E+04	1129	77	87
0.71	0.202	2.344E+04	1127	77	86
0.711	0.202	2.352E+04	1126	77	86

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.712	0.201	2.361E+04	1124	77	86
0.713	0.201	2.369E+04	1123	77	85
0.714	0.200	2.378E+04	1122	76	85
0.715	0.200	2.387E+04	1120	76	84
0.716	0.200	2.395E+04	1119	76	84
0.717	0.199	2.404E+04	1117	76	83
0.718	0.199	2.412E+04	1116	76	83
0.719	0.199	2.421E+04	1115	75	83
0.72	0.198	2.430E+04	1113	75	82
0.721	0.198	2.438E+04	1112	75	82
0.722	0.198	2.447E+04	1110	75	81
0.723	0.197	2.456E+04	1109	75	81
0.724	0.197	2.465E+04	1108	74	81
0.725	0.197	2.473E+04	1106	74	80
0.726	0.196	2.482E+04	1105	74	80
0.727	0.196	2.491E+04	1104	74	79
0.728	0.196	2.500E+04	1102	74	79
0.729	0.195	2.509E+04	1101	73	79
0.73	0.195	2.518E+04	1099	73	78
0.731	0.195	2.527E+04	1098	73	78
0.732	0.194	2.536E+04	1097	73	77
0.733	0.194	2.545E+04	1095	73	77
0.734	0.194	2.554E+04	1094	73	77
0.735	0.193	2.563E+04	1092	72	76

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.736	0.193	2.572E+04	1091	72	76
0.737	0.193	2.581E+04	1090	72	76
0.738	0.192	2.590E+04	1088	72	75
0.739	0.192	2.599E+04	1087	72	75
0.74	0.192	2.608E+04	1086	71	75
0.741	0.192	2.618E+04	1084	71	74
0.742	0.191	2.627E+04	1083	71	74
0.743	0.191	2.636E+04	1081	71	73
0.744	0.191	2.645E+04	1080	71	73
0.745	0.190	2.655E+04	1079	70	73
0.746	0.190	2.664E+04	1077	70	72
0.747	0.190	2.674E+04	1076	70	72
0.748	0.189	2.683E+04	1074	70	72
0.749	0.189	2.692E+04	1073	70	71
0.75	0.189	2.702E+04	1072	70	71
0.751	0.188	2.711E+04	1070	69	71
0.752	0.188	2.721E+04	1069	69	70
0.753	0.188	2.730E+04	1067	69	70
0.754	0.187	2.740E+04	1066	69	70
0.755	0.187	2.750E+04	1065	69	69
0.756	0.187	2.759E+04	1063	68	69
0.757	0.186	2.769E+04	1062	68	69
0.758	0.186	2.779E+04	1061	68	69
0.759	0.186	2.789E+04	1059	68	68

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.76	0.186	2.798E+04	1058	68	68
0.761	0.185	2.808E+04	1056	68	68
0.762	0.185	2.818E+04	1055	67	67
0.763	0.185	2.828E+04	1054	67	67
0.764	0.184	2.838E+04	1052	67	67
0.765	0.184	2.848E+04	1051	67	66
0.766	0.184	2.858E+04	1049	67	66
0.767	0.183	2.868E+04	1048	66	66
0.768	0.183	2.878E+04	1047	66	65
0.769	0.183	2.888E+04	1045	66	65
0.77	0.182	2.898E+04	1044	66	65
0.771	0.182	2.908E+04	1042	66	65
0.772	0.182	2.919E+04	1041	66	64
0.773	0.182	2.929E+04	1040	65	64
0.774	0.181	2.939E+04	1038	65	64
0.775	0.181	2.950E+04	1037	65	63
0.776	0.181	2.960E+04	1036	65	63
0.777	0.180	2.970E+04	1034	65	63
0.778	0.180	2.981E+04	1033	64	63
0.779	0.180	2.991E+04	1031	64	62
0.78	0.179	3.002E+04	1030	64	62
0.781	0.179	3.013E+04	1029	64	62
0.782	0.179	3.023E+04	1027	64	62
0.783	0.179	3.034E+04	1026	64	61

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.784	0.178	3.045E+04	1024	63	61
0.785	0.178	3.055E+04	1023	63	61
0.786	0.178	3.066E+04	1022	63	60
0.787	0.177	3.077E+04	1020	63	60
0.788	0.177	3.088E+04	1019	63	60
0.789	0.177	3.099E+04	1017	62	60
0.79	0.176	3.110E+04	1016	62	59
0.791	0.176	3.121E+04	1014	62	59
0.792	0.176	3.132E+04	1013	62	59
0.793	0.176	3.143E+04	1012	62	59
0.794	0.175	3.155E+04	1010	62	58
0.795	0.175	3.166E+04	1009	61	58
0.796	0.175	3.177E+04	1007	61	58
0.797	0.174	3.189E+04	1006	61	58
0.798	0.174	3.200E+04	1005	61	57
0.799	0.174	3.212E+04	1003	61	57
0.8	0.174	3.223E+04	1002	60	57
0.801	0.173	3.235E+04	1000	60	57
0.802	0.173	3.246E+04	999	60	56
0.803	0.173	3.258E+04	997	60	56
0.804	0.172	3.270E+04	996	60	56
0.805	0.172	3.282E+04	995	60	56
0.806	0.172	3.293E+04	993	59	55
0.807	0.172	3.305E+04	992	59	55

alpha	**risk**	**cost, $/yr**	**T1, h**	**T2, h**	**T3, h**
0.808	0.171	3.317E+04	990	59	55
0.809	0.171	3.329E+04	989	59	55
0.81	0.171	3.342E+04	987	59	54
0.811	0.170	3.354E+04	986	58	54
0.812	0.170	3.366E+04	985	58	54
0.813	0.170	3.378E+04	983	58	54
0.814	0.170	3.391E+04	982	58	53
0.815	0.169	3.403E+04	980	58	53
0.816	0.169	3.416E+04	979	58	53
0.817	0.169	3.428E+04	977	57	53
0.818	0.168	3.441E+04	976	57	53
0.819	0.168	3.454E+04	975	57	52
0.82	0.168	3.466E+04	973	57	52
0.821	0.168	3.479E+04	972	57	52
0.822	0.167	3.492E+04	970	56	52
0.823	0.167	3.505E+04	969	56	51
0.824	0.167	3.518E+04	967	56	51
0.825	0.166	3.532E+04	966	56	51
0.826	0.166	3.545E+04	964	56	51
0.827	0.166	3.558E+04	963	56	51
0.828	0.166	3.572E+04	961	55	50
0.829	0.165	3.585E+04	960	55	50
0.83	0.165	3.599E+04	958	55	50
0.831	0.165	3.612E+04	957	55	50

alpha	**risk**	**cost, $/yr**	**T1, h**	**T2, h**	**T3, h**
0.832	0.164	3.626E+04	955	55	49
0.833	0.164	3.640E+04	954	54	49
0.834	0.164	3.654E+04	953	54	49
0.835	0.164	3.668E+04	951	54	49
0.836	0.163	3.682E+04	950	54	49
0.837	0.163	3.696E+04	948	54	48
0.838	0.163	3.711E+04	947	53	48
0.839	0.163	3.725E+04	945	53	48
0.84	0.162	3.740E+04	944	53	48
0.841	0.162	3.754E+04	942	53	48
0.842	0.162	3.769E+04	941	53	47
0.843	0.161	3.784E+04	939	53	47
0.844	0.161	3.799E+04	938	52	47
0.845	0.161	3.814E+04	936	52	47
0.846	0.161	3.829E+04	935	52	47
0.847	0.160	3.844E+04	933	52	46
0.848	0.160	3.860E+04	932	52	46
0.849	0.160	3.875E+04	930	51	46
0.85	0.159	3.891E+04	928	51	46
0.851	0.159	3.907E+04	927	51	45
0.852	0.159	3.922E+04	925	51	45
0.853	0.159	3.938E+04	924	51	45
0.854	0.158	3.955E+04	922	50	45
0.855	0.158	3.971E+04	921	50	45

alpha	**risk**	**cost, $/yr**	**T1, h**	**T2, h**	**T3, h**
0.856	0.158	3.987E+04	919	50	45
0.857	0.158	4.004E+04	918	50	44
0.858	0.157	4.021E+04	916	50	44
0.859	0.157	4.038E+04	915	49	44
0.86	0.157	4.055E+04	913	49	44
0.861	0.156	4.072E+04	911	49	44
0.862	0.156	4.089E+04	910	49	43
0.863	0.156	4.106E+04	908	49	43
0.864	0.156	4.124E+04	907	48	43
0.865	0.155	4.142E+04	905	48	43
0.866	0.155	4.160E+04	903	48	43
0.867	0.155	4.178E+04	902	48	42
0.868	0.154	4.196E+04	900	48	42
0.869	0.154	4.215E+04	899	47	42
0.87	0.154	4.234E+04	897	47	42
0.871	0.154	4.253E+04	895	47	42
0.872	0.153	4.272E+04	894	47	41
0.873	0.153	4.291E+04	892	46	41
0.874	0.153	4.311E+04	891	46	41
0.875	0.153	4.330E+04	889	46	41
0.876	0.152	4.350E+04	887	46	41
0.877	0.152	4.371E+04	886	46	40
0.878	0.152	4.391E+04	884	45	40
0.879	0.151	4.412E+04	882	45	40

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.88	0.151	4.433E+04	881	45	40
0.881	0.151	4.454E+04	879	45	40
0.882	0.151	4.475E+04	877	44	40
0.883	0.150	4.497E+04	876	44	39
0.884	0.150	4.519E+04	874	44	39
0.885	0.150	4.542E+04	872	44	39
0.886	0.149	4.564E+04	871	44	39
0.887	0.149	4.587E+04	869	43	39
0.888	0.149	4.610E+04	867	43	38
0.889	0.148	4.634E+04	866	43	38
0.89	0.148	4.658E+04	864	43	38
0.891	0.148	4.682E+04	862	42	38
0.892	0.148	4.707E+04	860	42	38
0.893	0.147	4.732E+04	859	42	38
0.894	0.147	4.758E+04	857	42	37
0.895	0.147	4.784E+04	855	41	37
0.896	0.146	4.810E+04	853	41	37
0.897	0.146	4.837E+04	852	41	37
0.898	0.146	4.865E+04	850	40	37
0.899	0.145	4.893E+04	848	40	36
0.9	0.145	4.921E+04	846	40	36
0.901	0.145	4.950E+04	844	40	36
0.902	0.144	4.980E+04	843	39	36
0.903	0.144	5.010E+04	841	39	36

alpha	risk	cost, $/yr	T1, h	T2, h	T3, h
0.904	0.144	5.041E+04	839	39	36
0.905	0.143	5.072E+04	837	38	35
0.906	0.143	5.105E+04	835	38	35
0.907	0.143	5.138E+04	833	38	35
0.908	0.142	5.172E+04	832	38	35
0.909	0.142	5.206E+04	830	37	35
0.91	0.142	5.242E+04	828	37	34
0.911	0.141	5.279E+04	826	37	34
0.912	0.141	5.317E+04	824	36	34
0.913	0.141	5.356E+04	822	36	34
0.914	0.140	5.396E+04	820	36	34
0.915	0.140	5.437E+04	818	35	34
0.916	0.139	5.480E+04	816	35	33
0.917	0.139	5.525E+04	814	34	33
0.918	0.139	5.571E+04	812	34	33
0.919	0.138	5.620E+04	810	34	33
0.92	0.138	5.670E+04	808	33	33
0.921	0.137	5.723E+04	806	33	33
0.922	0.137	5.778E+04	804	32	32
0.923	0.136	5.836E+04	802	32	32
0.924	0.136	5.898E+04	800	31	32
0.925	0.135	5.963E+04	798	31	32
0.926	0.135	6.033E+04	796	30	32
0.927	0.134	6.108E+04	794	30	31

alpha	**risk**	**cost, \$/yr**	**T1, h**	**T2, h**	**T3, h**
0.928	0.134	6.188E+04	792	29	31
0.929	0.133	6.276E+04	790	29	31
0.93	0.132	6.371E+04	787	28	31
0.931	0.131	6.476E+04	785	27	31
0.932	0.130	6.592E+04	783	26	31
0.933	0.130	6.723E+04	781	26	30
0.934	0.128	6.870E+04	779	25	30
0.935	0.127	7.038E+04	776	24	30
0.936	0.126	7.229E+04	774	23	30
0.937	0.125	7.447E+04	772	22	30
0.938	0.123	7.691E+04	770	21	29
0.939	0.121	7.962E+04	767	20	29
0.94	0.119	8.255E+04	765	19	29
0.941	0.117	8.567E+04	763	18	29
0.942	0.115	8.893E+04	760	17	29
0.943	0.113	9.231E+04	758	16	29
0.944	0.111	9.578E+04	755	15	28
0.945	0.109	9.933E+04	753	14	28
0.946	0.107	1.029E+05	750	13	28
0.947	0.105	1.066E+05	748	13	28
0.948	0.103	1.104E+05	745	12	28
0.949	0.101	1.142E+05	743	12	27
0.95	0.099	1.181E+05	740	11	27
0.951	0.097	1.221E+05	738	11	27

alpha	**risk**	**cost, \$/yr**	**T1, h**	**T2, h**	**T3, h**
0.952	0.094	1.262E+05	735	10	27
0.953	0.092	1.303E+05	732	10	27
0.954	0.090	1.345E+05	730	9	26
0.955	0.088	1.389E+05	727	9	26
0.956	0.086	1.433E+05	724	9	26
0.957	0.084	1.478E+05	721	8	26
0.958	0.082	1.524E+05	718	8	26
0.959	0.080	1.571E+05	715	8	25
0.96	0.078	1.619E+05	712	8	25
0.961	0.076	1.668E+05	709	7	25
0.962	0.074	1.719E+05	706	7	25
0.963	0.072	1.771E+05	703	7	25
0.964	0.070	1.824E+05	700	7	24
0.965	0.068	1.879E+05	697	6	24
0.966	0.066	1.935E+05	694	6	24
0.967	0.064	1.993E+05	690	6	24
0.968	0.062	2.052E+05	687	6	24
0.969	0.060	2.114E+05	683	5	23
0.97	0.058	2.177E+05	680	5	23
0.971	0.056	2.243E+05	676	5	23
0.972	0.054	2.310E+05	672	5	23
0.973	0.052	2.380E+05	669	5	22
0.974	0.050	2.453E+05	665	5	22
0.975	0.048	2.528E+05	661	4	22

alpha	**risk**	**cost, $/yr**	**T1, h**	**T2, h**	**T3, h**
0.976	0.046	2.607E+05	657	4	22
0.977	0.044	2.688E+05	652	4	21
0.978	0.042	2.773E+05	648	4	21
0.979	0.040	2.862E+05	644	4	21
0.98	0.038	2.956E+05	639	4	21
0.981	0.036	3.054E+05	634	4	20
0.982	0.034	3.157E+05	629	3	20
0.983	0.032	3.266E+05	624	3	20
0.984	0.030	3.381E+05	619	3	20
0.985	0.029	3.504E+05	613	3	19
0.986	0.027	3.635E+05	607	3	19
0.987	0.025	3.776E+05	601	3	19
0.988	0.023	3.928E+05	594	3	18
0.989	0.021	4.093E+05	587	3	18
0.99	0.019	4.273E+05	580	3	18
0.991	0.017	4.472E+05	572	2	17
0.992	0.015	4.695E+05	563	2	17
0.993	0.013	4.947E+05	554	2	16
0.994	0.011	5.237E+05	543	2	16
0.995	0.009	5.581E+05	531	2	15
0.996	0.008	6.001E+05	517	2	15
0.997	0.006	6.541E+05	500	2	14
0.998	0.004	7.303E+05	478	1	13
0.999	0.002	8.603E+05	445	1	12

VITA

Xiaole Yang was born in Yibin, China in 1983. She graduated with her B.S. in biotechnology from Tianjin University of Science & Technology, China in 2005. She enrolled in the Chemical Engineering Department at Texas A&M University in August 2005 as a doctoral student. She joined the Mary Kay O'Connor Process Safety Center in Fall 2007. Since then she has been working on the development of dynamic operational risk assessment under Dr. Sam Mannan's guidance.

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