SYSTEMATIC FRAMEWORKS FOR RELIABILITY, AVAILABILITY, AND MAINTAINABILITY (RAM) CONSIDERATIONS IN CHEMICAL PROCESS DESIGN

A Dissertation

by

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ABSTRACT

Failures in the chemical process industry may lead to severely negative impacts on sustainability, health and wellbeing of workers and adjacent communities, company profit, and the stability of supply chains. The conventional approach in handling equipment failures has usually been focused on operational strategies. This approach overlooks the critical role of process design in mitigating failure. When availability is considered in a proposed design, it is traditionally through fixed availability values. This leads a design team to generate single-point estimates regarding the potential economic performance of the design. The aim of this dissertation is to present systematic methodologies that account for failure, and the uncertainty around it, early enough during the conceptual design stage. Availability models are developed using a simple Markov process with each item being in one of two states: operating or under repair. Since failure and repair rates are uncertain inputs, two methods of incorporating uncertainty are presented: Bayesian updating and Monte Carlo simulation. Critical process subsystem(s) that are more failure-prone than others are identified. An availability-weighted profitability metric is also presented to include the effects of the failure-repair cycle on revenue and profit. Then, design alternatives that improve the availability of the subsystem(s) in question can be evaluated based on their economic potential. This problem is presented by an optimization formulation with the objective of maximizing the availability-weighted incremental return on investment.

After examining the effects of equipment failures on process profitability, a wider look at other factors affecting the reliability of the oil and gas supply chain is performed. One of the most important considerations for the safe and continuous operation of process plants is the reliability of feedstock supply. Feedstocks are primarily transported to plants using an extensive network of natural gas transmission and hazardous liquids pipelines. Shutdown incidents of those pipelines

impact supply delivery to dependent plants and can lead to production shortfalls or disruptions. In process design, a team often has a number of pathways to consider selecting from. These pathways may have different feedstocks, which are transported by pipeline systems. The economic risk potential of pipeline failures or incidents is a consideration that needs to be accounted for in the selection process. Most existing works on pipeline economic risks examine the topic from the viewpoint of the costs of lost commodity, cleanup and recovery, and litigation. To address economic risks from the perspective of the commodity customer, a systematic framework to determine the impact of pipeline shutdowns on process plant production and economics is presented.

DEDICATION

This dissertation is dedicated to my loving parents, Dr. Firas Al-Douri and Mrs. Zeinab Abdulla, and my brothers, Dr. Abdulhamid and Omar. Your love and compassion towards me is something I cherish deeply in my heart. You always inspire me to push myself in all my pursuits. I am truly indebted to you all for your support and encouragement throughout my studies.

Also, this dissertation is dedicated to the memory of two mentors I had the honor of working with during my time as a graduate student, Dr. Hisham A. Nasr El-Din (Department Petroleum Engineering) and Dr. M. Sam Mannan (Department of Chemical Engineering). I am grateful for the time I spent working with them, and I learned a lot from them. Their memory lives on through their transformative work and the many generations of students they mentored.

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CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a dissertation committee consisting of Professor Mahmoud El-Halwagi [advisor], Professor Ahmed K. Hilaly, Professor Chad Mashuga of the Department of Chemical Engineering and Professor Sergiy Butenko, Professor Nancy Currie-Gregg of the Department of Industrial and Systems Engineering, as well as Professor Vasiliki Kazantzi of the Department of Business Administration of the University of Thessaly (Greece).

All other work conducted for the thesis (or) dissertation was completed by the student independently.

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1. INTRODUCTION

1.1. A Brief History of Reliability Engineering

While reliability has been an important human attribute for a very long time, it has only been applied to technical systems for approximately hundred years. Reliability was used to compare the operational safety of one-, two-, and four-engine airplanes, and was measured as the number of accidents per hour of flight time. In the early 1930s, the theoretical basis for statistical methods in quality control of industrial products were laid down by Walter Shewhart, Harold F. Dodge, and Harry G. Romig. These methods were not brought into extensive use until the beginning of World War II. The increasingly complex nature of many technical systems made the field of system reliability a more pressingly important one. Also, automation increased the need for complicated control and safety systems. In the 1950s and early 1960s, research in the United States on intercontinental ballistic missiles and space led to the establishment of an association of engineers working on reliability issues relating to those areas. In the 1970s, interest in nuclear power plants in the U.S. and other parts of the world led to extensive research efforts related to the risk and safety aspects of building and operating those facilities. A product of these efforts was the report WASH-1400 (NUREG- 75/014), which represented the first safety analysis of a system as complex as a nuclear power plant. In the last three decades, risk analysis and reliability problems in the offshore oil and gas industry has been of growing importance. This is due to the progress of field development in the North Sea and Gulf of Mexico into deeper waters, where thousands of platforms operate in depths of up to 6,000 feet and a few operate in depths of 10,000 feet or more. The reliability of subsea systems is analogous to spacecraft as low reliability cannot be compensated by enhanced maintenance due to the operating environment (Rausand and Høyland, 2003).

1.2. Basic Concepts

The concept of reliability is interconnected with similar concepts such as: maintainability, availability, quality, and dependability. In this section, precise definitions of these concepts from recognized international institutions are given.

1.2.1. Quality

Quality commonly denotes conformity of a product to its specifications as manufactured. A formal definition by the International Standards Association (ISO) is given as “the totality of features and characteristics of a product or service that bear on its ability to satisfy stated or implied needs (ISO 8402).

1.2.2. Reliability

Reliability is defined as “the ability of an item to perform a required function, under given environmental and operational conditions and for a stated period of time” (ISO 8402). Here, the term “item” can refer to any component, subsystem, or system that can be considered an entity. While quality is the conformity of a product/service to its specifications, reliability is the ability to continue to comply with them over its useful life. Thus, reliability can be considered as an extension of quality into the time domain.

1.2.3. Maintainability

Maintainability is defined as the probability that a failed item will be restored or repaired to a specified condition within a period of time when maintenance is performed according to prescribed procedures (BS4778, 1991). The restoration or repair of an item is usually through the performance of a repair action or corrective maintenance.

1.2.4. Availability

Availability is a function of the reliability and maintainability characteristics of the item being examined. A formal definition of availability is “the ability of an item (under combined aspects of its reliability, maintainability, and maintenance support) to perform its required function at a stated instant of a time over a stated period of time” (BS4778, 1991). There are three subtypes of availability: operational, achievable, and inherent. *Operational availability* includes unplanned and planned maintenance and time lost to operational logistics and administration. *Achievable availability* reflects availability including planned and unplanned maintenance times. *Inherent availability* includes only corrective maintenance time. While operational availability is the most comprehensive and realistic measure, it is of the least importance in design because administrative and logistic time delays are outside the design team’s control.

1.2.5. Dependability

The International Electrotechnical Commission (IEC) defined dependability as a term that “describes the availability performance and its influencing factors: reliability performance, maintainability performance and maintenance performance” (IEC 60300). This definition has been interpreted as the sum of three elements, as show in Figure 1.1, which are:

- Attributes: ways to assess dependability
- Threats: Issues that can affect dependability
- Means: Ways to increase dependability

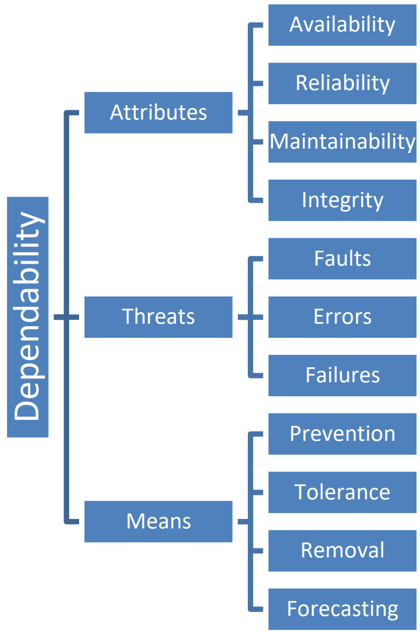

Figure 1.1: Terminology diagram for dependability, based on Laprie (1985).

1.3. Repairable vs. Non-Repairable Items

In reliability terminology, an item can refer to anything from a small component to a large system. There are two types of items: repairable, and non-repairable. The state of an item at a time *t* can be described by the state variable X(t) as follows:

$$\boldsymbol{X(t)} = \begin{cases} \mathbf{1} \ \boldsymbol{if\ the\ item\ is\ functioning\ at\ time\ t} \\ \mathbf{0} \ \boldsymbol{if\ the\ item\ is\ in\ a\ failed\ state\ at\ time\ t} \end{cases}$$

Repairable items are those that can be brought back from a failed state to a functioning state, such as compressors and pumps. Non-repairable items are those that cannot be brought back into a functional state after a failure, such as bearings and gaskets.

1.3.1. Repairable Items

Repairable items experience changes in state from function to failure as can be seen in Figure 1.2. The time in which the item is in a functional state is referred to as the mean time between failures (MTBF). On the other hand, the time in which the item is in a failed state is referred to as downtime.

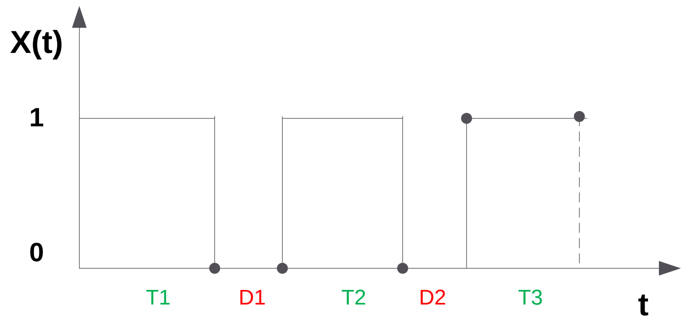

Figure 1.2: State variable for a non-repairable item.

1.3.2. Non-Repairable Items

Non-repairable items are either in a functional or failed state. The lifetime of the item is represented by the time in which it is functional, as shown in Figure 1.2.

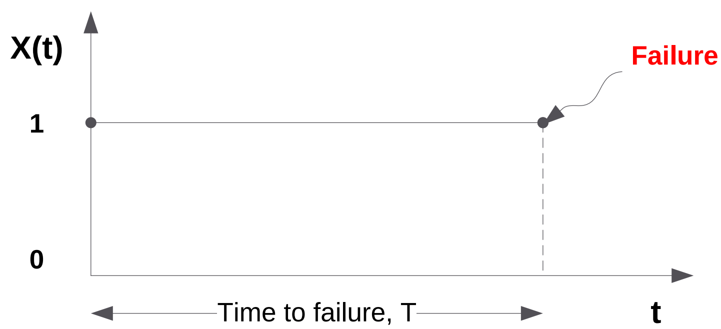

Figure 1.3: State variable for a repairable item.

1.4. Reliability, Availability, and Maintainability (RAM) Mathematical Representation

In measuring the reliability of an item, we use a probabilistic metric, which treats reliability as the probability that an item does not fail (or in other words, survives) the time interval (0,t]. This can be expressed by the reliability function *R(t)* as follows:

$$\mathrm{R(t)} = \mathrm{Pr\{T \geq t\}} = 1 - \mathrm{F(t)} = 1 - \int_0^t f(u)du = \int_t^\infty f(u)du$$

where *f(t)* is the probability density function (pdf) and *F(t)* is the cumulative distribution function (CDF) of the failure distribution. The most common metric used to describe the reliability of an item is the mean time to failure (non-repairable) or mean time between failures (repairable). Mathematically, it is described as the mean or expected value of the probability distribution defined by *f(t):*

$$MTTF = E(T) = \int_0^\infty t\, f(t)dt$$

The failure distribution of an item can be described by one of many distributions: exponential, lognormal, Weibull, or gamma. The exponential distribution indicates a constant failure rate and is commonly used, while other distributions are time-dependent.

In the event of a repairable item failure or breakdown, repair or restoration times are used to quantify its maintainability. The repair process is generally divided into several subtasks and delay times. Supply delay involves the delay time in obtaining spare parts/components required to complete the repair process. This time may involve administrative lead times, production/procurement lead times, and transportation times. This time is influenced mainly by the quantity and range of different components needed. Supply delay may not necessarily occur at the beginning of the repair process, but after the diagnosis subtask has identified the needed components. Maintenance delay time is the time spent waiting for resources such as personnel and test and support equipment, including both administrative and travel times. The supply and maintenance delays are influenced by external factors not part of the system itself, so they are not considered as part of the inherent repair time of the item. The inherent repair time of an item is the sum of the following subtasks' durations: access, diagnosis, repair or replacement, and validation/verification. Similar to the failure distribution, the repair time rate can be either be constant or time-dependent. Constant repair rates are indicated by an exponential distribution, while most time-dependent rates are indicated by the lognormal distribution. There are several metrics used to evaluate maintainability such as: mean-time-to-repair (MTTR), median time to repair, mode (most likely) repair time, and number of maintenance hours per operating hour. If *T* is a continuous random variable representing the time to repair a failed item, the probability that a repair is accomplished within time t is as follows:

$$\Pr\{\mathrm{T} \leq \mathrm{t}\} = \mathrm{H(t)} = \int_0^t h(t')dt'$$

The mean-time-to-repair (MTTR) can be determined from the following equation:

$$MTTR = \int_0^\infty t\, h(t)dt = \int_0^t \big(1 - H(t)\big)dt$$

Availability is a function of the reliability and maintainability characteristics of an item. Over an elapsed period of time, it is the percentage of time the item or system was available to perform its function(s):

$$Availability = \frac{Uptime}{Uptime + Downtime}$$

The above formula is useful from a historical point of view when evaluating a period of time that has already passed. Formally, availability is defined as the probability of an item to perform its required function at a stated instant of a time or over a stated period of time (BS4778, 1991). Depending on the definition of uptime and downtime, there are three main different forms of availability: inherent, achieved, and operational.

Inherent availability is based on the failure and repair time distributions, and is viewed as a design parameter. As such, it considers only unscheduled corrective maintenance. Achieved availability takes into consideration both unscheduled and scheduled (preventive) maintenance time distributions. Operational availability considers unscheduled and scheduled maintenance time as well as the time lost to administrative and logistical delays. In comparing the three types above, inherent and achieved availability is of more interest to a design team as spare parts and repair capability can vary widely depending on the location or company in question.

1.5. Process Design Cycle

The typical plant life cycle includes the following stages: (1) conceptual design, (2) basic design, (3) detailed design, (4) startup, installation, and commissioning, and (5) production. At the conceptual design phase, different design alternatives are screened primarily on the basis of their economic performance, but other factors such as safety and environmental impacts are play a role. In this stage, block flow diagrams of candidate designs are developed and stoichiometric targeting is performed to identify feedstock and utility requirements. Also, economic analysis such as plant capital and operating costs is performed to compare design candidates. The economic analysis of these alternatives can be used to optimize the designs, thereby performing trade-offs to obtain a design that is economically sound under anticipated conditions. For example, the extent of heat recovery is a trade-off between energy costs and heat exchanger costs (based on area). After carefully examining all candidate designs, the best design is selected based on several factors such as commercial track record, technology maturity, and safety. Afterwards, the project advances to the detailed design stage where specifications for equipment (vessels, pumps, heat exchangers) are made. In this stage, a design team usually works with contractors from engineering, procurement and construction (EPC) companies to quickly and efficiently complete this stage. Modifications can be made at this point to the selected design, although most of these are done at the equipment selection level, not as changes to the flowsheet. After design details are finalized, the project advances to the procurement and construction phase where EPC companies can place bulk orders for equipment, piping, wires, and valves. After that phase is completed, the plant is readied for startup and to begin operations.

1.6. Research Objectives

In this thesis, the problem of integrating RAM performance measures in the economic assessment of proposed alternatives in the conceptual design stage is examined. This problem has both a management side and an engineering side (Grievink et al. 1993). The management side is concerned with the transition required in an organization that aims to embrace RAM tools in conceptual design. This involves incurring changes to the business and work processes of an organization and can be a difficult task. Moene (2000) explored the challenges in incorporating reliability goals in project development at a major oil company. On the other hand, the engineering side focuses on developing reliability engineering tools to improve system effectiveness.

Existing reliability engineering tools and optimization approaches can be too complex to enable the integration of RAM metrics into the economic evaluation of design alternatives in the conceptual design stage. Accordingly, this work is a novel contribution to literature in the following ways:

- A systematic framework to account for equipment failure and their impact on process profitability in the conceptual design stage is proposed. By incorporating failure effects on profitability, different design configurations with unique RAM characteristics can be evaluated to determine economically-optimal RAM levels for a process subsystem or system.
- The above framework is enhanced by taking a probabilistic view of the impact of equipment failure and repair/restoration times. This is accomplished using Monte Carlo simulation to obtain a distribution of process availability values.
- Classic inherent availability estimation uses failure and repair times. In this work, a modified availability metric using restoration times instead of repair times to obtain a more encompassing view of the effects of downtime on process profitability.
- After examining the effects of equipment failures on process profitability, it is desired to take a wider look at other factors affecting the reliability of the oil and gas supply chain. One of the most important considerations for the safe and continuous operation of process plant is the reliability of feedstock supply. The majority of feedstocks are transported to plants using an extensive network of natural gas transmission and hazardous liquids pipelines. Shutdown incidents of those pipelines impact supply delivery to dependent plants and can lead to production shortfalls or disruptions. Most existing works on pipeline economic risks examine the topic from the viewpoint of the costs of lost commodity, cleanup and recovery, and litigation. To address economic risks from the perspective of the commodity customer, a systematic framework to determine the impact of pipeline shutdowns on process plant production and economics is presented.

1.7. References

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2. MITIGATION OF OPERATIONAL FAILURES VIA AN ECONOMIC FRAMEWORK OF RELIABILITY, AVAILABILITY, AND MAINTAINABILITY (RAM) DURING CONCEPTUAL DESIGN*[1]

2.1. Abstract

Abnormal process situation may lead to tremendous negative impact on sustainability, wellbeing of workers and adjacent communities, company's profit, and stability of supply chains. Failure of equipment and process subsystems are among the primary causes of abnormal situations. The conventional approach in handling failure-based abnormal situations has usually focused on operational strategies. Such an approach overlooks the critical role of process design in mitigating failure, while simultaneously considering the effects of such failure on process economic performance. The aim of this work is to introduce a systematic methodology that accounts for failure early enough during the conceptual design stages. Once a base-case design is developed, the methodology starts by identifying the sources of failure that are caused by reliability issues including equipment, operational procedures, and human errors for a given process system or subsystem. Bayesian updating and Monte Carlo techniques are utilized to determine the appropriate distributions for the failure and repair scenario(s), respectively, in question. Markov analysis is used to determine the system availability. Next, the process revenue is described as a function of inherent availability. The effects of failures are incorporated into profitability calculations to establish an economic framework for trading off failure and profitability. A case

[1] Reprinted with permission from "Mitigation of operational failures via an economic framework of reliability, availability, and maintainability (RAM) during conceptual design". Ahmad Al-Douri, Vasiliki Kazantzi, Fadwa Eljack, M. Sam Mannan, & Mahmoud M. El-Halwagi. *Journal of Loss Prevention in the Process Industries*, *67*, 104261. Copyright [2020] by Elsevier.

study on an ethylene plant is solved to demonstrate the applicability and value of the proposed approach.

2.2. Introduction

2.2.1. Process Upsets and Abnormal Situations

An abnormal situation is any upset or event that requires immediate action to prevent serious consequences such as harm to personnel, damage to equipment, or a major environmental release. Particularly important causes of abnormal situations include the failure of a major piece of process equipment, failure of a process utility system, or a major upset in unit operating conditions. Other reasons include variability in raw materials, process drift, and operator error. Typically, it is a combination of events that are not normally expected to occur at the same time that cause an abnormal situation to occur. Failure-based abnormal situations have a wide range of effects on the process as they can lower product quality, reduce production rates, or cause catastrophic shutdowns. Other consequences of abnormal situations on the company whose facility is affected include liability payments, increased insurance premiums, and damage to the company's public image (Speegle, 2007).

Failure-based abnormal situations pose an economic challenge to the process industry. They can result in fires and explosions, off-specification product, equipment failures, schedule delays, or emergency shutdowns all of which can cause significant financial losses for plants. In a recent survey, the Aberdeen Group (2017) determined that unplanned downtime cost the industrial manufacturers approximately $50 billion per year, ranging between $10,000 and $250,000 per hour. Examples of these events include the Phillips disaster in October 23, 1989 in Pasadena, Texas which caused $1.6 billion in damages and the death of 23 employees and the injury of 314 more. Another event was the fire and explosion in the propylene refrigeration section of an ethylene plant in Port Arthur, Texas in April 29, 2006 which caused approximately $250 million in damages but no deaths or serious injuries (Marsh, 2013). Bullemer and Reising (2015) compiled incident reports of abnormal situations from five plants in Europe and North America to identify their sources. While most abnormal situations occurred because of an interaction of multiple sources, the authors characterized the causes of these failures into three basic types of sources: equipment, process, and people and work context. The results are shown in Figure 2.1 below. For example, plant operators attempted to maximize production by pushing the limits of the process, which increased the probabilities of equipment failures and errors by operations personnel. Recent research efforts have endeavored to utilize waste resources (e.g., flares) during abnormal situations by using cogeneration and water-treatment systems (e.g., Kazi et al., 2016; Kamrava et al., 2015; Dinh et al., 2014). A preventive approach is to try to mitigate the abnormal situations before they occur by addressing reliability, availability, and maintainability as discussed in the following section.

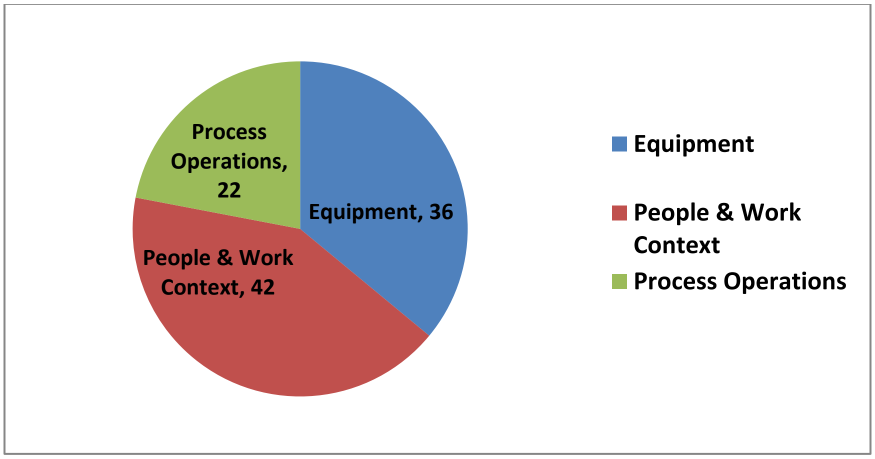

Figure 2.1: Sources of abnormal process losses, based on Bullemer and Reising (2015).

2.2.2. Reliability, Availability, and Maintainability (RAM)

The findings by Bullemer and Reising (2015) indicate that equipment failures are a major contributor to abnormal process losses in chemical production facilities. The factors responsible for equipment failures can be attributed to their design, manufacturing, or use (Rausand & Øien, 1996). Some equipment (even among the same type) are less inclined to fail than others for reasons largely attributed to their design (Dhillon, 2005). These equipment are said to be more reliable than others, indicating they are less prone to failure. Reliability is defined as "the ability of an item to perform a required function, under given environmental and operational conditions and for a stated period of time" (ISO 8402). Despite its importance, the study and development of reliability goes back to World War II when it became necessary to deal with the frequent failures of electronic equipment (Bernstein et al. 2006). Reliability can be extended to include the maintenance characteristics to determine an availability level for the equipment or component being analyzed. Availability is defined as the ability of an item to perform its required function at a stated instant of a time over a stated period of time (BS4778, 1991). Achieving a high level of availability is important for profitability in a manufacturing plant. There are three subtypes of availability: operational, achievable, and inherent. Operational availability includes unplanned and planned maintenance and time lost to operational logistics and administration. Achievable availability reflects availability including planned and unplanned maintenance times. Inherent availability includes only corrective maintenance time. While operational availability is the most comprehensive and realistic measure, it is of the least importance in design because administrative and logistic time delays are outside the design team's control. Availability is a function of the reliability and maintainability characteristics of the system/subsystem. While reliability has been defined previously, maintainability is defined as the probability that a failed system/component will be restored or repaired to a specified condition within a period of time when maintenance is performed according to prescribed procedures.

Several recent works have examined the integration of RAM analysis in the design of engineering system. In the automotive and aircraft industries, surveys have indicated reliability is in the top two important criteria for customers when selection of a product (Murthy et al. 2008; Deutsche Automobil Treuhand GmbH, 2018). The integration of RAM analysis in the design of engineering systems has been examined in several recent works. In the automotive and aircraft industries, surveys have indicated reliability is in the top two important criteria for customers when selection of a product (Murthy et al. 2008; Deutsche Automobil Treuhand GmbH, 2018). The challenge therefore has been to incorporate expected reliability in the product development/design phase. To achieve this goal, quantitative and qualitative methods of RAM analysis have been mapped to determine the expected levels of reliability for an automotive or aircraft system during product development (Bertsche (2008); Johansson et al. (2013); Johansson et al. (2018)). In subsea oil and gas systems, fiscal metering reliability and maintenance are vital factors because precise flow measurement of a petroleum product is very important to fulfill contractual obligations between suppliers and consumers (Statoil, 2015). By connecting relevant concepts and models of systems and RAM engineering, Zhang et al. (2018) developed a framework to be applied to the design of subsea fiscal oil export metering system using stochastic Petri Nets (SPN).

Plant availability has been a critical consideration in the design and operation of chemical processes. Since it represents the expected fraction of operating time, availability is an important factor in predicting the productivity and profitability of a plant. While reliability, availability, and maintainability (RAM) analyses for components or equipment in operation have been performed, there is a need to examine how inherent RAM characteristics can be integrated into the determination of an economically-optimum level of reliability for a system/subsystem during the process design phase. Sharda and Bury (2008) presented a discrete event simulation model to understand the impact of different critical subsystems on overall plant production capabilities using historical failure data. However, a discrete events approach does not guarantee optimal solutions.

The evaluation and optimization of the RAM characteristics of an engineering system has led to the development of reliability engineering. According to Zio (2009), this field addresses the following issues: (1) causes, mechanisms, and consequences of system failures; (2) measurement and evaluation of system reliability in design and operations; (3) development of reliable systems by reliability-based design, to which this work is relevant.

Process design is composed of the following stages: feasibility studies, conceptual design, preliminary design or front-end engineering design (FEED), detailed design and equipment selection, and finally the engineering, procurement, and construction (EPC) phase. Typically, economic performance is used to optimize the design after the conceptual design phase while reliability and safety are considered after the detailed design phase. In order to increase availability of a system/subsystem at the design stage, reliability and/or maintainability characteristics must be increased. This is a complex task as many factors can influence reliability and maintainability throughout a system/subsystem's life cycle. The problem of integrating RAM assessment and optimization into the conceptual design phase and techno-economic analysis reports is examined in this work. Integrating RAM analysis into process design has a management side and an engineering side (Grievink et al. 1993). The management side is concerned with introducing changes and affecting a transition in an organization in order to use RAM tools in design. Moen (2000) explored the challenges a major oil company dealt with when it incorporated reliability goals into the project development phase. As for the engineering side, it is concerned with the development of reliability engineering tools to improve system effectiveness. Goel (2003) developed a framework for integrating RAM attributes into the conceptual design stage to obtain qualitative RAM targets. Sader et al. (2019) illustrated the impact of safety, sustainability, reliability, and resilience on the economic profitability of the process and proposed an integrated framework for handling the multiple objectives.

This paper presents a framework that can be used to develop an optimization problem to determine an economically-optimum level of availability for a system/subsystem based on its costs and benefits.

2.2.3. Problem Statement

Given the RAM characteristics for a process subsystem, it is desired to determine the effect potential design configurations with improved RAM characteristics can have on process profitability. The optimization problem can be used to make design decisions regarding installing redundant units (active or standby) or choosing equipment with different RAM characteristics with the objective of maximizing a chosen profitability measure (e.g. return on investment, payback period) of the potential configuration. In this problem, the system/subsystem can be formulated as a number of process stages ($n \in N$) and the potential units (M) for each stage are a subset of set N. A set of potential units $m \in M\_n$ is given with its inherent RAM characteristics (failure rate, mean-time-to-repair). The constraints will be equipment design equations to determine capacities, the inherent availability calculations (based on failure and repair data), and cost calculation equations for the equipment being examined. A case study of different design configurations for a four-stage cracked gas compression (CGC) section of an ethylene production plant will be presented to illustrate this analysis. In this case, the set is defined as the number of stages of the CGC, and the variables are the number of units in parallel in each stage ($y_{(n,m)}$). Each unit in each stage has a fixed failure rate, mean-time-to-repair, and cost. The constraints are the availability calculation equations for each unit, and the investment cost of each stage and of the whole CGC.

2.3. Theoretical Framework Description

The framework presented here is this work for the conceptual design phase of process design and to be integrated into the techno-economic analysis of a proposed design. A flowchart outlining these steps is given in Figure 2.2.

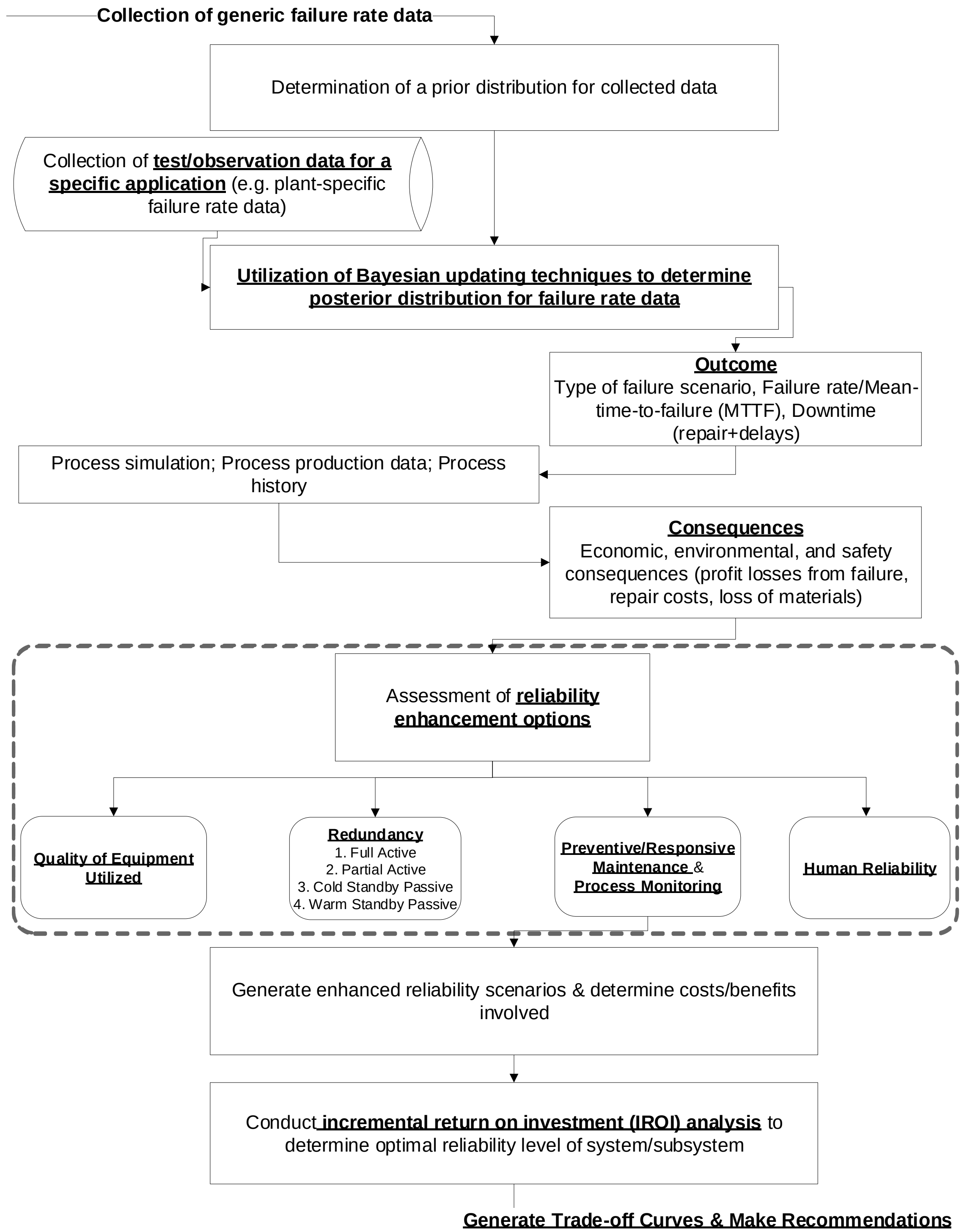

Figure 2.2: Framework for RAM improvement in conceptual design & techno-economic analysis

The methodology starts with identifying the sources of failure that are a result of reliability issues including equipment, operational procedures, and human errors for a given process system or subsystem. These failure sources can be identified using fault tree analysis, event tree analysis, or failure modes and effects analysis (FMEA). Failure sources in a system or subsystem can also be identified using failure data to determine the equipment or components that are more likely to cause failures and significant downtime associated with these failures.

The framework illustrated above can be applied to be both the design of a new system the improvement of an existing one. In the latter case, the condition that the asset (e.g. equipment) is still within the recovery period must be satisfied and has not fully depreciated. Several methods exist for determining annual depreciation charges such as: straight-line method, declining balance method, and the Modified Accelerated Cost Recovery System (MACRS) (El-Halwagi 2017b). For example, in the MACRS method, a class life and recovery period are defined for different equipment or industries. For petroleum refining and chemical manufacturing assets, the recovery periods are 10 and 5 years, respectively (IRS, 2009).

2.3.1. Assessment of Reliability, Availability, and Maintainability (RAM) Levels

2.3.1.1. Bayesian Updating Procedure

In this work, the failure rates of the centrifugal cracked-gas compressor are determined using a Bayesian estimation procedure. This is done because it is important to quantify uncertainties associated with the available data. In a Bayesian approach, the parameters of interest (mean or median of distribution) are treated as random variables whose values are unknown. A prior probability density function (pdf) is used to represent relevant prior knowledge including a subjectivist judgment regarding the parameter and distribution characteristics. This prior knowledge is combined with relevant information (plant-specific data, observations and tests) to obtain a posterior distribution for the parameter of interest. This approach is often called a *subjectivist approach* since the selection of the prior distribution and determination of the posterior distribution involve subjective judgement. The following equation is the mathematical representation for the Bayes' theorem for a continuous random variable (r.v.):

$$f((\theta|t) = \frac{h(\theta)l((t|\theta)}{\int_{-\infty}^{\infty} h(\theta)l((t|\theta)\,d\theta} \qquad (1)$$

where θ is the parameter of interest (e.g. parameter of time-to-failure distribution, mean time to failure, failure rate). Assuming θ to be a continuous r.v. allows for the prior and posterior distributions of θ to be represented by continuous pdfs. In the above equation, $h(\theta)$ is the prior distribution of θ and $l(t|\theta)$ is the likelihood function based on test or observation data. The choice of prior distribution reflects the state of knowledge regarding the parameter of interest (θ). The likelihood function is based on the type of test or observation data available and the distribution of interest.

In this work, the time-to-failure behavior of the centrifugal cracked-gas compressor follows the exponential distribution. As such, the parameter of interest is the compressor's constant failure rate (denoted by λ) and a gamma distribution is used as its prior distribution. The observation data available in this case are the number of compressor failure events observed in ethylene plants in two 4-year periods (1995-1999, 2001-2005). The Poisson distribution is appropriate for describing events in a given time period, and thus is used to define the likelihood function. Thus, a prior gamma distribution is updated with the event data represented by a Poisson likelihood function. Kaplan (1983) and Shafaghi (2008) can be consulted for a more detailed description of the equations used in the Bayesian updating procedure.

2.3.1.2. Markov Chain Analysis

To determine system availability, components are modelled using Markov analysis where a component/system is treated as being in one of several states. For a simple Markov process, a component is in one of two states: (1) operating or (2) under repair, as shown in the transition rate diagram in Figure 2.3. The failure and repair rates are the transfer rates between states.

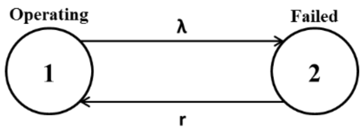

Figure 2.3: Transition rate diagram for a single component with repair.

For a system of *n* components in series with constant failure and repair rates, inherent availability is determined using the following equation:

$$A_{System} = \prod_{i=1}^{n} A_i = \prod_{i=1}^{n} \frac{r_i}{r_i+\lambda_i} \quad (2)$$

where for a component *i:* A_i is the component availability, λ_i and r_i are its failure and repair rates, respectively.

For components arranged in a parallel configuration (e.g. standby redundancy, active redundancy), the Markov transition diagrams are more complex as shown in Figures 2.4 and 2.5 for the cases of standby and active redundancies, respectively. These configurations are described in detail with their governing equations in Henley and Kumamoto (1981). In Figure 4, the first block indicates the operating component, the second one indicates the component on standby, and the third one indicates the component under repair. In this scenario, the redundant component (B) is assumed to be in a "cold standby" mode indicating that its failure rate is zero. In Figure 2.5, both components are operational as this is an active redundancy scenario. For both Figures 2.4 and 2.5, two repair stations are assumed to be available to allow for both components to be repaired simultaneously if needed.

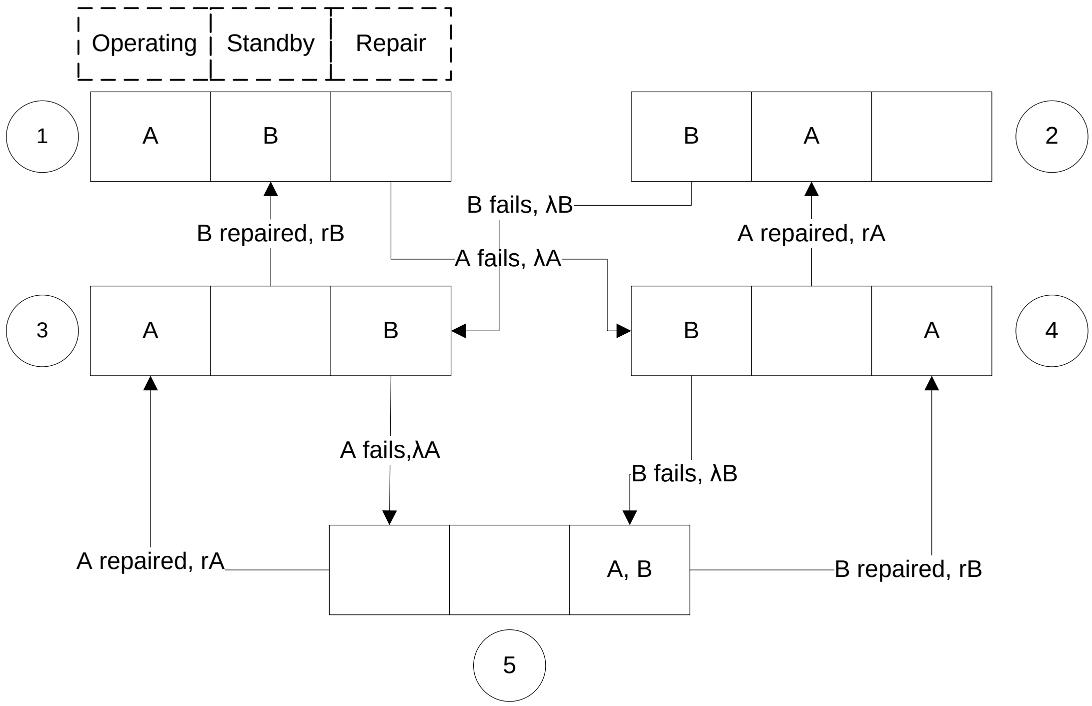

Figure 2.4: Markov transition diagram for redundant configuration with a cold standby component.

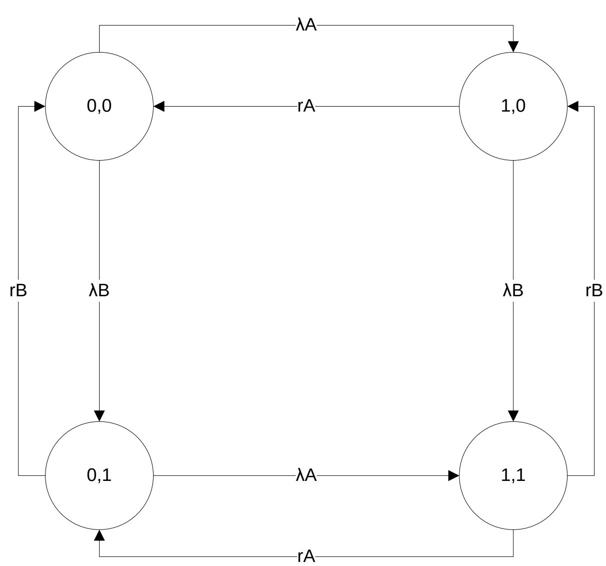

Figure 2.5: Markov transition diagram for a two-component parallel system.

2.3.2. Economic Evaluation of Potential Design Alternatives

The alternative design scenarios evaluated would be incremental projects in nature since they represent possible additions or modifications to the base case project. For each scenario, the additional capital costs and reduced revenue losses associated with the improved availability levels are determined. In such cases, each addition is justified by calculating its incremental return on investment ($IROI$) (El-Halwagi, 2017a):

$$IROI = \frac{\Delta Annual\ \ net\ (after - tax)\ profit\ of\ add - on\ project}{\Delta\, TCI\ of\ add - on\ project} \times 100 \qquad (3)$$

where $\Delta TCI\ of\ add - on\ project$ is the difference between the total capital investment (TCI) of the combined (addition/modification and base case) project and the TCI of the base case project.The choice among different design scenarios is an optimization problem where the objective is maximizing IROI. Mathematically, the problem can be formulated as a mixed-integer nonlinear program (MINLP) as follows:

$$\max_{d_i, o_i, A_i, I_i} IROI(d_i,\ o_i, A\ _i,\ I_i) = \frac{\Delta Annual\ net\ (after - tax)\ profit\ of\ add - on\ project}{\Delta\ TCI\ of\ add - on\ project} \times 100$$

s.t. $\quad \Delta Annual\ net\ (after - tax)\ profit\ of\ add - on\ project\ =$

$$\begin{bmatrix} \{Revenue(d_i,\ o_i, A\ _i,\ I_i) - Total\ Annualized\ Cost(d_i,\ o_i, A\ _i,\ I_i)\} * (1 - Tax\ Rate) \\ + Depreciation(d_i,\ A_i,\ I_i) \end{bmatrix} -$$

$$[\{Revenue\ (d_0,\ o_0,\ A_0, I_0) - Total\ Annualized\ Cost(d_0,\ o_0, A\ _0,\ I_0)\} * (1 - Tax\ Rate) + Depreciation(d_0,\ A_0, I_0)]$$

$$\Delta\ TCI\ of\ add - on\ project = TCI(d_i,\ o_i, A_i\ I_i) - TCI(d_0, o_0, A_0, I_0)$$

$$h_i(d_i, o_i,\ A_i,\ I_i) = 0$$

$$g_i(d_i, o_i,\ A_i,\ I_i) \le 0$$

$$\sum_{i=0}^{N} I_i \leq 1$$

$$d_{min} \leq d_i \leq d_{max} \quad o_{min} \leq o_i \leq o_{max} \quad A_0 \leq A_i \leq A_{max} \qquad \forall i \in 0, \ldots, N$$

In this formulation, d_i and o_i represent design and operational variables for each alternative, respectively, with $i = 0$ denoting the base case. Examples of design variables are reactor volume, compressor power ratio, or heat exchanger area; operational variables can be inlet and outlet temperatures and pressures and mass flowrates. Also, the equality constraint $h_i(d_i, o_i,\ A_i,\ I_i) = 0$ corresponds to the process model, covering mass and energy balances, for each design alternative i. Inequality constraints $g_i(d_i, o_i,\ A_i,\ I_i)$ correspond to process design and operational specifications such as equipment capacities. Integer variables I_i are discrete, binary (0,1) variables to represent discrete choices, in this case whether the design alternative *i* is chosen. The constraint for I_i allows the choice of only one design alternative. In this work, a base case and three design alternatives are considered, so the solution to the optimization problem is obtained numerically by evaluating all design alternatives individually to determine the choice with the maximum IROI.

2.4. Case Study Results and Discussion: Ethylene Plant Cracked Gas Compression

2.4.1. Case Study Overview

Ethylene is one of the main building blocks of the chemical industry and the most consumed of the olefin building blocks, with a worldwide production of about 150 million metric tons (MTT) as of 2016. This figure is expected to grow to approximately 175 MMT by 2020, and demand is growing as well. The traditional feedstock for ethylene production has been naphtha, but the shale gas boom in the United States has created the opportunity to use lighter feedstocks. The share of ethane as a feedstock for steam crackers in the U.S. increased from 45% to 65% (Ibbotson 2014), and is expected to increase from 36% to 40% on a global scale by 2021 (Lewandowski, 2016).

Steam cracking of hydrocarbons is a process in which high-pressure steam is used to break molecular bonds to produce olefins. The cracking of ethane to produce ethylene is given by the following equation:

$$C_2H_6 \rightarrow C_2H_4 + H_2$$

Three major steps comprise this process: cracking, compression, and fractionation. First, steam and hydrocarbons are fed into a tubular reactor where cracking takes place at a temperature of 750-870°C. To prevent secondary reactions, the exit gases are quenched to 550-600°C in a quench tower. Second, the exit stream is then compressed in a multi-stage compression system to pressure of 32-38 bar. After each stage, liquids are removed and the remaining gases are treated to remove acid gases. The stream then passes through a cooling train to condense water, and molecular sieves to dry the gases. Finally, a series of fractionators are used to remove methane, ethane, propane, and heavier fractions (Wells, 1999). Figure 2.6 shows the important steps in a steam cracking process.

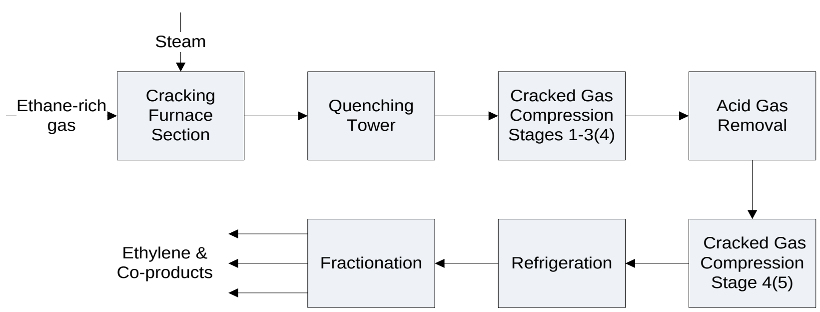

Figure 2.6: Ethylene production process schematic flow diagram.

Due to the vital role of ethylene in the petrochemical industry and its growing nature, it is important to examine the causes of production shutdowns or slowdowns in ethylene plants. These events cause lost revenues, equipment repair and/or replacement costs, and damage to a company's reputation which can have because of unmet contractual obligations. These monetary damages will impact the project's return on investment (ROI) and should be accounted for in profitability estimates at the design stage. In the following sections, the framework previously described will be applied to the process of ethylene production by ethane-rich gas cracking, with a specific focus on failures in the cracked gas compression system. This can be accomplished by a three-step process:

1. Analyzing and quantifying failures due to reliability issues and their consequences,
2. Identifying reliability improvement scenarios and assessing their impact, and
3. Evaluating the profitability of these projects relative to their capital costs.

2.4.2. Failure Causes in Ethylene Plants

A challenging aspect of reliability prediction or analysis is obtaining representative failure statistics since industry considers this information proprietary. Shah (2008) presented the results of an authoritative survey of the ethylene industry conducted by the Ethylene Producers' Committee (EPC), Rotating Machinery Subcommittee (RMSC), and Solomon Associates (SA) between 1995-1999 (96 plants) and 2001-2005 (108 plants). The latter figure accounted for 66 million metric tons of ethylene capacity. The results show that the major causes of production curtailment (both slowdowns and shutdowns) in ethylene plants were:

1. Pyrolysis furnace availability,
2. Fouling, freezing, or plugging of equipment, and
3. Major compressor malfunctions.

Over the survey duration, total annual capacity lost due to planned maintenance and inspection turnarounds averaged 1.6%. Unplanned slowdowns and shutdowns caused an annual average capacity loss of 4%. Furthermore, shutdowns accounted for an average annual capacity loss of

1.2% (about 1,260 KTA based on the 2001-2005 production capacity). This figure is significant since approximately 60% of ethylene production goes to polyethylene (LDPE, LLDPE, and HDPE), the most common material in packaging (Charlesworth, 2017). Using the current price of low-density polyethylene (LDPE), it is estimated that this capacity loss translates into an annual LDPE revenue loss of $143 million. When considering other uses of ethylene (HDPE, LLDPE, and ethylene oxide), hundreds of millions of dollars of revenue are lost due to an annual capacity loss of 1.2 %.

In the survey, compressor malfunctions were shown to be the major cause of shutdowns in ethylene plants (26% of capacity loss), while pyrolysis furnace availability was the major cause of slowdowns (34% of capacity loss). Another significant contributor to shutdowns was miscellaneous equipment failures (about 15%). These results are summarized in Figure 2.7.

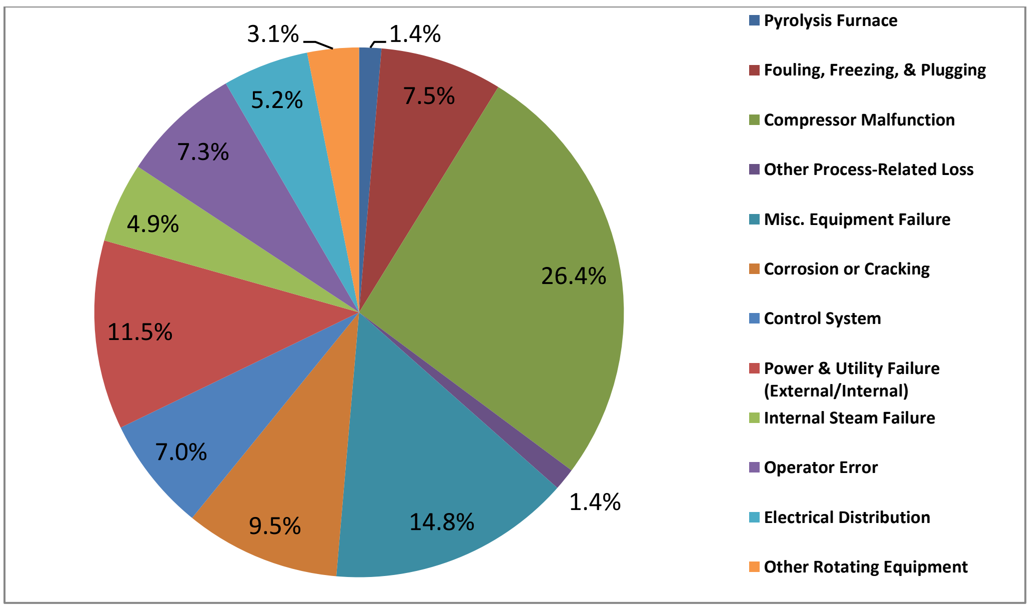

Figure 2.7: Cause categories of ethylene plant shutdowns (adapted from Shah (2008)).

Since compressor malfunctions are the major contributor to unplanned shutdowns in ethylene plants, it is important to further examine their failure causes and resulting economic losses. Also, decisions that can be implemented at the plant design stage to reduce those financial losses should be examined to determine their economic viability.

2.4.3. Compressors in Ethylene Plants

Olefin plants contain three major centrifugal compressor trains or strings: a cracked gas compressor, an ethylene refrigeration compressor, and a propylene refrigeration compressor. The cracked gas and propylene compressor strings are driven by steam turbines, while the ethylene compressor is driven by an electric motor as it requires only 20-40% of a cracked gas compressor's horsepower (Bloch and Geitner, 2012).

In this case study, the main concern will be the cracked gas compression section, shown in Figure 2.8. Cracked gas compressors are multi-stage centrifugal compressors that draw gas from the quench tower overhead vapor product and pressurize it for further separation. Among their characteristics are large volumes, high mass flowrates, low pressures, and multiple compressor sections to meet the required discharge pressures (Harvey, 2017). This section typically has 4-6 process stages, with a condenser and flash drum between each stage. Prior to the last compression stage, there is a caustic tower to remove acid gases (H_2S and CO_2). Figure 8 is a process flow diagram of a four-stage CGC section. The CGC system in a naphtha-type cracking plant usually has five stages because of the low suction pressure (0.17-0.30 barg), while ethane cracking plants have four stages. Depending on the capacity and vendor, the CGC system consists of three to four casings, a low-pressure (LP) section, a medium pressure (MP) section, and a high pressure (HP) section (Bowen and Jones, 2008).

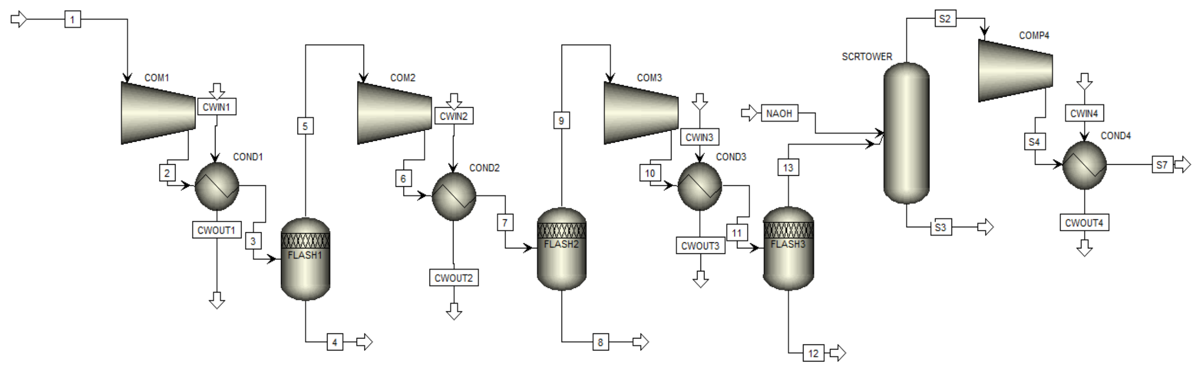

Figure 2.8: Process flow diagram of a four-stage cracked gas compression system.

The process specifications for a CGC section include: (1) maximum volumetric flowrate to each stage, (2) suction and discharge pressures for the 1st and last stages respectively, and (3) the maximum allowable discharge temperature. To prevent ethylene polymerization, the compressed gas is cooled using cooling water in a condenser and any liquids are removed via a flash drum after each stage. The maximum volumetric flowrate to each stage is the key criteria to determine compressor size and set a plant's capacity. For example, an ethane cracker with a production capacity of 1.5 million MTA has a CGC inlet volume flow of 200–280*10^3 m^3/hr.

2.4.4. Base Case RAM Modelling of the Cracked Gas Compression (CGC) Train

In this study, the equipment being considered is a multi-stage centrifugal compressor used in the cracked-gas compression section of an ethylene production plant. Two sources of failure rate data that were available: a collection of generic failure data, and plant-specific data. Ten generic failure rates for centrifugal compressors were collected in this study and are listed below in Table 2.1, along with their arithmetic and geometric means. The prior mean failure rate that will be utilized will be the geometric mean with a value of 4.02 failures/year.

Table 2.1: Generic centrifugal compressor failure rate data.

Source	**Failure Rate (Failures/10^E+6 hours)**	**Failure Rate (Failures/year)**
CCPS (1989)	84.5	0.669
Koolen (2001)	87.8	0.695
Moss (2005)	250	1.980
Dhillon (1988)	253	2.004
OREDA (2002)	564	4.469
OREDA (2015)	605	4.789
Moss (2005)	640	5.069
Moss (2005)	1700	13.5
OREDA (1992)	2450	19.4
Moss (2005)	2694	21.3
Arithmetic Mean	**933**	**7.39**
Geometric Mean	**508**	**4.02**

The plant-specific data in this work was obtained from Shah (2008) which presented ethylene process compressor reliability information based on a survey of multiple plants in five continents. The survey was conducted over two five-year periods: 1995-1999 and 2001-2005. Table 2.2 presents a summary of the number of plants and compressors surveyed along with the failure events and resultant downtimes over the survey period.

Table 2.2: Summary of failure events in ethylene plant compressors.

	1995-1999	**2001-2005**
Number of Plants Surveyed	96	108
Number of Compressors	202	223
Failure Events	800	770
Hours of Downtime for Major Compressors	58,073	43,900

Using the constrained non-informative prior gamma distribution from Atwood's (1992) work, the parameters for the prior distribution of the failure rate of a centrifugal compressor are determined using the equations stated previously. The ethylene plant-specific compressor survey results are used to calculate the posterior gamma distribution parameters. These results, with a two-sided 90% confidence interval, are reported in Table 2.3. While the prior distribution had a mean of 4.02 failures/year, using the plant-specific data resulted in posterior means of 0.792 failures/year (using 1995-1999 data) and 0.691failures/year (using 2001-2005 data), respectively. Taking into account both survey durations, the expected failure rate for the cracked gas compressor ranges between 0.677 and 0.839 failures/year. This is a much-improved estimate over the prior distribution confidence interval of 0.015 to 15.5 failures/year. The failure rate values used throughout this work will reflect the range determined by the Bayesian updating procedure.

Table 2.3: Prior and posterior parameters for centrifugal compressor failures.

Gamma Distribution Parameters	**Prior Distribution**	**Posterior Distribution**	
		1995-1999	**2001-2005**
α	0.5	800.5	770.5
β	0.124	1010	1115
Mean Failure Rate λ (failure/year)	4.025	0.792	0.691
5th Percentile Failure Rate	0.016	0.747	0.677
95th Percentile Failure Rate	15.5	0.839	0.760

Next, the availability of the cracked-gas compressor is determined using the failure rate distribution calculated with the Bayesian updating method and restoration time values. Due to the limited data available on repair/restoration times, a triangular distribution of restoration times (60, 200, and 660 hours) reported in OREDA (2015) was used to indicate the uncertainty surrounding this parameter. The cracked-gas compression train is estimated to have an availability of 88.5%.

Table 2.4: Cracked-gas compressor availability estimation.

Equipment	**Failure Rate (Failures/Year)**	**MTTRes (Hours)**	**Availability**
Stage 1	0.75	309	0.9716
Stage 2	0.77	309	0.9709
Stage 3	0.81	309	0.9694
Stage 4	0.85	309	0.9679
Overall Compression Train	**3.18**	**309**	**0.8851**

2.4.5. Preliminary Design & Cost Estimation of the Cracked Gas Compression (CGC) System

This case study is focused on the CGC system of an ethane-cracking ethylene production facility with annual capacity of 830,000 tonnes/year. The ethylene produced is used downstream for high-density polyethylene (HDPE) production using the suspension (slurry) polymerization process, as shown in Figure 2.9. The calculation of lost revenue will be on the basis of the amount of HDPE product lost.

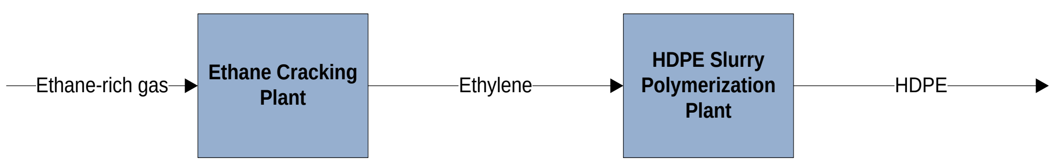

Figure 2.9: Block diagram of ethylene and polyethylene production complex.

For a plant with the stated capacity, the mass flowrate of the quench tower overhead vapor product entering the cracked gas compressor is 1.44x10^6 tonnes/year and its inlet temperature and pressure are 318 K and 1.56 bar (0.156 MPa), respectively (AlNouss et al. 2017). The stream is composed of ethylene, ethane, propane, and other gases, and its composition is shown in Table 2.5.

Table 2.5: Composition of CGC inlet stream (adapted from AlNouss et al. (2017)).

	Mass Flowrate (tonnes/year)
H2	73,376
CH4	124,350
C2H2	15,873
C2H4	969,311
C2H6	177,863
C3H6	15,873
C4H4	4,354
C4H6	21,677
C5H6	7,256
C6H6	17,324
H2S	1,451

The composition and mass flowrate can be used to size and determine the power requirements of the overall cracked gas compressor and its stages. Industrial compressors have a polytropic path expressed by the equation:

$$Pv^n = constant \qquad (4)$$

where P is the pressure, v is the volume, and n is the polytropic coefficient (the value of which depends on the design and operation of the machine). The work required for each stage is given by the equation (Coulson et al. 1999):

$$-W = \frac{ZRT_i}{M_w}\frac{n}{n-1}[(\frac{P_{i+1}}{P_i})^{\frac{n-1}{n}} - 1] \qquad (5)$$

where Z= compressibility factor (1for an ideal gas)

R = universal gas constant, 8.314$\frac{J}{K\,mol}$

T1 = inlet temperature, K

W= work done, J/kg

M_w= Molecular mass (weight) of gas

Using the gas composition and critical temperatures and pressures for each component, the overall gas mixture is determined to have a critical temperature and pressure of 177 K and 3.56 MPa, respectively. The inlet conditions (318 K and 0.156 MPa) indicate that the mixture is away from the critical point. Thus, the value of the polytropic compression coefficient (n) can be determined as follows:

$$n = \frac{1}{1-m} \qquad (6)$$

where

$$m = \frac{\gamma-1}{\gamma * E_p} \qquad (7)$$

where γ is the heat capacity ratio of the gas mixture and E_p is the polytropic efficiency. In a multistage compressor, the compression work for each stage will be equal. Each compression stage can be treated as a compressor by itself for the purposes of sizing and cost calculations. For a 4-stage system with an inlet pressure of 1.56 bar and an outlet pressure of 35.4 bar, a compression ratio of 2.2 per stage is calculated. Using the calculated work from the above equation, the actual work can be determined as follows:

$$Actual\ work\ required = \frac{Polytropic\ work}{Polytropic\ Efficiency, E_p} \qquad (8)$$

Most centrifugal compressor casings have nominal polytropic efficiencies between 0.76 and 0.78 (Couper et al. 2005). Subsequently the compression power requirement can be calculated using the following equation:

$Power\ (kW) =$

$\frac{Work}{Time}$…………………………………………………………………….………..…(9)

Using the procedure above, Table 2.6 lists the calculated values that are used to determine the power requirement for one stage of the cracked gas compressor, and the overall compressor also.

Table 2.6: Summary for power requirement calculations results for the first stage of a CGC.

Inlet Pressure (Mpa)	0.156
Inlet Temperature (K)	318
Efficiency (E_p)	0.78
Mixture Heat Capacity Ratio	1.275
n (Polytropic Coefficient)	1.382
Outlet Pressure (Mpa)	0.343
Outlet Temperature (K)	395.441
Reduced Temperature	2.019
Reduced Pressure	0.070
Molecular Weight of Gas	16.534
Polytropic Work (kJ/kmol)	2,329
Actual Work (kJ/kmol)	2,986
Power (kW)	8,249
Power (hp)	11,062

From Table 2.6, the cracked gas compressor is estimated to have an overall power requirement of 33,000 kW. After the power requirement is determined, the purchased equipment cost for a centrifugal compressor can be determined using the cost curve correlation (Towler & Sinnott, 2012):

$C_e = a + bS^n$…………………………………………………………………………..…(10)

where C_e= purchased equipment cost on a U.S. Gulf Coast basis for January 2010 (CEPCI=532.9)

a , b= cost constants (a=580,000 and b=20,000 for centrifugal compressors)

S= size parameter (kW for centrifugal compressors)

n= exponent for type of equipment (0.6 for centrifugal compressors)

Another consideration that should be included is how the RAM characteristics of the equipment affect its cost. Equipment with higher availability would have higher capital costs, which can be accounted for using the availability factor proposed by Ishii et al. (1997), as shown in the following equation:

$$Availability - Adjusted\ Equipment\ Cost = Delivered\ Equipment\ Cost \times e^{(\frac{A}{A_0}-1)} \quad (11)$$

where A_0 is a base, or standard, availability for a piece of equipment. The authors suggested using a value of 0.95 for the standard availability. Table 2.7 presents the results for the availability-adjusted equipment costs. The first stage cost twice as much as the other stages because is a double-flow configuration, which is two smaller compressors arranged back to back with a common discharge to enable a higher volume flow (Harvey, 2017). The four-stage centrifugal compression train was estimated to have an availability of about 88.5% and costs about $30 MM, after adjusting for availability.

Table 2.7: Delivered equipment cost for cracked-gas compression train.

	Sinnott & Towler (2012)		**Availability-Adjusted Cost**	
Compression Stage	**Cost (2010 $MM)**	**Cost (2019 $MM)**	**Availability**	**Cost (2019 $MM)**
Stage 1 (Double-flow configuration)	10.112	11.740	0.9716	12.010
Stage 2	5.056	5.870	0.9709	6.000
Stage 3	5.056	5.870	0.9694	5.991
Stage 4	5.056	5.870	0.9679	5.982
Overall Compressor	**25.280**	**29.350**	**0.8851**	**29.983**

The total capital investment (TCI) for the CGC can be estimated from the delivered equipment cost (centrifugal compressor) using the TCI Lang as follows (Peters et al. 2003):

$$TCI = TCI\ Lang\ Factor \times Delivered\ Equipment\ Cost \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(12)}$$

For a fluid processing plant, the TCI Lang Factor is 6.0, and the above calculation yields a TCI value of \$151.68MM for the cracked gas compressor.

Using values from Thiruvenkatswamy et al. (2016), the above economic analysis can be expanded to evaluate the profitability of the plant. This can be done by calculating a return on investment (ROI) value for the plant as follows (El-Halwagi, 2017a):

$$Return\ on\ investment\ (ROI) = \frac{Annual\ net\ (after-tax)\ profit}{Total\ Capital\ Investment\ (TCI)} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(13)}$$

where the annual net (after-tax) profit is determined by the following equation:

$$Annual\ net\ (after-tax)\ profit = (Annual\ income - Total\ annualized\ cost) * (1 - Tax\ rate) + Depreciation \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(14)}$$

Since all of the ethylene goes to HDPE production, the annual income is calculated from the HDPE sales and is based on the value of the least-available compressor stage (0.990639 for stage 4). Thus, the annual income is multiplied by the availability of stage 4, since its unavailability indicates the compressor, and the plant, are shut down. In the above equation, the total annualized cost (TAC) are defined as follows:

$$Total\ Annualized\ Cost = Annualized\ Fixed\ Cost + Annualized\ Operating\ Cost \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(15)}$$

The annualized fixed cost (AFC) is determined by the calculating the annual depreciation charge using the straight line method:

$$AFC = \frac{FCI_0 - FCI_s}{N} \qquad (16)$$

where FCI_0 is the initial value of the depreciable FCI, FCI_s is the salvage value of FCI at the end of service life, and N is the service life of the property in years.

The annualized operating cost (AOC) in this case is taken to be the total cost of heating and cooling utilities. Table 2.8 shows the economic metrics used in the ROI calculation for the base case plant. If a threshold of 10% is used to determine whether a project is an attractive investment, this plant is clearly a promising investment. Recent research contributions have illustrated the use of a return-on-investment framework for including sustainability and safety (El-Halwagi, 2017b; Guillen-Cuevas et al., 2018). In the calculations below, the plant was assumed to have an overall availability of 90%, based on the assumption of operating 330 days annually.

Table 2.8: Economic metrics for the base case ethylene plant.

Production Rate (MT/year)	830,000
Fixed Capital Investment ($MM)	871
Annualized Fixed Cost ($MM/year)	43.55
Tax Rate (%)	30
Heating Utility Cost ($MM/year)	593.9
Cooling Utility Cost ($MM/year)	78.6
Annual Operating Cost ($MM/year)	672.5
Annual Income ($MM/year)	1,041
Total Annualized Cost ($MM/year)	716
Annual net (after-tax) profit ($MM/yr)	**271.3**
Total Capital Investment ($MM)	**1,025**
Return on Investment (%/year)	**26.47**

2.4.6. Availability Improvement Options for Cracked-Gas Compression (CGC)

After the base case is established, design modifications to improve the RAM characteristics of the system are examined. These improvements can be the addition of a redundant compressor body for the most failure-prone stage, using parallel flow arrangements for one or more of the compression stages, or the use of equipment that are less failure-prone.

2.4.6.1. Equipment with Improved Inherent RAM Levels

One of the possible design modifications is to utilize equipment with improved availability characteristics (e.g. lower failure rates). These lower failure rates can be ascertained by comparing equipment factory acceptance testing data or repair facility records for the equipment choices being considered. For this scenario, the higher equipment quality is reflected in lower failure rate and lower mean time to restoration. This was achieved by setting the failure rate and repair times to 15% lower than the base case values. The results are shown below in Table 2.9, and indicate that the system availability and cost increase by about 3.5% and 1%, respectively.

Table 2.9: Availability calculation for a CGC system with better inherent RAM characteristics.

Equipment	**Failure Rate (Failures/Year)**	**MTTRes (Hours)**	**Availability**	**Availability-Adjusted Cost (2019 $MM)**
Stage 1	0.64	262	0.9793	12.11
Stage 2	0.65	262	0.9788	6.05
Stage 3	0.69	262	0.9777	6.04
Stage 4	0.72	262	0.9766	6.04
Overall Compression Train	**2.86**	**262**	<u>**0.9153**</u>	<u>**30.24**</u>

2.4.6.2. Parallel Split-Flow Arrangement of Equipment

In the case of a parallel flow arrangement, any stage of the compressor section can be replaced with two smaller compressors (A and B) in a parallel arrangement so that if one fails, the other would still operate at half the capacity. The parallel compressors would each compress half the mass flowrate of the original compressor, and would have half its power requirement. This would reduce the downtime for the compression section, but would incur additional capital cost due to having two smaller compressors instead of one. While this may be in contrast to economy-of-scale principles, it is desired to examine if the additional production uptime and revenue would make up for the capital cost incurred. The two parallel compressors in the stage would be smaller in size and have lower power requirements than one larger compressor. As such, they will be assumed to have a higher rotor speed and are more failure-prone due to stress and vibration problems caused by rotor instabilities. For this reason, the two parallel compressors in a stage were assumed to have higher failure rates (lower availabilities) than one large compressor. The availability calculations for this design scenario were performed using Equations (22) to (25) and the results are presented below in Table 2.10. The 4^{th}-stage parallel arrangement had an availability of 0.992. From a cost perspective, this would make the compressors less costly. In this design scenario, the compressor cost increases by about 8%, while its availability increases by about 3%.

Table 2.10: Availability calculation for a CGC system with 4th stage split-flow arrangement.

Equipment	Failure Rate (Failures/Year)	MTTRes (Hours)	Availability	Availability-Adjusted Cost (2019 $MM)
Stage 1	0.75	309	0.9743	12.04
Stage 2	0.77	309	0.9736	6.02
Stage 3	0.81	309	0.9723	6.01
Stage 4A	0.9	309	0.992	4.19
Stage 4B	0.9	309		4.19
Overall Compression Train	**3.83**	**309**	**0.9148**	**32.44**

2.4.6.3. Redundant Equipment

In the case of a redundant compressor stage, the fourth stage would have a standby compressor of the same power requirement and RAM characteristics of the operating stage. The standby compressor would be operational if the operating stage fails. This would improve the availability of the fourth compression stage, but would incur a significant capital cost to have a standby compressor body.

In this case, the inherent availability of stage 4 is the sum of the probabilities of the system being in states 0 and 1. Using the failure and repair rates of the base case (λ=0.85 failures/year and MTTRes=309 hours) and assuming the system is at steady-state, the inherent availability of stage 4 is determined to be 0.998 using equations (14) to (21). This design scenario would decrease the failure rate slightly and incur a 4% improvement in availability. However, the compressor cost increases by approximately 20% to $ 35.9 MM. The results are reported below in Table 2.11.

Table 2.11: Availability calculation for a CGC system with 4th stage redundancy.

Equipment	**Failure Rate (Failures/Year)**	**MTTRes (Hours)**	**Availability**	**Availability-Adjusted Cost (2019 $MM)**
Stage 1	0.75	309	0.9716	12.01
Stage 2	0.77	309	0.9709	6.00
Stage 3	0.81	309	0.9694	5.99
Stage 4	0.85	309	0.998	5.98
Redundant Stage 4	0.85	309		5.98
Overall Compression Train	**2.90**	**309**	**0.9135**	**35.96**

2.4.6.4. Comparison of CGC Alternative Design Scenarios

The alternative design scenarios discussed above are incremental projects in nature since they are possible additions or modifications to the base case project. In such cases, each addition is justified by calculating its incremental return on investment ($IROI_p$) (El-Halwagi, 2017a):

$$IROI_p = \frac{Incremental\ net\ (after-tax)\ profit\ of\ add\text{-}on\ project}{Incremental\ TCI\ of\ add\text{-}on\ project} \times 100 \quad (40)$$

Figure 2.10 illustrates the results for each of the RAM improvement scenarios examined in this study. A cracked-gas compression system with better inherent RAM characteristics is determined to be the most attractive choice as it has the highest incremental return on investment. The other two scenarios have IROI values of less than the minimum acceptable threshold of 10-15 %/year.

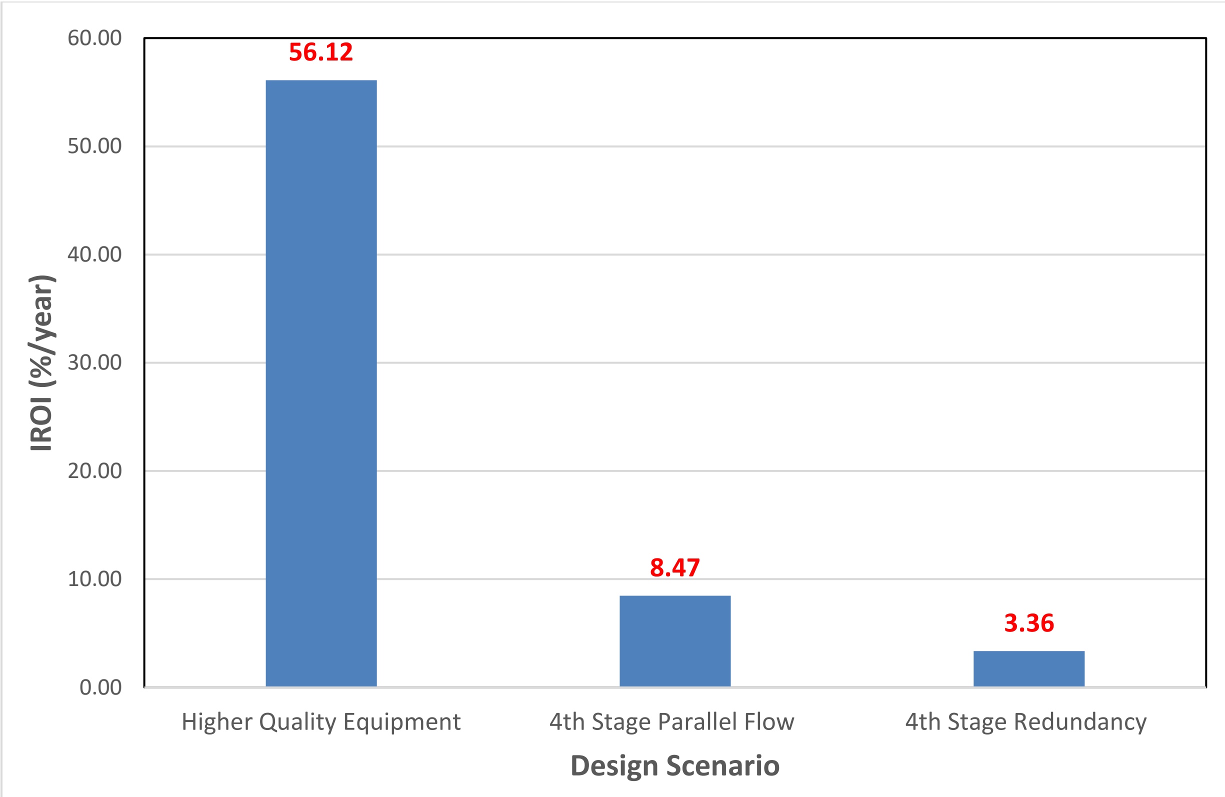

Figure 2.10: IROI comparison of CGC alternative design scenarios.

2.5. Conclusion

This work has introduced a systematic approach to mitigating failure using an economic framework during the conceptual design stage. The methodology starts with identifying the sources of failure that are caused by reliability issues including equipment, operational procedures, and human errors for a given process system or subsystem. These failure sources are identified using fault tree analysis, event tree analysis, or failure modes and effects analysis (FMEA). Bayesian updating of generic failure rate data with plant-specific data is utilized to estimate the appropriate distributions for the failure scenario(s) in question, while Monte Carlo techniques are used to estimate the repair scenario(s) distributions. Process simulation is used to account for reliability failure(s), which when combined with process data or history enable the evaluation of the economic, environmental, and safety consequences of the failure(s). Markov analysis is used to determine the system availability. Next, the process revenue is described as a function of inherent availability. The effects of failures are incorporated into profitability calculations using an incremental return on investment framework. Candidate design modifications are generated to enhance the availability of the section in question. These candidate designs are evaluated to establish an economic framework for trading off failure and profitability. A case study on an ethylene plant was solved to demonstrate the applicability and value of the proposed approach.

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3. INTEGRATING UNCERTAINTY QUANTIFICATION IN RELIABILITY, AVAILABILITY, AND MAINTAINABILITY (RAM) ANALYSIS IN THE CONCEPTUAL AND PRELIMINARY STAGES OF CHEMICAL PROCESS DESIGN*[2]

3.1. Abstract

Traditional analysis of a proposed process design uses average input values in the performance assessment model, thereby generating single-point estimates. The resulting estimates ignore reliability, availability, and maintainability (RAM) considerations, or assume a fixed value based on prior experience. As a result, a probabilistic view of the impact of equipment unavailability on process profitability is not considered. Recent works have proposed a financial framework for incorporating safety and sustainability considerations in the analysis of proposed designs. Based on this research, we propose a framework to integrate RAM aspects during the conceptual design stage in a probabilistic manner using Monte Carlo simulation. Subsequently, full distribution profiles of key process performance indicators are generated, including system and section availability, annual net profit, and return on investment (ROI). Probabilistic characterization of equipment availability also facilitates the prediction of potential safety and sustainability issues, as more frequent process upsets may result in increased flaring and other potential negative consequences. A modified availability metric, using restoration instead of repair times, is used in this work to obtain a more accurate view of expected downtime and thus its effects on profitability. A propane dehydrogenation (PDH) process system is used to demonstrate the application and benefits of the framework. The proposed approach allows designers and decision-makers to

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comprehensively assess the impacts of equipment RAM characteristics on process availability and economic performance.

3.2. Introduction

The chemical process design methodology involves determining specific objectives or customer needs, then developing and evaluating possible design solutions to ensure they satisfy those objectives in the best possible way. The number of feasible design alternatives is then further narrowed down by a variety of constraining factors. While some of these constraints are outside the design team's control (e.g., physical laws, government regulations, engineering standards), other critical factors, such as the choice of process or process conditions, materials, and equipment, are open in the trade space. Among the major constraints on any engineering design are economic considerations since prospective plants must also be profitable. Further, the number of alternative designs that can be evaluated is often also constrained by schedule considerations.

Li and Kraslawski (2004) presented an overview of the development of conceptual process design in the context of three scales: micro- (molecules), meso- (unit operations), and macro-scale (plant). At the macro-scale, the authors identified the main research issues that will dominate conceptual design to be: (1) combining knowledge of different disciplines, (2) dealing with uncertainties at the top decision level, and (3) developing optimization and simulation techniques for complex systems. In this work, the proposed addition to the traditional process design approach is the integration of reliability, availability, and maintainability (RAM) considerations in the economic evaluation of design concepts for a proposed plant while taking into account the uncertainties involved in the process system.

3.2.1. Safety and Sustainability Considerations in Process Design

Within the approach outlined above, the evaluation of process technology is usually based purely on techno-economic analysis. However, this approach excludes consideration of other critical aspects, such as safety and sustainability, until after the detailed design has been completed. Alternatively, these considerations can be integrated earlier into evaluations of the design of the process. For example, inherent safety principles are applied in the early stages of design (e.g. screening of alternative technologies) to enhance the safety characteristics of the process (Rahman et al. (2005); Kidam et al. (2016); Park et al. (2019)). Sustainability considerations, such as greenhouse gas emissions, total waste rate, and water footprint, have been used as indicators to assess the environmental impact of different process designs (Martínez-Gomez et al. 2016; Julian-Duran et al. (2014); Yang and You (2017)). Other process evaluation techniques include these considerations, but primarily from an economic perspective. El-Halwagi et al. (2017a) developed a sustainability-weighted return on investment metric (SWROIM) to evaluate the viability of process improvement projects and their impact on sustainability relative to the requisite capital investment. Guillen-Cuevas et al. (2018) extended the previous work by including safety considerations to develop a safety-and-sustainability-weighted return on investment metric (SASWROIM). In addition to these metrics, another approach is the use of loss functions to model the economic consequences of process unit deviations from target values (Hashemi et al. (2014); Khan et al. (2016)).

3.2.2. Reliability, Availability, and Maintainability (RAM) Considerations in Process Design

Similar to other engineering systems, the expected function of a chemical process plant can be interrupted due to failure(s) in one or more of its units. Some systems or units are less inclined to fail, usually due to inherent design characteristics; thus, they are considered more reliable (Dhillon, 2005). While reliability engineering is relevant to all aspects of the design and operation of a process plant, applying reliability analysis and prediction techniques at the conceptual and preliminary stages of the design process significantly aids the design team in the technology selection decision. By analyzing the possible failure modes and mechanisms of process units or subsystems, the consequences of these failures and their effects on the economic potential or profitability of the design can be estimated. These consequences include revenue losses as a result of production slowdown or shutdown due to failure; costs of different maintenance regimes including labor (corrective, preventive, or predictive); environmental damages due to a large quantity of flaring; loss of life or injury to personnel or the public; and costs associated with environmental damages.

The problem of integrating RAM assessment and optimization into the conceptual design phase has been an active research area for many years. Early works examined the sensitivity of system reliability to parallel redundancies (Rudd (1962); Henley and Gandhi (1975)). More recently, Goel et al. (2002, 2003) considered the effects of availability and maintenance in chemical plant economics and concluded that revenues and operational costs must be affected by the system inherent availability. Their approach used an exponential relationship, first reported by Ishii et al. (1997), between investment and availability to compute the capital cost of each equipment piece. However, it is further noted that it can be challenging to obtain real-world data on the link between capital cost and inherent availability. Sharda and Bury (2008) presented a discrete event simulation model to understand the impact of different critical subsystems on overall plant production capabilities using historical failure data. The disadvantage of using a discrete events approach is that it does not guarantee optimal solutions. Aguilar et al. (2008) considered redundancy alternatives to address reliability issues in utility plants. Recent works have utilized Markov chains to model utility systems and production sites and determine their optimal designs (Lin et al. 2012;

Terrazas-Moreno et al. 2010). In addition, recent studies have utilized optimization methods to determine optimal allocation of redundancy (Ye et al. (2018), Andiappan et al. (2019)). Al-Douri et al. (2020) introduced an economic framework for failure mitigation during the conceptual design stage utilizing a Bayesian updating procedure to update generic failure rate data with plant-specific data.

3.2.3. Uncertainty Quantification

The previous survey shows that significant progress has been made in the inclusion of safety, sustainability, and reliability considerations as part of the evaluation of the design of chemical processes. However, these performance models are based on uncertain input variables and use average values leading to conclusions with significant levels of uncertainty regarding the overall performance profile of the process design. The use of average values is not recommended based on the "flaw of averages" concept in probability theory, which underscores that evaluating process performance at average conditions does not necessarily lead to an average process performance. In reality, different values for an input variable can have different consequences on the performance metric being examined. To address this, Monte Carlo (MC) simulation methods can be used to develop a model of the system in which uncertainties associated with key design variables are included. Seila et al. (2003) and Law (2014) provided comprehensive reviews of simulation modelling methods and applications to operations research and finance. Monte Carlo techniques have been used to analyze complex industrial systems in areas such as project portfolio management, finance and accounting, and operational risk evaluation (Savage 2003; Kuppens et al. 2018). Kazantzi et al. (2013) presented a systematic solvent selection approach for a safety-constrained system, using MC simulation to evaluate system performance in the presence of economic and regulatory uncertainties. Kazi et al. (2018) used an optimization framework and MC simulation to explore the effects of uncertainty in flaring sources of an ethylene process on the selection of flare reduction alternatives. Specific applications of MC simulation to systems availability analysis have been demonstrated for a cooling tower pump system (Alexander, 2003) and an offshore installation (Zio et al. 2006). Recent work has also combined structural reliability techniques and MC simulation to formulate stochastic performance models for optimizing the design and operational reliability of chemical processes (Abubakar et al. 2015a; b; c).

3.2.4. Problem Formulation

The constraints on the solutions to a process design problem are both external and internal, but the decisive factor is the economic performance, as plants must be economically viable. Traditional economic performance assessment and valuation approaches have been proven inadequate when applied to complex engineering systems, especially in the early design phase, leading to insufficient outcome characterization (de Neufville and Scholtes, 2011; Savage, 2003). This kind of economic appraisal framework is usually based on specific economic metrics, such as ROI, IRR, NPV etc. at average conditions and does not correspond to realistic representations of uncertain input variables (such as equipment RAM characteristics in this case), which could have asymmetric impacts on economic performance outcome. Hence, there is a need to provide an explicit way to embed and quantify uncertain conditions in a process system, especially when RAM considerations are of particular importance at the early design stage.

In this work, the aim is to present an integrated framework which combines knowledge from the fields of process synthesis and design with reliability engineering into the economic analysis of process design alternatives in a probabilistic manner. RAM considerations will be included by collecting failure and repair data from two versions of the Offshore and Onshore Reliability Data (OREDA) Handbook—OREDA-02 and OREDA-15. Furthermore, the proposed approach enables the simultaneous inclusion of various sources of irreducible uncertainty (equipment RAM characteristics) as multiple model input (random) variables that becomes feasible (as opposed to the conventional sensitivity analysis where one model input at a time is considered varying).

As a result, full distribution profiles of economic performance outcomes are derived in the presence of uncertainty. The derived profiles are amenable to insightful statistical characterization, and risks and opportunities regarding the equipment and process design features can be identified and actively managed. According to the methodology followed in this study, all the uncertain model input variables are first identified and reasonable probabilistic representations through appropriately selected distribution profiles are assigned to them. Applying standard Monte Carlo techniques and performing random sampling from the above distributions, model input uncertainties are propagated through the model, and distribution profiles are generated that can be probabilistically characterized. The framework will be applied to a case study of a proposed propane dehydrogenation (PDH) plant using a RAM-weighted return on investment metric.

3.3. Description of Proposed Framework

3.3.1. Classical Process Design and Evaluation

The framework presented in Figure 3.1 begins with the same steps commonly used in the design process. These steps include identification of design objectives and sub-objectives, translation of customer needs into a design basis, development of block flow diagrams (BFDs) for promising alternative technologies, performing of stoichiometric targets of feed and product rates, and determination of profitability estimates for the alternative technologies. Evaluation of an alternative culminates in an estimate of a return on investment (ROI) value. The alternatives that do not meet the company's acceptable threshold ROI value are eliminated, and those that meet the criterion are considered for further study.

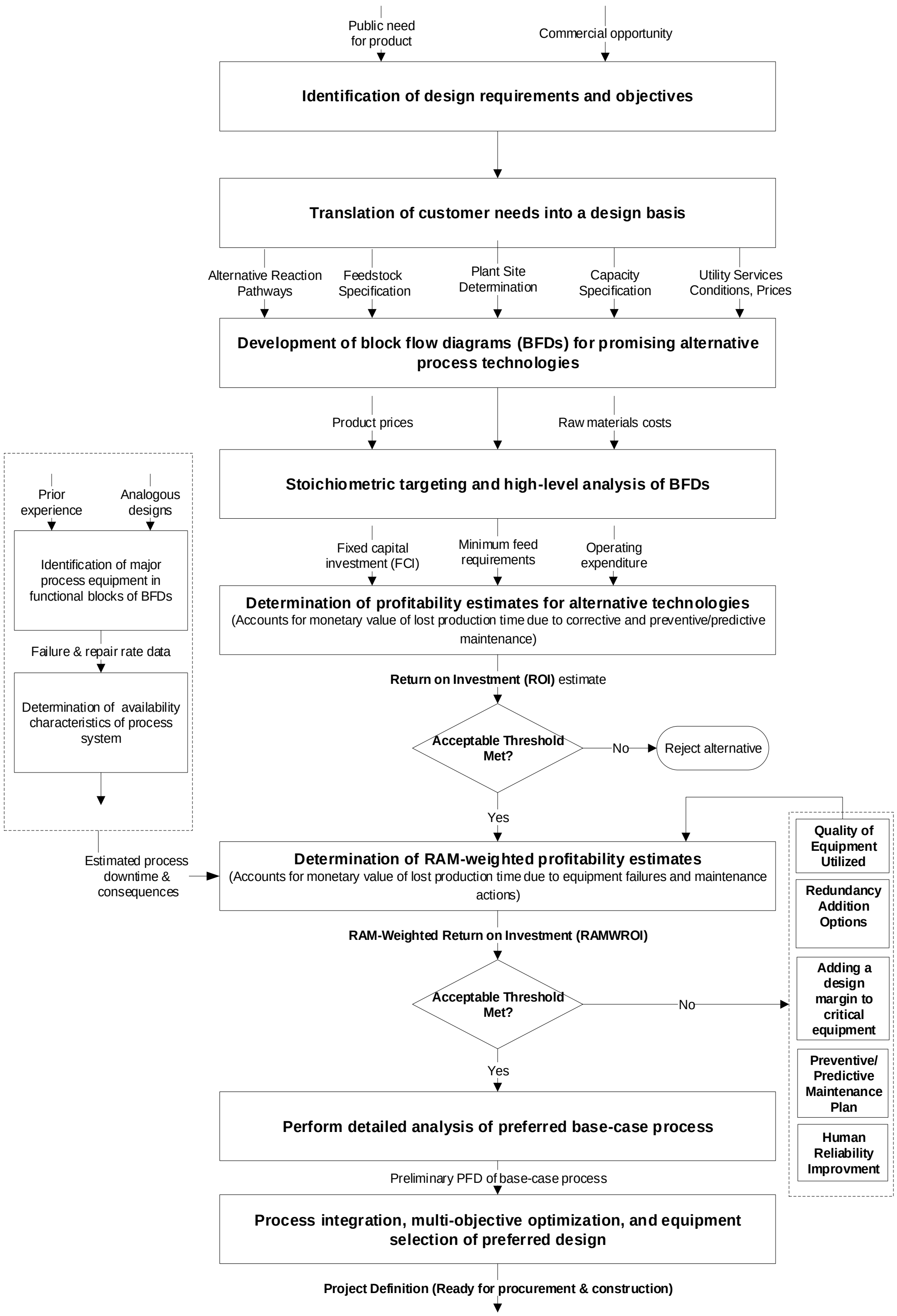

Figure 3.1: Framework for inclusion of reliability, availability, and maintainability (RAM) factors in process design.

3.3.2. Estimation of System RAM Levels for Proposed Design

At this stage of the design activity, the integration of reliability, availability, and maintainability (RAM) factors is considered. In order to estimate the availability of each process, preliminary knowledge of the equipment to be used for each major processing step is needed. This can be obtained through process flow diagrams (PFDs) of previous designs within a company or from literature references. Equipment failure rates (lower, mean and upper) and restoration manhours data (mean and maximum) for the proposed PDH plant were derived from two versions of the OREDA Handbook for Onshore and Offshore Reliability Data (OREDA 2002, 2015). A weighted failure rate, $\hat{\lambda}$, was then calculated using the formula described by Vatn (1997):

$$\hat{\lambda} = \frac{\lambda_o^2 + \lambda_N^2(\lambda_o/\lambda_N + |\lambda_o - \lambda_N|/SD_N)^2}{\lambda_o + \lambda_N(\lambda_o/\lambda_N + |\lambda_o - \lambda_N|/SD_N)^2} \quad (1)$$

where SD_N is the failure rate standard deviation reported in the new edition, and λ_o and λ_N are the failure rate values from the old and new editions, respectively. In this work, the exponential distribution is used for failure and restoration times, meaning the failure and restoration rates are constant. Thus, the MTBF (mean-time-between-failures) value is the inverse of the weighted failure rate.

Conventional analysis of inherent availability utilizes the mean time to repair (MTTR) metric to represent the time that equipment or a system is not in operation. However, a more encompassing metric is the mean time to restoration (MTTRes), which is the time needed to restore an item to full operational status. It involves delays prior to and after repair actions, as well as time needed to ramp down and start up an equipment or system in the case of a failure event. The failure and restoration cycle described here is illustrated in a supplementary figure provided with this work.

The MTTRes metric captures important factors involved in the restoration process which can decrease the overall availability of a system and are important to consider when assessing its profitability. These factors include: ability of plant personnel to identify and mitigate failure events, responsiveness of management in allocating resources for maintenance needs, and the skill level of maintenance personnel. For a system in series, a modified system availability, A_{total}, using MTTRes can be estimated from the following equation:

$$A_{total} = \prod_{i=1}^{n} A_i = \prod_{i=1}^{n} \left(\prod_{k=1}^{m} \frac{MTBF_k}{MTTRes_k + MTBF_k} \right)_i \quad \text{(2)}$$

where A_i is the availability of a block, and $MTBF_k$ and $MTTRes_k$ are the mean time between failures and mean time to restoration, respectively, of the equipment making up the block. Then, the block with the lowest availability is identified as the critical process step causing the most significant downtime and having the most adverse impact on process profitability.

3.3.3. RAM-Weighted Economic Evaluation

Using the estimated system availability range, a modified return on investment metric (ROI) range can be calculated as follows:

$$ROI\left(\frac{\%}{year}\right) = \frac{ANP\left(\frac{\$}{year}\right)}{TCI\ (\$)} * 100 \quad \text{(3)}$$

where ANP is the annual net (after-tax) profit and TCI is the total capital investment. This profit can be calculated by the following equation, modified from the profit equation in El-Halwagi (2017b):

$$\text{ANP} = \{Availability * (Annual\ Revenue - Annual\ Operating\ Cost) - Depreciation\} * (1 - Tax\ Rate) + Depreciation \quad \text{(4)}$$

The purpose of this modified profitability metric is to determine the inherent RAM characteristics of a process design alternative and their effect on profitability estimates. Different design modifications to improve RAM levels of critical equipment are then assessed to determine their feasibility and the extent to which they enhance process profitability. These modifications may include the quality of purchased process equipment, over-design of equipment, addition of redundant components or subsystems, preventive and predictive maintenance plans, and measures to improve human reliability. The choice of design modification is made based on calculating its incremental return on investment (IROI) as follows:

$$IROI\left(\frac{\%}{year}\right) = \frac{\Delta ANP(\frac{\$}{year})}{\Delta TCI(\$)} \qquad (5)$$

3.3.4. Uncertainty Quantification Approach

Figure 3.2 below illustrates the approach used to determine the expected ranges for process RAM characteristics and profitability. Using a representative distribution for the constituent equipment RAM characteristics (MTBF, MTTRes), a design team is able to obtain a range of values for process system availability and economic metrics such as annual profit and return on investment. For each major piece of equipment, both failure and restoration data represent uncertain variables and were assigned triangular distributions, selected due to limited data, as follows:

$$Triangular_{Failure}(MTBF_{Minimum}, MTBF_{Mean}, MTBF_{Maximum}) \qquad (6)$$

$$Triangular_{Restoration}(MTTRes_{Minimum}, MTTRes_{Mean}, MTTRes_{Maximum}) \qquad (7)$$

In this manner, the uncertainty inherent in RAM characteristics is propagated through the economic evaluation, thereby allowing decision-makers in technical and business divisions of an organization to make better-informed decisions about potential projects.

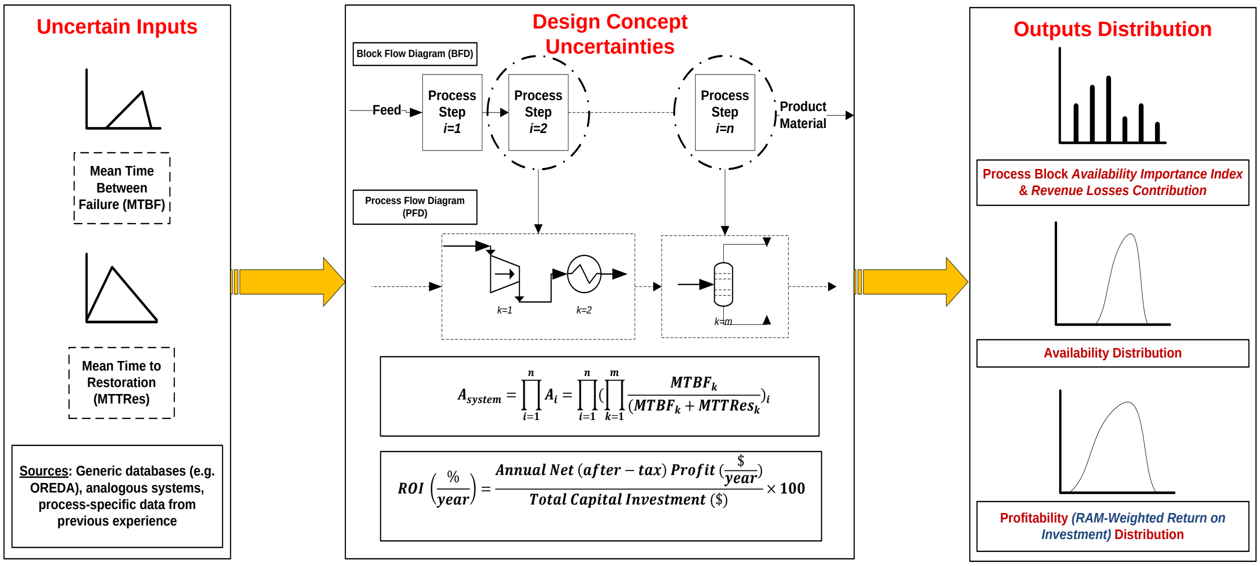

Figure 3.2: Uncertainty propagation of process RAM characteristics.

3.4. On-Purpose Propylene Production

3.4.1. Propylene Production Pathways

Propylene is the petrochemical substance with the second-largest production volume after ethylene, and an important raw material for producing polypropylene and propylene oxide, both major building blocks in plastics production. Traditionally, propylene has been produced as a byproduct of ethylene from steam cracking of hydrocarbons, or as a byproduct of gasoline in fluid catalytic cracking (FCC) in refineries. In 2012, steam cracking and FCC accounted for 90% of the global production of propylene. However, the shale gas revolution has caused a shift in North American cracker feedstocks from naphtha to ethane, leading to an increase in ethylene yield and a decline in propylene production. For refineries, gasoline prices dictate the propylene production in those facilities. If prices are high, propylene is produced and used to make octane-boosting alkylates. If demand is low, gasoline production is lowered causing propylene output to fall. In these two pathways, propylene supply, unlike propylene demand, is subject to developments in the gasoline and ethylene markets. That demand is expected to grow from 109 million tons in 2014 to about 165 million tons in 2030, approximately 12-14% greater than the amount of propylene that can be produced as a by-product of steam crackers and in refineries (Wood Mackenzie, 2014). The resulting gap between supply and demand can be filled by on-purpose propylene (OPP) technologies such as propane dehydrogenation, methanol-to-propylene/methanol-to-olefins (MTP/MTO), and olefin metathesis. The optimal method of producing propylene is subject to factors such as geographic location, feedstock prices and availability, market conditions, technology maturity, sustainability and safety (Guillen-Cuevas et al. 2018; Roy et al. 2016).

3.4.2. Propane Dehydrogenation Technologies

According to Eramo (2017), propylene demand grew at an average rate of 3.5 million metric tons (MMT) from 2011-2015, and is expected to increase to 4.5 MMT in the period of 2017-2021. With the decline in propylene production due to lighter feedstock in crackers, it is projected that approximately 30% of propylene production (38 MMT) will be produced by on-purpose technologies in 2023. In North America, propylene demand is expected to reach 20 MMT (about 15% of global supply), of which 5 MMT is expected to be via on-purpose routes. Currently, there are three PDH plants in the U.S. producing about 2 MMT of on-purpose propylene (Dina, 2017). These factors indicate that on-purpose propylene technologies will be essential to meet North American demand. Thus, this information establishes the need and commercial opportunity that exist for on-purpose propylene. In the PDH process, propane is converted to propylene over a platinum-alumina-based catalyst bed at high temperatures (550-650°C) and low pressures (2-3 bar). Overall selectivity towards propylene is 90 mole%, and one-pass conversion is 40 mole% (Gregor and Wei, 2005). The PDH licensing is dominated by Honeywell UOP’s OLEFLEX and

CB&I CATOFIN technologies. Of the 28 PDH units operating worldwide, 18 use the OLEFLEX technology. In this work, the OLEFLEX process was selected for examination.

3.5. Application of Proposed Framework

3.5.1. Propane Dehydrogenation OLEFLEX Process

To begin the plant design process, a block diagram of the PDH process is constructed showing the major processing steps in each route (Figure 3.3). The PDH process consists of the following major processing equipment and operations: depropanizer column, dehydrogenation reactors and interheaters, reactor effluent compressors and coolers, cryogenic refrigeration, pressure swing adsorption (PSA), propylene/propane separation. Fresh and recycled propane enter the depropanizer column where hydrocarbon (C4+) material is separated. The propane-rich stream in the overhead enters the refrigeration unit where its autorefrigeration property is utilized to cool the reactor effluent stream. The propane stream leaving the cold box is mixed with hydrogen and enters a fired heater where the mixture is heated to a temperature to 580-620 °C before entering the reactor system. The reaction occurs over a fluidized catalyst bed in a radial flow reactor to minimize pressure drop across the beds (Vora, 2012). To burn off resulting coke that is formed, a continuous catalyst regenerator (CCR) is used. The reaction is highly endothermic in nature (ΔH=124.3 kJ/mol) and a considerable temperature drop occurs in each reactor. Therefore, interstage heaters are needed to raise the outlet stream temperature. The reactor system effluent is a mixture of propylene; unreacted propane; light gases, such as methane, ethane and ethylene; diolefins; and heavier hydrocarbon components formed in the reactor. The effluent is then cooled and compressed from 96.5 kPa psia to about 1380 kPa in a multistage compressor with interstage coolers. The next step is to liquefy the hydrocarbon material and separate out the hydrogen in the cold box unit. Part of the hydrogen produced is sent to the dehydrogenation reactors and the rest goes to the selective hydrogenation process (SHP) reactors. The net hydrogen is then sent to the pressure swing adsorption (PSA) unit to ensure it meets pipeline quality specifications. The liquefied hydrocarbons from the cold box are sent to SHP reactors to convert the diolefins to propylene. Then, a deethanizer column separates C2 components from the liquefied hydrocarbons and propane-propylene splitter (superfractionator) produces the final propylene product. Unconverted propane is sent from the superfractionator bottoms to the depropanizer column as part of the feed.

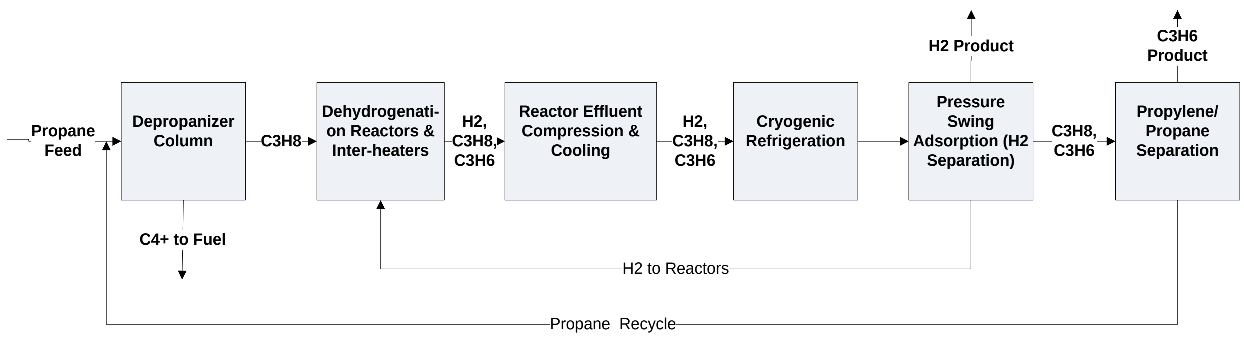

Figure 3.3: Block diagram of UOP OLEFLEX propane dehydrogenation (PDH) process.

3.5.2. High-Level Analysis of Block Flow Diagrams

A preliminary economic assessment of the proposed plant is performed using stoichiometric targeting to estimate the amount of raw materials needed for the process, operating expenditures, annual revenue and the capital investments. The capital and operating expenditures for the 450,000 MTA plant are estimated on the basis of the cost data in Agarwal et al. (2018), which reported on a simulation study with capital and operating investment estimates for a 600,000 MTA plant located on the U.S. Gulf coast. Those values and the prices for raw materials and product used in this study are shown in Table 3.1.

Table 3.1: Feedstock/product prices and economics for PDH process.

Feedstock/Product	**Minimum Flowrate in Metric Tons/Annum (MTA)**	**Price ($/MT)**
Propane	524,000	375
Propylene	450,000	1,100
Hydrogen	22,000	1,600
Process Economics Results		
Fixed Capital Investment (FCI), $MM	534	
Total Capital Investment (TCI), $MM	628	
Annual Net (After-Tax) Profit (ANP), $MM/year	180	
Return on Investment (%/year)	28.6	

3.5.3. Process Design Performance Evaluation

3.5.3.1. Estimation of System RAM Levels for Proposed Design

After the major equipment in each processing step are identified, failure and restoration manhours data for these equipment are collected from two versions of the OREDA database. Table 3.2 includes this data for the equipment in a propane dehydrogenation (PDH) process. The ranges for MTBF and MTTRes values in this table are representative of different installations as well as varying environmental and operational conditions under which the data was collected.

Table 3.2: Uncertain inputs into the availability estimation of a proposed propane dehydrogenation (PDH) design.

Processing Step	Major Equipment	Mean Time Between Failure (Hours)			Mean Time to Restoration (Hours)		
		Lower	Mean/Most Likely	Upper	Lower	Mean/Most Likely	Upper
Separation of C4+ materials in feed and recycle	Depropanizer column	8,174	10,146	12,695	10.0	44.5	359
Catalytic dehydrogenation reaction	Fired heater (charge heater)	266	909	41,239	2.0	66.7	706
	Dehydrogenation reactor	5,255	10,632	50,383	1.0	47.0	474
	Reactor feed-effluent heat exchanger	13,325	15,838	20,017	1.0	55.4	419
Continuous catalyst regeneration (CCR)	Continuous catalyst regenerator	5,255	10,632	50,383	39.0	47.0	474
	Turbocompressor feed cooler	13,325	15,838	20,017	1.0	55.4	419

Compression and cooling of reactor effluent	Steam turbine	6,160	10,317	21,529	9.3	16.0	31
	Multi-stage centrifugal compressor	2,700	3,145	3,815	16.9	28.9	1,481
	Turbocompressor discharge cooler	13,325	15,838	20,017	1.0	55.4	419
Cryogenic refrigeration	Heat exchanger	13,325	15,838	20,017	1.0	55.4	419
	Flash drum	6,849	13,522	37,823	5.9	16.9	409
	Isentropic expander	1,207	3,348	181,048	10.0	44.5	728
Hydrogen Separation	Selective hydrogenation process (SHP) reactor	5,255	10,632	50,383	39.0	47.0	474
	Pressure swing adsorption (PSA) unit	8,174	10,146	12,695	10.0	44.5	359
Product Recovery	De-ethanizer column	8,174	10,146	12,695	10.0	44.5	359
	Propylene-propane splitter (superfractionator)	8,174	10,146	12,695	10.0	44.5	359

The Monte Carlo simulation tool in the Palisade® @Risk software was used to generate 50,000 random samples for each equipment's MTBF and MTTRes values. Two sampling methods are available for use in this simulation feature: Latin Hypercube and Monte Carlo. For this work, Latin Hypercube sampling was used as the sampling method because it avoids the clustering that can occur with Monte Carlo sampling, providing a better chance for all values from the input distribution to be sampled. Equation (2) is used to calculate availability for a subsystem or system in series. The resulting availability for each major equipment piece, processing section, and the overall process are not point estimates, but rather a range of values that can be fit to a probability distribution using the @Risk software.

Figure 3.4 shows the probability density distribution for the process system's availability. These results show that the standard deviation is low, indicating that the upper and lower confidence limits do not differ significantly from the mean value of total inherent availability (72.7%). The result is a range of estimated system availability that is significantly different from projections assuming a fixed system availability value of 80% or 85%. Greater accuracy with respect to system availability estimates allow for more accurate outlooks of a plant's projected profitability. Further refinement of the availability estimate is possible if in-house failure and repair data is available to the design team.

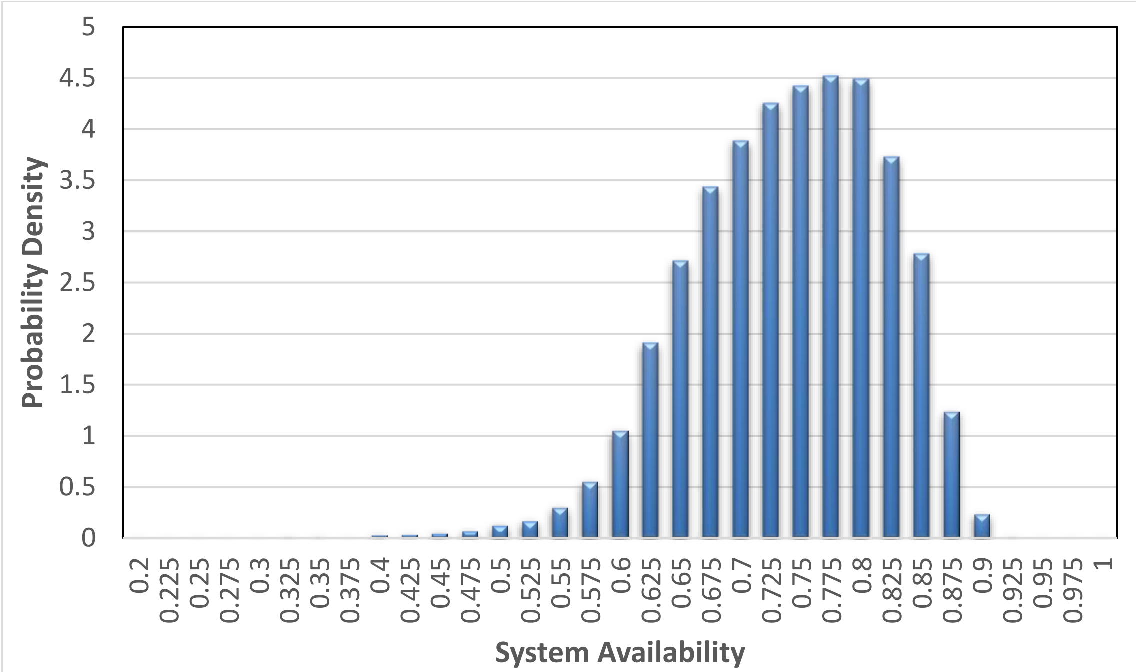

Figure 3.4: Probability density graph of overall PDH process availability.

3.5.3.2. RAM-Weighted Economic Evaluation of Proposed Design

Uncertainties in equipment RAM characteristics are included in the calculation of the process profitability using the modified return on investment (ROI) metric, as described previously. A Monte Carlo simulation was performed to obtain a distribution profile for this indicator. The probability distribution profile for the modified ROI is shown in Figure 5. The results estimate a mean ROI value of 23.9 %/year and a standard deviation value of 7.45%/year. The coefficient of variation, defined as the ratio of the standard deviation to the mean, can be utilized to examine and compare the variability from the mean value for both availability and ROI. These values were determined to be 0.109 for system availability, and 0.312 for ROI. This indicates that there was less variability from the mean value (0.745) for system availability (Figure 4) than from the mean value (23.7%) for ROI (Figure 5).

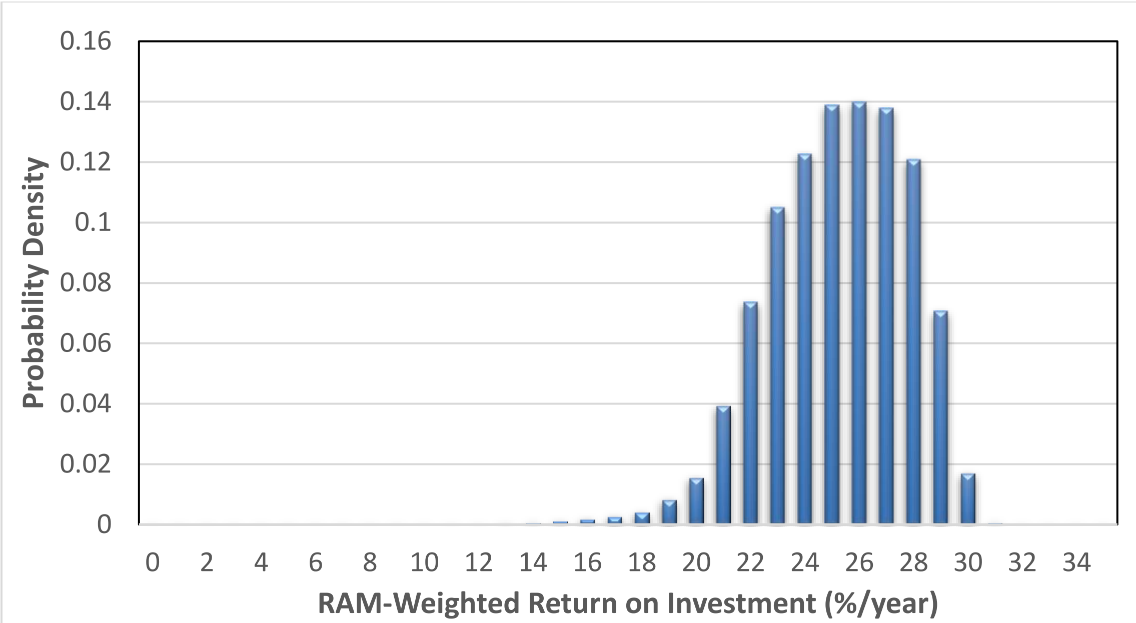

Figure 3.5: Probability distribution profile for the modified ROI of proposed PDH process.

A table in the supplementary materials of this work shows the range of results for the main economic parameters used to evaluate the proposed PDH process design. The 5% and 95% tails represent the lower and upper limits of the 90% confidence interval for all the parameters presented. The range of possible system availability is reflected in the annual revenue losses, annual profit, and return on investment. All of the categories displayed a moderate level of skewness (between -1 and 1), indicating the resulting distributions are moderately asymmetric.

The results of this work emphasize the importance of explicitly including uncertainty in all input variables used in the process performance assessment framework. Identification and characterization of the uncertainty associated with performance assessments improves the understanding of risks and design sensitivity, leading to more informed decisions regarding proposed designs.

3.5.3.3. Section Analysis of Process RAM Characteristics and Profitability

In addition to the results presented, the availability of individual process blocks can be estimated to identify critical units and determine the impact of their downtime in realtion to revenue losses. Figure 3.6 shows the mean section availability for each of the process blocks, along with the 90% confidence bounds. This captures the range of possible availabilities for each section, depending on the equipment failure and restoration rates. Also, the figure illustrates that the compression and cooling of reactor effluent section has a significantly lower availability than the other section, even when considering the predicted upper limit of its availability. The compression and cooling of reactor effluent section includes a steam turbine-driven multi-stage centrifugal compressor, which typically experience higher failure rates than non-rotating machinery.

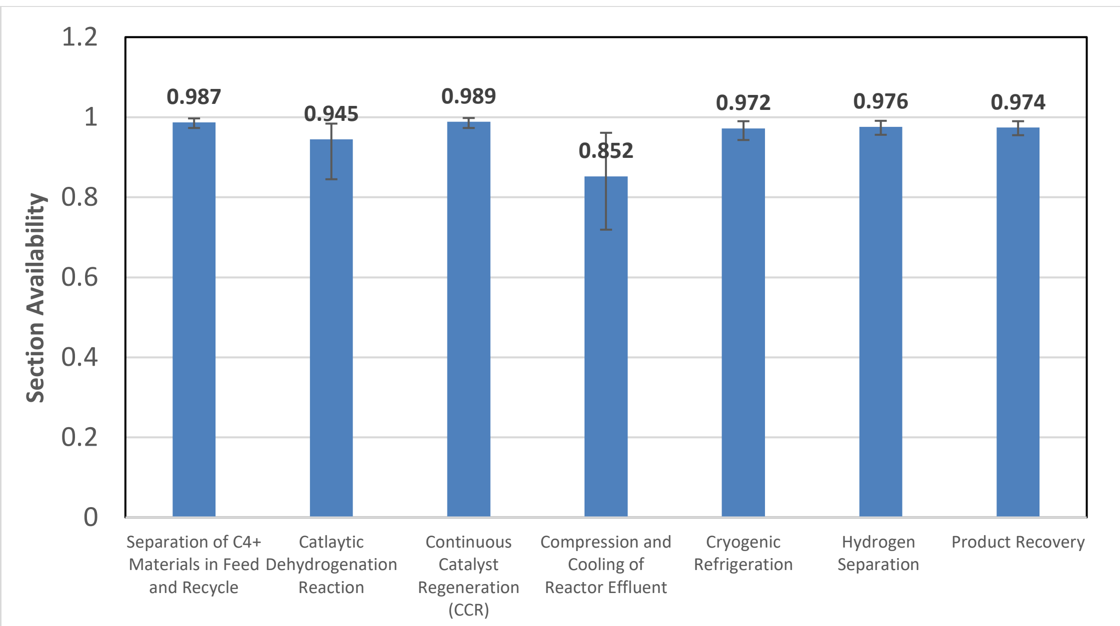

Figure 3.6: Section availability of individual process blocks for a proposed PDH process.

Using the section availability data, the contribution of each section to the overall process revenue losses (presented in the supplementary table) can be determined. From the results shown in Figure

3.7, it is clear that the compression and cooling of reactor effluent section is the largest contributor to overall revenue losses due its significantly lower availability. In this case study, this section accounts for approximately 60% of annual revenue losses for a PDH process.

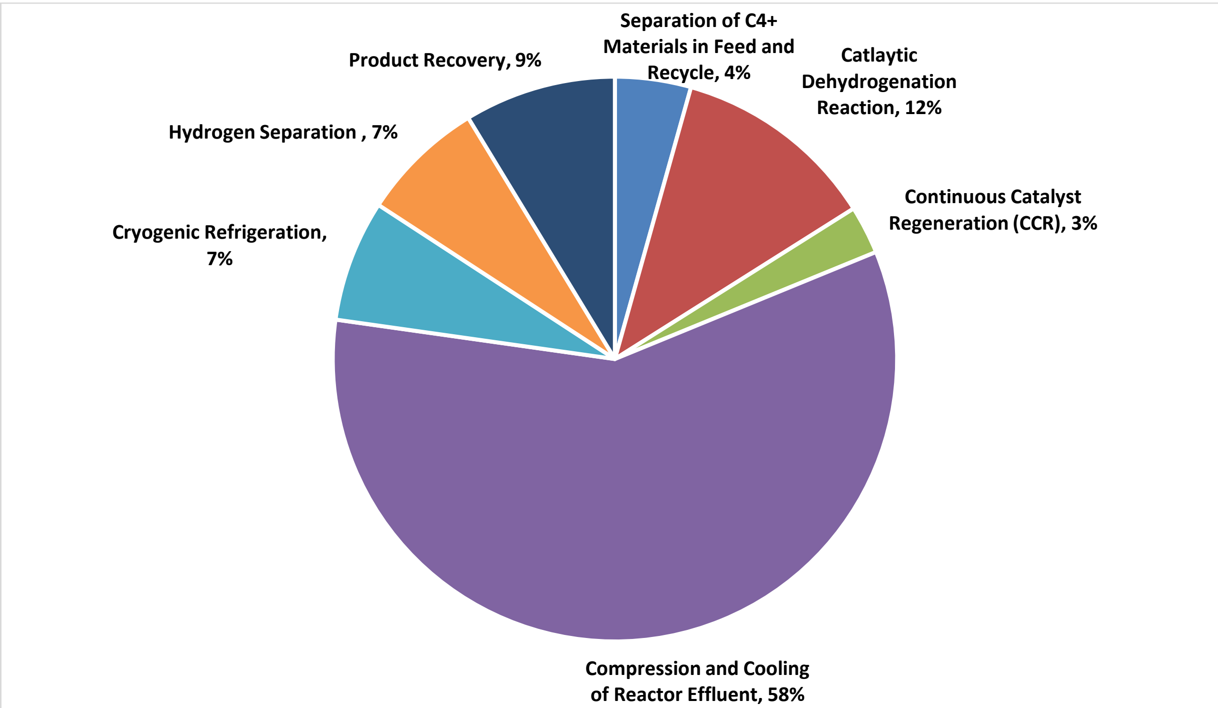

Figure 3.7: Contribution of processing sections to revenue losses.

3.5.4. Design Modifications

Four design modifications to the compression and cooling of reactor effluent section are evaluated to determine their effect on ROI. The proposed modifications for the multi-stage centrifugal compressor are as follows:

(1) Compressor with higher reliability (increased MTBF)

(2) Compressor with shorter restoration time (decreased MTTRes)

(3) Compressor with both a lower failure rate and shorter restoration time

(4) Addition of a second, parallel flow compressor train, with each train handling 50% of the flowrate.

The first three modifications can be realized by either obtaining equipment that are: (1) known to have enhanced RAM characteristics due to previous operating experience, or (2) larger vessels that provide a surge capacity in the case of process upsets. The latter case can be achieved by selecting a centrifugal compressor with a greater design pressure ratio and discharge temperature than needed for the process. The configuration for the base case and modifications 1-3 are illustrated in top part of Figure 9.

For the compression and cooling section of a PDH process, the discharge temperatures for the two compressor stages are 138°C and 355°C, respectively. Accordingly, the compressor selected should have a higher specified discharge temperature than those values. This results in equipment that have higher pressure ratios and power rating, which typically incur higher capital costs. The desired margin between the discharge temperature and compressor design temperature limit depends on many factors including: (1) likely operating conditions (clean or fouling service), (2) operating environment due to location, and (3) an organization's financial resources. Higher design margins provide greater protection against failures, thus increasing overall equipment availability. The relationships between equipment capacity, availability, and cost is beyond the scope of this work and have not been established for the chemical process industries. Several works have examined those relationships for electronic equipment using correlations and discrete data (Fratta et al. 1976; Majumdar, 1976; Govil, 1985).

The fourth modification, a parallel flow configuration, employs two equal-size centrifugal compressors for the first and second stage of the compression system with the same design specifications and RAM characteristics as the base case. Each compressor in the parallel arrangement is designed to take 50% of the flowrate in the base case design. This configuration, shown in Figure 3.8, incurs much higher capital costs than the other modifications due to the loss of economy-of-scale.

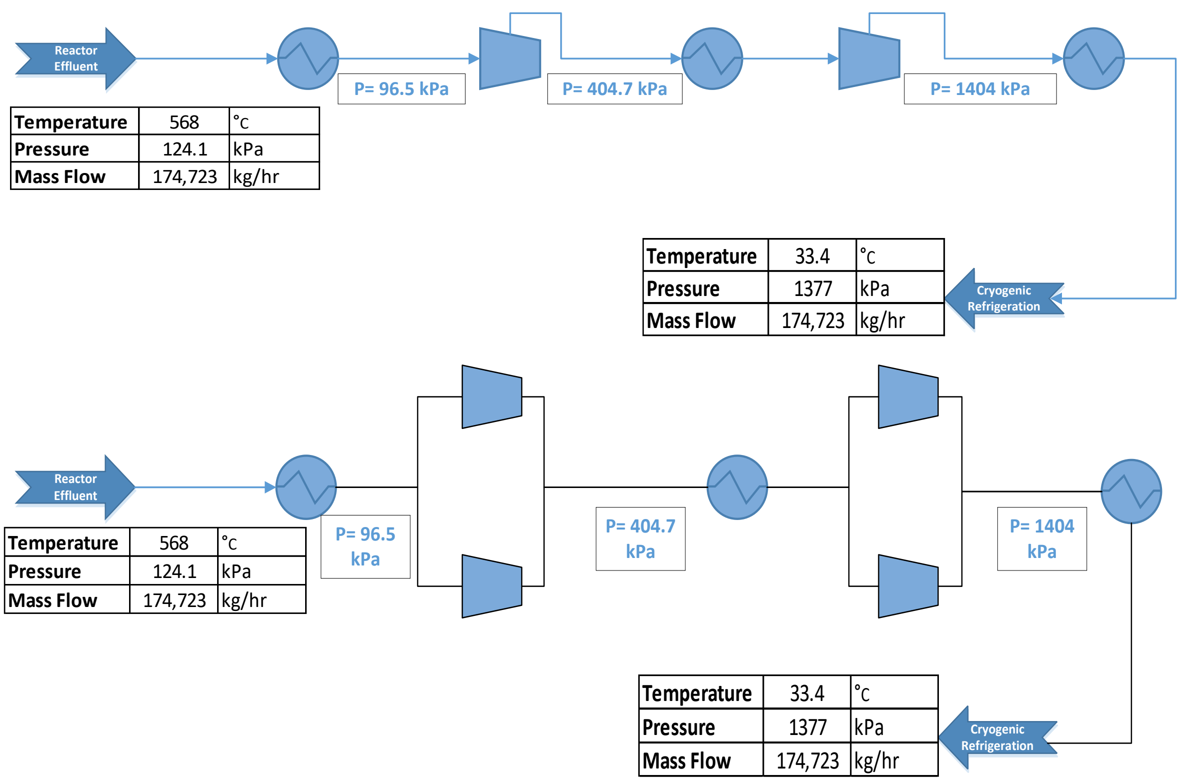

Figure 3.8: Compression and cooling section configurations for (top) base case design and modifications 1-3, and (bottom) modification 4 (parallel flow arrangement).

The availability, cost, and revenue losses associated with each modification are shown in Table 3.. The parallel flow configuration has the highest availability and thus achieves the greatest reduction in revenue losses from equipment unavailability. However, it does present a significantly greater increase in installed costs over compared to the other modifications.

Table 3.3: Availability and economic parameters for proposed design modifications.

Alternative	MTBF (Hours)	MTTRes (Hours)	Availabi -lity	Installed Cost ($MM)	Revenue Losses Due to Unavailabili -ty ($MM)	Reduction in Revenue Losses (%)
Base Case	3,226	509	0.845	34.1	94.7	-
Lower Failure Rate	3,449	509	0.871	36.7	77.6	18.1
Shorter MTTRes	3,226	458	0.876	37.1	75.3	20.5
Lower Failure Rate and Shorter MTTRes	3,449	458	0.883	37.7	71.6	24.4
Parallel Flow with Base Case RAM Levels	2,419	208	0.921	51.8	51.9	45.2

In this case study, a minimum ROI value of 15% was selected as an appropriate threshold for acceptability of a design. Figure 3.9 presents the results for both the ROI and IROI metrics for the proposed designs for the cooling and compression section. Note that the base case, as well as all alternatives, exceed the ROI threshold. However, only the parallel flow configuration exceeds the 15% threshold for the IROI metric, with a value of approximately 26%/year. This configuration provides the most significant improvement in equipment availability and increase in annual profit over the base case. Despite the higher capital cost, the additional revenue generated by greater equipment availability results in the configuration having the highest IROI. Hence, it would be recommended as the optimal design configuration for the compression and cooling section of a PDH plant.

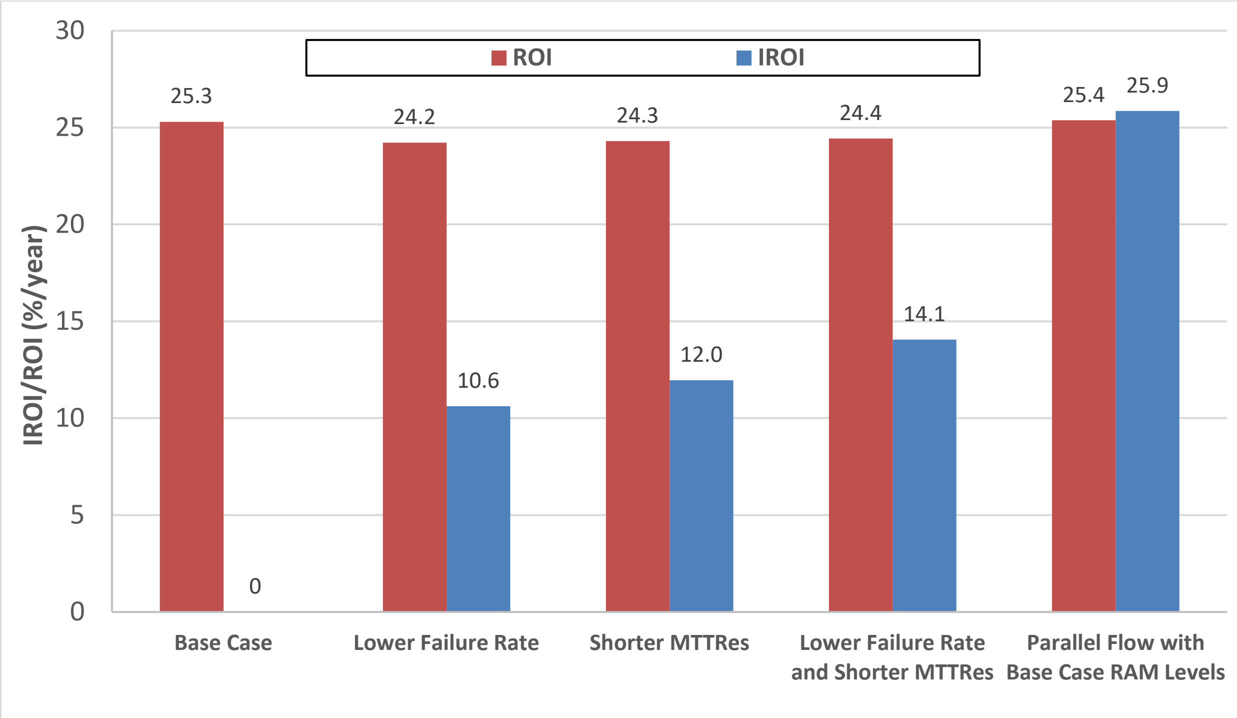

Figure 3.9: Comparison of ROI and IROI for alternative design scenarios of a PDH process compression system

The improvement of system availability has a positive impact on both profitability and sustainability because it reduces flaring that occurs due to equipment failures. In the case of a PDH process, valuable propane feedstock, propylene product, and other chemicals can be flared in a failure event. This incurs additional costs to replace lost feedstock, reduces plant revenue, and results in fines due to the greenhouse gas emissions released during flaring. These fines can have an adverse effect on a company’s reputation and future growth.

This approach can be further augmented by considering sustainability aspects along with RAM characteristics. For example, CO_2 emissions reductions can be selected as a sustainability indicator. Two scenarios that can be considered are implementing: (1) a waste heat recovery (WHR) system to recover medium temperature heat from the fired boilers, and (2) an offgas recovery system to recover the deethanizer offgas stream and use it as fuel, thereby reducing natural gas consumption.

3.6. Conclusions

This paper presents a framework to integrate uncertainty quantification of equipment RAM characteristics into economic analyses of chemical process designs during the conceptual development stage. Instead of the standard practice of using average or fixed values, this framework employs distributions for failure and restoration data of process equipment to estimate an availability range for a base case design using Monte Carlo simulation. Using restoration instead of repair times accounts for delays in the maintenance process which increase downtime and negatively impact availability and economic performance. By doing so in a probabilistic manner, full distribution profiles of the key performance indicators, instead of single-point estimates which is the case in a deterministic approach, are generated and associated to their statistical characterization. These process economic performance indicators include: annual net profit, annual revenue losses, and return on investment. This approach also allows for identifying which specific section(s) in a process contribute significantly to revenue losses due to equipment unavailability. Proposed design modifications can then be examined to determine how best to improve availability for the section(s) in question in an economically-optimal way using an incremental return on investment (IROI) metric. A case study involving a propane dehydrogenation (PDH) plant was used to demonstrate the merits of integrating uncertainty quantification in RAM estimates used in system performance assessments. This approach differs significantly from practices which consider system design modifications to improve availability based solely on budgetary constraints. In summary, the proposed framework can be implemented by decision-makers, design engineers, and operations teams to make better-informed decisions on the economic potential of a project or design modification. This approach can also be extended to characterize the sustainability and process safety impacts of project or system modifications.

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4. IMPACT OF HAZARDOUS MATERIALS PIPELINES INCIDENTS ON CHEMICAL PROCESS PLANT PRODUCTION

4.1. Abstract

Reliability of feedstock supply is an important consideration for the safe and continuous operation of chemical plants. An extensive pipeline network transports natural gas and hydrocarbon liquids from producing areas to refineries and chemical plants for fuels and chemicals production. Incidents involving spills or releases and shutdowns of those pipeline can occur due to a number of causes including corrosion, equipment malfunction, excavation damage etc. These incidents involve economic, environmental, and safety risks. Economic risk is primarily considered to be cost of asset damage, commodity released and associated cleanup. Economic risks to downstream users due to disruptions in pipeline operations is not often considered with appropriate importance. In this work, an appropriately developed stochastic framework is presented to determine the disruption impact of pipeline incidents on downstream chemical production. Incident data are statistically analyzed to determine meaningful distributions for incident rates, spill/release quantities, and pipeline shutdown durations. A case study on the production of propylene via three different pathways (crude oil, propane, and natural gas) is presented to illustrate the methodology and underline the variability of the process production impact due to variations in risk occurrence characteristics. Using specific process chemistry and mass balances, more precise risk profiles for the product shortfall and cost of lost sales can be generated.

4.2. Introduction

An integral part of the economic development and stability of any nation is maintaining a reliable supply service of essential fuels (e.g. crude oil, petroleum products, natural gas) to meet demands by various sectors. This is accomplished through a midstream infrastructure of pipelines, waterways, and storage facilities as shown in Fig. 4.1. As of 2019, the United States has approximately 321,000 miles of natural gas transmission pipelines and 225,000 miles of hazardous liquid pipelines. A further 2.26 million miles of gas distribution pipelines are present (Pipeline and Hazardous Materials Safety Administration, 2021). These pipelines networks transport commodities from producers, refiners, or gas processors to residential, commercial, and industrial customers.

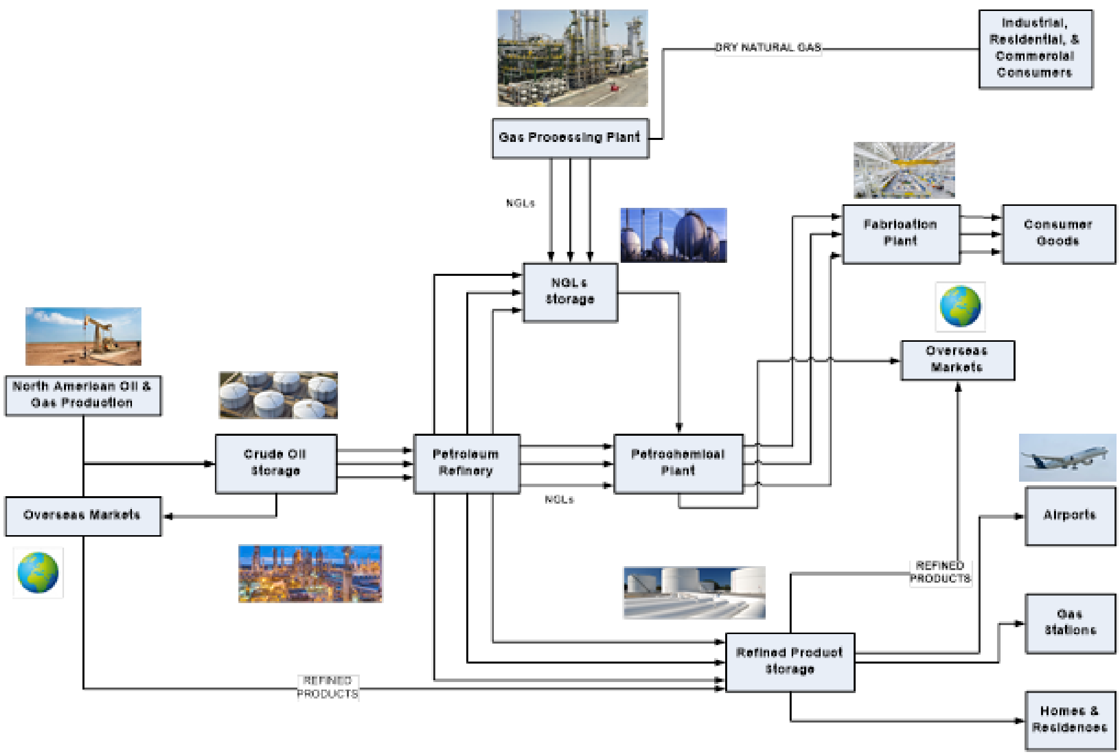


Figure 4.1: Graphic of America's integrated midstream infrastructure.

Nearly all natural gas and approximately 80% of crude oil is transported by pipelines, although the latter fluctuates on a year-to-year basis (U.S. DOE EIA, 2020). Fig. 4.2 shows the pipeline transport volumes of hazardous liquids and natural gas from 2000-2019. The increasing trend, especially after 2008, highlights the important and growing role of pipeline in transporting hazardous materials. With the presence of such an extensive network of pipeline operations, it is important to quantify the frequency and consequences of pipeline incidents. In 2019, a total of 657 incidents occurred causing 11 fatalities and 36 injuries, and incurring an economic loss of $228 million (Pipeline and Hazardous Materials Safety Administration, 2021).

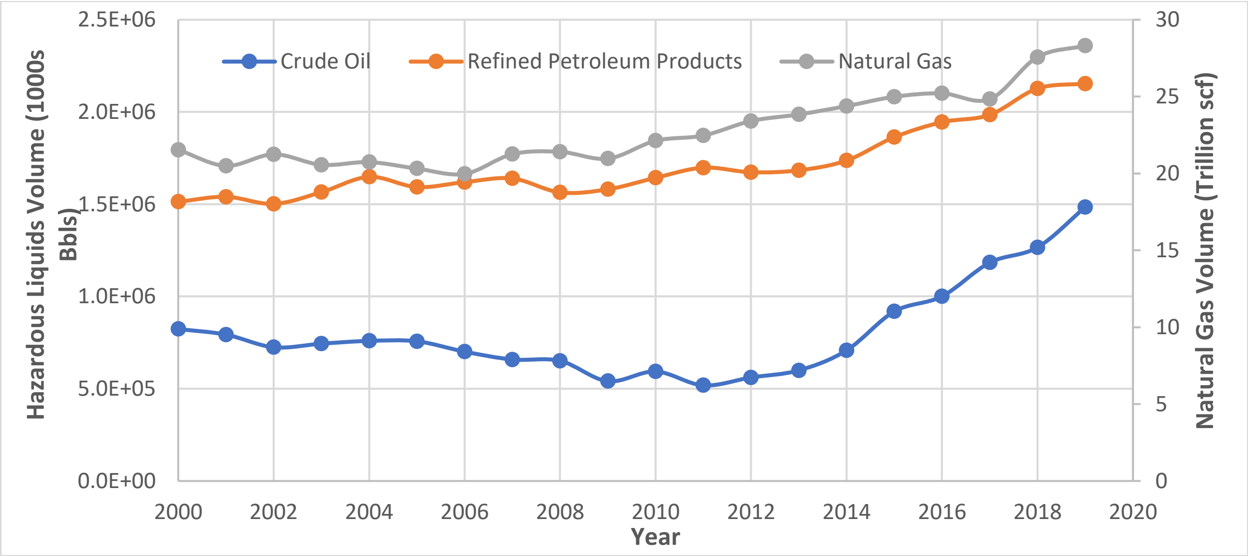


Figure 4.2: Hazardous liquids and natural gas transport volumes in 2000-2019 (U.S. DOE EIA, 2020).

Pipeline incidents involving hazardous materials releases are associated with several types of risks: safety (injuries or fatalities, fires, explosions), environmental (release of natural gas or hazardous liquids), and economic loss (direct asset loss). The interruption of commodity supply to a customer is another risk that has economic implications on both the supplier and consumer, leading to loss of revenue and production curtailment/shortfall and impacting a company’s reputation and possibly its future business potential. For example, in February 2021, a winter storm caused natural gas production to be halved in Texas for approximately a week due to freeze-offs at wellheads, gas processing plants, and pipelines leading to extensive power outages across Texas and other states (Calma, 2021; Silverstein, 2021). The loss in natural gas and power supplies resulted in 80% of the U.S. olefin capacity being offline for several days, surpassing the disruption caused by some recent hurricanes in the Gulf of Mexico (Hydrocarbon Processing, 2021). Thus, in addition to failure frequency estimation, the consequences of those failures are of particular interest in the area of pipeline risk assessment.

4.2.1. Pipeline Risk Assessment Models Overview

Researchers in pipeline risk assessment have developed both qualitative and quantitative models to describe the risks and consequences associated with hazardous materials pipelines. Qualitative models use fuzzy fault tree analysis (Khan and Abbasi, 2000; Yuhua and Datao, 2005) and a combination of historical data analysis and a scoring methodology for assessing relative risk to determine priorities for pipeline repairs (Dziubiński et al. 2006). Quantitative models (Muhlbauer, 2004; Han and Weng, 2010; Han and Weng, 2011; Vianello and Maschio, 2014; Witek et al., 2018) combined failure probability and consequence analysis to determine the individual and societal risks of oil and gas pipeline systems, mainly from incidents caused by corrosion. Some research works focused on certain factors contributing to pipeline risks, such as layout or third-party activities. Bubbico (2018) used statistical analysis to determine effect of pipeline layout (above-ground or underground) on the distribution of the probability of occurrence of hazardous materials pipeline failures. Other works developed an event tree framework to provide improved quantitative descriptions of immediate and delayed ignition events (Pontiggia et al., 2019; Vairo et al., 2021). Third-party interference can be accidental disturbances due to excavation activities or damage from nearby industries, or it can be intentional due to sabotage and malicious activities. Fault tree approaches have been used to assess the failure probability of pipelines due to third-party interference (Liang et al., 2012; Li et al., 2016). A dynamic model for analyzing risk under uncertainty has also been illustrated for a case of third-party damage of a subsea pipeline (Li et al., 2018). Another work used a Bayesian network model for unintentional interference and a game-theory approach for malicious activities (Cui et al., 2020).

4.2.2. Economic Risk Considerations

In terms of economic risk, several works have examined the costs of incidents based for different pipeline systems. Park et al. (2004) developed a computer program for risk assessment and management of a city gas pipeline in Korea. The consequences of a small-scale leak, large-scale release, and a pipeline rupture were correlated to cost. Restrepo et al. (2009) presented a framework to determine the economic costs of hazardous liquid pipelines incidents based on the costs of: product loss, property damage, litigation, and cleanup and recovery. Simonoff et al. (2010) extended the previous work and considered the costs of product loss and property damage in natural gas transmission and distribution pipelines. Shi et al. (2021) defined economic risk as the amount of natural gas lost due to corrosion, equipment impact, or a compressor station failure. The authors accounted for the slow dynamics of high-pressure transmission lines by indicating that certain pipeline segments and compressor stations have a greater impact on gas flow than others. Another approach has been to assess environmental risks due to offshore pipeline spills in monetary terms (Bovicini et al., 2015; Bonvicini et al., 2018).

4.2.3. Uncertainty Considerations in Pipeline Risk Assessment

Another important aspect of hazardous materials pipeline risk assessment is uncertainty quantification. This includes probability of pipeline failures, probability of certain types of incidents, as well as the probability of a set of consequences. Milazzo et al. (2015) focused on loss of containment incidents and presented a qualitative assessment of uncertainties associated with them. Yu et al. (2018) combined the analytical hierarchical process (AHP) and expert knowledge with interval analysis to establish an interval quantified risk assessment model for maintenance processes in onshore pipelines. Bayesian networks have also been extensively used in quantitative approaches to handle model uncertainty. Kabir et al. (2015) proposed a fuzzy Bayesian belief network for safety assessment of oil and gas pipelines. Their findings determined that construction defect, overload, mechanical damage, bad installation, and quality of worker as the most influential factors leading to pipeline incidents. Bayesian networks have also been utilized to analyze failures caused by corrosion and external interference in buried urban natural gas pipelines (Wang et al., 2017; Zhang and Weng, 2020). Structural integrity analysis (accounting for material properties, crack size, defected zone thickness, among other factors) has also been used to estimate oil and gas pipelines (Adib et al., 2007; Soares et al., 2019). Pipeline age is a significant factor affecting the structural integrity of natural gas pipelines, and one of the main degradation mechanisms affecting older pipelines is corrosion. Dundulis et al (2016) presented a framework to estimate overall failure probability of natural gas transmission lines using structural integrity analysis and update the resultant probability by applying the Bayesian method. The authors used the Monte Carlo simulation technique to address corrosion rate uncertainty, which impacts the defected zone thickness, and propagate that uncertainty throughout the model.

4.2.4. Problem Statement

Currently, there is no methodology that considers the downstream effects of hazardous materials pipelines incidents on the production of chemicals. The uncertainty surrounding quantitative parameters of those incidents (event frequency, material release quantity, disruption duration) and their impact needs to be accounted for as well. Most studies consider the economic risk associated with pipeline incidents to be the cost of lost asset, lost commodity (natural gas or crude oil) and associated cleanup. That is highly valuable from the perspective of pipeline operations. In this work, the economic risk is considered to be the downstream chemical production disruption resulting from pipeline incidents. Thus, this study aims to accomplish the following: 1) present a systematic framework for quantifying the effects of hazardous materials pipeline spills/releases and disruptions on downstream facilities in the chemical industry, and 2) characterize uncertainty associated with pipeline incidents and propagate its economic impact on process performance the chemical industry.

4.3. Methodology

The approach presented in this work, shown below in Fig. 4.3, starts with the definition of the incident categories being considered. As previously mentioned, the objective is to quantify the frequency and consequences of supply disruptions in hazardous liquid and natural gas pipelines on an industrial consumer (e.g. chemical plant). For this purpose, three categories of incidents are considered:

a) any releases: Any non-zero release of hazardous materials.

b) significant spills/releases: For hazardous liquid pipelines, significant spills are those equal to or greater than 50 barrels for crude oil and 5 barrels for highly volatile liquids (HVLs). For natural gas pipelines, significant releases are defined as incidents with 3 MMscf or more of natural gas released.

c) significant spills/releases and shutdowns: Incidents that meet the above criteria of significant spills/releases and require a shutdown for any period of time.

(d) shutdowns: Incidents that required a shutdown for any period of time, regardless of whether a spill/release is involved.

According to PHMSA, the definition of a significant incident is one where any of the following applies: (1) fatality or injury requiring in-patient hospitalization, (2) $50,000 or more in total costs in 1984 dollars, (3) HVL releases of 5 barrels or other liquid releases of 50 barrels or more, and (4) liquid releases resulting in an unintentional fire or explosion. Using this basis, significant spills are defined as incidents that meet criteria (3) for liquid pipelines. Since no similar criteria are mentioned regarding gas releases, 3 MMscf was considered in this work as the minimum release criterion for natural gas pipelines. Next, the database(s) used should be mined for data about the incidents being examined. In this work, the U.S. Department of Transportation PHMSA incident database is used. Relevant data needed are: unintentional and intentional release volumes, shutdown duration, and age of pipeline upon failure Following that, a preliminary analysis of the incident data is needed to examine the differences between the incident categories and annual trends in number of incidents and release quantities. However, incident frequency and release quantity are factors of the pipeline network mileage and delivered volumes. It would therefore to necessary to obtain the normalized incident rates (on a 1000 miles-year basis) and release quantities (on a volume delivered basis: bbls for hazardous liquids and MMscf for natural gas) to render them comparable and consistent and facilitate the subsequent analysis. After completing the preliminary analysis, statistical representations of the incident frequency, spill/release quantity, and shutdown duration are needed to account for the uncertainty associated with those variables. For this purpose, a discrete distribution is generated for incident frequency, while continuous distributions are generated for release quantities and shutdown durations. The best-fit distributions for these variables are ranked by the @Risk software on the basis of the Akaike information criterion (AIC), which estimates the quality of each statistical model compared to other models. Since this work is concerned with the impact of pipeline supply disruption, shutdown incidents will be the category of interest for this step. For a given supply network with known pipeline mileage, the percentage and cost of feedstock disruption can be determined using the following equation:

$$Annual\ Percent\ Feedstock\ Supply\ Disruption\ (\%) =$$

$$\frac{(Incident\ Rate)\times(Shutdown\ Duration)\times(Pipeline\ Flowrate)\times(Pipeline\ Length)}{Annual\ Feedstock\ Requirement}\times 100 \ldots\ldots\ldots\ldots(1)$$

where the incident rate is in events/(1000 miles-year), shutdown duration is in days/incident, and pipeline flowrate is in MMscf/day (for natural gas) or barrels/day (for hazardous liquids). The effect of these pipeline shutdowns on chemical production facilities, in terms of percent shortfall of annual production, can be determined using the reaction chemistry and mass balance of constituent processes. Using the distributions generated for incident frequency and shutdown duration allows for the propagation of the inherent uncertainties in those parameters to the disruptions in chemical production. As a result, a probabilistic risk profile of production shortfalls is obtained.

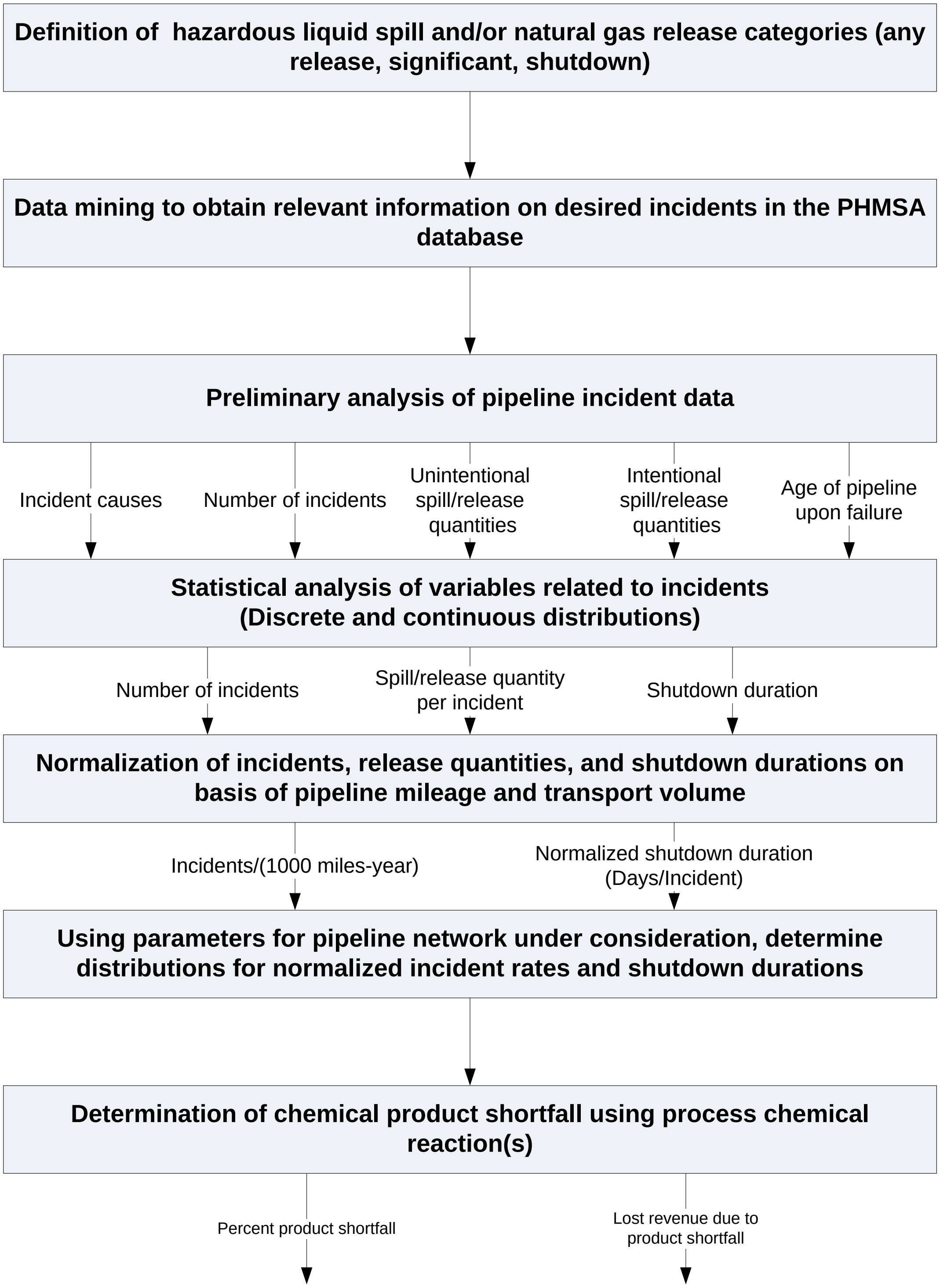


Figure 4.3: Framework for the downstream economic risk analysis of pipeline incidents under uncertainty

4.4. Preliminary Analysis of Pipeline Incident Data

4.4.1. Incident Frequency Analysis

In some incidents, both a significant spill/release and a shutdown occur. This category is of importance because it combines both the loss and disruption of commodity flow. Fig. 4.4 shows the relationship between the number of spills/releases, significant spills/releases, and shutdown events for crude oil, natural gas liquids/liquified petroleum gases, and gas transmission pipelines. Two major observations about the pipeline systems are noted. First, the number of significant releases is notably higher for gas transmission (642) compared to crude oil (359) and NGLs (124). Second, the number of incidents in which both a significant release/spill and a shutdown occurred is larger for gas transmission (390) than both crude oil (274) and NGLs (90).

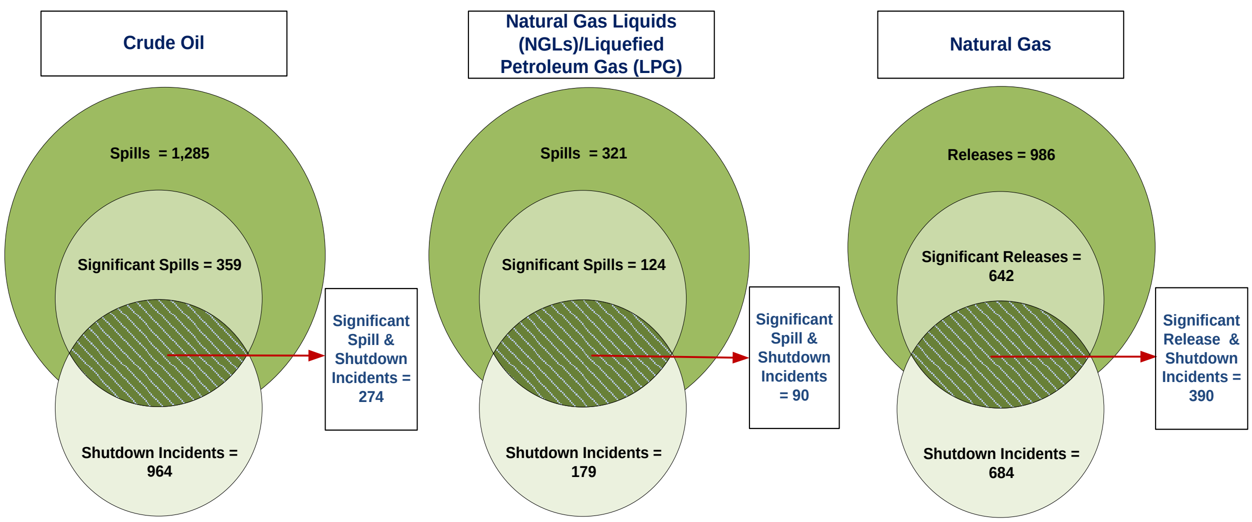


Figure 4.4: Incident frequency for onshore crude oil, NGLs/LPG, and gas transmission pipelines.

One of the most common performance indicators used refers to the number of pipeline incidents or failures in a time interval per cumulative length of the system during this time interval. While the number of incidents is important, the changing mileage of the pipeline network make comparison over time and between systems more valuable if normalized over annual mileage. The incident frequencies were normalized over the pipeline mileage figures obtained from the PHMSA database.

For crude oil pipelines, shown in Table 4.1, the annual number of significant spills ranged between 31 and 43, while the number of incidents with a significant spill and shutdown ranged between 20 and 32. Over the ten years surveyed, 21% to 39% of spill incidents were significant; in turn, 21% to 29% of those incidents involved a shutdown. Between 2015 and 2019, both categories showed a decline in the number of events and normalized incident rate.

Table 4.1: Incidents and normalized incident rate for crude oil pipelines

		Number of Incidents			Incidents/ (1000 miles-year)		
Year	**Crude Oil Mileage (miles)**	**Any Spill**	**Significant Spill**	**Significant Spill & Shutdown**	**Any Spill**	**Significant Spill**	**Significant Spill & Shutdown**
2010	54,631	88	31	22	1.611	0.567	0.403
2011	56,100	88	34	26	1.569	0.606	0.463
2012	57,463	117	35	28	2.036	0.609	0.487
2013	61,087	155	33	29	2.537	0.540	0.475
2014	66,943	151	38	28	2.256	0.568	0.418
2015	73,055	144	40	33	1.971	0.548	0.452
2016	75,710	143	43	32	1.889	0.568	0.423
2017	79,211	134	42	31	1.692	0.530	0.391
2018	80,790	139	31	25	1.720	0.384	0.309
2019	83,351	126	32	20	1.512	0.384	0.240

For NGLs pipelines, the annual number of significant spills ranged between 5 and 17, while the number of incidents with a significant spill and shutdown ranged between 5 and 13. Over the ten years surveyed, 25% to 55% of spill incidents were significant; in turn, 60% to 100% of those incidents involved a shutdown. Between 2015 and 2019, both categories showed a decline in the number of events and normalized incident rate, however, 2017 was an outlier year showing an increase. Table 4.2 shows the results for NGLs pipelines

Table 4.2: Incidents and normalized incident rate for NGL/LPG pipelines

		Number of Incidents			Incidents/ (1000 miles-year)		
Year	**NGL/LPG Pipeline Mileage**	**Any Release**	**Significant Release**	**Significant Release & Shutdown**	**Any Release**	**Significant Release**	**Significant Release & Shutdown**
2010	57,980	27	15	11	0.466	0.259	0.190
2011	58,599	33	16	11	0.563	0.273	0.188
2012	59,861	13	5	5	0.217	0.084	0.084
2013	62,768	16	9	7	0.255	0.143	0.112
2014	65,792	26	9	6	0.395	0.137	0.091
2015	67,676	34	17	13	0.502	0.251	0.192
2016	68,729	38	14	9	0.553	0.204	0.131
2017	69,163	54	17	13	0.781	0.246	0.188
2018	70,306	44	13	8	0.626	0.185	0.114
2019	72,615	36	9	7	0.496	0.124	0.096

For gas transmission and gathering (GTG) pipelines, greater variation in the number of incidents was observed in Table 4.3. The number of significant releases ranged between 43 and 86, while incidents with a significant release and shutdown ranged between 23 and 48. Approximately 50% to 70% of release incidents were significant; in turn, 50% to 85% of those incidents involved a shutdown. Compared to crude oil pipelines, a higher percentage of gas transmission pipeline releases were significant and involved a shutdown. Also, the number of incidents and normalized rate for the latter two categories displayed an increasing trend between 2016 and 2019.

Table 4.3: Incidents and normalized incident rate for gas transmission and gathering (GTG) pipelines.

		Number of Incidents			Incidents/ (1000 miles-year)		
Year	**GTG Mileage (miles)**	**Any Release**	**Significant Release**	**Significant Release & Shutdown**	**Any Release**	**Significant Release**	**Significant Release & Shutdown**
2010	312,289	80	37	32	0.256	0.118	0.102
2011	312,644	100	61	42	0.336	0.195	0.134
2012	309,209	83	55	23	0.278	0.178	0.074
2013	309,686	87	58	29	0.281	0.187	0.094
2014	309,342	108	70	43	0.349	0.226	0.139
2015	308,954	123	85	52	0.405	0.275	0.168
2016	308,574	84	53	37	0.272	0.172	0.120
2017	309,442	101	73	42	0.330	0.236	0.136
2018	310,085	103	75	42	0.345	0.242	0.135
2019	310,550	117	75	48	0.377	0.242	0.155

Comparing the three pipeline systems, both crude oil and NGL/LPG pipelines have a higher incident rate per cumulative length over time than GTG pipelines. However, while a decreasing incident rate was observed for liquids pipelines, an increasing trend was the case for GTG pipelines. This is an important observation which can impact both the power generation and petrochemical sectors as they are increasingly dependent on natural gas as feedstock in place of coal and crude oil, respectively.

4.4.2. Unintentional and Intentional Release Quantity Analysis

From 2010 to 2019, approximately 330,000 bbls of crude oil and 202,000 bbls of NGLs/LPGs were released as a result of pipeline incidents. Also, GTG pipeline incidents resulted in approximately 16,400 MMscf of natural gas being released in an unintentional manner, with another 2,460 MMscf intentionally (15% of unintentional value). As with the incident frequency, comparing spill/release volumes over a time horizon is better informed if it is on a normalized basis as follows:

For crude oil pipelines, significant spill incidents accounted for approximately 97% of the overall spill volume, as shown in Table 4.4. An average of 75% of that volume was due to incidents where a significant spill and shutdown occurred. The spill volume displayed significant variation across the time period surveyed, ranging between 15,000 and 53,000 barrels; however, the overall trend is a decreasing one. While the number of incidents decreased from 2016 to 2019, the spill volume and spill rate depended on the incident category being examined. Incidents with a significant spill and shutdown displayed a decreasing trend, while the other two categories had an increase in spill volume from 2018 to 2019.

Table 4.4: Spill volume and normalized spill rate for crude oil pipelines

		Spill Volume (Bbls)			Normalized Spill Rate ((Bbls Spilled/ Bbls Transported)/ year)		
Year	**Crude Oil Volume Transported (1000 Bbls)**	**Any Spill**	**Significant Spill**	**Significant Spill & Shutdown**	**Any Spill**	**Significant Spill**	**Significant Spill & Shutdown**
2010	593,535	52,677	52,211	40,522	8.875E-05	8.797E-05	6.827E-05
2011	518,308	35,248	34,546	20,343	6.801E-05	6.665E-05	3.925E-05
2012	561,100	14,837	13,999	13,282	2.644E-05	2.495E-05	2.367E-05
2013	599,580	43,576	42,025	38,782	7.268E-05	7.009E-05	6.468E-05
2014	707,823	16,955	16,267	12,559	2.395E-05	2.298E-05	1.774E-05
2015	918,703	19,662	18,940	15,587	2.140E-05	2.062E-05	1.697E-05
2016	1,000,827	43,765	41,472	39,256	4.373E-05	4.144E-05	3.922E-05
2017	1,183,714	40,538	39,467	25,693	3.425E-05	3.334E-05	2.171E-05
2018	1,266,235	26,021	25,006	22,443	2.055E-05	1.975E-05	1.772E-05
2019	1,484,132	36,697	35,635	13,004	2.473E-05	2.401E-05	8.762E-06

For NGLs pipelines, significant spill incidents accounted for 201,000 bbls, about 99% of the total spill volume, as shown in Table 4.55. About 84% of that volume was released during incidents where a significant spill and shutdown occurred. Compared to crude oil, a larger variation in the spillage volume is observed, ranging between 3,200 and 55,000 bbls. Between 2017 and 2019, the incident rate decreased but the normalized spill rate did not follow a clear trend, almost doubling from 2017 to 2018 and then decreasing by an order of magnitude.

Table 4.5: Spill volume and normalized spill rate for NGLs pipelines

		Spill Volume (Bbls)			Normalized Spill Rate ((Bbls Spilled/ Bbls Transported)/year)		
Year	**NGLs/LPGs Supplied (1000s Bbls)**	**Any Release**	**Significant Release**	**Significant Release & Shutdown**	**Any Release**	**Significant Release**	**Significant Release & Shutdown**
2010	825,879	15,713	15,612	15,251	1.903E-05	1.890E-05	1.847E-05
2011	821,345	23,872	23,627	4,307	2.906E-05	2.877E-05	5.244E-06
2012	839,282	11,023	11,004	11,010	1.313E-05	1.311E-05	1.312E-05
2013	912,806	40,323	40,278	40,296	4.418E-05	4.412E-05	4.415E-05
2014	891,630	5,472	5,365	5,365	6.138E-06	6.017E-06	6.017E-06
2015	930,667	12,750	12,606	3,649	1.370E-05	1.354E-05	3.921E-06
2016	929,942	6,924	6,780	6,127	7.445E-06	7.291E-06	6.588E-06
2017	962,528	27,950	27,766	27,336	2.904E-05	2.885E-05	2.840E-05
2018	1,099,970	54,693	54,581	52,582	4.972E-05	4.962E-05	4.780E-05
2019	1,145,706	3,153	3,066	2,985	2.752E-06	2.676E-06	2.606E-06

For gas transmission pipelines shown in Table 4.6, total release (unintentional and intentional) quantities did not necessarily follow the trend in incident frequency. For example, the lowest number of release incidents occurred in 2012, but that did not correspond to the lowest release quantity. Compared to the quantities under the any release category, the significant release category represented 95-98%, while the significant release and shutdown category represented a wider range of 51-89%. This indicates that up to 50% of the annual release quantity can be missed if only that category is considered. Annual release volumes and release rates did not display significant variation, averaging about 1,640 MMscf and 7E-05 (MMscf released/MMscf transported), respectively.

Table 4.6: Release volume and normalized spill rate for gas transmission and gathering pipelines.

		Release Volume (MMscf)			Normalized Release Rate ((MMscf Released/ MMscf Transported)/ year)		
Year	**Volume Delivered (MMscf)**	**Any Release**	**Significant Release**	**Significant Release & Shutdown**	**Any Release**	**Significant Release**	**Significant Release & Shutdown**
2010	22,127,046	1,926	1,896	1,725	8.706E-05	8.567E-05	7.796E-05
2011	22,467,053	1,518	1,485	1,235	6.757E-05	6.611E-05	5.498E-05
2012	23,411,423	1,620	1,605	1,207	6.918E-05	6.855E-05	5.154E-05
2013	23,838,925	1,352	1,336	746	5.670E-05	5.604E-05	3.128E-05
2014	24,381,082	1,701	1,672	1,089	6.976E-05	6.857E-05	4.465E-05
2015	24,989,285	1,792	1,770	1,146	7.172E-05	7.081E-05	4.585E-05
2016	25,212,159	1,531	1,510	1,252	6.072E-05	5.989E-05	4.965E-05
2017	24,839,976	1,953	1,932	1,046	7.864E-05	7.779E-05	4.213E-05
2018	27,528,222	1,371	1,358	952	4.980E-05	4.934E-05	3.460E-05
2019	28,267,179	1,650	1,627	1,170	5.837E-05	5.758E-05	4.141E-05

4.4.3. Shutdown Incidents Frequency and Duration

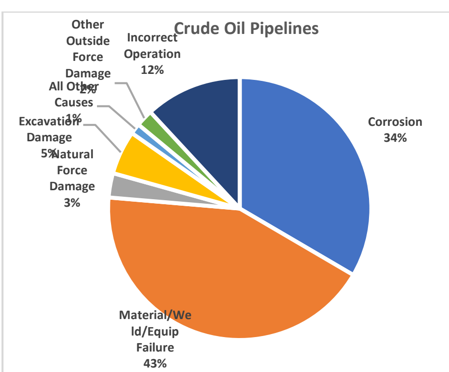
In addition to analyzing the overall spill/release volumes, incidents involving a pipeline shutdown, regardless of whether there was a spill/release associated, need to be examined to determine shutdown duration differences between the three pipeline systems surveyed. These incidents will be the focus of the statistical analysis section of this work. This measure is important because shutdowns of any duration can cause interruptions to critical supply chains. Table 4.7 below shows the breakdown by shutdown duration for crude oil, NGLs/LPGs, and gas transmission and gathering pipeline systems. Notably, shutdowns with a duration of 7 days or longer are more common in GTG pipelines than their crude oil and NGLs/LPGs counterparts. They constitute 28% of GTG incidents compared to 24% and 16% in crude oil and NGLs. Also, shutdowns lasting one month (31 days) or longer were 17% of GTG incidents, more than twice that of crude oil and NGLs pipelines. This data suggests that gas pipelines are more prone to lengthier shutdowns than their crude oil and NGLs counterparts. For industrial consumers who rely on a reliable gas supply for utilities and as feedstock, it is useful to know the probability distribution of shutdown durations to be better prepared to mitigate negative effects, such as production delays/interruptions.

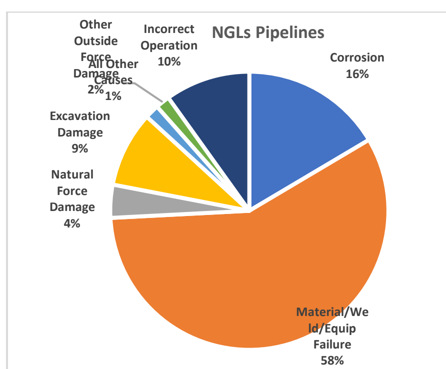
Table 4.7: Shutdown durations for pipeline systems.

	Pipeline System					
	Crude Oil		**NGLs/LPGs**		**Gas Transmission & Gathering (GTG)**	
Shutdown Duration	**Count**	**Percent**	**Count**	**Percent**	**Count**	**Percent**
< 24 Hours	**548**	57%	**89**	50%	**237**	35%
1-7 Days	**296**	31%	**63**	35%	**213**	31%
7-31 Days	**78**	8%	**20**	11%	**104**	15%
1-6 Months	**35**	4%	**7**	4%	**67**	10%
6-12 Months	**5**	1%	**0**	0%	**51**	7%
> 1 Year	**2**	0%	**0**	0%	**12**	2%
	964	**100%**	**179**	**100%**	**684**	**100%**

4.4.4. Shutdown Incident Causes

The Pipeline Hazardous Materials Safety Administration (PHMSA) has seven major pipeline failure causes to which incidents or accidents are attributed to: corrosion, excavation damage, natural force damage, other outside force damage, material/weld/equipment failure, incorrect operation, and other causes. The causes for the shutdown incidents between 2010 and 2019 were compiled in Fig. 4.5 for the three pipeline systems being examined in this work. There was a difference between the hazardous liquid pipelines and natural gas and transmission pipelines. For both crude oil and NGLs pipelines, the three leading causes were as follows: (1) material/weld/equipment failure, (2) corrosion, and (3) incorrect operation. Corrosion was a greater contributor in crude oil pipelines than their NGLs counterpart, accounting for a third of all shutdown accidents. For NGLs pipelines, material/weld/equipment failures caused nearly 60% of shutdown accidents. For natural gas transmission and gathering pipelines, the three leading causes for shutdown incidents were: (1) material/weld/equipment failure, (2) excavation damage, and (3) corrosion. It is notable that excavation damage caused nearly 20% of GTG shutdowns, almost twice as much as in hazardous liquid pipelines.





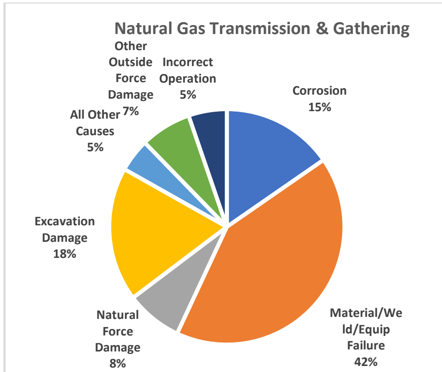


Figure 4.5: Breakdown of causes of shutdown incidents for crude oil, NGLs, and natural gas transmission and gathering pipelines.

4.5. Statistical Analysis of Pipeline Incident Data

In the previous section, pipeline incident data were presented to observe trends and differences within the three systems being analyzed. These variables displayed different degrees of variation, making it important to quantify the uncertainty associated with them. This data can be processed using statistical software package(s) to obtain probability distributions for the metrics being examined, such as incident rate, spill/release rate, and shutdown duration per pipeline length. In this work, uncertainty is integrated using the Monte Carlo simulation tool in the @Risk® software to generate 50,000 random samples for the variables being considered. Two sampling methods are available for use in this simulation feature: Latin Hypercube and Monte Carlo. For this work, Latin Hypercube sampling was used as the sampling method because it avoids the clustering that can occur with Monte Carlo sampling, providing a better chance for all values from the input distribution to be sampled. In turn, these probability distributions can be utilized to generate probabilistic outcomes of the impacts of pipeline incidents on industrial consumers (e.g. petrochemical facilities, power plants). For this section, the focus will be on shutdown incidents.

For crude oil pipelines, Table 4.8 shows the probability distributions results for incident rate and shutdown duration obtained. The annual incident rate is described by a normal distribution, with a mean and mode of about 1.04 incidents/(1000 miles-year). As for shutdown duration, the best fit for the data-driven probability distribution was a lognormal one with a mode of 10.8 days/(1000 miles-year). As shown in the table, the mode values for shutdown duration is smaller than the mean value, indicating the data are right skewed. In both cases, this indicates that the majority of the data points were on the lower end (smaller spill volumes and shorter shutdown durations). Comparing the three variables, the coefficient of variation results indicate that shutdown duration has the greatest variability relative to the mean. This is attributed to that while most incidents required shutdowns lasting a few hours or days, a small number of incidents resulted in shutdowns of 1 month or longer. Fig. 4.6 shows the probability density function for crude oil pipelines incident rate and normalized shutdown duration.

Table 4.8: Statistical analysis results of crude oil pipelines

Variable	**Distribution**	**Mean**	**Standard Deviation**	**Shift**	**Mode**	**Coefficient of Variation (%)**
Incident rate, *incidents/ (1000 miles-year)*	Normal	1.05	0.047	-	1.04	4.51
Shutdown duration, *days/ (1000 miles-year)*	Lognormal	14.7	5.61	-0.152	10.8	50

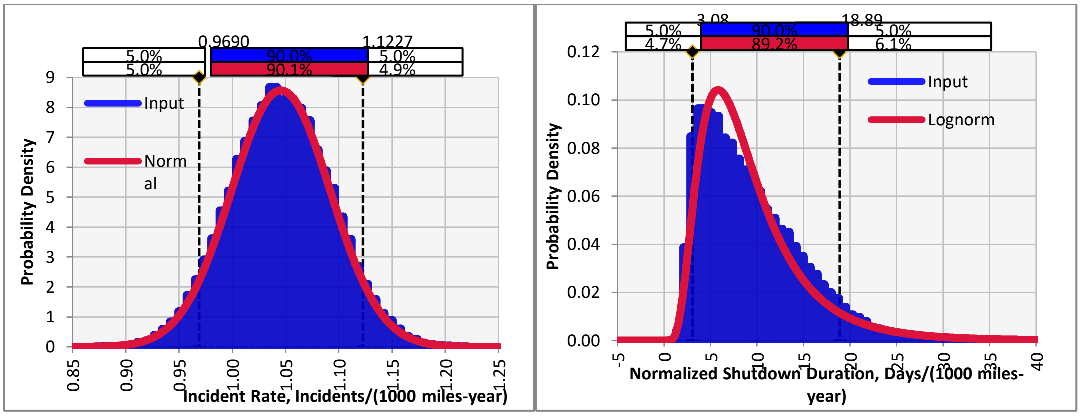
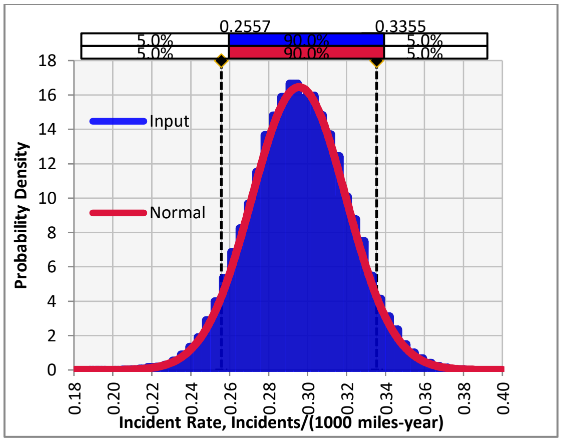


Figure 4.6: Probability density functions for crude oil pipelines incident rate (left) and normalized shutdown duration (right).

Table 4.9 shows the distributions for the relevant variables for NGLs/LPGs pipelines. This system showed a lower incident rate and normalized shutdown duration than crude oil pipelines. The 90% confidence interval for shutdown duration was between 1.18 and 2.36 days/(1000 miles-year), significantly shorter than for crude oil. This is explained by the lower incident rate and that 55% of shutdowns lasted less than 24 hours, as shown previously in Table 4.7. Fig. 4.7 shows the probability density function for NGLs pipelines incident rate and normalized shutdown duration.

Table 4.9: Statistical analysis results of NGLs/LPGs pipelines

Variable	Distribution	Mean	Standard Deviation	Shift	Mode	Coefficient of Variation (%)
Incident rate, *incidents/ (1000 miles-year)*	Normal	0.296	0.0242	-	0.296	8.21
Shutdown duration, *days/ (1000 miles-year)*	Lognormal	1.88	0.365	-0.167	1.61	21.6



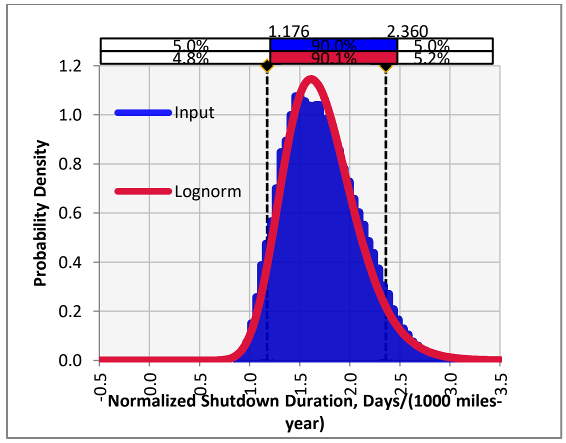
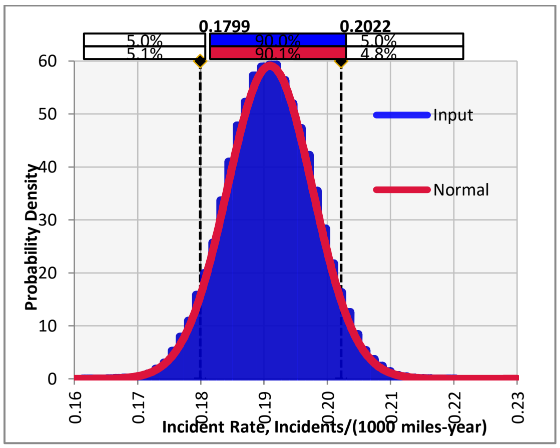


Figure 4.7: Probability density functions for NGLs pipelines incident rate (left) and normalized shutdown duration (right).

Table 4.10 shows the distributions for the relevant variables for gas transmission and gathering pipelines. As the preliminary analysis indicated, the incident rate for GTG pipelines is about a third of that of crude oil. Normalized shutdown durations were determined to be almost equal to crude oil pipelines, which is a factor of the lower incident rate in GTG pipelines. Fig. 4.8 shows the probability density function for natural gas transmission and gathering pipelines incident rate and normalized shutdown duration. Despite having a higher percentage of shutdowns longer than 7 days, the lower incident rate for GTG pipelines led to this result. This was interesting to note as it indicates that reliable commodity supply can be more likely for natural gas than crude oil due to the shorter normalized shutdown periods.

Table 4.10: Statistical analysis of results for gas transmission and gathering pipelines

Variable	Distribution	Mean	Standard Deviation	Shift	Mode	Coefficient of Variation (%)
Incident rate, *incidents/ (1000 miles-year)*	Normal	0.191	0.0067	-	0.191	3.55
Shutdown duration, *days/ (1000 miles-year)*	Lognormal	9.36	5.52	-1.68	11.2	27.1



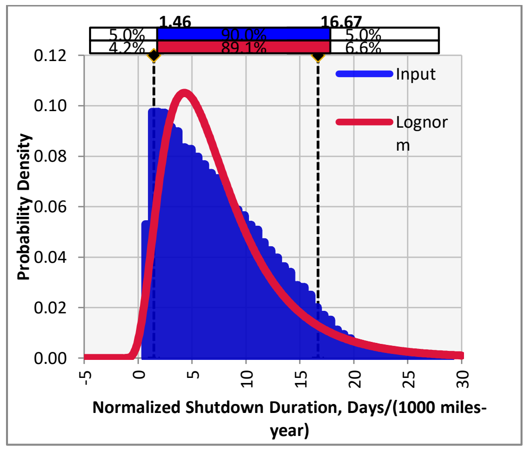


Figure 4.8: Probability density functions natural gas pipelines incident rate (left) and normalized shutdown duration (right).

The distributions mentioned in the results were determined to be the best fit by the @Risk software on the basis of the Akaike information criterion (AIC), which estimates the quality of each statistical model compared to other models. For all three pipeline systems, the annual incident rate probability was determined to be normally distributed with coefficients of variation at approximately 10% or below. The majority of the shutdown durations were in the category less than 7 days. Accordingly, the normalized shutdown durations for all systems had lognormal distribution and thus were right-skewed, as indicated by the mode values being smaller than their mean values.

4.6. Case Study: Impact of Pipeline Incidents on Propylene Production Pathways

The pipeline network connects production fields to refineries, gas processing plants, chemical plants, and deliver vital products needed by consumers and businesses. They move crude oil from oil fields and offshore production areas to refineries where it is processed into fuels and petroleum products, then to terminals where fuels are transported by trucks to retail outlets. For natural gas pipelines, three main types of pipelines exist: gathering lines, transmission, and distribution. Gathering pipelines move gas from a production location (well pad) to a gas processing facility where impurities (e.g. water, carbon dioxide, sulfur) are removed and natural gas liquids (ethane, propane, and butane) are fractionated and transported by dedicated liquids pipelines for use as chemical feedstocks and other applications. Transmission pipelines move large amounts of dry natural gas from producing regions to distribution companies. Depending on the operational area, pressure in a transmission line section ranges from 200 to 1,500 psi. To boost gas pressure, compressor stations are located approximately every 50-60 miles to make up for pressure loss due to friction resulting from the gas moving through the steel pipe. Large industrial, commercial, and electric generation customers receive natural gas directly from high-capacity transmission lines. Upon reaching a local distribution company, it passes through a gate station where pressure is reduced from 200-1,500 psi to 0.25-200 psi and an odorant is added. From the gate station, utilities deliver gas to customers via small-diameter distribution pipelines (American Gas Association, 2021).

In this section, the aim is to determine the impact of pipeline shutdown incidents on the production of a chemical processing facility. These incidents would cause a shortfall in annual production capacity and thus impact the projected annual sales of the facility. This can result in failure to meet contractual obligations to customers which damages a company's reputation, thereby risking further losses in the future (e.g. loss of potential customers, litigation costs). For this work, three pathways for the production of propylene are evaluated to determine which is most likely to result in production shortfalls and financial losses. Fig. 4.9 shows the three propylene production pathways: (1) steam cracking in a refinery, (2) natural gas to methanol via reforming and conversion followed by methanol-to-olefins, and (3) propane dehydrogenation.

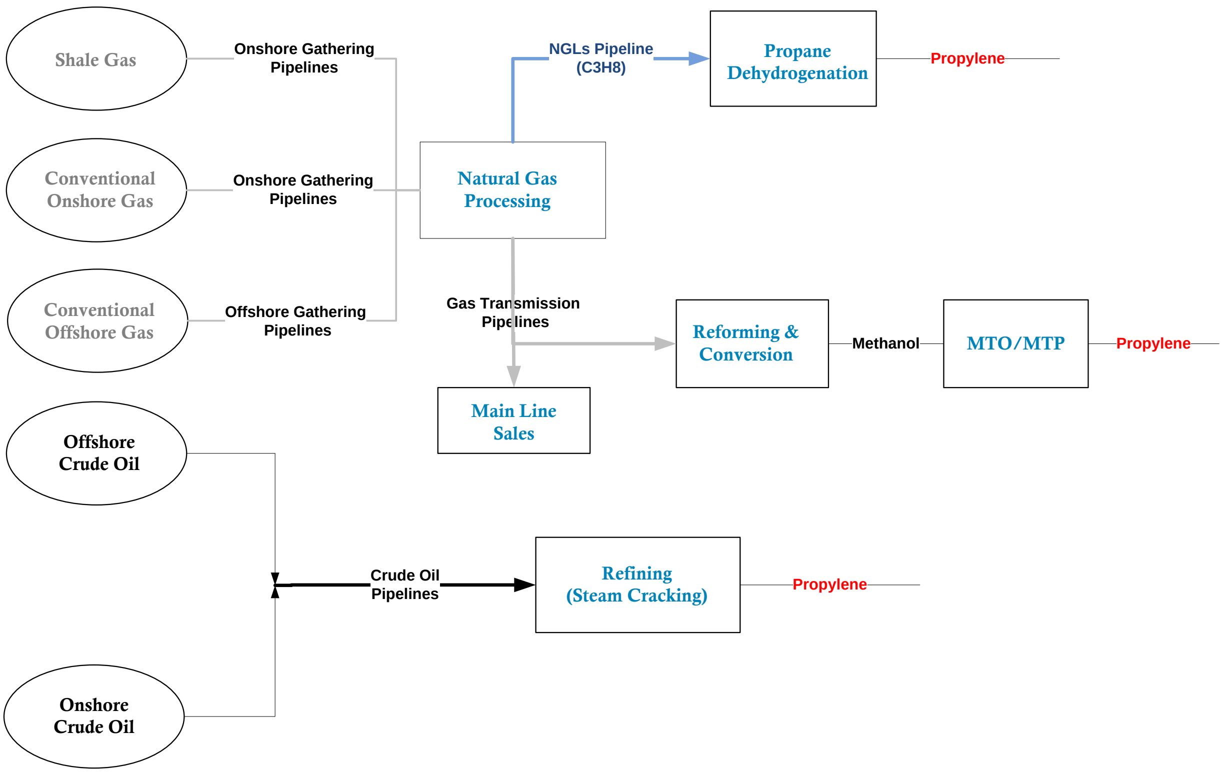


Figure 4.9: Propylene production pathways diagram.

For pipeline mileage, this work used 500 miles as the total length for hazardous liquids pipelines and both natural gas gathering and transmission pipelines. The production capacity, feedstock requirements, and base feedstock prices (as of February 2021) are based on existing facilities and are shown below in Table 4.11. The propylene market price as of February 2021 ($760/MT) is used as the base price in this case study. Based on it, annual expected revenue for a plant operating at a capacity 750,000 metric tons per annum (MTA) is about 572 $MM/year. Financial losses due to pipeline incidents will be measured in terms of the percent shortfall in propylene production.

Table 4.11: Parameters for propylene production pathways.

Production Pathway	Feedstock	Feedstock Price	Feedstock Requirement	Pipeline Length (miles)
Refinery steam cracking unit	Crude oil	$60/bbl	94,000 bbls/day	500 miles
Methanol, Methanol-to-olefins (MTO)	Natural gas	$3.40/MMBtu	350 MMscf/day	Gathering line: 250 miles Transmission line: 250 miles
Propane dehydrogenation (PDH)	Propane	$0.90/gal	24,300 bbls/day	Gathering line: 250 miles NGLs line: 250 miles

First, the pathways will be evaluated in terms of the volume percentage annual disruption to feedstock supply and the cost of lost feedstock. The disruption cost is calculated based on the base prices shown in Table 4.11, and the comparisons will be made on the basis of the mode (most likely) value. From Table 4.12, both categories are determined to be lowest when propane is used in a PDH facility and greatest with natural gas in the methanol followed by a methanol-to-olefins pathway. The cost of lost feedstock is greatest for crude oil, as evidenced by a 1.1% disruption leading to an annual cost of $134MM. In the previous section, a significant coefficient of variation (50%) was observed for crude oil pipeline normalized shutdown durations, which helps explain the wide range seen for crude oil feedstock disruption and cost.

Table 4.12: Percent feedstock disruption and its cost.

	Annual Percent Feedstock Disruption (%)				**Annual Cost of Lost Feedstock ($MM)**			
Pathway	**5% Tail**	**95% Tail**	**Mode**	**Mean**	**5% Tail**	**95% Tail**	**Mode**	**Mean**
Crude Oil	0.841	2.39	1.19	1.51	94.5	268	134	169
Propane	0.657	0.74	0.688	0.696	2.21	2.49	2.30	2.34
Natural Gas	1.35	2.92	1.42	1.99	5.25	11.3	5.5	7.75

To measure the impact on production facilities, the percent shortfall in annual production of propylene and its cost in lost sales needs to be examined, shown in Table 4.13. This is accomplished by using the feedstock disruption results combined with the reaction chemistry foreach pathway as follows:

$$Annual\ Production\ Shortfall\ (\%) = \frac{(Annual\ Feedstock\ Disruption)\times(Yield)}{Annual\ Uninterrupted\ Production\ Capacity} \times 100 \qquad (2)$$

In this case, both percent shortfall and lost sales cost were lowest for the propane pathway and greatest for crude oil. Some refineries store crude oil near or on-site at their facilities; however, the volume differs based on many factors, and is thus not considered in this work. Propylene shortfall percentage is shown to be the least (0.608%/year) for the propane dehydrogenation pathway, which is of growing importance in the U.S. due to the increased availability of NGLs as a result of the shale gas revolution. PDH plants accounted for 11.4% of global propylene production in 2018, up from 3% in 2005 (Rabenhorst, 2019). Ultimately, the economic driving force behind PDH plants is a large propane-propylene price spread. For the natural gas pathway, pipeline incidents result in a methanol shortfall of about 0.55%. For a MTO facility, 5,200 MT/day of methanol produces 882 MT/day of each ethylene and propylene. On this basis, the mode value for propylene shortfall is about 3.65%.

Table 4.13: Percent product shortfall and its cost.

	Annual Percent Propylene Shortfall (%)				Annual Cost of Lost Sales ($MM)			
Pathway	**5% Tail**	**95% Tail**	**Mode**	**Mean**	**5% Tail**	**95% Tail**	**Mode**	**Mean**
Crude Oil	5.10	14.4	7.21	9.10	29.1	82	41.1	51.9
Propane	0.584	0.656	0.608	0.618	3.34	3.75	3.47	3.52
Natural Gas	3.49	7.53	3.65	5.15	7.74	16.7	8.11	11.4

The case study above shows the economic impacts of pipeline shutdowns on both midstream and downstream facility operators. These incidents can cause monetary losses for both organizations through shortfalls in commodity or product sales and affect a company's reputation resulting in future financial losses. The decision on which pathway is most profitable is not solely based on feedstock disruption probability, but involves many considerations such as geographic location, feedstock availability, and economics.

4.7. Conclusions

The proposed methodology in this work provides an approach for the quantitative assessment of the impacts of hazardous materials pipelines incidents on downstream consumers, specifically petrochemical production facilities. Appropriate Monte Carlo simulation framework is used to analyze and quantify the uncertainty associated with incident frequency and shutdown durations. A preliminary breakdown of the causes of these shutdown incidents was obtained showing that material/weld/equipment failures were the leading cause for all three pipeline systems. However, it was notable that excavation damage was only a significant contributor (~20%) to natural gas transmission and gathering pipelines. The probability distributions generated for these variables are used to stochastically characterize disruptions of feedstocks (crude oil, natural gas, or propane) to a petrochemical plant. This approach provides a more extensive manner of assessing the impact of uncertainty on the implementation of different feedstock supply pathways to the demand sites. Using process chemistry and mass balances, risk profiles for the product shortfall and cost of lost sales can be generated. The results can provide valuable insights in terms of planning for operational and economic impacts of feedstock disruptions due to pipeline failures. While most previous works considered the safety and environmental implications of hazardous materials pipeline failures, this methodology can be considered as a tool to evaluate their economic risks from the perspective of a petrochemical facility. This work provides an approach to bridge organizational boundaries between midstream and downstream operators. A case study on three pathways to produce propylene was used to illustrate the methodology. Using natural gas or propane as feedstock was determined to cause less product shortfalls, and therefore lower costs of lost sales, than crude oil.

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5. CONCLUSIONS & RECOMMENDATIONS

5.1. Conclusions

This work is aimed at presenting an economic framework for the integration of reliability, availability, and maintainability (RAM) considerations in the conceptual process design phase. The motivation behind this work is that as a process plant life cycle advances from conceptual design to basic design and onwards, incurring changes on it becomes more difficult and expensive. As a result, the conceptual design stage presents the least-costly opportunity to incur changes and positively influence process profitability.

In Chapter 2, a systematic approach for failure mitigation using an economic framework during the conceptual design stage was introduced. An initial estimate for system availability is obtained using equipment failure rates collected from generic failure data sources. Next, a Bayesian updating procedure is implemented to estimate the appropriate distributions for the failure rates in question. This is done to quantify uncertainties associated with the failure data available. Only point values for equipment repair rates are used. Failure and repair rates are then used in a simple two-state Markov analysis to obtain system inherent availability. By describing process revenue as a function of system availability, the effects of equipment failure and repair rates are incorporated into the profitability calculations. To improve the base case availability, candidate design modifications are generated and evaluated based on their incremental return on investment (IROI). These evaluations establish an economic framework to trade off system availability and profitability.

In Chapter 3, a systematic framework to integrate uncertainty quantification of equipment RAM characteristics in the economic analysis of chemical process designs during the conceptual development stage. This framework can be utilized by decision makers, design or operations teams to make better-informed decisions on the economic potential of a project or design alternative. A modified availability metric was introduced using mean time to restoration (MTTRes) values in place of mean time to repair (MTTR). This was done because the MTTRes metric includes delays prior to and after the corrective repair process in addition to the time needed to shut down and start-up the item. Thus, it presents a more encompassing view of the repair process and estimates the time required to restore an item to full operational status. This is of great importance as it correlates with the concept of recoverability, which is one of the four main elements of process resilience. By using the MTTRes metric, a modified system availability which estimates the probability that the system is operating at full capacity is obtained. In addition to the modified availability metric, the analysis was carried out in a probabilistic manner to obtain a range of system availability values. This is in contrast to the traditional practice of using a deterministic, point value for RAM characteristics at the conceptual design stage. As a result, full distribution profiles of process economic performance measures (e.g. annual revenue, annual profit, and return on investment (ROI)) are obtained. Using this approach, the process section(s) that contribute significantly to revenue losses are identified. Finally, design alternatives to the section(s) in question are evaluated, using the incremental return on investment (IROI), to determine the economically-optimal alternative to select. This approach differs from the current practice of considering RAM improvement modifications based on budgetary constraints only.

In Chapter 4, the problem of reliability was considered on the supply chain scale, and the approach presented aimed to bridge the organizational boundaries between midstream and downstream operators. In process design, the alternatives being evaluated have different feedstocks. The uninterrupted supply of this feedstock is of paramount importance to the safe and profitable operation of the plant. The selection of the best alternative is made based on economic, safety, and environmental considerations, among others. In this work, a stochastic framework to compare design alternatives based on the economic risks of feedstock supply reliability is presented. This framework can be used to analyze and quantify the uncertainty associated with annual incident rate and shutdown durations. Next, the probability distributions generated for those variables can be used to stochastically characterize feedstock disruptions to a petrochemical plant. Using process yields, risk profiles for product shortfalls and lost sales revenue can be obtained. The approach presented was demonstrated on a case study for propylene production from three pathways: crude oil, natural gas, and propane.

5.2. Recommendations for Future Work

In order to further improve the potentials of this work, the following are areas recommended for future work:

- Industry-specific data sources: More sources of failure and repair data, that are specific to the chemical process industry, are needed to be able to better evaluate the availability of a proposed design or design(s). This data could be from similar types of systems or maintenance records. This issue is a difficult one to tackle as understandably, chemical companies are hesitant to publish or share failure and repair rates of their equipment or systems. In this work, generic sources were used for equipment failure and repair rates, mainly from the Offshore and Onshore Reliability Database (OREDA) 4th and 6th editions. However, obtaining process-specific data can improve the quality of the RAM estimation being conducted at the conceptual design stage. For example, the failure and repair rates of centrifugal compressors can differ significantly based on the type of service they are in (fouling or non-fouling). The effects of various influencing factors on the failure rate of the system being analyzed can be considered. These factors can be environmental, design, and operational ones. This analysis has been conducted for electronic components but it is more difficult to perform for process equipment as these factors have not been widely developed in the process industries. Also, from generic data, it is difficult to determine the effect of equipment sizing (e.g. compressor power rating) on RAM characteristics. The wider availability of this data would, in turn, improve the economic assessment of the proposed design.

- Time-dependent RAM models: In this and other research works, RAM data are mean-time-between-failure (MTBF) and mean-time-to-repair (MTTR). This is assumed to be constant over the lifetime of the system being examined. The metric obtained from this data will be a steady-state, inherent availability. If lifetime data are obtained, it is possible to model the failure-repair-failure-repair cycle of a system as a stochastic point process, defined as "isolated events occurring at instants distributed randomly over a time continuum" (Ebeling, 2003). These models can be: (1) a renewal process where the assumption is that the system is replace upon failure or repaired to an "as good as new" condition, or (2) a minimal repair process where only a small percentage of the parts composing the system are replaced/restored. If a failure-repair-failure-repair cycle is described by a minimal repair process, the system will not achieve steady-state. In the case of chemical process plants, a minimal repair process is the most appropriate model to characterize the failure-repair-failure-repair cycle. The minimal repair process can be described by one of several intensity functions: non-homogenous Poisson process (NHPP), power law process, or a bounded intensity process (BIP). After determining the failure process intensity function and the mean of the repair distribution, an interval availability for the system can be determined. This approach simulates the fact that complex systems

- Inclusion of process availability, safety, and environmental considerations in economic performance measure: In Chapters 2 and 3, an availability-weighted return on investment metric was introduced and demonstrated through the case studies presented. Previous works have included various sustainability indicators (CO_2 emissions reduction, fuel savings, etc.) and safety indicators (fire and explosion damage index) in a sustainability and safety-weighted return on investment metric. An interesting extension to the work in this dissertation and other works is to combine process availability indicator with appropriate safety and sustainability indicators to assess the profitability of a design and its modifications on the basis of all three considerations taken into account.
- Multi-criteria framework for the impact of pipeline incidents: The work in Chapter 4 has the potential to be extended by incorporating other considerations into the assessment of the alternative pathways. For example, environmental considerations, such as greenhouse gas emissions factors, can be incorporated o obtain a life cycle assessment of each pathway. Also, an appropriate safety index or indices can be selected to assess each alternative's potential safety performance. By including these considerations, a multi-criteria framework for comparison of the potential pathways can be developed taking into account the potential economic, safety, and environmental performance of each pathway.