RISK MEASURES CONSTITUTING RISK METRICS FOR DECISION MAKING IN THE CHEMICAL PROCESS INDUSTRY

A Dissertation

by

KATHERINE PRIYA PREM

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

DOCTOR OF PHILOSOPHY

December 2010

Major Subject: Chemical Engineering

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Approved by:

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ABSTRACT

Risk Measures Constituting Risk Metrics for Decision Making in the Chemical Process Industry. (December 2010)

Katherine Priya Prem, BS., Texas A&M University

Chair of Advisory Committee: Dr. M. Sam Mannan

The occurrence of catastrophic incidents in the process industry leave a marked legacy of resulting in staggering economic and societal losses incurred by the company, the government and the society. The work described herein is a novel approach proposed to help predict and mitigate potential catastrophes from occurring and for understanding the stakes at risk for better risk informed decision making.

The methodology includes societal impact as risk measures along with tangible asset damage monetization. Predicting incidents as leading metrics is pivotal to improving plant processes and, for individual and societal safety in the vicinity of the plant (portfolio). From this study it can be concluded that the comprehensive judgments of all the risks and losses should entail the analysis of the overall results of all possible incident scenarios. Value-at-Risk (*VaR*) is most suitable as an overall measure for many scenarios and for large number of portfolio assets. *FN*-curves and *F$*-curves can be correlated and this is very beneficial for understanding the trends of historical incidents in the U.S. chemical process industry.

Analyzing historical databases can provide valuable information on the incident occurrences and their consequences as lagging metrics (or lagging indicators) for the mitigation of the portfolio risks. From this study it can be concluded that there is a strong statistical relationship between the different consequence tiers of the safety pyramid and Heinrich's safety pyramid is comparable to data mined from the HSEES database. Furthermore, any chemical plant operation is robust only when a strategic balance is struck between optimal plant operations and, maintaining health, safety and sustaining environment.

The balance emerges from choosing the best option amidst several conflicting parameters. Strategies for normative decision making should be utilized for making choices under uncertainty. Hence, decision theory is utilized here for laying the framework for choice making of optimum portfolio option among several competing portfolios. For understanding the strategic interactions of the different contributing representative sets that play a key role in determining the most preferred action for optimum production and safety, the concepts of game theory are utilized and framework has been provided as novel application to chemical process industry.

DEDICATION

This work is dedicated to my wonderful parents for their innumerable sacrifices and for instilling in me the desire to learn and to work diligently; to my brother, my sister-in-law and my niece, for always believing in me. This work is also dedicated to my most respected professors, Dr. M. Sam Mannan and Dr. Mahmoud M. El-Halwagi, without whose selfless support and constant encouragement, the successful completion of my studies would not have been possible.

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Above all, I would like to thank Almighty God for being the source of all wisdom, grace and for the inspiration to better myself through the avenue of education.

NOMENCLATURE

ALARP	As Low As Reasonably Practical
ATSDR	Agency for Toxic Substance and Disease Registry
BI	Business Interruption
BLEVE	Boiling Liquid Expanding Vapor Explosion
CBA	Cost Benefit Analysis
CCPS	Center for Chemical Process Safety
cdf	cumulative distribution function
CPQRA	Chemical Process Quantitative Risk Analysis
EAL	Expected Annual Loss
ENFY	Expected Number of Fatalities per Year
EPA	Environmental Protection Agency
ETA	Event Tree Analysis
EUT	Expected Utility Theory
FN-curve	Frequency Number Curve
F$-curve	Frequency Dollar Curve
FTA	Fault Tree Analysis
GT	Game Theory
HAZOP	Hazard and Operability Analysis
HSE	Health and Safety Executive
HSEES	Hazardous Substance and Emergency Events Surveillance

LOPA	Layers Of Protection Analysis
NFPA	National Fire Protection Association
OREDA	Offshore Reliability Data
pdf	probability distribution function
PHA	Process Hazard Analysis
QRA	Quantitative Risk Analysis
RMP	Risk Management Program
SRS	Scenario Risk Spectrum
VCE	Vapor Cloud Explosion
VaR	Value-at-Risk

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1. INTRODUCTION

1.1. Importance of Research

Man has been analyzing risk since time immemorial. Whether a decision is to be made in a simple case of crossing the street or a complex case of shutting down a chemical plant, accurate risk analysis is inherently necessary. In the past, however, improper risk analysis and/or the lack of understanding of the stakes at risk have resulted in many major catastrophes. Some examples of major catastrophic incidents with huge economic and societal losses within the U.S. are: a) the Phillips explosion in Pasadena Texas in 1989 which resulted in 23 fatalities, 314 injuries and over $715 million losses (Lepkowski, 1989), b) the Texas City disaster of 1947 which resulted in 4,000 deaths and cost an estimated $75mil in 1947 dollars (Stephens, 1997), and c) the BP Texas City refinery incident of 2005 which is estimated as the most costly incident in recent times with a loss of $2 billion while fatally injuring 15 workers and injuring another 70 workers (Baker *et al.* panel report, 2007). The recent BP-Transocean Deepwater Horizon incident caused by the failure of the blowout preventer could become the most costly incident to date. All these estimations of loss are due to damages to the facility, with loss of turnover and business interruption (Mannan, 2005).

Catastrophes are high profile incidents that, although have low probability of occurrence, almost always result in huge financial losses to the company in terms of both

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This dissertation follows the style of *Journal of Loss Prevention in Process Industries*.

the loss of assets in the plant and the adverse societal impacts (*i.e.*, fatalities, injuries). For example, the Texas City disaster of 1947, due to the Grandcamp ship explosion which was hauling ammonium nitrate, is considered "the worst disaster, resulting in the largest number of casualties, in American history" (Stephens, 1997). The Red Cross and the Texas Department of Public Safety estimated that approximately 4,000 people were negatively impacted by this incident. There were over 468 fatalities with another 100 persons missing and 3,500 injured. The estimated present value property losses of this catastrophe are about $700 million, not including the 1.5 million barrels of petroleum which can be estimated at an additional present value of $3.5 billion. There are other several major incidents such as the Flixborough Incident in UK (1974), the Bhopal Gas Tragedy (1984), the Piper Alpha Incident (1989) and more recently the Buncefield Incident (2005) (Mannan, 2005, BMIIB, 2008) which also have resulted in staggering economic loss and negative societal impact. Most often major regulations result from understanding the causes of such catastrophes. Hence, predicting these catastrophes before they actually occur would be very useful.

From historical incidents it can be concluded that deviations from normal operating procedures and a series of failures, equipment operations and/or human error, almost always result in catastrophes leading to huge financial losses to the companies. The losses are incurred because of structural damages, fatalities and injuries. Although rare events, because catastrophic incidents result in extreme losses, it is significantly important to study them and incorporate suitable methodology to provide both leading indicators and lagging indicators (or metrics) to boost safer operations and prevent future catastrophes. Having a good framework for determining the leading indicators for potential incidents is pivotal to aid in understanding the risks in order to prevent major catastrophes. Incorporating lagging indicators which will provide information about the previous incident trends in the process industry will also enable the understanding of the stakes at risk. If the portfolio risks leading to potential catastrophic losses and the lagging indicators are both studied collectively, then it aids in providing the complete picture for understanding the severity of the stakes at risk. Such information will be very beneficial for decision makers and regulators to make suitable risk-informed decisions by establishing proper risk reduction measures.

The advantages of performing a risk analysis are many. AIChE/CCPS (2000), and Pasman et al. (2009) have stressed the utility of performing quantitative risk analysis in order to improve process safety. However, for typical industrial plants, the number of risk values that result from a full-fledged quantitative risk analysis pertaining to different potential incident scenarios could range from hundreds to thousands. There is, therefore, a need to develop a framework or a methodology to fully understand the risk values resulting from quantitative risk analysis (QRA) studies.

Presently, the ever increasing complexities in the chemical process industry emphasize the serious need for a complete risk analysis of entire plant portfolios (including both tangible and intangible assets). However, loss expenses from catastrophes as seen from the examples are only calculated after the incident has already occurred. If the incidents and their expected losses are calculated at the time of performing the risk analysis, then the decision maker is provided with more useful information for making risk informed decisions which are less subjective as opposed to risk-based decision making, which is currently the norm. Hence, the need for making a business case for improving the process safety is critical in understanding the stakes at risk. Therefore, estimating the loss expenses in monetary terms, which is based on good scientific basis, to enable management and regulators to better understand the portfolio risks for making sound risk-informed decisions for the safety of the chemical plants, is extremely important.

For understanding the stakes at risk comprehensively, an approach for expressing risks as a broad set of measures is needed. This approach forming a metrics should include factors such as the prediction of potential accidents, the proper representation of all the stakes at risk, the overall cost benefit analysis (CBA) for the portfolio as a whole, the identification of the most risky scenarios with a potential to lead to catastrophes and capturing historical incident trends from the US process industry. The risk analysis and the estimation of losses of potential catastrophes serve as leading indicators and the historical trends of incidents serve as the lagging indicators. A methodology which would include important and highly relevant information projected to indicate future potential incidents as well as utilize the historical process industry trends would not only increase the safe operations of the plant but, also increase the productivity by improving all the processes during the life cycle of the plant.

Amidst all the information provided by the leading indicators and the lagging indicators, it is also crucial to provide decision makers with the tools to help choose the safest portfolio options from various portfolio options. The portfolio options could be different process designs at the initial design phase of projects, different equipment that need to be installed in already existing plant during management of change a plant with a neighborhood in its vicinity and so on. The area of decision making for improving safety and ensuring optimum production has not previously been studied in the field of chemical engineering. Including a framework for this along with the leading and lagging indicator information would fully enable decision makers to make risk-informed decisions for safer operations and prevent future catastrophes.

1.2. Problem Statement

Major accidents and concerns for improving safety have resulted in the establishment of regulatory bodies such as the Occupational Safety and Health Administration (OSHA) in the U.S. and Health and Safety Executive (HSE) in the UK. These agencies are commissioned to regulate and inspect for safety standards to prevent accidents and ensure public safety. The company managements - which make key business decisions directly affecting the safety of chemical plants and, the regulatory bodies, rely heavily on risk analyses to make sound risk-informed decisions for safer plant operations. Management and regulators use QRA to evaluate risks and penalize companies violating safety regulations, to identify areas of the plant for cost effective risk mitigation and, to set up safety standards for plant operations. Quantitative risk assessment (QRA) is one of the most rational methods to obtain information on potential risks of accidents in the chemical process industry (Royal Society, 1983; CCPS, 2000). However, understanding the stakes at risk and making business decisions for improved safety is lacking. Additionally, the decisions made by company managements and standards set by regulatory bodies are often times highly subjective and ‘risk-based’ rather than ‘risk-informed’.

For larger plants, the number of scenarios can be about a thousand or more. If QRA is performed for public safety purposes, the impact to society, *i.e.* the intangible risks and disruptions, are determined and usually expressed as the number of fatalities. However, for internal safety examination and business decisions, possible tangible property damages, as well as intangible losses such as injuries and fatality are also very relevant. For prevention measures, prioritization is unavoidable. There is a need to fully understand the overall risk values for sound business decisions for promoting safety while abating the risks.

The importance of quantitative risk assessment to identify the potential incidents and their consequences is exemplified in the complex chemical industry processes. Once the risks of the potential incidents are quantified, the challenging task of correctly estimating the stakes at risk and choosing the safest alternative still persists. The approach for solving this problem is to monetize the portfolio risks in addition to the traditional expression of risk in terms of the probability of fatalities.

There is currently limited scope and insufficient information for decision making in the chemical process industry. So, in the chemical process industry, the following problems persist: a) The inclusion of societal risk is lacking. Major accidents have a significant negative impact outside the plant facility and hence including the negative societal impact is significantly important. It is widely accepted that the consideration of intangible (societal) risk is crucial to estimate the overall portfolio risks (HSE, 1989).

However, much research is needed to capture and quantify societal risks, b) The risk representation in terms of entire distribution is lacking, c) The economic loss estimation to obtain the maximum possible losses for worst case scenarios is also lacking. The knowledge of the entire damage-loss distribution in monetary terms, such that it pertains to all scenarios, to obtain valuable insight for better understanding of risks and decision making is also required. Furthermore, at present decisions made after performing the risk analysis are highly subjective. Decisions made based on incomplete understanding could result in major catastrophes as seen from historical incidents in process industry.

Therefore, the focus of this work is to address the four fold problems depicted in Fig 1. Firstly, it is difficult to predict scenarios for complex portfolios because proper risk assessment had to be done to consider all credible scenarios for mitigation of risk. Once the risks of the potential incidents are quantified, the challenging task of correctly understanding the stakes at risk by choosing the safest alternative still remains. Secondly, there is no systematic method to monetize and represent all risks. Hence there is a need for the systematic inclusion of potential negative impact of the tangible and intangible (societal) risks of a portfolio. Thirdly, there is a need for a quantitative risk assessment based tool to help understand the stakes at risk with a combination of both leading indicators and lagging indicators. Fourthly, there is a need for a framework to help decision makers make better risk-informed decision making.

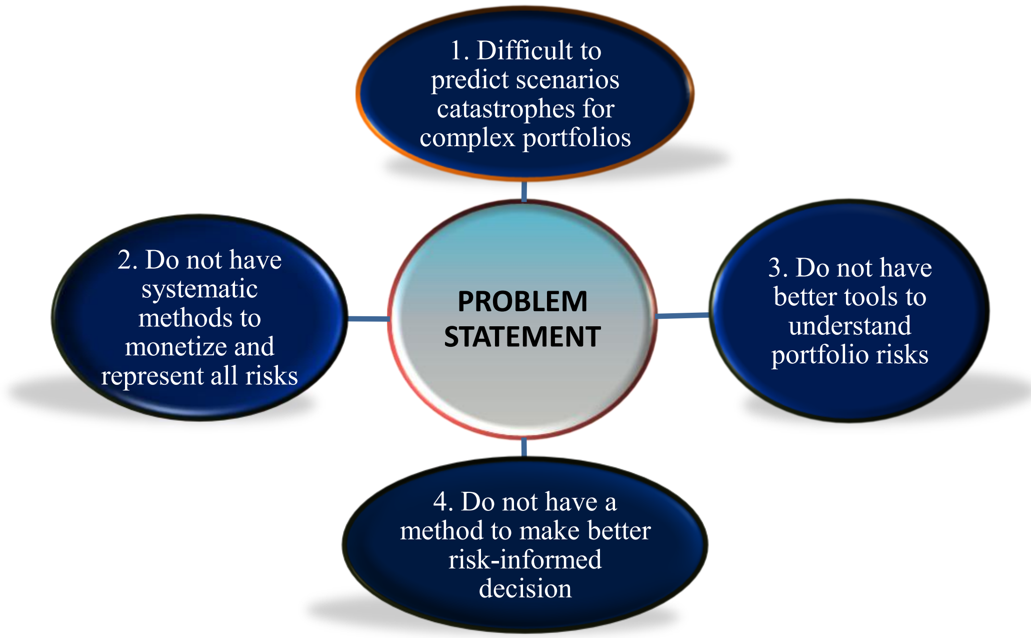


Figure 1. Research problems for establishing research objectives

If the research problems stated in this section are addressed, it will greatly benefit the chemical process industry management and regulators in estimating risks of complex chemical processes, obtain the stakes at risk in monetary terms, represent the risks in understandable manner while including both tangible and intangible risks for improving process safety and preventing major industry catastrophes. Such methodology will prove to be a powerful tool in the process industry where none exists today. Section 2 will provide the background information of all the different concepts utilized in this research.

2. BACKGROUND AND PREVIOUS WORK

In order to address the problems stated in Section 1, concepts from different fields of study have been compiled to develop the proposed research methodology. Previously, limited work exists in this area of study. This section, therefore, focuses on introducing all concepts with previous work for outlining the gaps in previous research and in making a business case for process safety.

2.1. Quantitative Risk Analysis (QRA)

The most important step in understanding the stakes at risks for potential incidents of portfolio is performing the QRA. Fig. 2 shows the different aspects that constitute QRA in chemical process industry (CCPS, 2000; Crowl & Louvar, 2002).

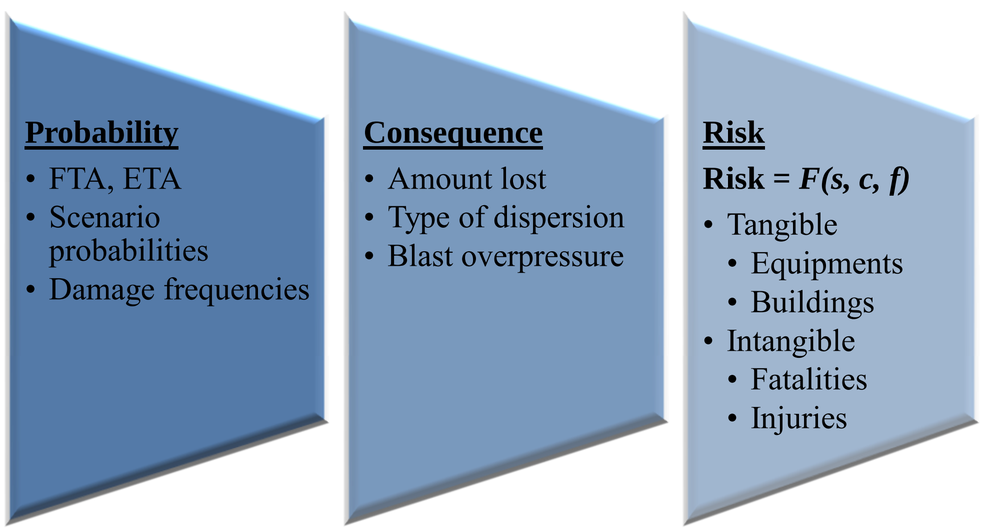


Figure 2. Steps for estimating total portfolio risk

In the chemical industry, the task of managing risks is challenging and one must know about all the risks involved. Quantitative risk assessment has been established as one of the effective methodology for studying risks in the process industry (Stallen, Greets and Vrijling, 1996; Pasman, 2003; Wang.Y, 2005). Much emphasis has been placed on the accurate quantification of the risks in chemical process industry. QRA gives the measure of risk in terms of the probability of occurrence of an undesired event along with its potential consequences in terms of fatalities, injuries and property losses (AIChE/CCPS, 1994; AIChE/CCPS, 1996; AIChE/CCPS, 1999). Quantitative risk analysis originated in the nuclear industry and is now also widely used in the electronics industry, aviation industry, civil engineering, chemical process industry and more recently in biotechnology. QRA is an effective method to quantify the portfolio risks (AIChE/CCPS, 2000; Pasman *et al.*, 2009; Prem, Ng, Sawyer *et al.*, 2010).

In the world of complex chemical processing, the application of quantitative risk assessment methods to identify the potential accidents and their consequences is exemplified as a suitable means for studying the risks. This is because both the hazards and their consequences are quantified in a QRA study. In the chemical industry, quantitative risk assessments consider primarily the damages incurred by explosion, fire and toxic dispersion. Equation 1 provides the general form of process risk from quantitative risk assessment method as a function of scenario(s), consequence (c) and frequency (f).

$$\text{Risk} = F(s, c, f) \tag{1}$$

QRA follows after a preliminary qualitative or semi-qualitative process hazard analysis (PHA) step such as the HAZOP, What-If analysis or Bow-Tie analysis. The probabilities of occurrences of the deduced credible scenarios are determined next using methodologies such as the fault tree analysis (FTA) and the event tree analysis (ETA) (AIChE/CCPS,2000; Crowl & Louvar, 2002). Evaluating the scenario frequencies of credible scenarios using FTA will also enable determining the minimum cutsets which are the sequence of events that would have to fail in order to lead to the potential incident. The top event occurrence probability or frequency of potential incidents for each section of the plant can be calculated. In the chemical process industry, the failure of series of equipment and human error are leading causes for process industry incidents (Mannan, 2005). Hence, equipment reliability information such as the failure rate date, the mean time to failure, the mean time to repair and mean time to testing, are utilized in order to calculate the top event frequency of potential incidents in the FTA method. Probability estimation for potential incidents using ETA is generally based on historical information, reliability information and expert opinion. Consequences are estimated using source and consequence modeling (Wilson, 1995; AIChE/CCPS, 1999; Crowl & Louvar, 2002; Mannan, 2005).

The basic thermodynamic, reaction kinetics and transport phenomenon are utilized to model the type of release of chemicals or loss of containment in case of incidents. The amount of chemical released and the characteristics of the release can be estimated using source models. From source and consequence models developed for different physical phenomenon of releases, values such as the amount of liquid lost during release, the type of dispersion, the overpressures generated in case of explosions, the heat radiation in case of fires and, the type of structural damage and harm to people can be estimated. Based on overpressures generated and the heat radiation impingement, probit models (Crowl & Louvar, 2002) can be utilized to estimate structural damage to equipment within plant and structural damage outside plant facility. In addition, the type of societal damage such as lung damage, injuries and number of fatalities can also be estimated based on overpressure calculations using probit models (Crowl & Louvar, 2002).

Utilizing the principles of QRA helps identify all the possible scenarios that could lead to potential incidents along with their consequences. Therefore, the results of a QRA study are utilized by the company management to make business decisions during installation of new facilities, for land use planning and for the implementation of suitable safety measures for risk mitigation. Regulatory bodies also utilize the results of QRA to establish new regulations in the process industry (HSE RR703, 2009). Nevertheless, QRA has limitations in that there is a vast number of data generated as results from the assessment which must all be adequately analyzed. Properly understanding the stakes at risk following the QRA study could serve as leading indicators for safety related decisions to avoid major accidents.

Khan, Sadiq and Husain (2002) consider process operations to be the most hazardous activity after transportation and drilling operations in an offshore oil and gas facility. Khan, Sadiq and Husain state that oil and gas platform operational eventualities can be avoided by incorporating proper control measures in the early design stages. The authors describe a methodology or risk based process safety decision making for various process units such as separators and compressors.

The authors mention that any offshore facility is never fully safe because of the innumerable risks associated with it but safety can be heightened by optimum design configuration during the installation process. The aim is to reduce the risk to a level which is as low as reasonably practicable (ALARP) while also not going over the budget. In order to effectively find a middle optimum ground to address this problem of cost and benefit, there is a need for QRA. The authors recommend the use of QRA techniques early on in the project life cycle ideally because at this stage it is possible to have better engineering judgment to identify the major risks and “loss prevention expenditure” can be “targeted in areas where there is little benefit.” This will prevent expensive remedial measures from being taken in the later life cycle of the oil and gas platform and its operation. Khan et al., also utilize quantitative risk assessment methods for the safety design measures based on a feedback system of using fault tree for credible accidents.

Hasle, Kjelle`n and Haugerud (2008) indicate that the Norwegian offshore facilities have the most experience and know-how in preventing accidents through the design and implementation of good QRA methodologies. Hasle *et al.* study the principles used by the industry at different phases of design in two ways, namely, the human centered and the energy barrier perspectives. The human centered perspective focuses on the design of work place environment to enable the operators to function at an optimal level by minimizing the human errors and mitigating disturbances *i.e.*, safety is chief aspect of initial integral design. The human aspect for operational safety is a more demanding task and harder to demonstrate. However, it is being increasingly used while considering offshore oil and gas operation in the offshore industry, *i.e.*, safety is included as an add-on characteristic but not in combination for decision making.

This work addresses the process industry incidents with major loss potential. General health and well being of the workers are also considered. At each level safety aspects are reviewed to reduce the uncertainty due to feasibility of selected solutions to meet the basic regulatory and company specific requirements. Based on QRA studies, regulators and company management utilize risk curves which provide information about societal consequences.

2.1.1. Risk curves

In the Netherlands, the societal risk (SR) criteria is based on the probability of death caused by accidents for individuals and for the whole exposed population (Roodbol, 1998). Some useful definitions put forth by the authors are:

a) Individual risk (IR): Probability (frequency/year) that any one member of the general public, present 24 hrs per day and unprotected at a certain distance from the industrial activity, will be killed as a result of an accident at that activity.

b) Societal risk (SR): SR is defined as the relationship between the number of people killed in a single accident and the probability that this number will be exceeded.

Societal risk and the concept of risk aversion by Vrijling and van Gelder (1989) presents *FN*-curve as an accepted and fairly accurate description of the societal risk in order to communicate societal risk with the public and the decision makers. Vriling and van Gelder (1989) also agree that "risk should at least be judged from two points of view", the individual level and the societal level, both of which can be clearly seen from *FN*-curves.

2.1.2. *FN*-curves

A complete portfolio risk assessment will result in large number of frequencies and consequence information which must be represented in a systematic and relatively easy to understand manner (Stallen, Geerts and Vrijling, 1996). *FN*-curves are important types of farmer's curves or risk curves used for land use planning and licensing (Modarres, 2004; HSE, 1989). Generally, from the risk curves, it can be understood that the impact to the society (societal risk aversion) by a disaster increases sharply with the increase in the total number of victims. Societal or group risk, provides a measure for this disruption.

Performing QRA provides values for potential societal risks in terms of the number of fatalities (N) following an accident and the frequency of its occurrence (f) or cumulative frequencies (F). A suitable representation of societal risk is *FN*-curves (Evans and Verlander, 1997). Hirst (1998) has referred to *FN*-curves and f-N curves as important concepts for the assessment of risks to populations from hazardous installations. The frequency of accidents causing exactly N fatalities is $f(N)$. Hence, f-N curve is the plot of individual incident frequency $f(N)$ versus its respective consequence exacting N. *FN*-curves are cumulative distribution curves which are plotted with the values of the cumulative frequencies, F versus N or more fatalities (HSE, 2003). *FN*-

curves could be terminated at some maximum value, N_{max} and the number of fatalities range from 1 to N_{max}. Cumulative frequencies can be calculated using the following equation 2.

$$F(N) = f(N) + f(N+1) + f(N+2) + \ldots \qquad (2)$$

where, $f(N) = 0$ for $N > N_{max}$

More often, the decisions made by management and regulators are highly subjective and risk-based rather than risk-informed. A clearer understanding of the tolerability criteria of companies in conjunction with the risk aversion of the society would also prove to be helpful in business decision making.

Graphical presentation of information about the frequency of fatal accidents in a system and the distribution of the numbers of fatalities in such accidents is called Frequency-Number curve or simply *FN*-curves (Evans, 2003). The frequency $F(N)$ of accidents with N or more fatalities is plotted in *FN*-curves. *FN*-graphs are usually drawn with logarithmic scales, as F and N sometimes range across several orders of magnitude.

Evans (2003) indicates that the frequency of accidents with exactly N fatalities, $f(N)$, from the $F(N)$'s can be achieved from the *FN*-curves. Similarly, it is possible to get $F(N)$'s from the $f(N)$'s by summing the $f(N)$'s upward from N. Thus, $F(N)$-curves can be formed from information on the $f(N)$'s. We can write $f(N)$ as follows (equation 3);

$$f(N) = F(1)p(N) \qquad (3)$$

where, $p(N)$ is the probability for an accident with exactly N fatalities.

One can use the $p(N)$'s and "calculate standard statistical quantities such as the mean and standard deviation of the number of fatalities per fatal accident". Hence, every

FN-curve can implicitly represents the "overall accident frequency *F*(1), the probability distribution of fatalities in accidents *p*(*N*), the mean and standard deviation of number of fatalities per accident, and the mean number of fatalities per year" (Evans, 2003).

Two general methods can be used for constructing *FN*-curves:

(i) Calculating the *FN*-curve directly from empirical frequency data on past accidents and,

(ii) Developing and using a probability model to estimate the frequencies

Glickman (1996) provides modeling considerations in the analysis of risk management strategies and comments on societal risk by stating that it can be measured in two ways. Firstly, by way of *FN*-curves, which expresses the relationship between exceedance frequency and fatality. Secondly, by way of E(N), the expected number of fatalities in the concerned time period. The two measures are related as E(N) is the area under the *FN*-curve. *FN* gives the distribution of random variables *N*, while E[*N*] gives the expected value or mean distribution of *N*.

The Health and Safety Executive (HSE) of UK and the Netherlands Organization for Applied Scientific Research (TNO), both heavily generate *FN*-curves, for assessing the probable societal group risks for licensing and land use planning in order to invoke suitable safety and emergency response measures (Health and Safety Executive, 1989; Carter, 1995; Natuurplanbureau, 2004). The frequency exceedance curves provide the measure of the negative societal impact caused by the incidents (Carter & Hirst, 2000; Evans & Verlander, 1997; Health and Safety Executive, 1989, 1991, 1992, 2003; Health and Safety Executive, 2003; Hirst, 1998; Prem, Ng, Sawyer *et al.*, 2010).

FN-curves are a “means of presenting descriptive information about the fatal accident frequencies and fatality distributions” (Evans & Verlander, 1997; Evans, 2003; Carter & Hirst, 2000). They are very similar to histograms and in fact represent the same information differently. With *FN*-curves we can invoke reasonable criteria by which to decide if the risks in the system are tolerable or not. The criteria are also known as ‘societal risk criteria’.

FN-curves are not used just as mere presentational devices but, also as a test for the tolerability of the risks. *FN* criterion lines have been used by various authors for about three decades and are an important concept or feature of the *FN*-curves. If the *FN*-curve of a system completely lies below the lower criterion line, the system is regarded as tolerable. If some part of the *FN*-curve crosses the intolerable criterion line, then that system is considered intolerable. In case of intolerability, we have to take safety measures in order to lower the *FN*-curve by adopting suitable risk reduction measures. The region in between the intolerable and tolerable line is the “as low as reasonably practicable” (ALARP) region which is the tolerable risk region. Clearly, the upper intolerable line is most important to be considered first for risk reduction purposes.

The concept of criterion lines for *FN*-curves has been reviewed for the HSE by Ball and Floyd (1998) in the paper entitled *Societal Risks*. The HSE has cautiously recommended the proper use of the *FN*-curve criterion lines as mere guidelines for enhancing safety. In another publication *Reducing risk, protecting people* (HSE, 2001, paragraph 136) the HSE recommends an “*FN*-criterion point, if not a line, for single major hazardous industrial sites”.

Since *FN*-curves represent the probability distribution of fatalities in accidents, judgments about the tolerability of *FN*-curves must be based on probability distributions. Lindley (1985) suggests that for achieving consistency in decision making using *FN*-curves, the form of the criterion quantity to base decisions upon should also be "statistically expected value" of some function.

Fig. 3, shows the different criterion lines initially used by the UK HSE based on railway incidents for channel tunnel safety in the UK (Eurotunnel, 1994). Two numbers are needed to specify the intolerable criterion line. They are the slope and the intercept. The slope of the line is related to the societal risk aversion to large accidents relative to small ones. Hence, a steeper line would indicate a greater societal risk aversion. The intercept of the line determines the total frequency of fatal accidents that is regarded as just tolerable for the portfolio being considered. The choice of both the slope and intercept of the criterion *FN* line depends on the type of portfolio being considered. In practice, the intercept is typically determined with reference to standards set by similar decisions elsewhere, eg. Canvey Lines were deduced from HSE's Canvey island report (Evans & Verlander, 1997).

FN-curve shown in Fig. 3 has two criterion lines: (i) *FN*-curve upper limit Intolerable line. HSE used a standard of drawing a slope of negative one at 0.1 frequency previously which is shown in the figure. Any curve crossing this upper limit would indicate very high consequences and risks. (ii)Negligible line showed no threat of fatalities due to risk. The region between the two lines is the as-low-as-reasonably-practical (ALARP) region, where the threat to life can be significantly reduced by adopting risk mitigation strategies.

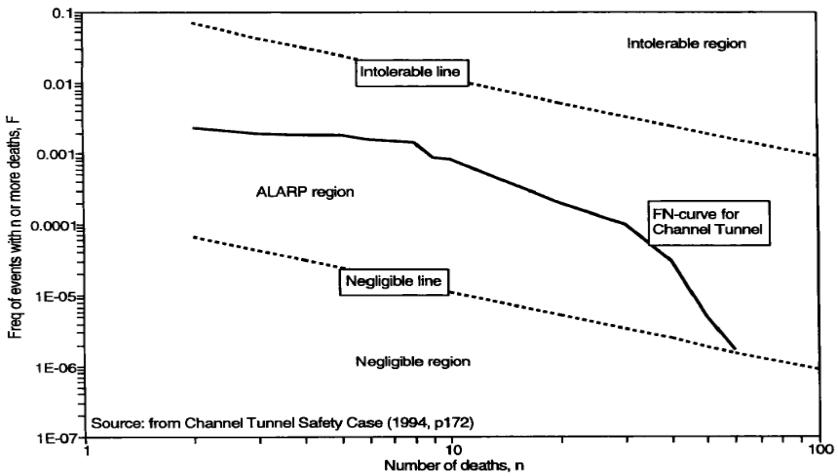


Figure 3. *FN*-curves for railway incidents in UK for channel tunnel safety case with criterion lines (source: HSE, 1994)

The criterion for decision making is different for different countries. The Dutch use more stringent criteria with a slope of -2. However, in cases where the companies which apply for licensing do not meet the set criteria, the decision making by regulators is based on qualitatively assessing the risks alongside the QRA performed and the emergency procedures in place for risk mitigation. There are no such criteria currently existing in the U.S. process industry. Understanding the risk tolerability of regulators/companies and risk aversion of the society could allow U.S. based processing companies to better manage their portfolio risks.

Fig. 4 adopted from Trobjevic provides the most recent criterion lines for risk intolerability based on QRA studies. THE UK-R2P2 has a criteria for intolerability published in the HSE document entitled 'Reducing Risks Protecting People' (HSE, 2001) set at 10^{-2} with a slope of -1. The old UK Land Use Planning (LUP) criteria matches the current Dutch criteria (old and new in Fig.4) set at 10^{-3} at a slope of -2. The new UK intolerable line adopted by UK-HSE based on its study of accident data for all facilities and for LUP is at 10^{-3} with a slope of -1.5. The Dutch criterion lines include only people working within the plant facility, whereas the UK-HSE criteria includes both people working inside and people residing outside the confines of the plant layout. The Czech and the French criteria are more relaxed in comparison to both the UK-HSE and the Dutch criterion line of intolerability for societal risks used for decision making.

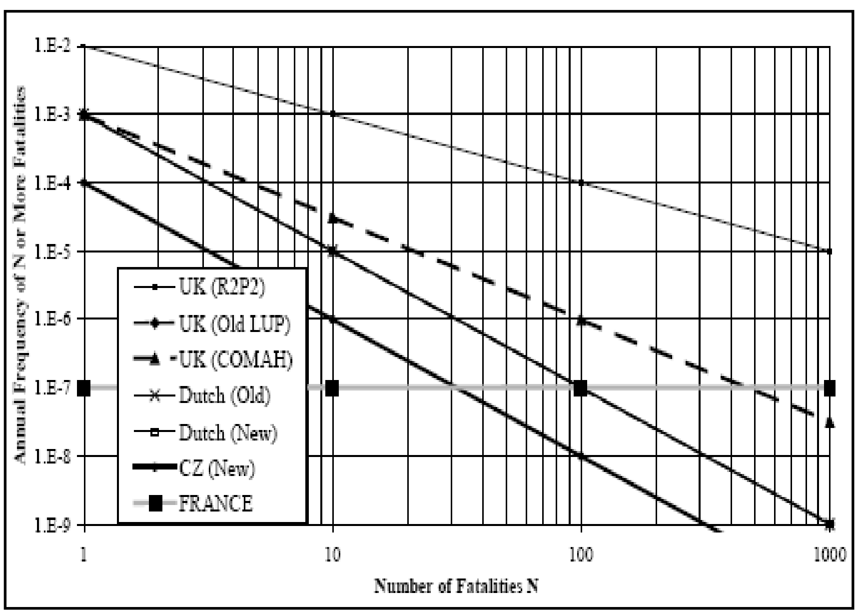


Figure 4. Comparison of *FN*-curves criterion lines (Source: Trobjevic)

The criterion lines for intolerability for both societal risks and individual risks are provided in Table 1 along with their specific risk aversion factors. The risk aversion factors are used as guidelines for LUP and licensing and hence are not absolute estimates of acceptability of societal risks in itself. Hence, this information must be considered along with other risk metrics to understand the stakes at risk.

Table 1. Comparison of *FN*-curve criterion line, individual risk and risk aversion factor (Adopted from Trobjevic, U.K.)

Criterion	***FN*-Criterion Line**	**Aversion Factor**	**Individual Risk**
UK (R2P2)	1.00E-02	1	1.00E-05
UK-Old	1.00E-03	2	1.00E-05
UK-New	1.00E-03	1.5	3.00E-06
Dutch-Old	1.00E-03	2	1.00E-05
Dutch-New	1.00E-03	2	1.00E-06

FN-curves are valuable tools that outline certain tolerability of risks as satisfactory or unsatisfactory. The criterion for tolerability is based on the perception of risk and the 'expected utility function'. Since, *FN*-curves represent a negative concept of potential fatalities resulting from incidents; the criterion of ‘expected utility function’ is also preferentially called the ‘expected disutility function’, ***D***. The classical decision theory renders itself towards consistent decision making for tolerability for *FN*-curves (Lindley, 1985).

The Health and Safety Executive (HSE) of UK has guidelines for land-use planning around hazardous installations (Health and Safety Executive, 1989) and has developed the concept of 'Risk Integral' as an important technical development (Carter and Hirst, 2000). The term "Risk Integral" is an expected disutility function for multiple fatality accidents. Several factors can be estimated from *FN*-curves which are briefly stated below.

FN-curves also have weighted risk indicator' factors applied to depict the nature of societal aversion by placing a greater emphasis on multiple fatalities. The weighted risk indicator factor is also called the 'aversion multiplier'. Greater the aversion multiplier implies that greater will be the number of expected fatalities. HSE provides the following relationship shown in equation 4 to account for societal aversion (Hirst, 1998).

$$\sum F(N) \cdot N = \sum F(N) \cdot N \cdot \left[\frac{(N+1)^a}{(N+1)^a - (N)^a}\right] \tag{4}$$

where, N = number of fatalities

$F(N)$ = frequency of occurrence of N

a = slope of FN-curve criterion lines

Different societal risk aversion factors result from the value of a, the slope of *FN*-curve which defines the various criterion lines for the curve. Schofield (1993), suggests the use of aversion multipliers $N^{0.5}$ and N to provide alternate ENFY risk aversion factors as shown below,

$$\Sigma f(N) \cdot N^{1.5} \text{ and } \Sigma f(N) \cdot N^2$$

Okrent et al., (1981) suggests the expected number of fatalities from *FN*-curves has the societal risk aversion factor of 1.2 (Hirst, 1998).

$$\Sigma f(N) \cdot N^{1.2}$$

Evans and Verlander (1997) provide the insight into judging *FN*-curves to assess the tolerability of so-called societal risk**.** The authors state that the current practical approach is based on the position of the *FN*-curves representing the risks from hazardous systems in relation to criterion lines. After estimating risks the authors suggest that judgments of decision makers must be based on societal risks. The authors call this process as risk appraisal or risk evaluation**.** Decisions cannot be made based solely on *FN*-curves and criterion lines. Hence, in addition to *FN*-curves, quantified risk values are also needed for decision making. For the life cycle of a plant, the decisions are essentially made based on some form of cost-benefit analysis would translate to net cash flow or net present value. Therefore, while risk curves are important risk information for determining leading indicators for incidents, the risk values must be represented in monetary terms.

Stallen, Geerts and Vrijling (1996) in their paper ‘three conceptions of quantified societal risk’ indicate that fatality is the only indicating factor of adverse consequence in risk management. The authors mention that time and space is ignored in assessing societal risk (SR) but is an important aspect which needs to be included in the SR estimation. With their inclusion SR will favor risk averse rather than a risk prone behavior. The SR assessments should imply judgments about the distribution of safety and other costs. The authors conclude that in order to make safety investments for the sake of lowering SR, a systematic and conditional representation of the SR is very essential.

Merz and Bohnenblust (1993) apply the methodology of marginal cost criterion and support the cost-effectiveness cost approach to reduce SR. They advocate that the SR should be decreased to the point of the least marginal cost. SR is defined as the "weighted sum of the probability p times consequence C" for different negative consequences as shown in equation 5.

$$SR = \Sigma(p_{Ni})* C_{Ni}*Q_{Ni} \qquad (5)$$

where, Q_{Ni} is the risk aversion factor for the consequence Ni.

Jorissen (2004) in his work, 'flood protection, safety standards and societal risk', judges SR at a national level based on flood statistics for Netherlands using *FN*-curves. The number of fatalities on a national level scale can be described as a probability density function (pdf). The pdf can be derived from available data or models. From the pdf a characteristic risk is obtained which is the SR. SR can be expressed as the "number of fatalities which during a year will not be exceeded with a certain probability" and is shown in equation 6.

$$SR = E(N_{di}) + k.\ \sigma(N_{di}) \qquad (6)$$

where, $E(N_{di})$ is the expectation of the number of fatalities for activity i

$\sigma(N_{di})$ is the standard deviation of the number of fatalities for activity i

k is the risk aversion factor for large accidents which can be calibrated to affect the probability of exceedance.

2.1.3. *F$*-curves

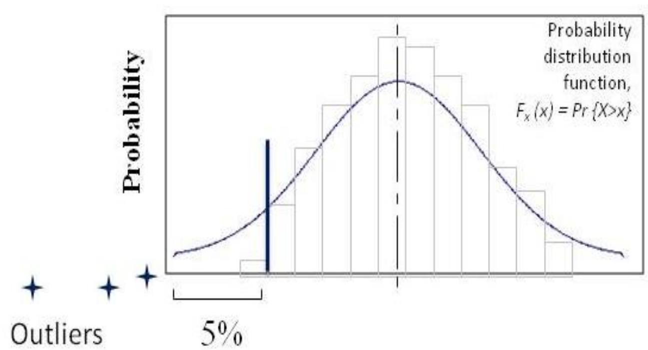
Besides estimating the harm to people, monetizing the damages will also be important for decision making to judge business prospects. Therefore, the effects of resulting potential monetary losses should also be graphically represented. This can be realized by constructing curves of cumulative frequency vs. monetary damage which is designated as *F$*-curves and are generated similar to *FN*-curve. Subsequently, performing this calculation will provide the cumulative frequencies for the entire set of scenarios which can be graphed against the accrued monetary loss. In addition to these risk curves, the risk values themselves should be monetized. For this purpose, the concepts of Value-at-Risk are utilized for tangible asset monetization in this work.

2.2. Value-at-Risk *(VaR)*

Value-at-Risk is a type of risk metrics to predict the market value of a portfolio. This concept is widely used by banks, security firms, energy merchants and other trading organizations. It is the "maximum amount of risk to be lost from any investment". Historic volatility and risk metrics are utilized by these organizations to track portfolio market risks. However, as *VaR* is a general concept, it can be implemented to assess the risks in the various chemical processes to predict future losses in monetary terms (Fang et al., 2004; Prem, Ng, Sawyer *et al.*, 2010).

Value-at-Risk is based on probability distribution for a portfolio's market value. Probability distribution helps characterize assets that have uncertain market values. Generally, some kind of weighting index is utilized in the financial industry. In the financial industry, *VaR* is extensively utilized to measure financial risks in the financial markets (Benning & Wiener, 1998). Markowitz first mathematically defined the concept of "risk" in financial industry as the variance on return of investment that should be minimized in order to maximize the portfolio return (Kondapaneni, 2005).

VaR can be defined as the expected portfolio loss at some confidence level - usually 5% loss or 95% gain (Butler, 1999; Jorion, 2007). In other words, *VaR* gives the difference between the profit value and its mean at a confidence level and a time horizon (Duffie & Pan, 1997). *VaR* measure provides the maximum expected loss due to an undesired event which helps represent the monetary risk to investors and management. Fig. 5 schematizes the maximum expected portfolio loss with confidence limit of 5% (outliers) for *VaR* measure. Hence, *VaR* is most suitable for extreme value risk analysis loss estimations. For estimating the *VaR* measure, the basic theme is to map the portfolio risks (R) to the probability of expected losses (P) by way of some mapping function (θ).



$$1 - F_L(x_{p*}) = P(L > x_{p*}) = p^* \text{ with } p^* = 0.05$$

Figure 5. Maximum expected portfolio loss with confidence level for *VaR* measure

In *VaR*, the returns will determine the value of the portfolio over time. If the value comes below a certain target threshold above the original investment value, it is considered a loss. *VaR* can be defined as the expected portfolio loss at some confidence level (Jorion, 2007) over a certain time horizon. The *VaR* for 99% confidence of loss (1% chance of loss to the company) is given by the following equation 7.

$$1 - F_L(x_{p^*}) = P\left(L > x_{p^*}\right) = p^* \text{ with } p^* = 0.01 \qquad (7)$$

x_{p^*} = target probability for 99% confidence

L = maximum expected loss for m asset values of portfolio

p^* = 1% loss probability

VaR is based on the concept of expected value in traditional statistics. If the investment on asset *n* is some value h_i and the return on this investment is the random variable R_i, then the weighted average of each expected return $E\,[R_i]$ is the total expected return on the portfolio, R_p as shown in equation 8 (Kondapaneni, 2005).

$$E[R_p] = \sum_{i=1}^{n} h_i E[R_i] \qquad (8)$$

Christopherson and Diebold (2000) & Berkowitz (2001) argue in order for *VaR* measure to be a coherent risk measure one should account for the kurtosis and fat-tails in the probability distribution function (pdf) and not just *VaR* as a single number itself. In that sense, the expected shortfall also known as C-*VaR* is defined as in equation 9.

$$ES_{t+k}(\alpha) = E[r_{t+k} | r_{t+k} \le VaR_{t+k}\,(\alpha) \qquad (9)$$

Markowitz (1957) provided the original approaches for portfolio risk is mean-variance analysis as shown in equation 10. If we have three assets with returns r_x, r_y and

r_z and we give them weights w_x, w_y and w_z such that the sum of weights is 1. The portfolio mean return is

$$r_p = w_x r_x + w_y r_y + w_z r_z \tag{10}$$

Bradley and Taqqu (2002) assume that the expected return is zero, then the *VaR* volatility equation for portfolio is as shown in equation 11.

$$VaR_p\,(\alpha) = \sigma_p F_p^{-1}\,(\alpha) \tag{11}$$

The portfolio volatility equation with Markowitz equation gives the portfolio *VaR* for specified consequence as shown in equation 12.

$$VaR_p\,(\alpha) = \{[F_p^{-1}\,(\alpha)]$$

$$\sqrt{w_x^2\sigma_x^2 + w_y^2\sigma_y^2 + w_z^2\sigma_z^2 + 2w_x w_y \sigma_{x,y} + 2w_x w_z \sigma_{x,z} + 2w_y w_z \sigma_{y,z}}\,\} \tag{12}$$

Kondapaneni (2005) explains *VaR* using the Delta–normal method assuming the portfolio is normally distributed for agricultural economic setting. Therefore, the returns are estimated to be normally distributed for application in agricultural studies. If the portfolio current value is p and the various risks which represent the present asset value is the vector R then Kondapaneni suggests that there needs to be a method to transform the R to some P. In his work the transformation has standard normal distribution. Therefore, theta is the mapping function that transforms the R into P as shown in equation 13. *VaR* for such a portfolio using the delta-normal method requires the evaluation of the mean and standard deviation for the P.

$$P = \theta(R) \tag{13}$$

The advantage of utilizing *VaR* in chemical industry is its ability to provide at a certain confidence level, the worst possible expected loss for potential deviating scenarios of a 'portfolio' of risks (representing an installation, a plant or a site). If the maximum loss due to potential accidents is determined for a portfolio then, we can maximize the portfolio return and also improve plant safety. The returns will determine the value of the portfolio over time. If the value comes below a certain target threshold above the original investment value it is considered a loss.

The advantage of utilizing *VaR* in chemical industry is its ability to provide at a certain confidence level, the worst possible expected loss for a large pool of potential deviating scenarios of a 'portfolio' of risks (representing an installation, a plant or a site). Based on the *VaR* value, management can make risk reduction decisions or choose between competing portfolio options.

The widespread adoption of *VaR* in the financial industry has been accompanied by criticism of *VaR* as a measure of risk. Summarizing a distribution in a single probability number at a loss threshold without due regard to what extent losses above the threshold can accumulate (the *pdf* goes asymptotically to infinite loss) is a weakness of *VaR*. In the chemical industry the value of the assets are not subject to such uncertainties.

Getting a model is more important step and *VaR* metric simply results based on that characterization. In other words, any *VaR* measure can support any *VaR* metric and *VaR* measure can be discussed disregarding a specific *VaR* metric it supports. In financial industry, some function θ is the mapping function which maps the entire vector space or n-dimension of risk key factors to a 1-D space of the portfolio market value. *i.e.*, given an R, we can get P.

So generally speaking there are two pieces to the puzzle to obtain *VaR* measurement.

(i) First is the key factor R identification. The R are observable factors such as financial variability, historical data etc, which will enable us to judge the type of joint distribution to use. We can then convert R to P.

(ii) The second puzzle piece is the mapping function that relates the P and R. Overtime, this formula can even change to reflect any changes made to the portfolio.

Both the puzzle pieces however, cannot by themselves give the information of how risky the portfolio is. Only combining the two pieces will give us an estimate of the worst possible loss. Fig.6 schematizes the transformation of portfolio risk to probability of potential incidents using mapping function, θ.

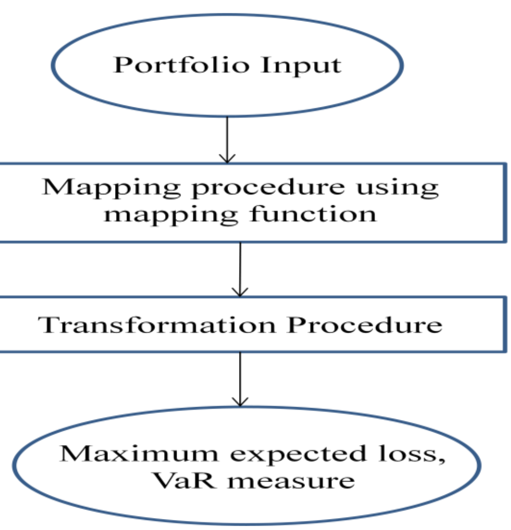


Figure 6. Schematic showing transformation of risk to probability of potential incidents using mapping function, θ

Risk is defined as the combination of the probability or frequency of occurrence of an event along with its magnitude of damage or consequence. For *VaR* purposes we will define the probability/frequency as the uncertainty and the magnitude of damage/consequence as the exposure as shown in equation 14.

$$VaR = \text{exposure x uncertainty} \tag{14}$$

Advantages of using *VaR*,

(i) Measure of worst loss of portfolio over time horizon at some confidence level

(ii) Bridge the gap engineers and scientists who calculate process risk and, the business leaders and policy makers who evaluate, manage, or regulate risk in a broader context (Fang et al, 2004)

(iii) Gives total cost-benefit analysis of entire portfolio via single probability distribution function (pdf) value

(iv) *VaR* for different time horizon calculations is possible

(v) Includes sensitivity analysis for reliable risk estimation

(vi) Gives a thorough risk and investment management analysis

The concept of risk analysis using QRA and *VaR* is fairly new. The method adopted by Fang et.al, is promising yet has several drawbacks: 1) Fang does not perform a CPQRA for an entire portfolio before *VaR* is calculated. Consideration of the CPQRA for a complete portfolio is essential for *VaR* because it gives the absolute expected damage for all scenarios. 2) *VaR* is calculated monetarily only in terms of the consequences for tangible assets. *VaR* should include both the frequency of occurrence and the consequences of accidents to avoid risk under-representation, 3) although extremely important, societal risk estimations are not considered. 4) the point estimates of *VaR* are considered as opposed to the entire distribution. Considering scenario risk distributions would help overcome uncertainties in *VaR* prediction.

Bagajewicz and Aseeri (2004) also utilize *VaR* concepts but, do so only to minimize the cost factor in solving problems of chemical plant design and optimization at its inception stage. For example, optimum profits in refineries are calculated using *VaR* by estimating crude oil market price fluctuations. Energy traders on financial exchanges also use *VaR* in this fashion for hedging risks.

For business decision purposes, the expression of losses in monetary units becomes important. Schupp et al., (2002) show the importance of economic analysis for a layers of protection analysis study. The risks estimated probabilistically in monetary units will provide the value of the risks as benefits or losses. *VaR* and QRA as a combined tool was first stated as the bridge between engineers who quantify the risks and the management who make business decisions based on the estimated risks by Fang, Ford and Mannan (2004). However, the approach of Fang et. al., is limited in scope because their study is not inclusive of the societal risk. Further their study does not consider the *VaR* value in combination with QRA. *VaR* is only calculated on the basis of consequences hence it does not provide the losses based on risk analysis. The study does not provide all the information for decision making. We address these issues in this paper by combining QRA with *VaR* so as to obtain losses based on fully quantified risk analysis.

The advantage of using *VaR* is its generality but, this also poses a challenge. The challenging task in this research is to find a way to determine the suitable probability distribution of a portfolio's market value by way of mapping it to QRA. Needless to say that if there are complexities involved in a portfolio assessment, then it is exposed to a greater source of market risk. However, in this work, QRA based *VaR* has risk consequences calculated from scientific models for most accurate loss of containment, fire and explosion scenarios. Therefore, relying on QRA as a precursor to *VaR* estimation will eliminate much of the uncertainty in estimated potential incident losses. Once *VaR* measure is obtained the lagging indicator information will be complete. Historical information should also be used to understand the trends of chemical process industry incidents in order to help prevent future incidents and catastrophes.

2.3. Incident Database Analysis

It is said that history repeats itself. However, in the chemical process industry, history repeating itself would be more damaging to the industry not only in terms of the financial losses but also in terms of the major regulatory restrictions, societal losses, and irreversible environmental damage (Khan & Abbasi, 1999). The Bhopal disaster (1984) is a classic example of the negative impact of a chemical incident (Bowonder, 1987). This single incident has brought about substantial regulatory changes throughout the US and worldwide (Willey et al., 2006). While no other incident can come close to the devastation racked by the Bhopal incident, there are other catastrophes which were major disasters such as the Texas City Incident (1947) (Blocker & Blocker, 1949), the Flixborough incident (1974) (Venart, 2004), the Phillips explosion (1989) (Lepkowski,

1989) and more recently the BP Texas City incident (2005) (Hopkins, 2010; Khan & Amyotte, 2007). Due to the nature of such incidents being rare events, there is only a limited amount of historical data available to understand them. Rare events generally have higher probability for causing damage on a catastrophic level. Therefore, retrospective consequence information harnessed from reported accident databases would lend itself valuable for monitoring process safety performance, for accident investigation and, also for applying suitable hazard analysis techniques and safety measures to prevent similar incident occurrences (Martilleni & Waddell, 2007). Database analysis would provide the required safety feedback or lagging indicator information for monitoring key performances in chemical manufacturing and petroleum refining facilities (Doval & Kovacs, 2009).

Accident databases typically require the reporting of accident details such as the type of chemicals released along with the quantity released, the cause of incident, the number of people fatally injured, the number of people hospitalized with serious injuries, the number of people sustaining minor injuries and the number of evacuation and/or shelter in place. The information can be used to summarize the types of incidents, the different initiation or causes for incidents, common chemical releases and the severity of their consequences. However, little effort has been made to harness the information contained in the databases to understand the frequency of the number of persons negatively affected, the accident consequence trends and the relationships between the consequences of industry incidents. Carter and Menckel (1990) stress the importance of accident investigation utilizing historical accident information in order to learn as much as possible from each accident to prevent future incidents. Harnessing the accident databases, which have a wealth of information, help in better understanding the large number of incidents, their consequence losses and causes for the incidents. Such incident and loss causation models provide statistically significant information depicting the industry incident profiles, which could greatly improve the safety systems and risk mitigation measures adopted to prevent future incidents (Bird & Germain, 1992; Storbakken, 2002). Database analyses results could also guide in making more efficient regulatory policies (Ferry, 1988).

One of the effective methods for studying the effects of incidents is the incorporation of societal losses (Stallen, Geerts & Vrijling, 1996). For the sake of understanding the societal losses from historical incidents, the relationship between exceedance frequencies and consequences such as fatalities and injuries can be generated. The relationships are representations of the societal consequences and the distribution of the number of fatalities and injuries for reported incidents. In general, exceedance curves are used to represent catastrophic losses that give the probability (or frequency if year is taken into account) of occurrence of some random variable (fatalities, $, injuries) such that it does exceed some fixed $, fatality or injury number. They are cumulative distribution curves as they describe the probability (frequency) of occurrence of random variables.

While exceedance curves focus on high impact (high risk) consequences such as fatalities and injuries, there is a need to understand the low risk consequences such as near-misses to prevent the escalation of losses leading to high consequences such as injuries and deaths. Heinrich (1932) in his domino theory mentions that in order to identify the steps that lead to high risk consequences, the knowledge of low consequences is essential. Based on the domino theory, Heinrich also proposed his safety pyramid (Heinrich, 1940). He stated that high consequences could be eliminated or limited by working on preventing and reducing the lower accident consequences. He studied over 1 million facilities and recorded the accident consequence ratio of 1:29:300 for major injuries, minor injuries, and no-injury incidents. According to his study, generally large number of high-probability incidents with low consequences would eventually have the potential to result in few low-probability events or catastrophes with high consequences (Heinrich et al., 1980). Hence, generating similar safety pyramids from current accident databases would enable the understanding of the incident consequence ratios and their trends in the process industry.

Similar to the safety pyramid developed by Heinrich, Bird (1969), Tye and Pearson (1975), have also developed similar safety pyramids (Heinrich et al., 1980; Okabe & Ohtani, 2009). Foraher (1993) generated the safety pyramid to include all injuries to the personnel of a company along with contractors (Lievre & Foraher, 1995). The equipment damages were related to serious incidents only and the unsafe acts had no realistic figures available. Lievre & Foraher (1995) provide safety pyramids as part of a system for the early detection of safety management failures. The data on the worst safety performances for six oil rigs were analyzed and safety pyramid was generated. The proposed safety pyramid helped undertake proper safety measures which are reported to have improved safety performance of drilling rigs around the world and decreased the lost time accident frequency of the company by half. The Heinrich Pyramid (Heinrich et al., 1980) also shows that a progressive increase of near-misses and minor incidents would eventually lead to a major accident. Referring to the Heinrich Pyramid, Mannan et al., (2005) indicate that the underlying causal factors for any incident are generally the same irrespective of which tier of the pyramid the incident would fall under. In general, safety pyramid has been conducted internally in some individual companies such as Conoco Phillips (2003) to understand the suitable safety initiatives (Masimore, 2007). However, this benefit does not promote information sharing across the process industry in order to improve safety and decrease the frequency of the number of incidents.

As process incidents are low-probability events, management should track the "near-misses" or "low-consequence" events such as evacuations and shelter-in-place, to study the accident propensity in order to prevent serious accident consequences (Heinrich, 1932; Rosenthal, 2008). Lakin (2009) suggests that the base of the pyramid and bottom up approach for accident investigation is much needed to better understand the top of the pyramid and the significant incident risks. Hence, limiting incident propensities and prevention of serious incident consequences can be possible by understanding the relationship between the different consequences of incidents. Generally, incident information in the lower tiers of the pyramid are available more than the top tier of the pyramid. Therefore, statistical methods to assess the relationship between the different levels of the safety pyramid will be useful in understanding the proximity to an injury or fatality. For example, if the data monitored by a company indicates a certain number of shelter in-place and evacuation, the statistical correlation could be utilized to estimate the proximity of the process operation which could result in injuries and fatalities. Mannan et al., suggest that it is only a matter of chance that low severity consequences result from incidents which could otherwise, under suitable conditions, easily have resulted in more serious consequences (Mannan et al., 2005). The current work utilizes the Risk Management Program (RMP) (EPA, 2009) and the Hazardous Substance Emergency Events Surveillance (HSEES) databases to analyze the incidents and their consequences. Based on the data of RMP for the years 1994 to 2009, collected in three separate tranches of 5-year reporting in 1999, 2003 and 2009, and the information contained in the HSEES database from 1996 to 2004, the exceedance frequencies for societal losses, the safety pyramids and the regression analyses were generated to understand the trends and factors influencing chemical process industry incidents. The objective of this work is to provide lagging indicator information by analyzing information collected in the databases for understanding the eminent societal risks (losses), to layout the different consequences using safety pyramids and to provide the statistical relationships between different consequences to effectively understand the industry trends for improving process safety.

2.4. Decision Analysis

Once the risks are quantified, the decision makers are faced with the challenge of choosing the optimum risk reduction measures. Risk mitigation strategies are always achieved with a cost and most often than not, the decision is to be made between conflicting factors of safety and production. Eliminating risk completely is possible only with a very high cost because it is governed by the law of diminishing returns. Further, risk reduction measures applied at one area of a portfolio should also ensure that the risks are not transferred elsewhere. Cost benefit analysis (CBA) must be performed to assess the benefits to the cost of reducing risks or the cost of choosing one portfolio option over another.

Any chemical plant operation is robust only when a strategic balance is struck between optimal plant operations, CBA for installing new risk reduction measures or processes and, maintaining health, safety and environment. The balance emerges from choosing the best option amidst several conflicting parameters of operations vs. safety. Most often the lack of fully understanding the operational risks lead to subjective decision making in the hope of improving safety. Hence, strategies for normative decision making are needed for making choices under uncertainty. Decision theory and concepts of expected utility theory can be effectively utilized for enabling a rational decision maker to choose the most preferred risk. Here, additionally a framework for choosing the most preferred option to trade-off between the conflict of production and safety is conceptualized as a game for strategic interdependent decision making.

Making intelligent decisions towards safety is especially difficult because of the complex processes, instrumentation for functional safety and choosing safer alternatives for preventing incidents. Almost always a series of process events occur in a sequence to cause scenarios with major losses. Decision makers have the tremendous burden of accounting for all the probable issues amidst inherent uncertainties and make judgment calls which are most accurate and least subjective. Additionally, decision makers most often work with multiple objectives (Clemen & Reilly, 2001). Adding another dimension to the case of the decision maker's plight is the fact that different conclusions invariably could result from different perspectives (Clemen & Reilly, 2001). All these factors render decision making as an arduous task which must be assiduously solved with a set of workable techniques.

Establishing a workable framework utilizing the already existing techniques can provide better decisions for complex problems with the goal of achieving multiple objectives. In process industry, generally the objectives are to increase production, selectively increase yield, reduce cost of production, increase profit, protect plant assets and personnel safety. Studies in process safety have shown that increasing process safety directly impacts other avenues of operations in helping to achieve the desired objectives stated in Section 1.2 (Fig. 1). Decision analysis acknowledges that a decision maker's decision is not perfect but, at the very least can help layout the plan of the actual problems and thus enable better decision making (Clemen & Reilly, 2001). Decision maker is assumed to be a rational thinker who utilizes the structure and guidance provided by the decision theory to recommend alternatives that must be intelligently selected (Clemen &Reilly, 2001, VonNeumann & Morgenstern, 1947).

Owing to the attributes of complexity, uncertainty, multiple objectives and problems of different competing perspectives leading to different conclusions, decision theory serves as an excellent guide for making trade-offs to arrive at a preferred course of action. The preferred course of action is the direct indication of the choice made to adopt the least risky alternative or the most preferred risk alternative among several competing risk alternatives. The concept of “most preferred” or “best” options are based on preferences or values which are synonymous in decision analysis (Meszaros & Rapcsak, 1996).

Zhou, Ang and Po (2004) classify the different kinds of decision analysis methods as single objective decision making methods (SODM), multiple criteria decision making methods (MCDM) and decision support systems (DSS). SODM is a class of methods for evaluating all the single objective situation alternatives with uncertainties. A common SODM method are the decision tree (DT) and the influence diagram (ID). These two SODMs provide concise representation of the decision problems (Janssen, 2001). MCDM is multiple criteria based approach allowing decision makers to choose alternatives based on some system of ranking by evaluation of several defined criteria (Brans & Vincke, 1985; Brans, Vincke & Mareschal, 1986). Decisions are based on trade-offs or compromises among many different conflicting criteria (Colson & Bruyn, 1989; Zeleny, 1982). MCDM can be further classified as multiple objective decision making (MODM) and multiple attribute decision making (MADM) (Yoon & Hwang, 1995). MODM methods are multiple objective mathematical programming models with defined constraints where optimized or “best” choices among conflicting objectives are chosen (Hwang & Masud, 1979). Multiple attribute decision theory is based on preference decisions made by prioritizing the alternatives after the evaluation of multiple conflicting attributes. Multiple attribute utility theory (MAUT) or expected utility theory (EUT) allows referencing of multiple attribute utility functions (Fishburn, 1970; Roy and Vincke, 1981; Keeney & Raiffa, 1976).

Special cases of MAUT are multiple attribute value theory (MAVT) and expected monetary value theory or expected monetary value (EMVT or EMV). MAVT entails values placed on the consequences of the alternatives and EMVT entails only decisions made based on comparisons of monetary values of assets. Another well known decision making method is the analytical hierarchy process (AHP) consisting of structuring, measurement and synthesis, to aid in better decision making (Saaty, 1980; Saaty, 1990). Meszaros and Rapcsak (1996) introduce a DSS group to support solution of wide class of decision problems. This requires the sensitivity analyses of decision parameters with weights in utility function. Zhou, Ang and Poh (2006) list recent publications on decision analyses for energy and environmental modeling. The authors list multi attribute utility theory, decision support systems and single objective decision making. Pohekar and Ramachandran (2004) show the application of multi criteria decision making for sustainable energy. Chen, Kilgour and Hipel (2008) provide importance of multiple criteria decision analysis for decision makers and provide methods for screening in the presence of multiple criteria.

Expected utility theory is adopted here because of its versatility to enable the study of other factors such as risk acceptability and societal risk aversion to certain processes which cannot be directly measured but can be preferenced and ranked to arrive at the “most preferred” risk trade-off, in addition to estimating the expected monetary value losses because of risks and the trade-off between implementing risk reduction safety systems. Blaise Pascal and Daniel Bernoulli were the first to provide the basics of EUT as early as the eighteenth century (Duarte, 1999). After this, it was not until the twenty first century when Von Neumann and Morgenstern (1947) laid down the axioms of EUT that the modern multi attribute utility theory studies came into focus as an important field of study.

The normative axioms of expected utility theory as put forth by non Neumann and Morgenstern are as stated:

(i) Preference order axiom – the decision maker is able to compare and rank alternative pairs as preferred to or indifferent to which enables the ranking of alternatives

(ii) Continuity axiom – in case of several alternatives, say x, y and r, r is preferred to x and x is preferred to y, then there exists some real λ, $\lambda r + (1-\lambda)x \sim x$

(iii) Independence preference axiom – If there are three different alternatives x, y and r, then $x>y$ will provide a combination of $\lambda x + (1-\lambda)r$ as the preferred option

Game theory is a powerful concept which attempts to mathematically elicit the strategic behavioral strategies where the choices made for success is dependent on the other available choices (Dixit & Skeath, 2004; Osborne, 2004). Emile` Borel first developed the concepts of game theory in 1938 (May, 1970). Game theory was first used to study the competitions between one individual compared to others loss, a concept called zero sum game. In 1944, John von Neumann and Oskar Morgenstern developed the concepts of game theory further and paved the way for modern game theory to be studied by many other scholars who studied the theory to be applied to many different fields (vonNeumann & Morgenstern, 1953). Concepts from this theory has now successfully been studied and applied in the field of economics, political science, evolutionary biology (Smith, 1982), social sciences, philosophy, security (Cox, 2009), international relations, international security, computer science, flood prediction and earthquake predictions and transportation route models (Roumboutsos & Kapros, 2008). The designing of game theory strategies for decision making is deemed as being more advantageous in terms of being more accurate and enabling better prediction of loss or gain (Aumann & Shapley, 1974; Wright, 2002).

An application of game theory approach is shown by Roumboutsos and Kapros (2008) for optimizing the cost for urban public transportation. Nash equilibrium method is used to identify the outcomes of the markets and is compared to case studies. The model is said to be good guide to help public transportation policy decision makers to identify the most cost-effective solutions concerning transportation. Wright (2002) utilizes game theory concepts and suggests that individuals who are enmeshed in role-playing situations of conflict will benefit from their level of experience and prior learning in forecasting accurate outcomes of uncertain future. Angelou and Economides (2008) utilize game theory to achieve solutions for a multi-criteria broadband technology business model for an irreversible information and communications technology industry problem. Information and communications technology business is stated as the most expensive sector in the information technology industry, one which traditional cost benefit analysis cannot handle because of its complexity. The authors attempt the modeling based on competitive player interactions. The authors utilize a method which is a combination of analytic hierarchy process, real options and game theory principles to achieve an optimal solution.

Regardless of which field the concepts of this theory is being applied to, the common theme remains that it is essentially a study of strategic interactions for understanding the relationships between conflicts because of competition and cooperation and, is generally the study of wide array of strategic interactions, all essential for more confident and independent decision making. The different classes of interactions can be classified in to different criteria. The aim of this theory is to then arrive at an equilibrium or 'Pareto optimal' solution (Chen, Kilgour & Hipel, 2008). Named after Vilfred Pareto, Pareto optimality is a measure of efficiency of the outcome of a game, where there is no other outcome that makes every player at least as well off. Pareto optimal solutions are hence different from Nash equilibrium solutions. Many different strategies exist for achieving equilibrium solution of which the well known and widely utilized method was given by John Nash (1950) called Nash equilibrium.

CCPS book on guidelines for process safety metrics (AIChE/CCPS, 2009) provides instructions and examples for effective process safety management utilizing both leading and lagging metrics. Importance is stressed on factors such as the effectiveness of tracking and understanding performance indicators, collecting, evaluating and communicating process safety metrics as a guide to the company corporate management and site levels. The authors also encourage the "adoption of a set of consensus process safety metrics". However, there are no guidelines or framework on how to include both leading and lagging metrics together, especially one which is scientific risk analysis based. Hence, this work focuses on laying the ground works for developing risk measures constituting risk metrics for process safety, which is described in the following Section 3.

3. METHODOLOGY

The approach to solving the four-fold problems defined in Section 2 is to first predict all portfolio scenarios and risks which will help understand the different types of incident scenarios. Once risks are quantified using the source and consequence models, the next step is to monetize the portfolio risks by the inclusion of business interruptions based on the loss of turnover of tangible assets, estimating the maximum possible financial loss for each scenario. The estimated expected loss is then to be graphically represented to pictorially show all the losses. The last objective is the decision making process to understand the benefits vs. cost for different scenarios to enable better-risk informed decisions. Fig. 7 schematizes the different research objectives.

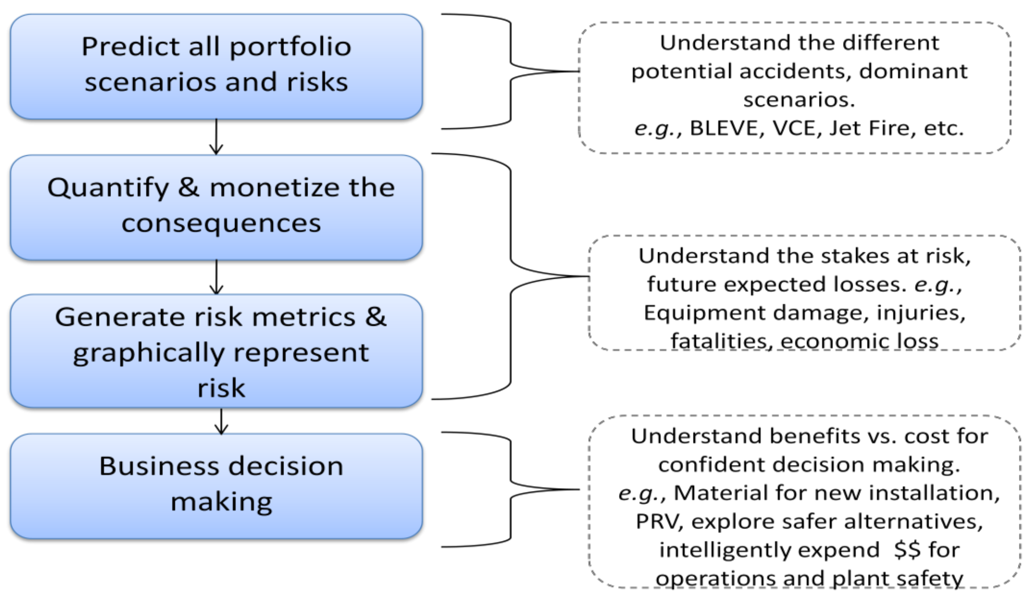


Figure 7. Schematic showing research objectives

Probabilistic methods are more cost-effective methods to analyze portfolio risks as they give results that are easier to communicate to decision makers. Therefore the proposed methodology will utilize the different concepts of probability theory to estimate the portfolio risks. The focus of this work is developing leading and lagging indicators by way of monetizing the asset loss and including societal consequences for potential accidents to make better business decisions. The proposed methodology utilizes the different concepts of probability theory to estimate the portfolio risks. Here a catastrophe is defined as the undesired event which results in one or more fatalities.

The proposed methodology for making the business case for process safety is as shown in Fig. 8 and includes the following steps:

(i) Risk estimation of a portfolio by Quantitative Risk Analysis (QRA)

(ii) The monetization of the tangible risks with the inclusion of the lost time of production

(ii) The estimation of the maximum portfolio loss using Value-at-Risk (*VaR*) approach (iv) The inclusion of intangible risks using tools such as *FN*-curves,

(v) Estimation of lagging metrics utilizing database analysis for estimating US chemical incident trends and,

(vi) The framework for choosing the most preferred option with decisions analysis concepts of expected utility theory (EUT) and game theory (GT)

The risks estimated in monetary terms can be expressed in a number of measures such as Value-at-Risk (*VaR)*, Expected Annual Loss (*EAL*) and Scenario Risk Spectrum

(*SRS*) with risk curves such as *FN*-curves and *F$*-curves, all together enabling better judgment and decision making.

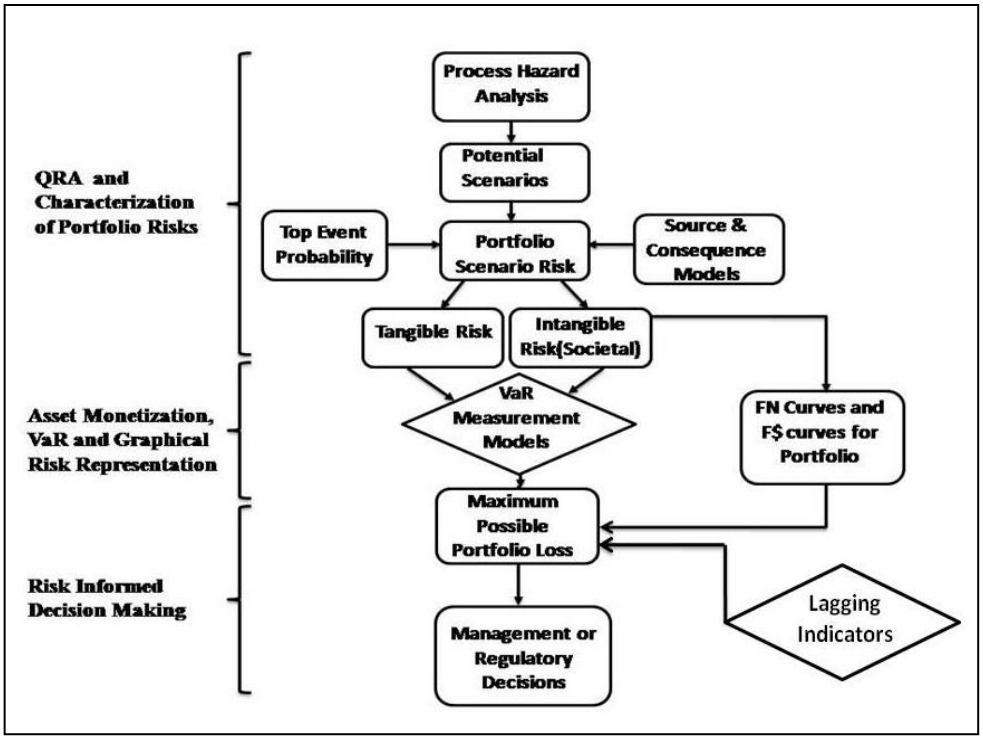


Figure 8. Research methodology for making business case in process industry

First step is the QRA study and characterization of the portfolio risks. Performing the process hazard analysis will provide information on all the potential deviating scenarios. The calculation of the event probabilities and the consequence estimation for each of the scenarios will provide the quantified results of QRA for all scenarios of a portfolio. The total portfolio risks are then classified as tangible risks and intangible risks (*i.e.*, societal risk). In our study, only societal risk pertaining to loss of life is considered to serve the purpose of studying extreme events. The tangible risks pertain to all process equipment repairs, lost production, business interruption, claims, environmental clean-up and other measurable asset value within the portfolio. If the portfolio risks leading to the potential damages are estimated early, then they would aid in better understanding the severity of the risks and enable risk-informed decision making in order to adopt proper risk reduction measures. Risk analysis of a plant provides the possible scenarios leading to hazardous material releases and in extreme cases fires and explosion, with many different consequences and frequencies. The probability density function of losses is found by summing all scenario frequencies and taking each scenario probability as the fraction of the total frequency. Interruption of the process operation has to be expressed in loss of turnover in view of fixed and variable costs and in a serious case in loss of market (Mannan, 2005). Once the portfolios risks are quantified and monetized, the next step in the methodology is the estimation of the possible Value-at-Risk.

VaR is calculated after all the assets of the plant are monetized. Damage to equipment, structures etc. can be expressed in repair and replacement costs. For the purpose of our study only tangible assets involved in the chemical processing within the plant are considered. Interruptions of the process operations are expressed in terms of the loss of turnover in view of fixed and variable costs of all assets of the chosen portfolio (Mannan, 2005).

In this study, the portfolio model chosen for the application of our methodology is schematized in Fig. 9. If we consider any chemical plant, it is generally surrounded either by several adjacent chemical plants or residential areas. If we assume that our plant includes residential areas (out-of-plant area) in its vicinity, then the consideration of the societal impact from potential accidents becomes inevitable.

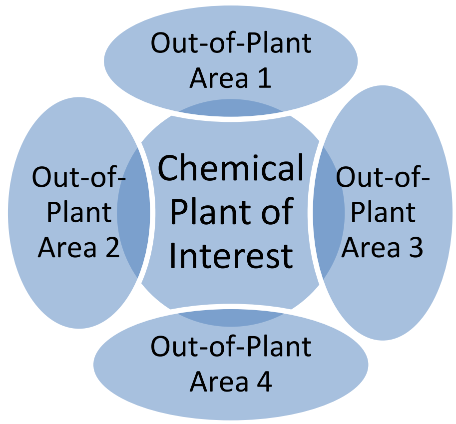


Figure 9. Portfolio model showing chemical plant surrounded by residential area in its vicinity

In the event of potential accidents, the loss of societal property such as buildings, hospitals, schools, also add to the total value lost outside the plant. The sum of the costs incurred due to potential loss of these assets would be the total societal cost as a measure of the societal risk. In this research, it is assumed that the risk of the possible loss of life far outweighs the risk of the loss of infrastructure in the residential areas for the purpose of decision making and hence those values are excluded.

Other than the portfolio model shown in Fig. 9, which is studied in this work, there could be another portfolio model shown in Fig. 10, which could also be used in the proposed methodology. Generally, a chemical plant is surrounded by many other chemical plants along its boundaries. In such cases, the entire portfolio could be considered as one large chemical plant. For the consideration of the out-of-plant area distance, to be included for QRA of the portfolio, it is noted that most high-impact incidents result in fatalities within a mile of the plant area (Kaszniak, Holmstrom and MacKenzie, 2007). Hence, an area of 1 mile radius from the portfolio of interest is considered for societal risk estimation.

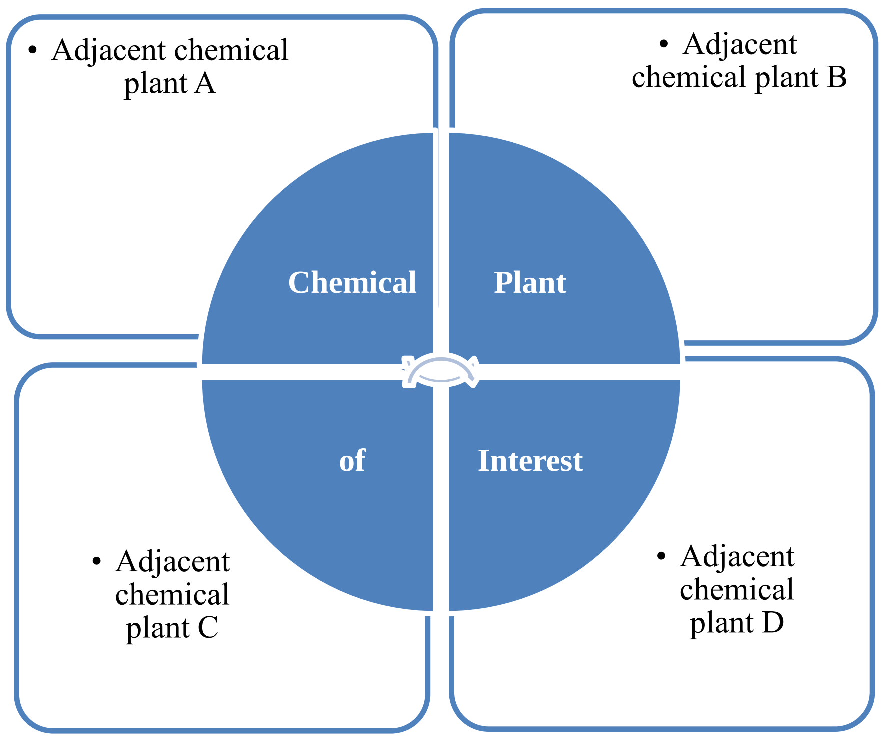


Figure 10. Portfolio model schematizing the chemical plant surrounded by adjacent plants

In the proposed methodology, the first step is performing the process hazard analysis which will provide information on all the potential deviating scenarios which could lead to explosions having catastrophic impact (Eckhoff, 2005). The calculation of the event probabilities and the consequence estimation for each of the scenarios will provide the portfolio risk for all scenarios. The portfolio scenario risks can be classified as total tangible risks and total societal and other intangible risks such as reputation loss. The tangible risks pertain to all process equipment repairs, lost production, business interruption, claims, environmental clean-up and other measurable asset value within the portfolio.

After the estimation of societal risk values such as number of expected fatalities and the number of expected injuries for the portfolio models, the societal risks can be graphically represented using farmer's curves such as the *FN*-curves, generated to indicate the adverse effect of the potential incidents on the public outside the plant. *F$*-curves could also be generated analogous to *FN*-curves as they would provide the measure of financial loss distribution for different potential incidents in a plant. These risk curves along with the maximum *VaR* expected losses would provide the means for understanding the stakes at risk for more confident decision making.

3.1. Scenario Development

After making an inventory of materials involved and their hazardous properties, a process flow sheet and a piping and instrumentation diagram, the hazard and operability study (HAZOP) method will have to be utilized to get the top event scenarios because of process deviations for the portfolio (AIChE/CCPS, 1992). Hazards and Operability (HAZOP) study is the most effective type of PHA and hence will be utilized in this research to ensure all potential scenarios are accounted for. HAZOP uses guide words to different nodes (sections or units) of the chemical plant to identify deviations (operability problems). HAZOP will be performed using plant operation information and P&IDs of the chemical plant of interest.

3.2. Probability Estimation of Scenarios

Probabilities for the undesired events are estimated by logically evaluating the series of events (cutsets) potentially leading to the undesired event (top event). The fault tree analysis (FTA) method effectively estimates the top event scenario probability (AIChE/CCPS, 1992). The failure rates from the CCPS and OREDA databases can be utilized to calculate the reliability of sub-systems leading to the top event. The failure of equipment generally corresponds to the basic events of a fault tree such as failure of equipment or human error. Event Tree Analysis (ETA) could also be employed for the deduction of potential catastrophic scenarios. ETA is similar to FTA except that the basic events are progressively built upon to obtain various deviating scenarios; each assigned its probability of occurrence (AIChE/CCPS, 1992; AIChE/CCPS, 2000).

3.3. Consequence Estimation

Source models will be utilized to calculate the discharge rate and total quantity of the material released. The chemical engineering principles of thermodynamics, reaction kinetics and transport phenomenon govern the principles behind the dispersion models that describe the material transportation downwind from its source release. Fire and explosion models will be used to estimate information such as thermal radiation, energy and overpressure. Estimation of the type of release, the quantity of release and its subsequent overpressure estimation if explosion occurs would enable the quantification of its impact to the surroundings of the plant. Adverse consequences *i.e.*, the number of fatalities and damage to buildings will be estimated from the probit (probability unit for damages) models (Mannan, 2005). Conservative (worst case) approach will be adopted while using the consequence models. Crowl and Louvar (2002), Lees Loss Prevention in the Process Industries (Mannan, 2005) and CCPS guidelines for consequence analysis of chemical releases (1994, 1996, 1999, 2000), provide well established source and consequence models for various process deviations. *FN*-curves and *F$*-curves will be developed to understand the consequences for different scenario frequencies. Developing the *FN*-curves and *F$*- curves for historical catastrophic incidents in the process industry will also help better understand the societal consequence trends. This could also help understand the societal risk aversion for certain process types of chemical industry processes.

3.4. Societal Risk Representation

Societal risk is the adverse impact (or consequence) on the society that could results from a potential chemical accident. SR for catastrophes could be in terms of fatalities, injuries, negative societal image of industry, environmental damages, etc. SR (fatalities) which cannot be directly measured in monetary terms is considered as intangibles. SR is rarely addressed in the overall risk analysis of a plant even though it is considered to be important (HSE, 1989). Some work has been done by HSE and researchers in Europe regarding inclusion of SR. However, the SR quantification is mostly qualitative. Societal risks are often not considered for risk estimation but its importance is nevertheless noted to be highly significant. For this study, even one loss of life is considered highly significant and hence one or more fatalities will be considered in the SR estimation models. Modeling fatalities outside plant area has generally not been considered by researchers in the past because of its complexity. However, including out-of-plant societal risk in the methodology for decision making is important and is one of the major objectives of this research.

Most high impact incidents have resulted in fatalities within a mile of the plant area (Kaszniak, Holmstrom and MacKenzie, 2007). Hence, an area of 1 mile radius from the portfolio of interest will be considered for SR estimation.SR typically translates into societal costs (SC). Hence, by SC estimation the SR could be monetized. Various types of damages to buildings, structures etc., which are outside the plant facility, can also be expressed in repair and replacement costs. Proposed equation 15 describes the total SC for a portfolio given by the summation of *n* possible societal risks due to damage to houses, governmental buildings and other structural buildings in the vicinity of the plant.

$$SC = \Sigma\, (SC_{Age\ Groups} + SC_{Schools} + SC_{Hospitals} + \ldots + SC_{(n\text{-}1)} + SC_n) \qquad (15)$$

For portfolio model studied in this work, the societal cost resulting from societal risks could further be classified into (i) direct societal cost and (ii) indirect societal cost. Direct societal cost is the cost of all the tangible damage to structural buildings such as hospitals, schools and houses in the residential areas and cleaning up of the environment. Indirect societal costs are costs stemming from intangible asset values such as cost of averting fatalities, litigation costs and production loss because of company’s loss of reputation. Such intangible asset values become only partly explicit in monetary terms and hence the intangible asset values are not considered in monetary terms in this work.

3.5. Database Analysis for Lagging Metrics

Two databases were mined to understand the incident trends in the US chemical process industry. The complete interpretations of the information harnessed from the databases would be utilized for the generation of societal consequences in terms of exceedance frequencies and safety pyramids. This information is valuable to the industry because it would enable the understanding of the incident profile in the process industry in order to help companies estimate the seriousness of near-misses and consequences of incidents occurring in their facilities, and the regulatory agencies to adopt more targeted standards for improving industrial safety. Once safety pyramids are generated, the relationships between the different consequences in the different tiers of the pyramids were studied by utilizing statistical correlations. The collective effect of lower consequences in leading to higher consequence incidents (fatality) would also studied by performing regression analysis. Fig. 11 shows the overview of objectives of RMP and HSEES database analysis in order to provide lagging indicator information to complement the leading indicator information in the novel methodology.

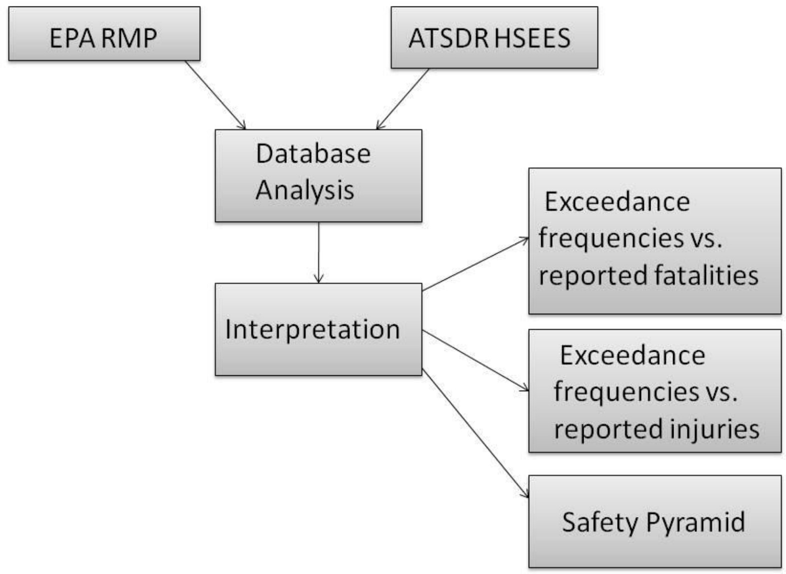


Figure 11. Overview of objectives of RMP and HSEES database analysis

The occurrence of the incidents and the size of global losses incurred are random. For the selection of the safest alternative or choosing the best risk reduction measures, it is therefore important to consider the time value of money. The time value of money for various assets could be analyzed using the vonNeumann-Morgenstern expected utility theory (vonNeumann and Morgenstern, 1947, 1953). The estimation of portfolio losses based on QRA studies, the expected Value-at-Risk of portfolio, the risk curves and the database analysis information can be utilized into the decision analyses phase (discussed in Section 5 under decision analyses framework) will help the decision maker to choose between risky or uncertain options by the comparison of their expected utility values. The expected utility values are weighted sums of the multiples of utility values of outcomes (in our case damage loss) and their respective probabilities. The explanation for calculating expected values basics for decision theory is provided by Ross (2006).

The last part of this work is to utilize the QRA-*VaR* based information for decision analysis in the presence of competing portfolios. The basic outline for the decision analysis based on QRA and *VaR* is provided in Fig. 12. The probability and consequences from the QRA which is translated into monetary value utilizing *VaR* concepts along with the societal risk curves for both leading and lagging indicators can be utilized for decision analysis. Expected utility theory and game theory concepts could be applied to choose the most preferred risk portfolio option via identifying dominant contributors.

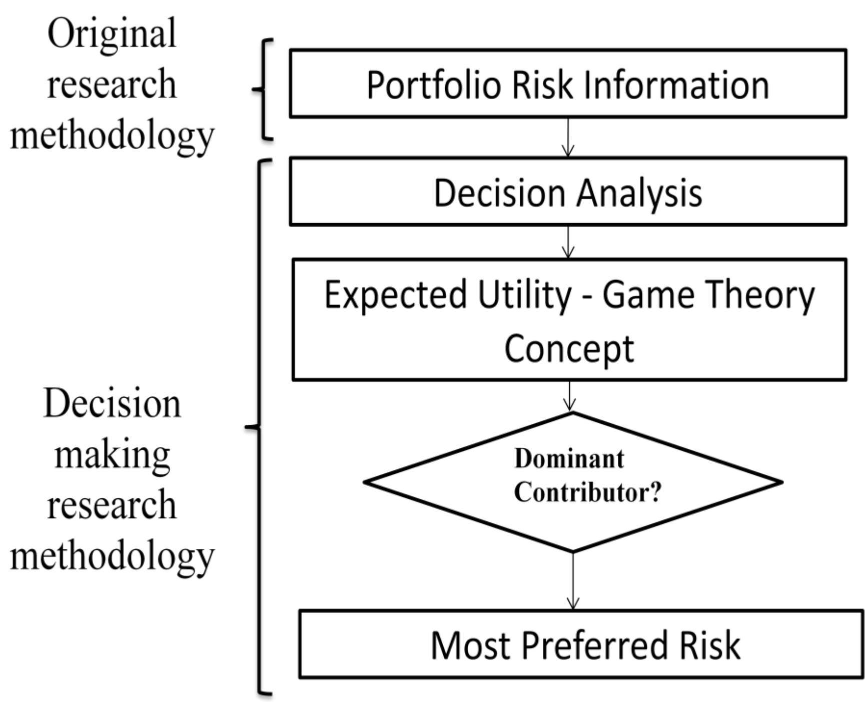


Figure 12. QRA and *VaR* based decision making framework

4. RESEARCH RESULTS

The following section provides results of distillation process separating hexane and heptanes in order to explain the methodology for calculating the expected losses of assets of a portfolio for scenarios which could result in potential incidents. This is the leading metrics for risk assessment. The lagging metrics for the study provides results from analyses of the NRC database and the HSEES database. Both databases provide risk curves, basic incident trend information and the safety pyramids for incidents which have occurred in the U.S. chemical process industry. The last part of this section will focus on the decision analysis framework in applying the expected utility theory and game theory principles to chemical process industry for improved decision making in order to choose the most preferred risk option.

4.1. Leading Metrics for Portfolio Risk Assessment

In order to apply the principles of our novel methodology, the following case study provided in the CCPS book on the guidelines for performing a chemical process QRA is considered as shown in Fig. 13. The case study involves a distillation column consisting of two feed streams of 58% (wt) hexane and 42% (wt) heptane, which are to be separated. The detailed description of the process can be found in CCPS – Chemical Quantitative Risk Analysis Chapter 8.2. The case study has been modified by the authors, in that all the possible scenarios are developed and their respective outcome frequencies have been calculated according to the assigned probabilities. For simplicity, the low and medium level scenarios are assumed to occur not more than once in a year.

It is assumed that the closest neighborhood in the vicinity of the plant housing 200 people. The population is assumed to be clustered more closely at the vicinity of the portfolio. This assumption is valid to study the worst case scenarios. The worst case weather having atmospheric stability class F with wind speed up to 1.5 m/s provides the most conservative consequence estimates with respect to relative frequencies of incidents.

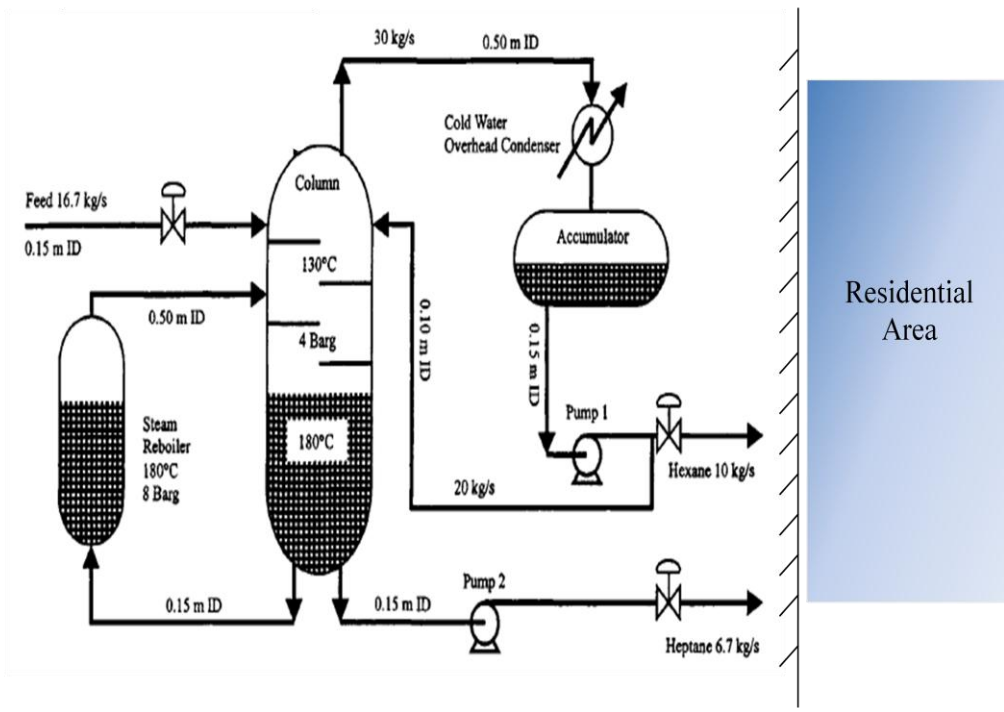


Figure 13. Portfolio of hexane-heptane separation process with residential area in its vicinity (adapted from AIChE/CCPS, 2000)

The importance of studying major incidents and monetizing the assets are stressed, the methodology for making business decisions from the economic analysis is developed and the methodology is demonstrated by applying it on a case study. For this purpose, credible scenarios and their incident outcome frequencies were first developed. The quantified portfolio risks were classified as tangible risks and intangible risks. The tangible risks was monetized and the expected loss using *VaR* were calculated. The *VaR* values and the economic losses enabled concluding that the column, full bore line rupture and the reboiler are the critical assets for risk mitigation in the plant. Societal Risk model were developed to account for intangible risk. *FN*-curve and *F$*-curve were generated according to the consequences of the potential scenario risks.

In this case study, the distillation column system contains flammable materials. Hence, fire and explosion outcomes are considered as potential incidents for which the probabilities have been evaluated by event tree analysis method. Complete rupture of column, accumulator, reboiler and condenser are assumed to be the most devastating cases leading to fire and explosion scenarios such as BLEVE, VCE and Flash Fires. Catastrophic failure and full bore rupture of the vessels are assumed to provide similar consequences assuming that in both cases all the contents of the vessels are instantaneously released. The details of the consequences of scenarios are explained in case study 2 of the CCPS guidelines for chemical process quantitative risk assessment (2000).

For the monetization of plant assets, five equipment are considered in the plant facility. The total tangible cost owing to the lost production time in the event of an incident is calculated based on the losses accrued because of the failure of the equipment. In a chemical plant the asset prices are fixed and hence the statistical variation of asset prices is considered to be unchanging. Table 2 lists the equipment considered for this case study and their asset values with the lost time of production in case of failure.

Table 2. Cost of portfolio assets

Equipment	Cost ($)	No. present	Final Cost ($)	Lost Prod. Time (days)
Accumulator	40,000	1	40,000	60
Condenser	75,000	1	75,000	90
Distillation Column	300,000	1	300,000	365
Piping (per ft.)	100	4000 ft	400000	180
Reboiler	65,000	1	65,000	30
		Total	880,000	

Once the different equipment along with their cost and the minimum lost time of production is accounted for, the next step is to assess the different credible scenarios that could result in potential incidents. In this work, a series of scenarios ranging from low to medium to high risk are deduced by utilizing the event tree analysis type of PHA method. The event tree for the incident is adopted from the CCPS guidelines example (2000) as shown in Fig. 14. If we consider an instantaneous release from equipment, *e.g.*, column, then it could immediately find an ignition source or could have no immediate ignition source available. The contents of the column are flammable and hence there is a good chance that if the liquid were to instantaneously release and if there is ignition source it could result in a BLEVE. Similarly if there is delayed ignition based on the type of release and the amount released, the consequence could be either a VCE or a flash fire. It is rarity to have no available ignition source in the process facilities as seen in many historical incidents. Event tree analysis method was used to deduce credible scenarios for different equipment for the hexane-heptane process.

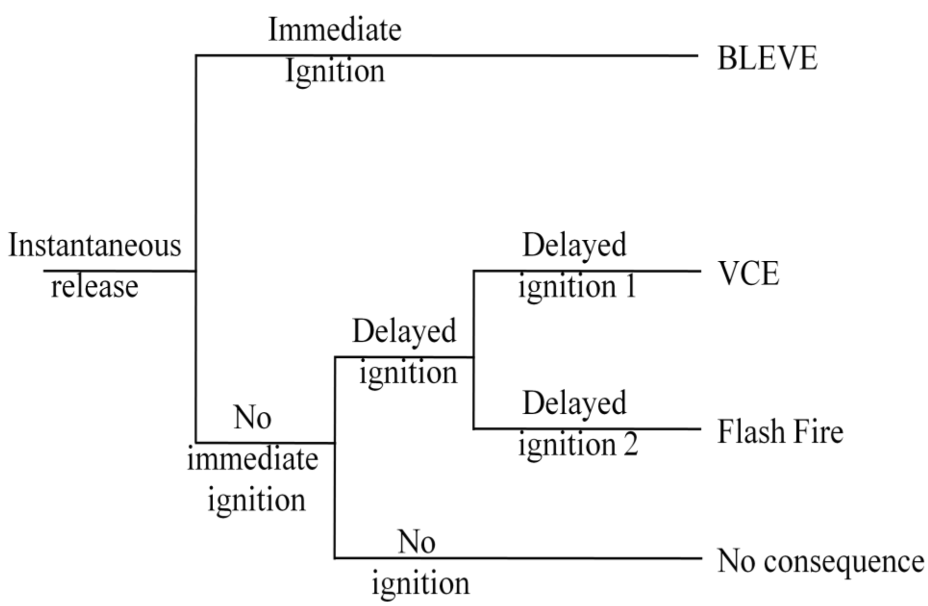


Figure 14. Event tree analysis for potential portfolio incidents

The different credible scenarios deduced from ETA method are used for each equipment in the facility. For different equipment, scenarios which could lead to low, medium and high risk incidents. The incident consequences for each of the scenarios are also identified. For example, for a credible scenario of small leak in reboiler, the possible consequences could be slip hazard if the flammable leak finds no ignition source. In case of ignition of the contents of the leak for an hour, a small fire could result. In the event of this incident, it is assumed that the reboiler could have minor damage and the reboiler could be out of service for a minimum of 2 days. In this manner different scenarios along with their incident consequences are provided in Table 3.

Table 3. Potential scenarios and the consequences based on event tree analysis

Scenario	**Incident consequence**
Small leak in reboiler	Slip hazard, possible small fire; lasting 1 hour; 2 days production loss
Small leak in piping	Slip hazard, possible small fire; lasting 2 hours; 1 week production loss
Accumulator tube leak	Slip hazard, possible small fire; 0.5 day production loss
Reboiler leak, continuous release	Slip hazard, possible small fire; lasting 2 hours; 1 week production loss
Column overhead liquid leak, continuous release, immediate ignition	Possible flash fire; can be quickly extinguished, damage repaired in one day
Column shell vapor leak, continuous release, delayed ignition	Possible flash fire; can be quickly extinguished, damage repaired in one day
Condenser tube leak, vapor release, immediate ignition	Possible jet fire; lasting 1 hour; 1 day production loss
Catastrophic reboiler failure, instantaneous release, immediate ignition	Possible BLEVE followed by fire; damage to surrounding equipment; 2 months out of production

Table 3. (Contd)

Scenario	Incident consequence
Full bore rupture of pipe, delayed ignition, instantaneous release	Possible VCE followed by fire; 3 months out of production
Catastrophic column failure, instantaneous release, immediate ignition	Possible BLEVE; 12 months loss of production
Catastrophic rupture of column, continuous release, delayed ignition	Possible VCE, 12 months of production

The next step is to estimate the probability of loss and incident outcome frequencies for each of the incidents. In the case study, the probability loss is assumed based on information from CCPS (2000). The incident frequencies which are provided in the CCPS guidelines for QRA is utilized for the different scenarios based on the type of consequences and the dominant wind direction. The probability of occurrence of each incident is multiplied with the relevant incident frequency to obtain the final incident outcome frequency. This is shown in Table 4. Generally probability loss are estimated based on expert judgment and historical information. Frequencies are estimated from equipment reliability and failure rate data. For clarity, the different incident types are color coded to match the incidents listed in Table 2. For example, the incident type entitled “High 1”, which relates to catastrophic reboiler failure as previously shown in Table 3 is assumed to have a probability of occurrence of 0.3 with the incident frequency of 2.30E-05 which results in an incident outcome frequency of 6.90E-06.

Table 4. Incident types with loss probabilities and incident outcome frequencies

Incident Type	Pr. Loss	Incident Freq (yr^{-1})	Incident Outcome Freq (yr^{-1})
Low 1	0.70	3.70E-04	2.59E-04
Low 2	0.80	3.70E-04	2.96E-04
Low 3	0.75	3.70E-04	2.78E-04
Low 4	0.85	3.70E-04	3.15E-04
Medium 1	0.45	2.30E-05	1.04E-05
Medium 2	0.75	2.30E-05	1.73E-05
Medium 3	0.46	2.30E-05	1.06E-05
Medium 4	0.4	2.30E-05	9.20E-06
High 1	0.30	2.30E-05	6.90E-06
High 2	0.4	2.30E-05	9.20E-06
High 3	0.25	2.30E-05	5.75E-06
High 4	0.35	2.30E-05	8.05E-06

Generally, source and consequence models are utilized to estimate the consequence information such as the amount of leak, the resulting overpressure, the area affected by the resulting fire or explosion and the number of people affected. In the case study, the consequences estimated from the CCPS book is utilized for simplicity. If a BLEVE were to result about 60,000lb of flammable liquid is estimated to be released with a diameter of 600ft and fire height of 450ft. If a VCE were to result, then the radius of the are affected by explosion would be 800ft with an overpressure of 3psi. If the leak is smaller then it could result in a flash fire with diameter of about 480ft centered at 270ft downwind. In case of jet fire, the diameter of are affected is about 100ft. It is evident from these results that explosions are more severe in causing potential damage to facility and residential area in the plant vicinity where as the jet fire would have no potential threat to residential areas.

Table 5 provides information about the different incidents with cumulative probabilities and assumed societal consequences. The incident outcome frequencies for the 12 different scenarios listed in Tables 2 and 3 are utilized to calculate the incident outcome probability and the cumulative probability density values. The assumed societal losses in terms of fatalities include people both inside and outside the plant facility. The assumption of fatalities for low risk incidents is extreme but is thus chosen to assess the risk aversion using UK-HSE intolerability criterion lines for fatalities that could occur in case of low risk scenarios. For higher risk scenarios large number of fatalities is assumed as is the case for major historical catastrophes.

Table 5. Incidents with cumulative probabilities and societal consequences

Incident Outcome Freq. (1/yr)	Incident outcome probability, pdf	Cum. probability density, cdf	Societal Loss (people)
2.59E-04	1.04E-03	1.04E-03	1
2.96E-04	1.18E-03	2.22E-03	3
2.78E-04	1.11E-03	3.33E-03	5
3.15E-04	1.26E-03	4.59E-03	10

Table 5. (Contd)

Incident Outcome Freq. (1/yr)	Incident outcome probability, pdf	Cum. probability density, cdf	Societal Loss (people)
1.04E-05	4.16E-05	4.63E-03	12
1.73E-05	6.92E-05	4.70E-03	15
1.06E-05	4.24E-05	4.75E-03	20
9.20E-06	3.68E-05	4.78E-03	25
6.90E-06	2.76E-05	4.81E-03	75
9.20E-06	3.68E-05	4.85E-03	100
5.75E-06	2.30E-05	4.87E-03	150
8.05E-06	3.22E-05	4.90E-03	200

The final outcome is to estimate the total expected monetary loss for incident scenarios by using the business interruption loss and the plant asset damage loss in the event of equipment failure. Table 6 provides the information for calculating the total loss with business interruption for each potential incident scenarios. The first step is estimating the sales revenue by multiplying production cost and product price. Total production cost is calculated with the fixed and variable production costs. The capital investment is calculated next, based on the nominal capacity investment and the production capacity. The value of depreciation is calculated for a time period of 10 years. The next step is calculation of the required cash flow using the capital investment and the nominal capacity investment. The total loss is calculated for each of the equipment based on lost time of production and business interruptions based on loss of turnover. The total loss is based on initial investment, lost capital and clean-up costs. The liability costs are excluded in this study which would be additional costs.

Table 6. Sequence of equations to calculate the total loss with business interruption

Raw material production cost, variable = Production capacity * Product price Production cost, total = Production cost fixed + Production cost variable Production Cost, fixed = Operating labor + Maintenance + (Energy, overheads, support, insurance)
Capital investment plant = Nominal capacity investment * Production capacity Investment = Capital investment plant – Production capacity – Equipment fixed cost Depreciation = Capital investment plant / 10
Cash flow required = 3 * capital investment plant * nominal capacity investment Cash flow before tax = Sales revenue – Production cost, total Taxable cash flow = Cash flow before tax – Depreciation
Total loss = Investment + Lost capital + clean-up + {Liability} Business Interruption (BI) = Equipment lost production time * (Cash flow before tax + Production cost, fixed) Total loss including BI = Total loss + BI

Table 7 shows the calculations for the case study asset loss for different potential incident scenarios based on information provided in the previous table. Cash flow that is taxable is calculated using the operating cost, the maintenance, energy, overheads, support and insurance. Based on the assumed values, the variable production cost is estimated at $63mil for a production capacity of 1.2 mil lb/yr of desired component.

Table 7. Case study asset loss calculations

Loss calculations	**Amount**
Production capacity A	1,200,000 lb/yr
Product price, B	$ 520
Sales revenue, A*B	$ 624,000,000
Prod.Costs, fixed with Fixed Capital investment = 4.6 * equipment cost	$ 4,103,200
Prod.Costs, variable	$ 63,000,000
Prod.Costs, total, C	$ 67,103,200
Nominal capacity investment	$ 500/ (lb/yr)
Capital investment plant, D	$ 600,000,000
Depreciation 10 yr, 0.1D	$ 60,000,000/yr
Cash Flow required: 3*Investment D/10yr	$ 90,000,000/yr
Cash Flow (before tax), A*B-C	$ 556,896,800/yr
Cash flow, taxable, A*B-C-0.1D	$ 496,896,800/yr
Tax, 40%	$ 198,758,720/yr
Operating labour	$ 20,000,000/yr
Maintenance	$ 7,000,000/yr
Energy, overheads, support, insurance etc.	$ 20,000,000/yr
Production costs, fixed	$ 47,000,000/yr
Raw mats, prod.costs, variable	$ 63,000,000/yr

Based on the lost time of production that is assumed, the total loss due to catastrophic failure for every equipment is calculated. Here, estimation of the percentage of business interruption to the total cost for loss indicated that the distillation column is the most critical equipment. In this case, the cost of equipment assumed is small compared to the total capital investment of plant. Therefore, the investment costs for the equipment are similar when rounded to the nearest million. In case of the failure of the equipment due to an incident, the capital lost is assumed to be 60% of the investment cost including the equipment. This is assumed as the conservative estimate for losses incurred from incidents. Business interruption costs are inclusive of equipment loss production time, cash flow before tax and fixed production cost. The total loss includes the initial investment, the capital lost due to failure of the equipment and the cost of clean-up excluding liability costs.

According to calculations shown in Table 8, the worst expected losses for this case study is $181 million from BLEVE due to column failure and $90 million from VCE because of full bore pipe rupture. The worst case loss because of reboiler failure and BLEVE is $30 and $21 million from VCE due to instantaneous release of contents from column failure. These values support the fact that as the severity of the incident consequences increases the expected loss to the companies also substantially increases for catastrophes. For this case study the full bore rupture of the pipe, the column failure and the reboiler failure are the most critical equipment because the failure of these equipment leads to major losses and adverse societal consequences.

Table 8. Probability and asset loss with business interruption (BI) for different scenarios

Incident	**Event**	**Pr. Loss**	**Incident Freq (1/yr)**	**Incident Outcome freq. (1/yr)**	**Repairs and replace ($)**	**BI ($)**	**Clean up of envi. ($)**	**Loss with BI (Mil. $)**
Small leak in reboiler	Slip hazard, possible small fire; lasting 1 hour; 2 days production loss	0.7	3.70E-04	2.59E-04	6,500	1,962,400	100,000	2.07
Small leak in piping	Slip hazard, possible small fire; lasting 2 hours; 1 week production loss	0.8	3.70E-04	2.96E-04	40,000	6,868,402	200,000	7.11
Accumulator tube leak	Slip hazard, possible small fire; 0.5 day production loss	0.75	3.70E-04	2.78E-04	4,000	490,600	100,000	0.59
Reboiler leak, continuous release	Slip hazard, possible small fire; lasting 2 hours; 1 week production loss	0.85	3.70E-04	3.15E-04	65,000	6,868,402	200,000	7.13
Large liquid leak from piping, instantaneous release, delayed ignition	Possible flash fire; lasting 5 hours; 2 weeks production loss	0.45	2.30E-05	1.04E-05	400,000	13,736,803	200,000	14.34
Column overhead liquid leak, continuous release, immediate ignition	Possible flash fire, no blast; can be quickly extinguished, damage repaired in one day	0.75	2.30E-05	1.73E-05	300,000	981,200	0	1.28
Column shell vapor leak, continuous release, delayed ignition	Possible jet fire; 1 week loss of production	0.46	2.30E-05	1.06E-05	300,000	6,868,402	500,000	7.67

Table 8. (Contd)

Incident	Event	Pr. Loss	Incident Freq (1/yr)	Incident Outcome freq. (1/yr)	Repairs and replace ($)	BI ($)	Clean up of envi. ($)	Loss with BI (Mil. $)
Condenser tube leak, vapor release, immediate ignition	Possible jet fire; lasting 1 hour; 1 day production loss	0.4	2.30E-05	9.20E-06	75,000	981,200	100,000	1.16
Catastrophic reboiler failure, instantaneous release, immediate ignition	Possible BLEVE followed by fire; damage to surrounding equipment; 2 months out of production	0.3	2.30E-05	6.90E-06	16,250	29,436,007	1,000,000	30.45
Full bore rupture of pipe, delayed ignition, instantaneous release	Possible VCE followed by fire; 3 months out of production	0.37	2.30E-05	8.51E-06	400,000	89,289,220	1,000,000	90.69
Catastrophic column failure, delayed ignition, continuous ignition	Possible BLEVE; 12 months loss of production	0.25	2.30E-05	5.75E-06	300,000	180,540,840	1,000,000	181.84
Catastrophic rupture of column, instantaneous release, delayed ignition	Possible VCE, 6 months of production	0.35	2.30E-05	8.05E-06	150,000	20,605,205	500,000	21.26

Table 9 shows the calculations of losses for plant units along with BI losses. The clean-up cost was estimated to be 50,000 for all scenarios for simplicity but this value could differ in actuality. The equipment loss percentage because of BI was calculated and it is seen that the most critical equipment is the column followed by the piping and the condenser. The total percentage of loss due to business interruption compared to the overall loss is estimated to be 19% for this case study.

Table 9. Loss for plant units along with BI for scenarios

Unit	Clean up (Mil $)	Total loss (Mil $)	Business interruption (Mil $)	Total with BI (Bil $)	BI - % total loss
Accumulator	0.050	958	92	1.1	9%
Condenser	0.050	958	138	1.1	13%
Distillation Column	0.050	956	561	1.5	37%
Piping (per ft.)	0.050	958	277	1.2	22%
Reboiler	0.050	958	46	1.0	5%
		Total	1114	5.9	19%

Table 10 shows the Portfolio equipment with maximum lost days of production to estimate the upper bounds for BI loss for individual equipment and the plant facility as a whole. The distillation column is assumed to be out of service for 3 years in the event of a catastrophe followed by the reboiler at 1.5 years out of service and the condenser 9 months. The number of days for repairing piping is still assumed the same as before because it is assumed that it takes the same amount of time to repair pipework.

Table 10. Portfolio equipment with maximum lost days of production to estimate the upper bounds BI loss

Unit	Lost Prod. Time (days)
Accumulator	180
Condenser	270
Distillation Column	1095
Piping (per ft.)	180
Reboiler	450

Table 11 shows the calculation of losses for plant equipment with BI loss with maximum number of days of lost time of production in case of catastrophic incidents. The cleanup cost is assumed to be \$ 50,000 for all scenarios for simplicity in this case also. The equipment loss percentage because of BI is calculated and it can be seen that the most critical equipment once again is the column followed by the reboiler and the condenser. However, the total percentage of loss due to business interruption compared to the overall loss is estimated to be 40%. The BI loss for distillation column is estimated at 63% and reboiler at 41%. For catastrophic incidents, the number of lost days of production is much greater and hence the losses because of BI for individual equipment and portfolio as a whole is also higher, as expected.

Table 11. Upper bound loss for plant units along with BI

Equipment	Liability & cleanup (Mil $)	Total loss (Mil $)	Business Interruption (BI) (Mil $)	Total loss with BI (Bil $)	BI % total loss
Accumulator	0.05	958	265	1.2	22%
Condenser	0.05	958	397	1.4	29%
Distillation Column	0.05	958	1611	2.6	63%
Piping (per ft.)	0.05	957	265	1.2	22%
Reboiler	0.05	958	662	1.6	41%
		Total	3200	8	40%

Fig. 15 shows the losses incurred if the different scenarios were realized. Low risk incidents have the lowest loss. Medium and high risk incidents have greater losses both in terms of damage to equipment and fatalities (as shown in figure 9). The 95% *VaR* gives a loss of $7mil/yr (*i.e.*, 95% confidence that losses do not exceed $7 mil/yr) and the 99% *VaR* gives a loff of $90mil/yr (*i.e.*, 99% confidence that loss will not exceed $90mil/yr). Values exceeding the cut-off limits are the *VaR* break values. Any scenario above the chosen cut-off must include risk mitigation measures to reduce risks. BLEVE and VCE are most serious types of explosions causing severe societal consequences and economic loss. It is the choice of the decision maker to choose the most preferred confidence level that is accpetable under different circumstances. Hence, if the decision maker is more risk averse, 95% confidence limit is chosen as the cut-off beyond which all other scenarios risks are mitigated by adopting rigorous risk reduction measure. In this case choosing the more risk averse 95% confidence level for *VaR* is more conservative. Using this confidence limit also indicates that the most critical equipment failures are the full bore pipe rupture, the column and reboiler failures.

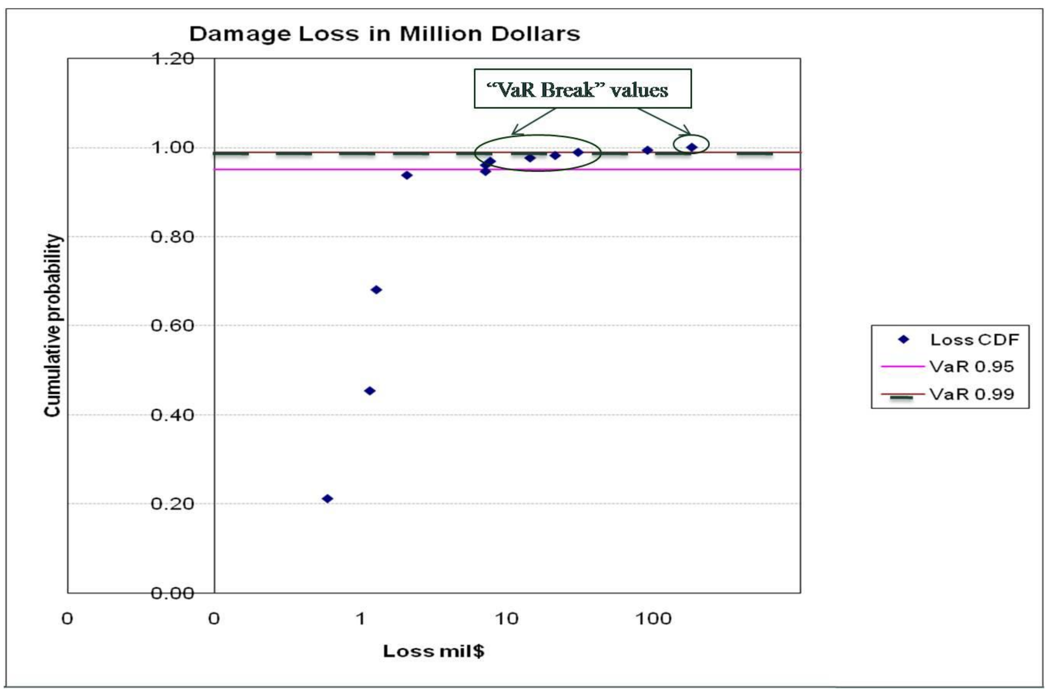


Figure 15. Cumulative probability and *VaR* with total BI

The *FN*-curves and the *F$*-curves both indicate that the damage to society and the company are interrelated and show similar trends. As the number of fatalities increases, the economic loss of the company increases analogously. The number of potential fatalities in this case study includes workers from within the plant as well as the people outside the plant. If it is assumed that the road running parallel, next to the plant has many people travelling in the peak hours of traffic, then, for catastrophic scenarios, we assume that in-plant fatalities is a maximum of five.

In this case study, *FN*-curve is plotted for each potential accident based on the values of fatalities assumed. Fig. 16 shows the *FN*-curve for the scenarios with UK and Dutch intolerable criterion lines. Applying the UK intolerable criteria, it is observed that it is never acceptable to have fatalities resulting from low risk scenarios. The medium risks fall below the intolerable line; however, they are in the ALARP region indicating that the risks should be decreased to the lowest possible level. The high risk scenarios generally all fall above the intolerable line, indicating that such multiple societal losses is unacceptable based on the scenario occurrence frequencies. Applying the Dutch intolerable criterion line, which is only for societal losses outside plant vicinity, it is observed that all the scenarios fall above the stringent criterion line with slope of -2. Regardless of the criterion, it is important to note that these criterion lines are more like guidelines for implementing safety measures for risk mitigation. Hence, monetization of losses should also be included in the decision making process and not just *FN*-curves.

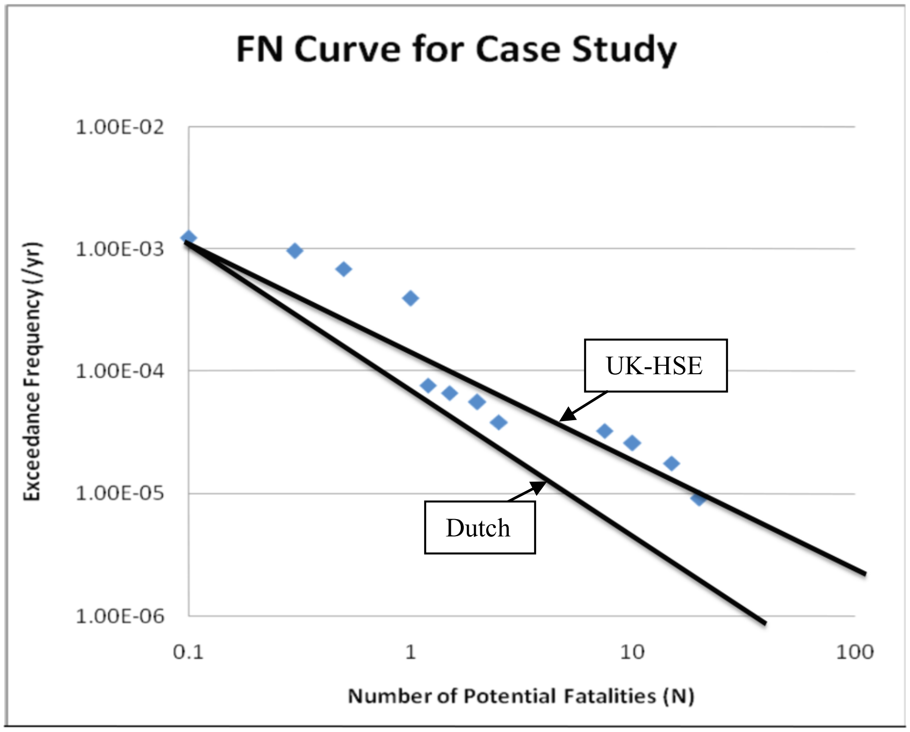


Figure 16. *FN*-curve for the scenarios with UK and Dutch intolerable criterion lines

Applying the UK intolerable criteria to Fig. 17 showing all criterion lines for the *FN*-curve as per UK-HSE, it is seen that having fatalities for lower risk events is unacceptable. The medium risk values, fall below the intolerable line in the As Low As Reasonably Practicable (ALARP) region. The ALARP region in the UK criterion lines is the region in between the intolerable and the tolerable line, where the risks are considered tolerable but, should be further decreased whenever possible. The four medium risk data points within the ALARP region indicate that the risks should be decreased to a level which is "as low as reasonably practicable". Here, the high risk scenarios are those which clearly have high consequence and low probability. These extreme risk event data points all fall above the intolerability line, indicating that proper safety measures must be sought to decrease the portfolio risks. If suitable protection devices are implemented in the plant facilities, these risk levels can be brought closer to the tolerable criterion line given that the required cost for implementing appropriate protection devices and safety measures are available. Similar to the UK-HSE criterion lines, the Dutch regulatory body also utilizes criterion lines except with a risk aversion factor of negative slope of 2. However, the Dutch criterion lines only apply to loss of life outside the plant facility without including the loss of life within the plant facility (Vrijling & van Gelder, 1989; Stallen, Geerts, & Vrijling, 1996). The focus of this work is establishing a novel methodology for risk-informed decision making for entire portfolio and hence the Dutch criterion is not applicable for this study.

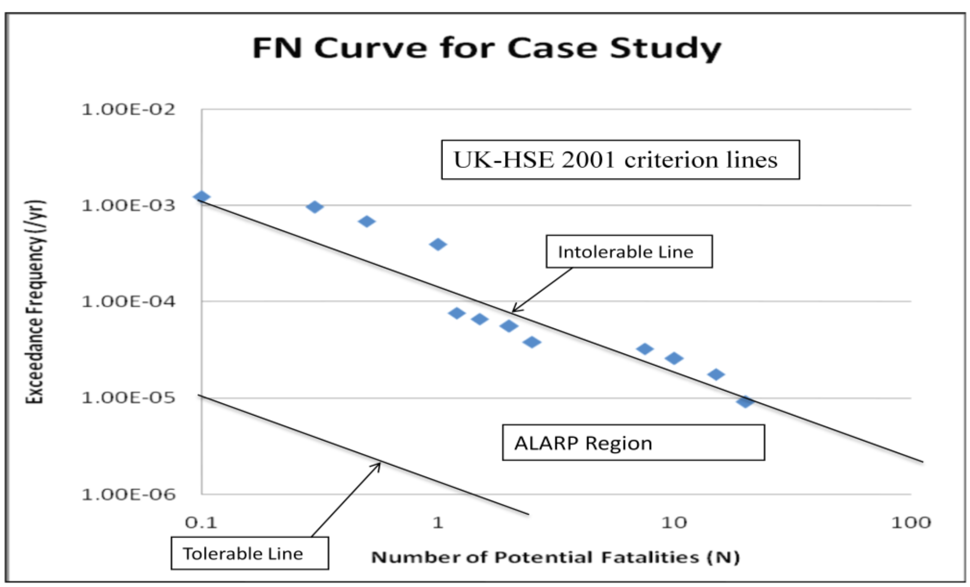


Figure 17. *FN*-curve showing all criterion lines as per UK-HSE

The criterion lines are more like guidelines for implementing safety measures for risk mitigation (Evans & Verlander, 1997; Trbojevic, 2005). Hence, in this work, monetized asset loss in the form of *VaR* curve and *F$*-curve are also included along with the *FN*-curve. In Fig. 18, the frequency of exceedance curve in monetary terms for asset losses pertaining to different scenarios is shown. The cost of the incident increases with the severity of the incident consequence. The *F$*-curves also fall from left to right similar to *FN*-curves indicating that the two curves could be correlated. If a correlation indeed exists, it would be valuable to generate *FN*-curves and *F$*-curves for historical accidents, which generally have information about the number of fatalities (N) and the amount of loss ($). Generation of such curves for historical incidents would be beneficial for studying the trends in the industry frequency of occurrence of similar historical incidents.

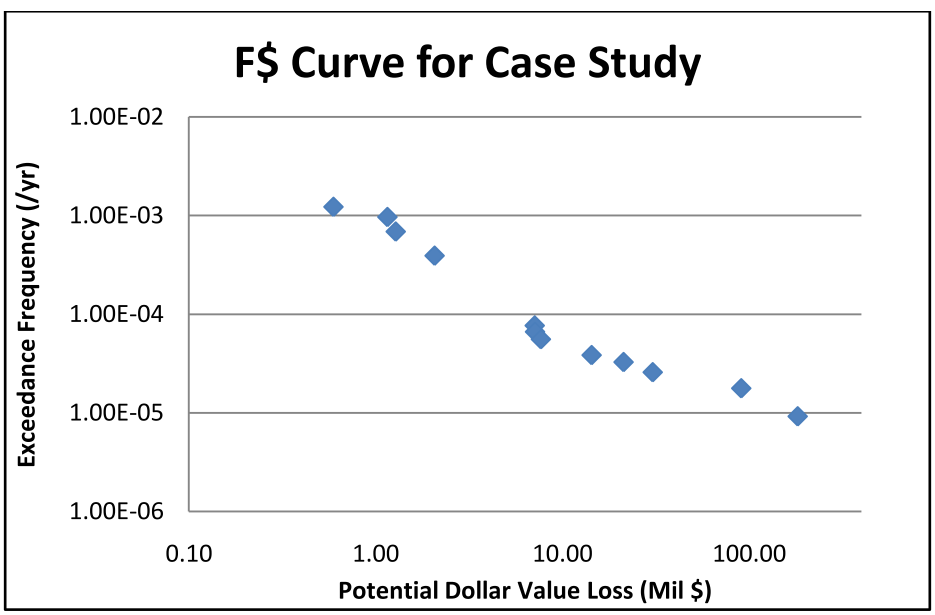


Figure 18. *F$*-curve for all portfolio scenarios

4.2. Lagging Metrics for Portfolio Risk Assessment

Federal regulation, 40 CFR Part 68, has required industrial facilities using large amounts of extremely hazardous substances to file a Risk Management Plan with the US Environmental Protection Agency (EPA, 2009). This information is then categorically populated in its national information system known as the RMP database. According to the Clean Air Act Amendment of 1990 section 112r, the Environmental Protection Agency (EPA) is required to publish regulations for chemical accident prevention in facilities with hazardous substances (EPA, 2009; Kleindorfer et al., 2007). The Risk Management Program focuses on reducing chemical incident risks at the local level, to aid emergency responders in developing strategic preparedness and response plan and to educate the general public about the chemical hazards.

The RMP database includes incident information for fixed facilities which are reported from the chemical and petroleum sectors of the process industry. An incident is reportable in the RMP if it involves the release of more than the specified threshold quantity of the chemical defined under the RMP rule. Furthermore, the incidents should have taken place within five years from the date of its submission and must have resulted in consequences such as deaths, injuries, evacuation, and/or property damage (Elliott et al., 2008). The total number of facilities covered under the RMP rule is approximated to be 14,000 facilities (Kleindorfer et al., 2007). All 50 US states having facilities covered under the RMP rule must report incidents to the RMP. An average number of 158 incidents were reported per year in the RMP between 1994 and 2009.

The facilities covered under the RMP rule are similar to the European Union facilities covered under the Seveso II Directive (Wettig & Porter, 1998). The Seveso Directive is established to control major accident hazards involving dangerous substances and to limit consequences for man and the environment by increasing community protection both effectively and consistently (Wetting & Porter, 1998). Hence, both the RMP and the Seveso Directive exists to reduce the number and consequences of process incidents and prevent damages. The data collected from the Seveso II Directive plants are utilized to perform full-fledged quantitative risk assessment leading to the generation of risk curves such as FN-curves by the Dutch National Institute for Public Health and Environment to understand the severity of the accident consequences (Natuurplanbureau, 2004).

Facilities covered under the EPA-RMP Rule are obligated to report incidents if their consequences exceed the specified damage criteria. Initially the facilities covered under the RMP Rule could report the accident data populated in the facility for five years by June 1999, which was the first wave of filing. However, the time to report an incident was amended to within six months of the date of the occurrence of the incident and the facilities were needed to submit the incidents by June 2004, which was the second wave of accumulated accident filing (Kleindorger at al., 2007). The third wave of reported incidents was filed by 2009. Under both rules, the facilities covered have to report incidents which exceed the specified threshold of consequences. However, there exists a more stringent rule for the facilities to report incidents under the Seveso II Directive than the facilities under the EPA-RMP Rule. For example, single fatalities and hospitalizations under 24 hours are reportable under RMP Rule while they are not required by the Seveso II Directive (Wettig & Porter, 1998). The RMP reportable incidents could be considered as “near-misses” in comparison to Seveso II incidents (Kleindorfer et al., 2007). The analysis of RMP database could help draft better regulations and policy conclusions about the nature and consequences of accidental chemical releases in US facilities. Hence, the study of EPA-RMP database is significantly important.

The other database studied in this work is the Hazardous Substance Emergency Events Surveillance (HSEES) from the Agency for Toxic Substance and Disease Registry (ATSDR). The HSEES database was established in 1990 to collect acute releases of hazardous substances requiring cleanup or neutralization and threatened releases resulting in events such as evacuations. The goal of HSEES as the only federal database for addressing health effects from hazardous substance releases is to reduce the accident related mortality and injury rates experienced by employees, emergency responders and general public. There is no specification of threshold limit for hazardous chemicals released in facilities to be reportable to HSEES database and hence the number of facilities which can report to HSEES is greater than that of the RMP database.

On an average about fifteen participating states report about 8000 hazardous substance incidents annually in the HSEES database. The fifteen states are Alabama, Colorado, Iowa, Louisiana, Michigan, Minnesota, Missouri, New Jersey, New York, North Carolina, Oregon, Texas, Utah, Washington, and Wisconsin. Information such as the chemical released as primary compound or secondary or tertiary compound, the time and place of release, weather circumstances, the number of major injuries, the number of deaths and public health action such as evacuation are reported by facilities (Kleindorfer et al., 2007).

The HSEES data incorporate all incidents resulting in releases and consequences critical for identifying, preventing, and mitigating the consequences of potential incidents. The information collected in HSEES can help management in planning better accident prevention strategies. It can also be utilized by regulatory agencies to develop and pass standards more strategically focused to reduce serious consequences from hazardous substance releases. Hence, the study of HSEES database is invaluable. The next section explains the analysis performed by utilizing the two accident databases.

In this work, information such as the number of incidents, number of njuries, number of people hospitalized and treated, number of evacuations and shelter in-place, as reported in both the databases were utilized for analysis. From the two databases, the reported incidents considered were from the alkali manufacturing, chlorine manufacturing, basic organic and inorganic chemical manufacturing, cyclic crude and intermediate manufacturing, ethyl alcohol manufacturing, fertilizer, industrial gas, fertilizer manufacturing, pharmaceutical, medicine and polystyrene manufacturing. Petroleum refinery related sectors including LNG extraction, oil and gas extraction, all pipeline transportation of LNG and all other petrochemical manufacturing were considered as available only in the RMP database.

From the RMP data, all the petrochemical industry events were collectively analyzed and then only the petroleum industry related events were analyzed separately.

In this work, a total of 2,623 data points representing chemical manufacturing/processing and petroleum refining incidents reported in the RMP from 1994 to 2009 were analyzed. About 33,000 data were studied from HSEES database from 1996 to 2004. The persons, who are hospitalized and treated without immediately being discharged after treatment, were considered as major injuries. The symptoms or injuries because of hazardous substance releases, where persons are treated and immediately released from hospitals, were considered as minor injuries. Evacuations were considered as low consequences where as high consequences were considered to be injuries and deaths. In the RMP database, the numbers of people evacuated and sheltered in place are available whereas in the HSEES database only the number of people evacuated are available. Hence, the information as provided is utilized for data analyses in this study.

Both the RMP and HSEES databases were analyzed for the number of annual incidents reported along with the total number of annual injuries. The different initiating causes of failure leading to the incidents were analyzed to understand the percentage of incidents occurring because of reasons such as equipment failure and human error. The societal losses were analyzed by generating the relationship between exceedance frequencies along with fatalities and injuries. These relationships are solely measures of exceedance frequencies of incident consequences with respect to the number of years of data analyzed. In case of the RMP database, additionally, the exceedance frequencies are generated for incident consequences based on the number of years of data reported and the average number of facilities covered under the RMP rule. In the databases all single fatalities are accounted for, all double and triple fatalities are also accounted for to get the total number of 'n' occurrences reported. Once the different 'n' were accounted for, the number of facilities (for RMP its 14,000) and number of years of data(16 yrs) were used to estimate frequency values. Then the frequencies were ordered from highest to the least and were summed to get cumulative frequencies in order to generate exceedance curves (cumulative distribution curves) as double log graphs. They are exceedance curves because a random variable (N) occurring will still be measured against these values (n) for assessing the severity of the consequence of that random variable, *i.e.*, S(n) = Pr (N > n). The different accident consequences were utilized as reported in the databases to generate the safety pyramids. Furthermore, the relationships between the different consequences in the different tiers of the pyramids were studied by utilizing statistical correlations.

The collective effect of lower consequences in leading to high consequence (fatality) was also studied by performing regression analysis. The complete interpretation of the information harnessed from the databases which are utilized for the generation of societal consequences in terms of exceedance frequencies and safety pyramids, enable the understanding of the incident profile in the process industry in order to help companies estimate the seriousness of near-misses and consequences of incidents occurring in their facilities, and the regulatory agencies to adopt more targeted standards for improving industrial safety.

4.2.1. RMP and HSEES databases annual accident statistics

In this work, the three tranches of reported incidents in the RMP from 1994 to 2009 were collectively studied to understand the incident profile. The data analyzed from HSEES database relate to events that were reported from 1996 to mid-2004 (Prem, Ng & Mannan, 2010).

Fig. 19 shows the total chemical process industry reported incidents in comparison with the petroleum industry related incidents. From this figure it can be seen that there is a steady decline in the number of incidents reported in the process industry as a whole as well as in the petroleum industry from 1998 to 2000. From 2000 to 2003, the numbers of incidents reported were about the same. In 2004, there is an increase in the reported incidents with a maximum of about 250 reported incidents. From 2004 to 2008, the average number of reported incidents was about 200 incidents. The proportion of the number of incidents reported by the petroleum industry in comparison with the total number of reported petrochemical incidents remains constant and shows a decreasing trend from 2002 to 2009. One reason for this decline might be due to the establishment of safety management programs such as the RMP rule for improving on-site safety.

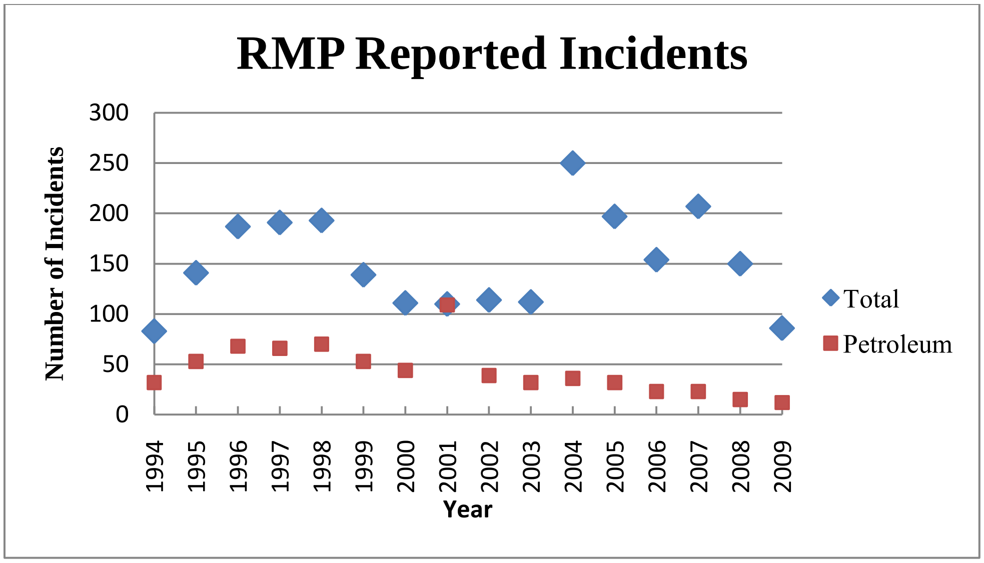


Figure 19. Total number of petrochemical and petroleum incidents reported annually in the RMP database

Fig. 20 shows the trend in the number of reported injuries for the entire process industry in comparison with the reported injuries for the petroleum industry. The percentage of reported petroleum injuries to total reported injuries were estimated to understand the percentage of petroleum related incidents out of the overall incident injuries reported. In 2001, out of the total injuries the maximum of 63% injuries were attributed to petroleum-related incidents while it was 54% in 1997. According to this analysis, more than 50% of the total numbers of reported injuries were from the petroleum industry incidents periodically every three to four years. The data point for 2005 is high owing to the BP Texas City incident reporting.

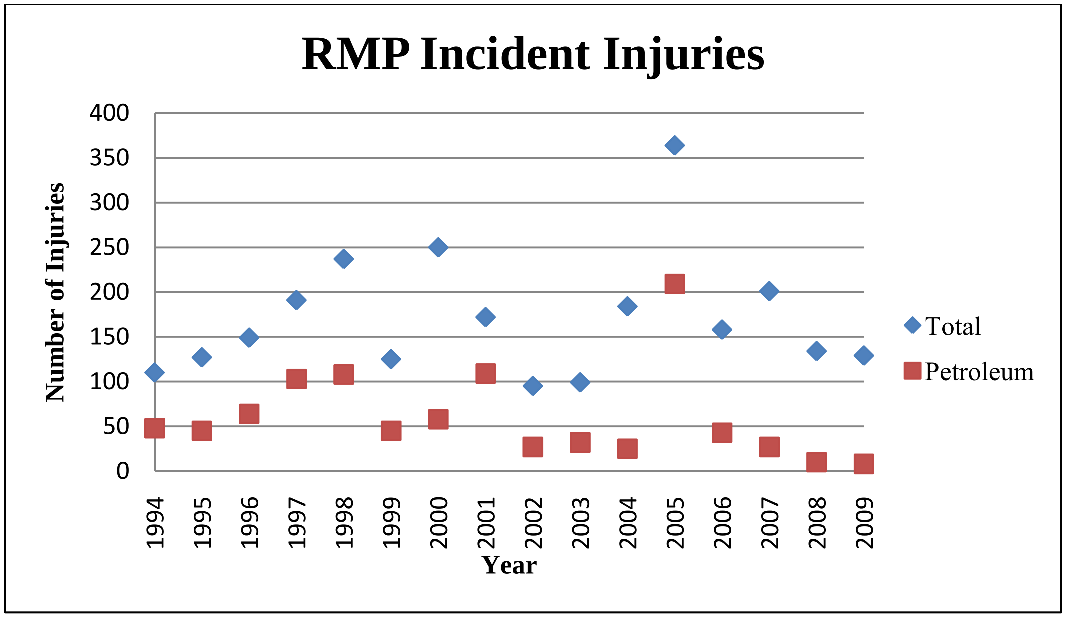


Figure 20. Total number of injuries of petrochemical and petroleum incidents reported annually in the RMP database

Fig. 21 shows the chemical process industry related incidents reported in HSEES. In this figure, the data for year 2004 is excluded for two reasons: (i) the 2004 data only depicts incidents until mid-year and (ii) only those states which have reported during 1996 and 2004 have been utilized to study the reporting trends. Hence, Louisiana, New Jersey and Utah have been excluded for more accurate estimates of the reporting trends. From this figure it can be seen that there is an increase in the number of reporting with the maximum number of incidents reported during the year 2002. The increasing trend in reporting could be because of two reasons, (i) the actual number of incident occurrences themselves increased due to the increasing complexity of the technological systems in place, and/or (ii) more facilities would have started reporting to the database as HSEES established itself as reliable database. Nevertheless, in order to fully understand the reporting and make concrete conclusions about the industry trends based on HSEES database, more years of data are needed for analysis.

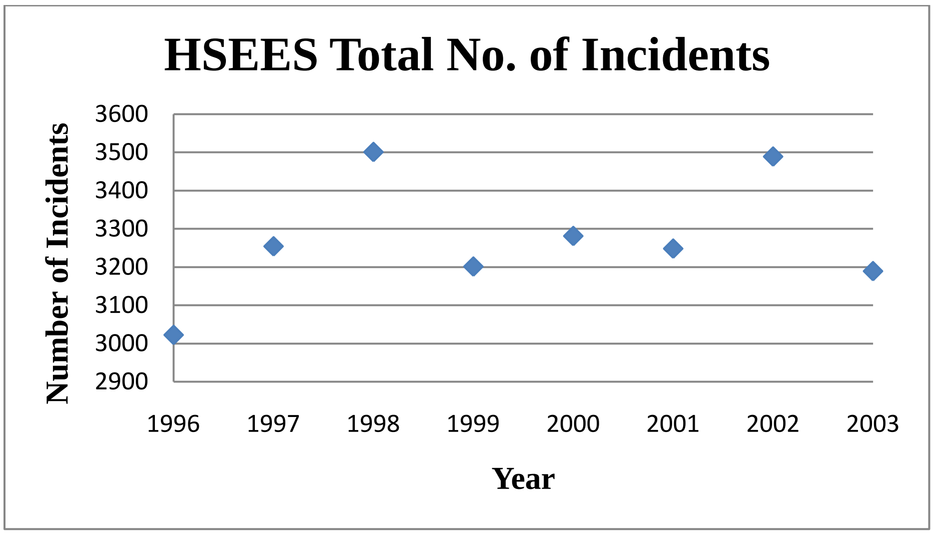


Figure 21. Total number of incidents reported annually in HSEES database

Fig. 22 shows the chemical process industry related major incidents reported in HSEES from 1996 to 2004. According to the reporting, there is an increase in the number of major injuries with a maximum of 79 major injuries in the year 2000. Initial reporting in 1996 might not accurately represent the actual number of major injuries because of the possibility of reluctance to report to a new program. The incidents for the year 2004 only accounts for major injuries collected until mid-year. From the figure, it can be seen that once again in order to fully understand the industry trends, more data in years are needed to be studied.

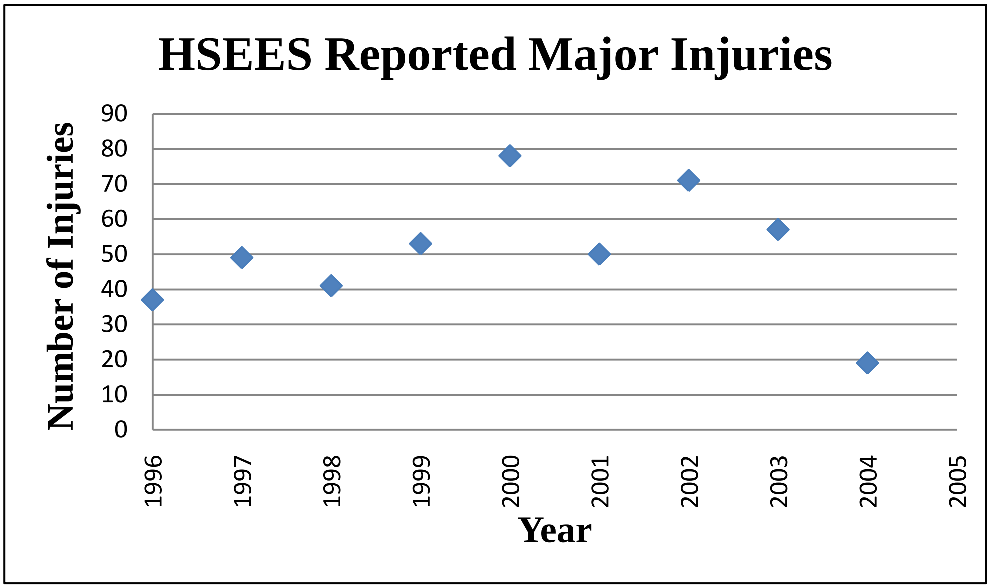


Figure 22. Total number of major injuries reported annually in HSEES database

Fig. 23 shows the graph of minor injuries reported in HSEES. In this case, the number of minor injuries reported is an average number between 400-500 injuries with maximum number of minor injuries for the year 2000. In 2000, the number of minor injuries reported peaked with approximately 900 cases. Once again it is important to note that the analysis of more years of data could provide more detailed information on the reporting trends and the number of injuries in the chemical industry.

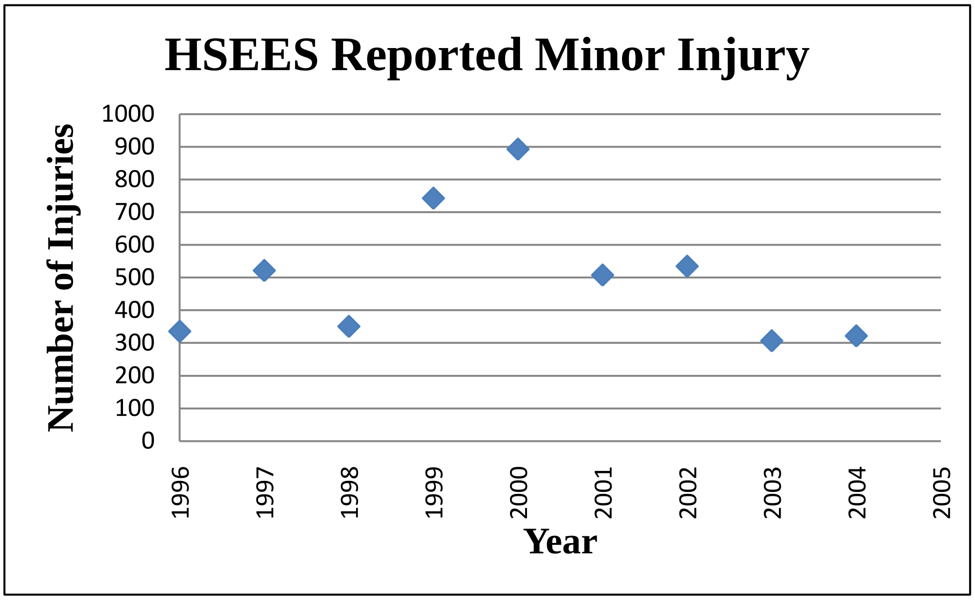


Figure 23. Total number of minor injuries reported in HSEES database

Fig. 24 shows the percentage of initiating causes of failures resulting in incidents for all reported process industry. Equipment failure was the major cause for the occurrence of an incident with approximately 57% of all incidents reported to have occurred because of equipment failure. The second reason for the incidents to occur was because of human error at approximately 37%. Natural and unknown causes for incidents were 2% and 4% respectively for all RMP reported industry incidents.

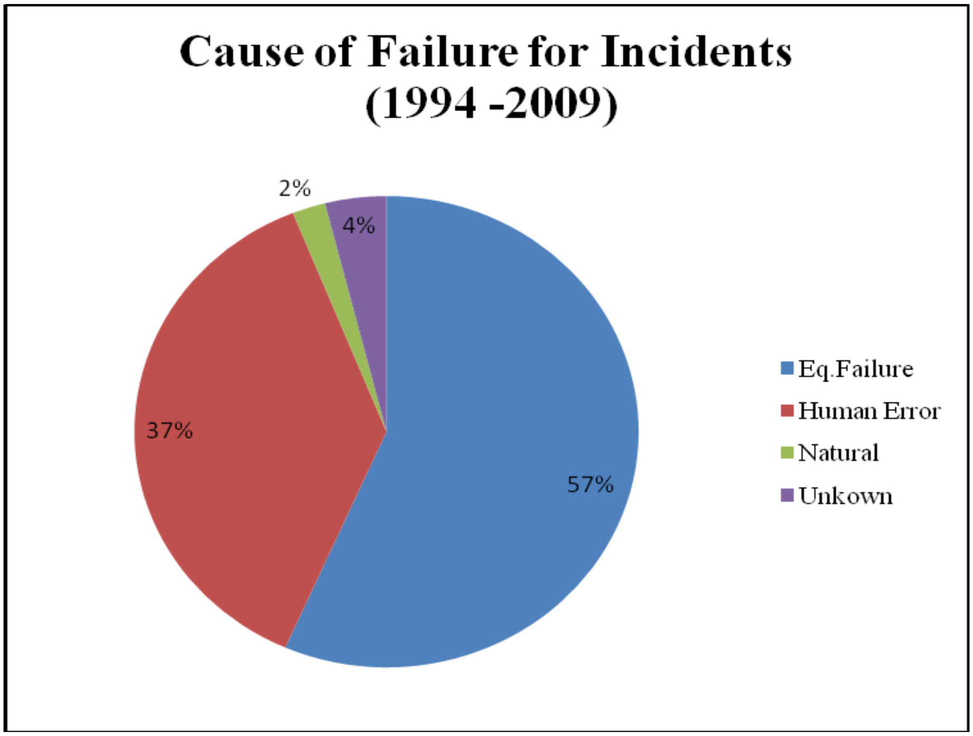


Figure 24. Different initiating causes of failures for all reported RMP incidents

Fig. 25 indicates the different initiating causes of failures leading to reported petroleum incidents in the RMP database. The equipment failure resulted in about 58% of total incidents with human error contributing to about 37% of all petroleum-related incidents. The incidents which occur due to natural and unknown causes accounted for 2% and 3% respectively. In both cases shown in Figs. 7 and 8, the percentages of incidents resulting from each of the initiating causal factors were almost the same with major cause of initiating failure to be equipment failure followed by human error.

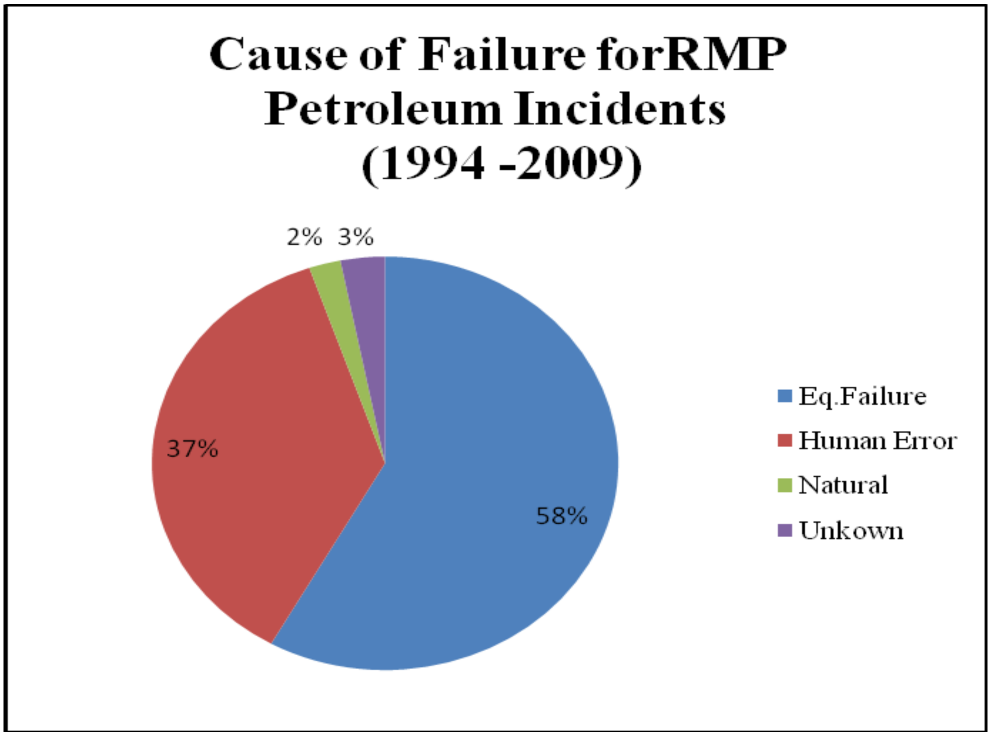


Figure 25. Different causes of failures leading to reported RMP petroleum incidents

Fig. 26 shows the pie-chart for different causes of failures resulting in incidents in the HSEES database. HSEES data collect several other different categories for causes of failures which are more specific than the RMP database. The equipment failure resulted in about 63% of all incidents, human error accounted for about 21%, deliberate damage accounted for about 6% of all incidents and system or process upsets was about 3%. Other causes including bad weather collectively resulted in about 7% of the reported incidents. Here damages because of deliberate act are separated from human error. Deliberate damage is defined as any damage due to willful or intentional act. If the cause for failure were also considered as human error, then the HSEES database compares well with the RMP causes for failures. Both databases would then have approximately 60%

of incidents caused by equipment failure and about 30% of incidents caused by human error.

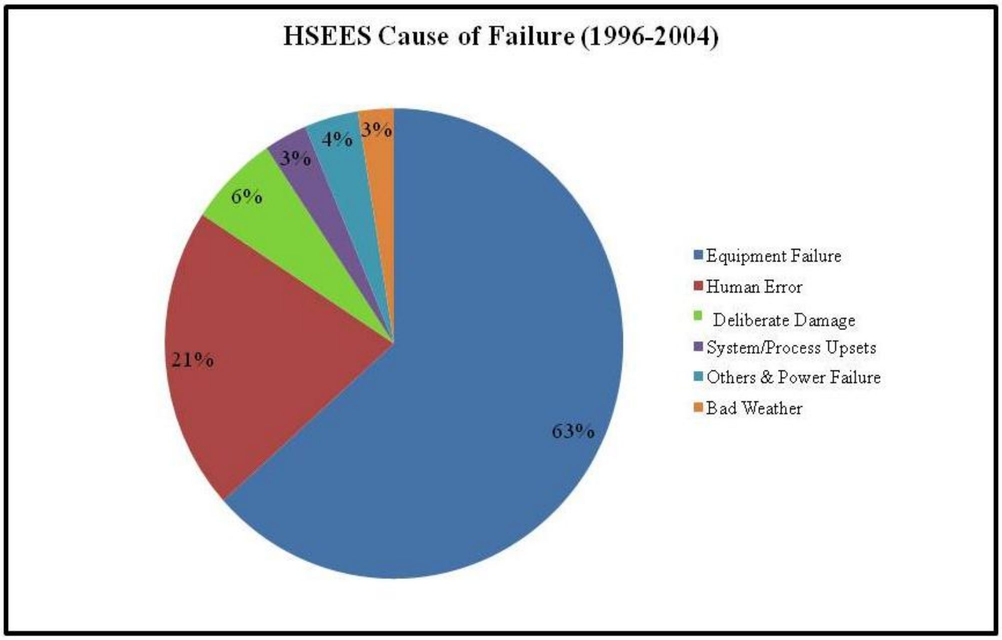


Figure 26. Different causes of failures leading to reported HSEES incidents

4.2.2. Societal loss from database information

Fig. 27 shows the relationship between exceedance frequencies and fatalities for all covered RMP facilities. This figure provides the profile of the number of fatalities for all facilities (approximately 14,000 facilities) per year covered under the RMP rule. The curves were generated using the total number of facilities covered under the RMP and the number of fatalities that occurred. Data from 1994 to 2009 were considered in order to include all the fatalities reported in the RMP database. In this figure, the single fatality occurs at an exceedance frequency of about 1/1,000 facilities and the maximum reported fatality of 17 occurs at an exceedance frequency of about 1/10,000 facilities. It is noteworthy that neither database has the information on the actual number of employees and the number of hours worked. Hence, these exceedance curves are not like the true frequency-number curve generated by either the UK HSE or the Dutch TNO for their facilities (Health and Safety Executive, 1989; Evans & Verlander, 1997; Natuurplanbureau, 2004). These exceedance curves generated here are solely generated to study the societal loss trend based on the number of years of data and the number of facilities covered in case of RMP database.

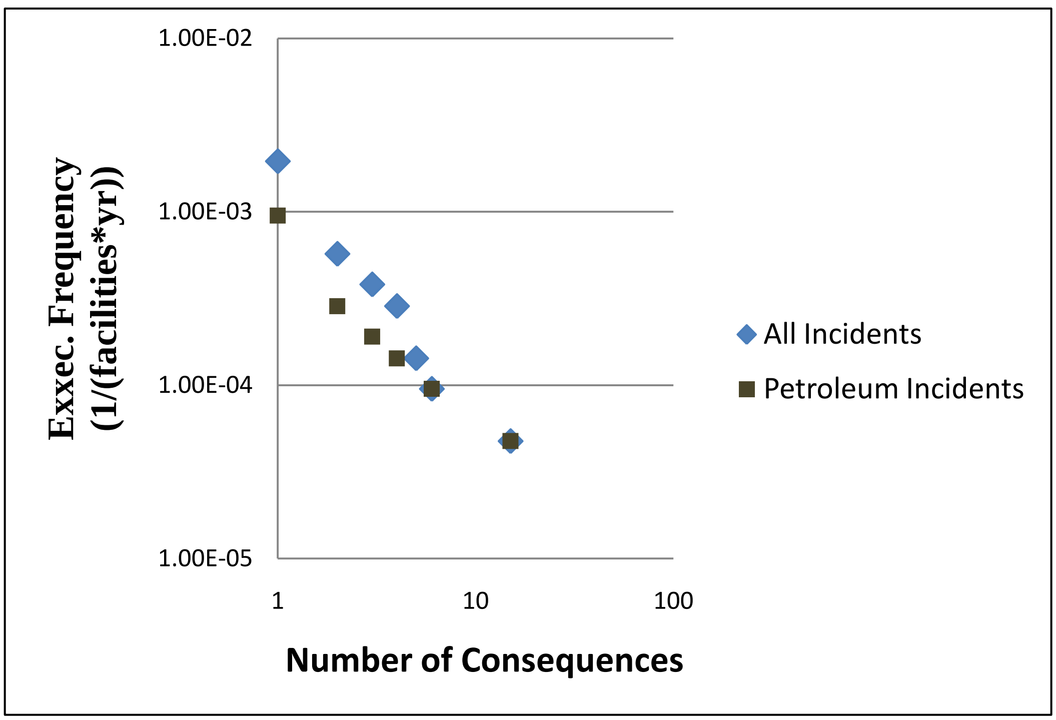


Figure 27. Relationship between exceedance frequencies and fatalities for all covered RMP facilities

Fig. 28 shows the relationship between the exceedance frequencies per year and the fatalities for both reported database incidents. The exceedance curves indicate that for low probability events the number of fatalities occurring is greater. The exceedance frequencies are calculated per year only because of the unavailability of information of the total number of facilities that report to HSEES. From this figure it can be observed that the single fatalities for both RMP and HSEES databases occur at higher exceedance frequencies, where as multiple fatalities occur at lower exceedance frequencies. Further, as the number of fatalities is greater, the exceedance frequencies are almost similar for such cases.

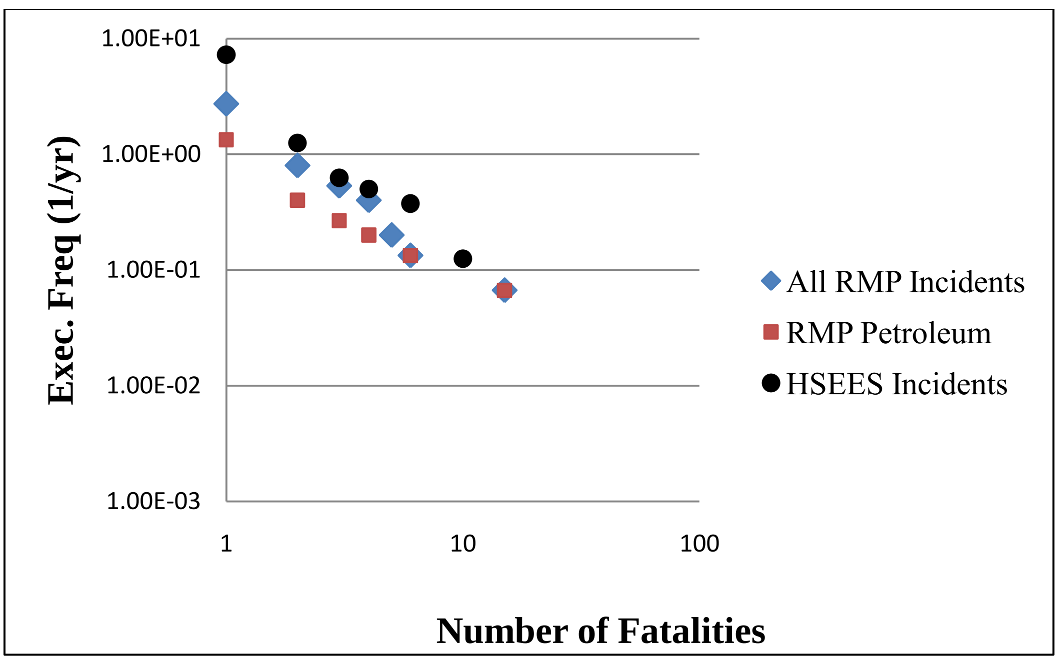


Figure 28. Relationship between the exceedance frequencies per year and the fatalities for both reported database incident

Fig. 29 provides the relationship between exceedance frequencies per facilities-year and injuries reported in the RMP database. The curves generated indicate a fatality for every 10 facilities. Also in comparison to the fatalities, single injuries occur almost an order of magnitude more frequently. Multiple injuries occur at a fairly lower frequency because major incidents lead to large number of injuries and such events are rare events. The relationship between exceedance frequencies and the number of injuries for incidents which have occurred in petroleum refineries covered under the RMP Rule are also presented. Here, it can be seen once again that single injury occurs at a lower frequency per facility for petroleum related injuries than that of the overall petrochemical industry. Multiple injuries occur at similar exceedance frequencies for the overall petrochemical industry and the petroleum industry incidents.

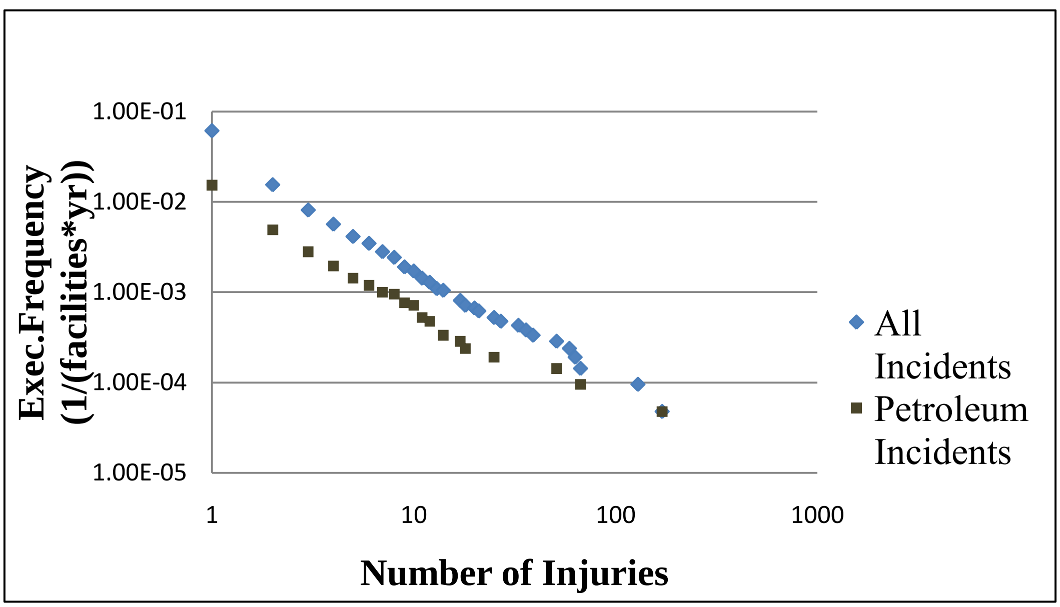


Figure 29. Relationship between exceedance frequencies per facilities-year and injuries reported in the RMP database

Fig. 30 shows the relationship between exceedance frequencies per year and the reported injuries in both databases. From these curves it can be seen that single injuries occur at a very high frequency, with almost one injury per day in HSEES. Again, similar to the RMP, the multiple injuries (over 100 injuries) occur at similar exceedance frequencies in the HSEES data. This would indicate that facilities in general are more risk averse in detecting and preventing incidents which would result in multiple fatalities but not single injuries.

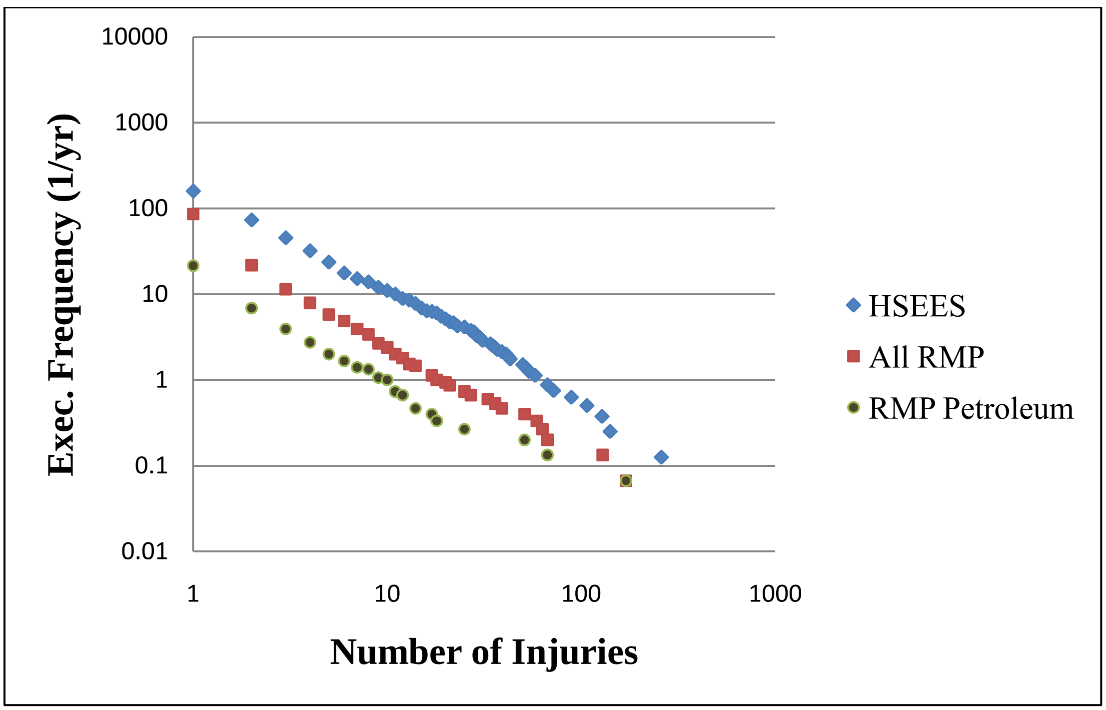


Figure 30. Relationship between exceedance frequencies per year and reported injuries in both databases

4.2.3. Accident propensity and relationship between consequences

For the sake of comparison of the generated safety pyramids with the safety pyramid proposed by Heinrich, only the top three steps or layers of the generated safety pyramid are utilized. This is because neither the RMP database nor the HSEES collects information about the near-misses. Fatalities are the loss of life reported in the databases. In the databases, the major injuries are injuries sustained by persons rendering them unfit for work and, being hospitalized and treated for more than 24 hours. Hospitalization with immediate release and first aid treatment are considered as minor injuries. Evacuations are also considered in the safety pyramids as low consequences of reported events to understand the domino theory of Heinrich.

Fig. 31 shows the safety pyramid for accident statistics for all reported EPA-RMP incidents. The ratio of fatalities: injuries: hospitalizations: evacuations was 1:31:109:6470 while the ratio of major injury: minor injury: near-misses in Heinrich Pyramid was 1:29:300. If it is assumed that one major injury indicated by Heinrich is an actual Fatality, then the results from the generated safety pyramids in this study can be comparable with the Heinrich safety pyramid. The major injuries reported in RMP for one single fatality is 31 as opposed to 29 from the Heinrich's safety pyramid. This could imply that, generally more low consequences would eventually have the potential for one fatality in facilities covered under RMP rule. This could also indicate that owing to the broad base (large number of evacuations), there is greater chance to curtail the failures at the low consequence levels before it leads to high consequences in RMP facilities.

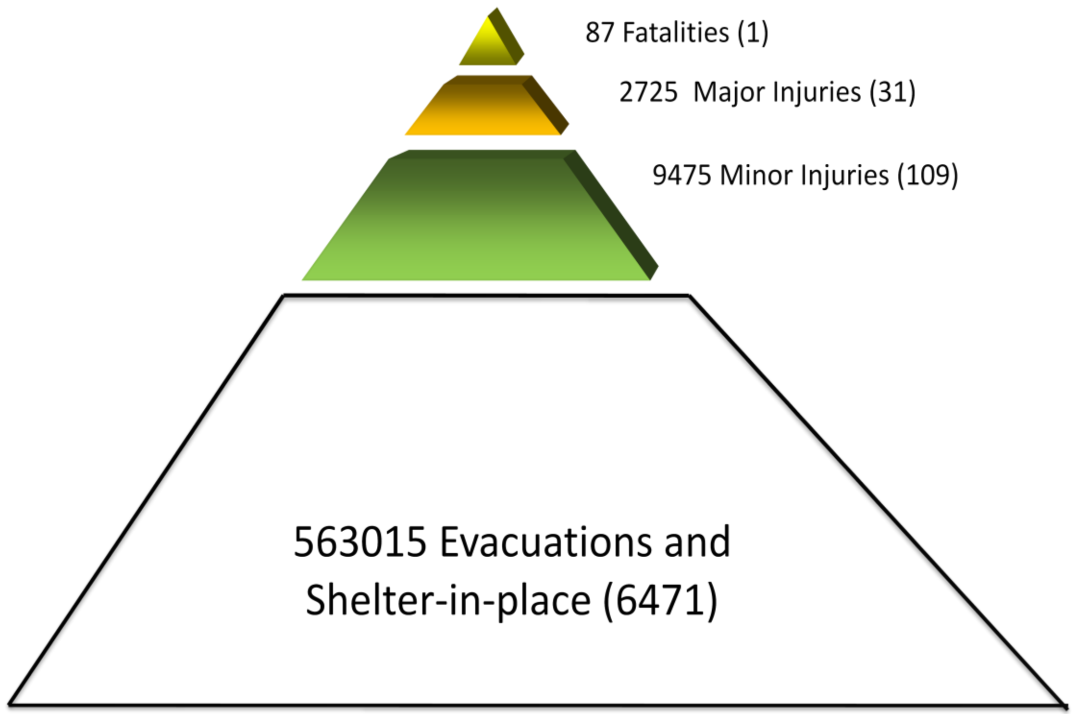


Figure 31. Safety pyramid for accident statistics for all reported EPA-RMP incidents

Fig. 32 shows the safety pyramid for accident statistics reported for petroleum industry in the RMP database. The ratio of this safety pyramid is 1:22:41:7013. In comparison to the Heinrich's safety pyramid, there is large number of "near-misses" in terms of evacuations and shelter-in-place because of the broad base. However, the first three levels of the safety pyramid are narrow indicating once again that if causal analysis of low consequence events are investigated in a timely manner, it would aid in preventing or limiting the occurrence of high stakes at risk consequences. So in order to prevent serious consequences from resulting, safety measures must be adopted properly once the reasons for the evacuations have been investigated.

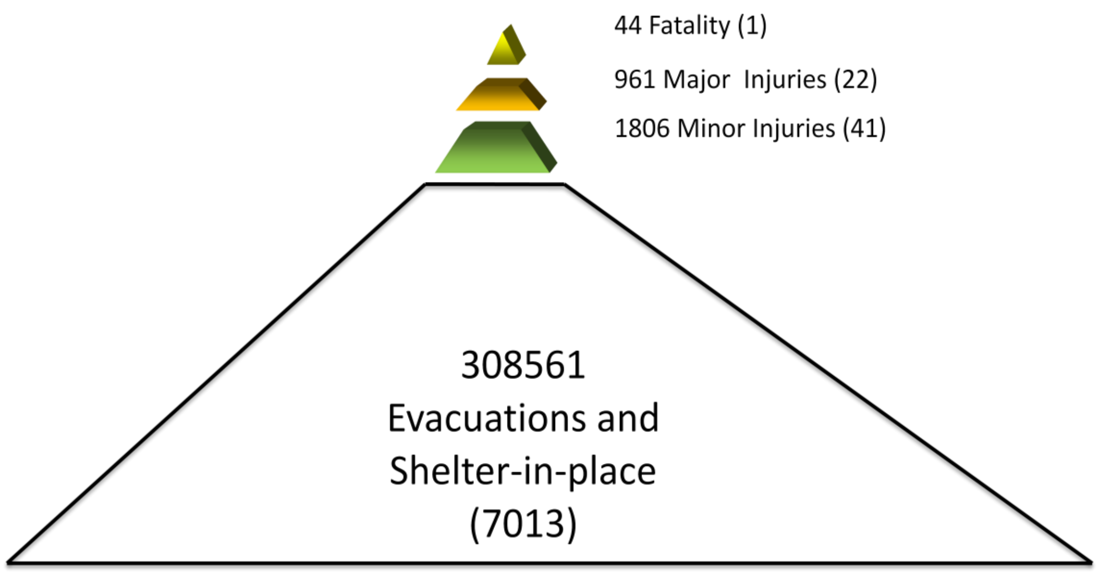


Figure 32. Safety pyramid for accident statistics for petroleum industry reported in EPA-RMP database

Table 12 shows the proportion of incidents occurring from petroleum-related operations and chemical manufacturing/processing to that of the total petrochemical incidents reported in the RMP database. In general, the incidents resulting in major consequences such as fatalities is of equal proportion for both petroleum and chemical processing incidents even though the number of petroleum incidents is only about 28%. About 55% of incidents which caused mass evacuations and shelter-in-place are due to petroleum-related incidents. This table shows the seriousness of consequences from petroleum-related incidents is greater than chemical processing facilities considering that fewer number of petroleum refining incidents are reported. Hence adequate safety measures must be implemented in petroleum refineries because even though fewer accidents result, their consequences are higher. It is noteworthy that there are fewer petroleum incidents reported in RMP compared to chemical incidents. However, the consequences are almost comparable thereby implying that petroleum industry incidents result in more severe consequences because of their large manufacturing or processing capacities.

Table 12. EPA-RMP percentage of petroleum and chemical incidents to total petrochemical incident consequences

Consequence	**Total**	**Petrochemical**	**Chemical**	**%Petroleum**	**%Chemical**
Incidents reported	2528	707	1821	28	72
Fatalities	87	44	43	51	49
Total Injuries	2725	961	1764	35	65
Hospitalization & Treatment	9475	1806	7669	19	81
Evacuation & Shelter in place	563015	308561	254454	55	45

Fig. 33 shows the safety pyramid for all reported incidents in the HSEES database. The ratio between the different consequences is 1:4:35:389. This pyramid is narrow and indicates that there is greater chance of high consequences resulting from low consequence events because there is insufficient time to investigate the causal factors for low consequence events. This could also indicate that there is a greater chance that the same scenarios could result in either low consequences or high consequences if an accident were to occur. In comparison to the safety pyramid of Heinrich, this safety pyramid is narrow with smaller ratios for the different steps of the pyramid. This indicates that there is generally a greater chance of higher consequences resulting from incidents reported in HSEES.

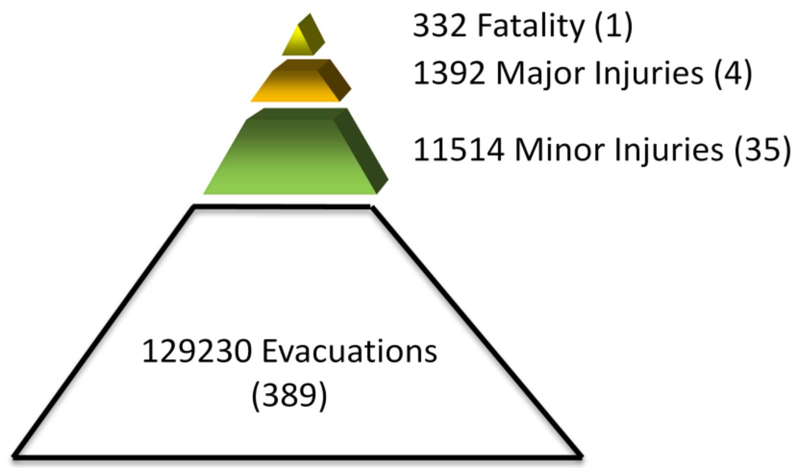


Figure 33. Safety pyramid for all reported incidents in the HSEES database

Since the HSEES safety pyramid indicates the greater possibility for the low consequences resulting from incidents to escalate to high consequence events, the HSEES database was studied in details by generating safety pyramids for different types of causes for failure which resulted in HSEES incidents. Fig. 34 schematizes the safety pyramid from incidents reported in HSEES database as a result of failure due to human error. In this case, the safety pyramid has broad base with 34,066 evacuations with 1,652 minor injuries, 218 major injuries leading to the chance of total of 30 fatalities. The incident consequence ratio is 1:7:55:1136 for fatality: major injuries: minor injuries: evacuations. This pyramid indicates that generally there is sufficient time to prevent future incidents resulting in more serious consequences if the root causes for the incidents resulting in low consequence events are investigated in timely manner.

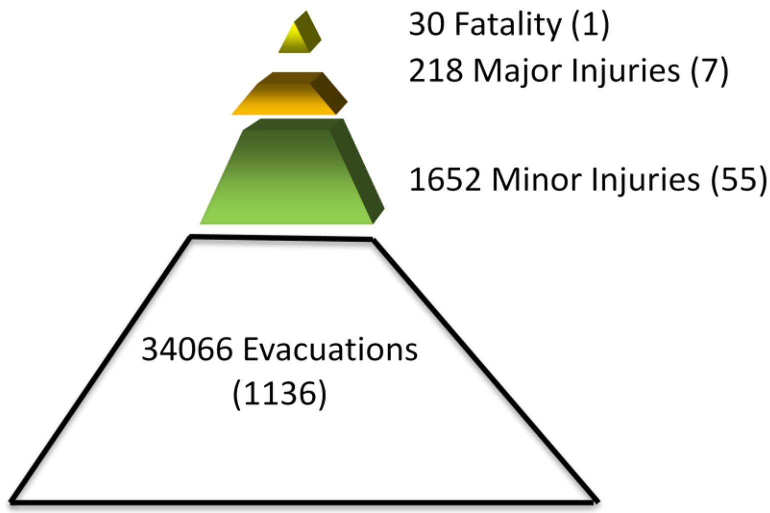


Figure 34. HSEES safety pyramid for incidents reported because of human error

Fig. 35 depicts the safety pyramid from reported incidents in HSEES because of equipment failure. The ratio of this pyramid is 1:10:128:3592. This pyramid has the broad base showing "near-miss" incidents or evacuations. This pyramid indicates that before serious consequences result from an incident, proper safety measures set in place such as reliability studies and maintenance of equipment could greatly decrease the probability of occurrence of high consequences. Also, in this case, the tracking of near-misses and understanding of the causal factors could greatly decrease the chance of low consequences of incidents escalating to more serious ones.

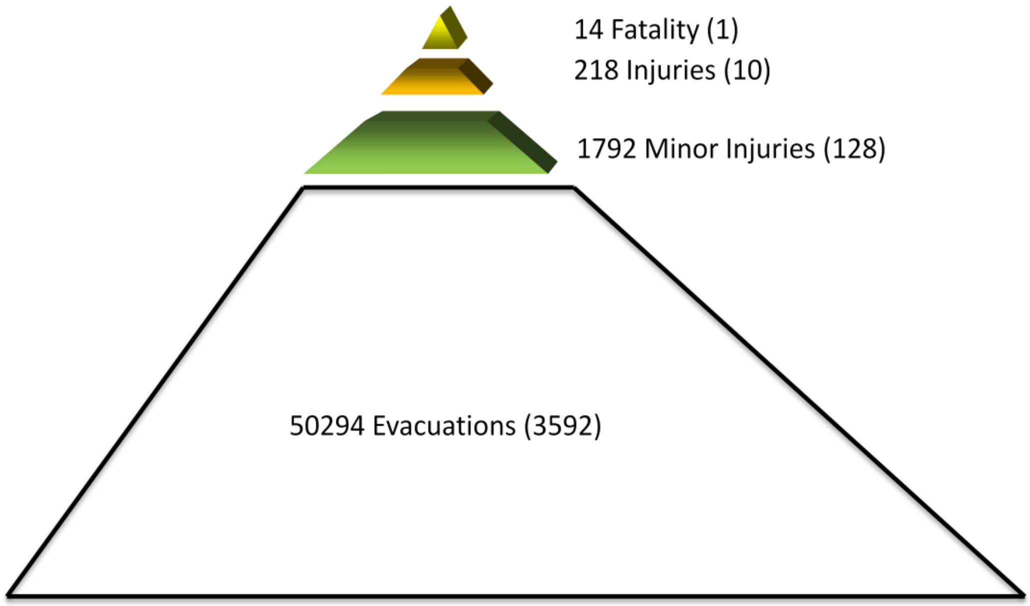


Figure 35. HSEES safety pyramid for incidents reported because of equipment failure

Fig. 36 shows the safety pyramid generated for reported incidents in HSEES which have occurred because of unknown causes. The ratio of this safety pyramid is 1:3:63:1505. This safety pyramid is narrow at the top three tiers indicating that there is sufficient time to identify and rectify the reasons for events causing evacuations thereby increasing the chances of limiting the occurrence of events with more serious consequences owing to the broad base of the safety pyramid with respect to the top tiers.

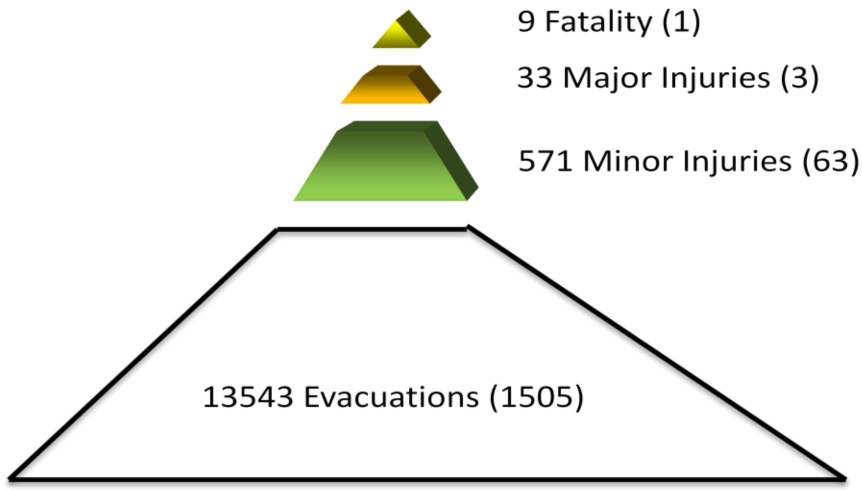


Figure 36. HSEES safety pyramid for incidents reported because of failure from unknown causes

Fig. 37 shows the HSEES safety pyramid due to failure from natural causes. The ratio of this pyramid is 1:2:3:21. This safety pyramid is the narrowest of all. In this case, the stakes at risk due to unknown cause such as hurricane is very high and equally result in major and minor consequences. Hence, adequate safety measure must be sought to prevent adverse consequences.

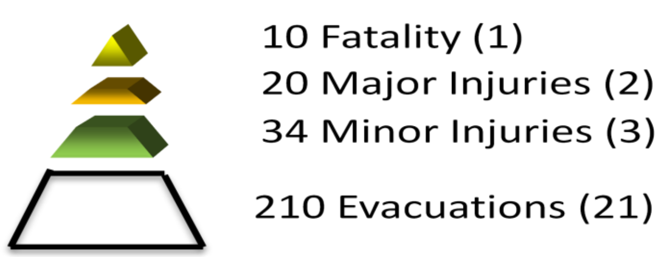


Fig. 37. HSEES safety pyramid for incidents reported because of failure from natural causes

Once the safety pyramids are generated, it is important to understand whether there is any relationship between the different steps of the pyramid (*i.e.*, different reported consequences). If there is a statistically significant relationship, then it would support the domino theory of accident consequences suggested by Heinrich. Therefore, the following work focuses on establishing any existing relationship between each of the consequences of the safety pyramids and also studies the relationship between high consequences such as fatalities with the combined effect of other reported low consequences. Hence, the correlation and regression analysis have been performed for safety pyramid data for overall incidents reported in both databases using the PASW software (formally known as SPSS).

The correlation matrix for the different consequence types used to generate the safety pyramids are shown in Table 13 for HSEES database. The four variables used for the correlation are the number of fatalities, the number of major injuries, the number of minor injuries and the number of evacuations without the shelter in place. The cells of the correlation matrix provide the correlations for all variables in the rows and variables in the columns. The first cell having the Pearson correlation coefficient of 1 implies that the variable is correlated with itself. This is true along the major diagonal for all variables correlated with themselves. The cells along the diagonal are symmetric. For other correlations, the Pearson correlation signifies the R value, the significance number is the p-value and N is the number of years that have data for both variables. The most important information to note from this matrix is that the number of fatalities correlated with the number of major injuries and the number of evacuations are statistically significant. Similarly, the correlation between the number of major injuries and number of minor injuries are statistically significant and hence there is a valid relationship between them. Also, evacuations correlated with number of fatalities and number of minor injuries are statistically significant, indicating that there exists a relationship between the three variables. Hence, from this matrix it can be concluded that most of the variables or indicators have a strong individual correlation with each other in HSEES database.

Table 13. HSEES correlation coefficient matrix results from PASW

		No. of fatalities	No. of major injuries	No. of minor injuries	No. of evacuations without shelter- in-place
No. of fatalities	Pearson Correlation	1	0.655	0.447	0.658
	Sig. (2-tailed)		0.055	0.228	0.054
	N	9	9	9	9
No. of major injuries	Pearson Correlation	0.655	1	0.697*	0.495
	Sig. (2-tailed)	0.055		0.037	0.176
	N	9	9	9	9
No. of minor injuries	Pearson Correlation	0.447	0.697*	1	0.723*
	Sig. (2-tailed)	0.228	0.037		0.028
	N	9	9	9	9
No. of evacuations without shelter in place	Pearson Correlation	0.658	0.495	0.723*	1
	Sig. (2-tailed)	0.054	0.176	0.028	
	N	9	9	9	9

The regression analysis for HSEES was performed with fatalities as the dependant variable and the number of major injuries, the number of minor injuries and evacuations as the predictor (independent) variables. Very strong collective relationship of the predictor variables to the dependent variable was observed implying that the number of lower consequence events influences the high consequences. The multiple correlation coefficient, R, was 0.82 indicating strong relationship between the predictor variables and the dependant variable. The R^2 value of 0.67 indicated that 67% of the variance in average fatality values could be predicted by the combination of the predictor variables.

The linear multiple regression was performed for four categories of consequences from HSEES database to collectively analyze the effect of the predictor variables on the dependant variable 'fatality'. Equation 1 shows the regression equation along with the constant and all coefficients of the predictor variables. The constant value of -3.91 in the regression equation indicates that in case of all the predictors being set to zero, the resulting fatalities will be negative, *i.e.*, there will be no fatalities.

However, based on the database analyses of reported incident consequences, there is no possibility of having fatalities without lower consequences and this equation supports the fact. In other words, whenever there is an incident with the potential to result in high consequence such as fatalities, there will more likely also exist low consequences such as injuries and evacuations.

The regression equation indicates the presence of relationship between the lower tiers and the upper tiers of the safety pyramid. From the regression equation, it can be seen that the coefficient of the number of major injuries per incident was 0.247 which is the value that would be added to the number of expected fatalities in case there was a major injury as a result of an accident. In case of one minor injury resulting per incident, the value of 0.017 would be deducted from the value of expected fatalities. Similarly, for every evacuation made, the expected fatalities value should be increased by a value of 0.001. The regression equation resulting from the analysis is shown in equation 16.

$$F = -3.91 + 0.247\ X_1 - 0.017\ X_2 + 0.001\ X_3 \qquad (16)$$

where: F = number of fatalities,

X_1 = number of major injuries per incident,

X_2 = number of minor injuries per incident, and

X_3 = number of evacuation per incident.

Table 14 shows the pair-wise correlation between the different incident consequences reported in the RMP database. From this Table it can be seen that there is no significantly statistical individual correlation between the different variables when compared two-by-two, except the number of fatalities per year with total evacuations and shelter-in-place and, major injuries per year with minor injuries per year.

Table 14. EPA-RMP correlation coefficient matrix from PASW

		No. Fatalities	No. of major injuries	No. of minor injuries	No. of Evacuations and shelter in place
No. of fatalities	Pearson Correlation	1	-0.209	-0.33	.721**
	Sig. (2-tailed)		0.456	0.229	0.002
	N	15	15	15	15
No. of major injuries	Pearson Correlation	-0.209	1	.913**	0.099
	Sig. (2-tailed)	0.456		0	0.727
	N	15	15	15	15
No. of minor injuries	Pearson Correlation	-0.33	.913**	1	-0.028
	Sig. (2-tailed)	0.229	0		0.921
	N	15	15	15	15
No. of evacuations and shelter in place	Pearson Correlation	.721**	0.099	-0.028	1
	Sig. (2-tailed)	0.002	0.727	0.921	
	N	15	15	15	15

The regression analysis was performed on the RMP data with fatality as the dependent variable and the number of major incidents per incident, number of minor injuries per incident and, the number of evacuations and shelter-in-place as the independent or predictor variables. The multiple correlation coefficient, R, was 0.79 indicating the existence of strong relationship between the predictor variables and the dependant variable. The R^2 value of 0.62 indicates that almost 62% of the variance in the average fatalities could be predicted by the combination of the predictor variables.

The linear multiple regression was performed for four categories of consequences to collectively analyze the effect of the predictor variables on the dependent variable ‘fatality’. Equation 17, shows the regression equation with constant value of 2.379, which indicates that in case of all the predictors being set to zero, the resulting fatalities is a positive number. However, in reality, this is highly unlikely because historically, accidents occur only after a series of near misses and low consequences before adverse consequences result. Furthermore, this could indicate that the stakes at risk of consequences reported in RMP is greater because of the type of incidents reported in the RMP being more serious. The other regression coefficients are 0.007 for major injuries per incident, which implies the value that would be added to the number of expected fatalities in case there was a major injury as a result of an incident. In case of one minor injury resulting from an incident, the value of -0.002 would be deducted from the value of expected fatalities. Similarly, for every evacuation made, the expected fatalities value should be increased by a value of 0.0004. The negative coefficients indicate that there is an inverse relationship between fatalities and injuries. Most importantly, the equation does indicate that a relationship exists between the different tiers of the pyramid which supports the claim of Heinrich (Heinrich, 1940).

$$F = 2.379 + 0.007\, X_1 - 0.002\, X_2 + 0.0004\, X_3 \qquad (17)$$

where, F = number of fatalities, X_1 = number of major injuries per incident, X_2 = number of minor injuries per incident, X_3 = number of evacuation and shelter-in-place per incident. From the analyses of the two databases an attempt has been made to understand the frequencies of incidents, their resulting reported consequences particularly the number of fatalities, injuries, evacuations and shelter-in-place (available only for RMP) and, develop the relationship between the different consequences which make up the safety pyramids. From the study it can be deduced that generally the number of incident occurrences reported have decreased annually (especially in the last few years) for both databases. The reason for this could be because of the increased awareness of process safety and the implementation of risk mitigation measures mandated by regulatory.

The relationship between exceedance frequencies and societal losses were generated to understand the societal impact of incidents reported in the two databases. Generally, the exceedance curves for fatalities are about one order of magnitude lower than that of the exceedance curves for injuries. While the HSEES database has many more datapoints than the RMP database, it is observed that generally, injuries occur at higher frequencies than fatalities for both databases. The multiple injuries (over 100 injuries) occur at similar frequencies for both the RMP and the HSEES data indicating that the facilities in general are more risk averse in detecting and preventing multiple consequences but not single injuries or fatalities. Furthermore, generally societal losses such as fatalities mostly occur within the confines of plant facilities.

In order to understand the ratios of different consequences resulting from incidents, the safety pyramids were generated for the two databases. Due to the availability of large number of HSEES data and because the data had a greater potential to escalate to serious consequence events based on the shape of the overall HSEES pyramid, the information from HSEES were utilized to generate safety pyramids for the different initiating causes of failures leading to incidents. As seen in Figs. 31-37, the safety pyramids indicate that for any accident, under suitable conditions, the resulting consequences could escalate into more serious consequences if the factors leading to the incidents were not indentified and rectified in timely manner. Among the safety pyramids generated for the different causes for failures in the HSEES database, the safety pyramid for natural and unknown causes were more serious or "risky" because of the greater potential for consequences to result in serious or adverse consequences under suitable conditions.

Pair-wise correlation and regression analysis were also performed on data reported in both databases. The individual correlations performed between different consequences indicated that no single factor could sufficiently describe its effect on other consequence. Only in some cases such as the total number of evacuations with the number of people hospitalized and treated and, major injuries per year with minor injuries per year from RMP data the correlations were statistically significant based on the PASW study. Similarly, from the HSEES database, number of fatalities with number of major injuries, fatalities with minor injuries, fatalities with number of evacuations and, number of major injuries with number of minor injuries were statistically significant based on the PASW study indicating the existence of relationship between those consequences.

For understanding the collective relationship of lower tier consequences with that of fatality, the statistical regression analyses were performed using PASW software for data reported in both databases. Collectively, the lower steps of the pyramid have statistically significant relationship with the top level of the safety pyramid, which is in agreement with the domino theory of Heinrich. If the domino theory of Heinrich were utilized, then the number of fatalities and major injuries (societal losses) could significantly be decreased by exclusively focusing on decreasing the number of low consequence occurrences such as evacuations. Hence, facilities and regulatory agencies tracking the different consequences could utilize the regression equations pertaining to the two databases to estimate the propensity of accident consequences to result in potential high-risk incidents or high-consequence events. RMP data could specifically be utilized by all US facilities covered under the RMP rule, especially the petroleum industry and HSEES data could be utilized in general by all US chemical facilities especially those housing hazardous substances.

Fig. 38 shows a novel concept of representing losses using three dimensional representation of incident risk analysis, property damage and type of incident consequences. Such representations connecting important information will prove to be useful to see the interrelationship between important factors mined from the database. In this figure, if the risk aversion (RA) is considered to be increased from RA5 to RA1, with RA1 representing the most risky scenario consequences, the RA could be related to the frequency of *FN*-curve HSE tolerable criterion as follows: RA5 <10E-06, 10E-06 ≤ RA4 ≤10E-05, 10E-05 ≤ RA3 ≤10E-04, 10E-04 ≤ RA2 ≤ 10E-03 and RA1 ≥ 10E-03. It is seen from Fig. 38 that as the seriousness of the risk aversion increases, the consequences in terms of the average property damage loss per incident reported in HSEES also increases. The property damage loss for RA1 incident with potential fatalities could result in approximately $8mil.

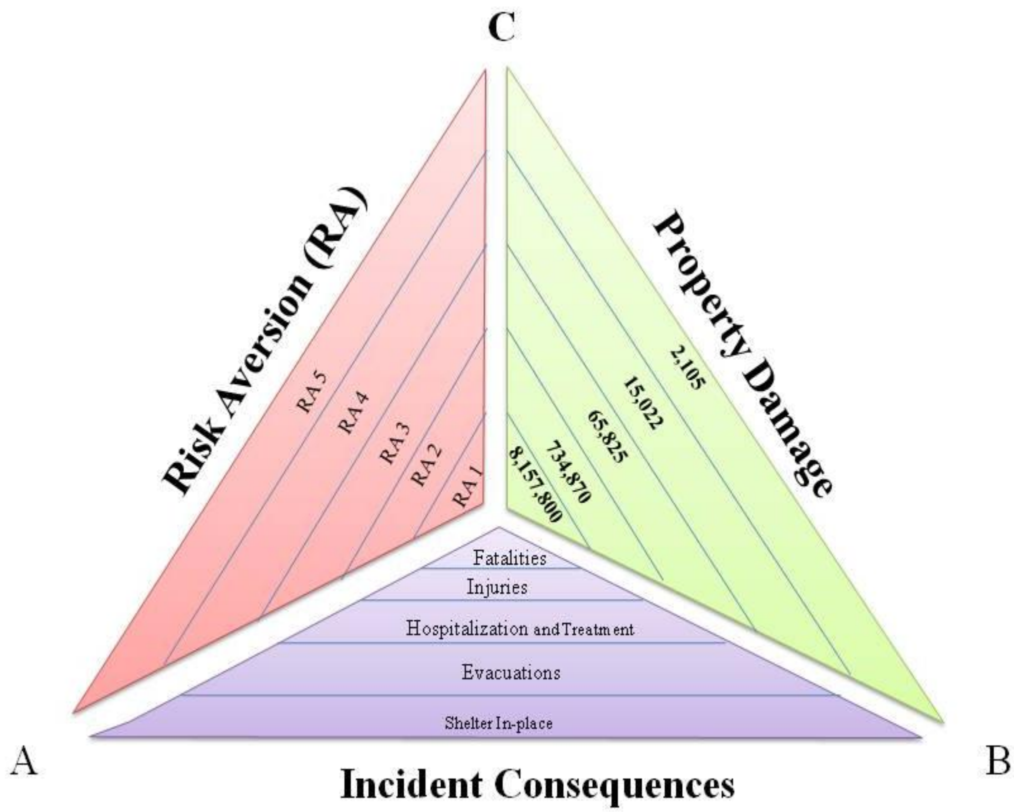


Figure 38. Three dimensional representation of incident risk analysis, property damage and type of incident consequences

4.3. Expected Utility Theory and Game Theory

In chemical engineering, the use of expected utility theory and application of game theory concepts is a novel approach. The first step is the quantitative risk analysis using QRA to estimate the different portfolio scenarios inclusive of expected tangible losses and societal losses and, converting the expected tangible consequences in monetary form (Prem, Ng and Mannan, 2010). Performing a QRA for preventing catastrophes would provide the account of the different types of equipment and areas of the process plants which are more susceptible to failure or damage to cause an extreme incident (Prem, Ng, Sawyer *et al.*, 2010; Pasman *et al.*, 2009). The next step is to assess the conflict between the risk of scenario options and the safety measures to be implemented for risk mitigation (or risk reduction) for the deduced scenarios.

Expected utility principles could be most effectively utilized to decide which design alternative is most preferred in the presence of competing design alternatives. For each of the different portfolios, the different criteria have to be evaluated and estimates must then be compared. For understanding how the different criteria interact to provide optimality for that particular option or portfolio, game theory concepts can be utilized by choosing dominant criteria among the multi-criteria. The preferred is to utilize the Nash equilibrium method for achieving multi-criteria equilibrium solution for each design or portfolio option. Nash equilibrium would provide the ideal solution of the multi-criteria problem treated as a game involving strategic players (different criteria with different strategies for risk reduction) in which no gain is unilateral (Dixit & Skeath, 2004). In other words, the gain will benefit the overall portfolio performance. Once, the different portfolio options have an equilibrium solution, they can then be studied further for assessing the maximum expected utility to choose the most preferred option for a trade-off between risk because of production and risk reduction for safety. Fig. 39 shows the novel decision making framework for ensuring optimum solution of most preferred risk is chosen by a decision maker.

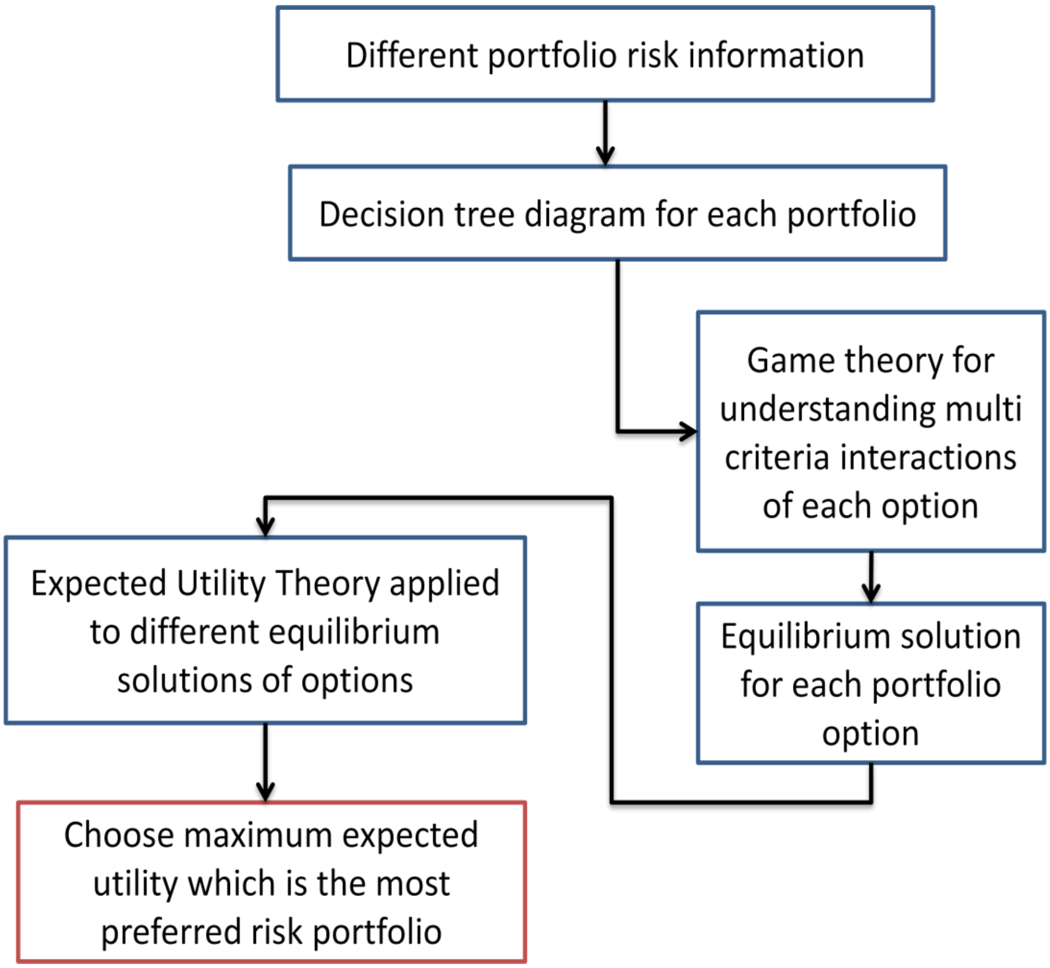


Figure 39. Decision making framework based on risk analysis in the chemical process industry

The problem of decision making is essentially that of evaluating the competing options or alternatives available and choosing the most preferred risk option. Hence, the different parameters to be considered for decision making should first be classified into representative groups. The representative groups would consist of similar parameters. For example, different types of equipment for one particular process could be classified as one representative set. Similarly, another representative set could be all intangible aspects such as environmental damages, loss of possible reputation, societal risk aversion, possible job losses and risk tolerability of companies. Loss because of incident consequences such as initial setup cost, insurance cost, falling share prices of products in the event of major incidents could be considered another different criteria for decision making. While there are representative sets for expected losses, whether tangible or intangible, there should also be representative sets for safety systems such as active safety systems like safety instrumented systems and passive safety systems such as containment and blast wall. The representative sets should clearly be distinct in function, in terms of the amount of expected monetary loss and whether the representative set is tangible or intangible representative set. This way, all the losses estimated from QRA studies can all included in the decision making process.

For each of these sets if the decision is to be made between different design options, either during new installation or during management of change process, then expected utility theory concepts should be utilized and most preferred option chosen based on most preferred risk. If the decision is to be made for choosing the preferred process for a portfolio design, among competing safety alternatives for mitigation risks based on QRA-*VaR* study recommendations, then game theory concepts can be utilized to understand the strategic interactions between the different representative sets.

Usually decision analyses are based on desirability of an alternative which depends on attributes of parameters. In the proposed framework, the parameters are classified into representative sets to consider which set serves as the dominant criteria regarding monetary value loss, production performance level, the potential risk level of portfolio scenarios and societal risk acceptance by the public. For each attribute or representative set which is the dominant contributor, it can be termed as the decision factor. For the decision factor utility functions would represent how the factor would contribute to the value of each alterative. Individual utility functions for different decision factors for each alternative would then be combined to identify the highest utility value as the optimum design option (Ang and Tang, 2007). Therefore, the utility of highest utility value would be the maximum expected utility value of all dominant contributor decision factors based on the representative set as shown by equation 18.

$$E\ (U_{max}) = \max\left(\sum_j p_{ij} * u_{ij}\right) \qquad (18)$$

where, u_{ij} = utility of representative decision factor

p_{ij} = probability of representative decision factor

Regardless of what type of decision analysis method is used the final step has to be sensitivity analysis. Final step in decision analyses is to check if the option chosen is the most preferred option or not. Hence sensitivity analyses should be performed. Chen, Kilgou and Hipel (2008) provide an overview for obtaining Pareto optimality based on screening. Other screening techniques based on tradeoff weights, non-tradeoff weights, aspiration levels and data development analysis are also mentioned as methods which can be used subsequently after the basic Pareto optimality screening. More future study needs to focus on developing screening methods for EUT and GT Nash equilibrium solutions in application to chemical process industry safety.

4.3.1. Example illustrating the use of expected utility theory

The following illustrates the use of utility to estimate the maximum utility to choose the most preferred option from conflicting alternatives. For each decision factor one utility function represents how that attribute contributes the value for overall utility. Thus, individual utilities are combined to estimate overall utilities for portfolios of study and the most optimum design option or portfolio option is selected. Here, the alternative with highest value for safety and production in comparing two different offshore platform designs is chosen as the best option. The maximum expected utility criteria provides more than a dollar value placed in decision making. If utilities for different consequences are known, u_{ij} and the probability of achieving that utility is p_{ij}, then the expected utility value of each alternative will be as shown in equation 19.

$$E(U_i) = S_j\ (p_{ij} * u_{ij}),\ i = 1,2,3\ldots n \text{ and } j = 1,2,3\ldots m \qquad (19)$$

The alternative with highest expected utility is provided by the maximum expected utility value as shown in equation 20.

$$E(U_{opt}) = \max\ (S_j\ (p_{ij} * u_{ij})) \qquad (20)$$

For the sake of explanation, two offshore platform designs are considered as conflicting portfolio options for decision making. The cost of Design A is estimated at \$10mil and design B is estimated at \$12mil. The annual height of wave as described by Ang (1990) is assumed to be 30m high with a covariance of 0.2. If the wave height is greater than 40m for design A and greater than 44m for design B, then the platforms could collapse. It is assumed that the cost of installation of design A is \$10mil and design B is \$12mil. In case of the collapse of design A the company will lose \$60mil and for design B the loss is \$65mil. If the probabilities for collapse, C, and platforms being intact, I, from the wave height distribution are adopted from Ang (1990), then the following decision tree shown in Fig. 40 could result.

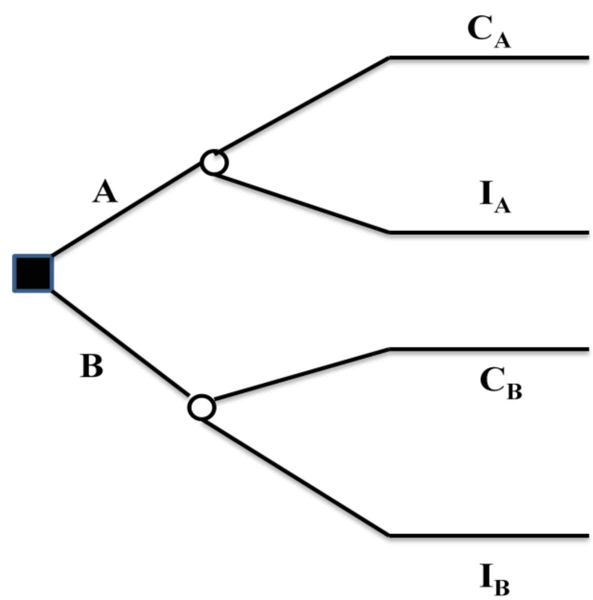


Figure 40. Decision tree for collapse and intact scenarios for two platform designs

If lognormal distribution is assumed and probabilities for platform collapsing and remaining intact are calculated for both designs, then the following values would result.

P_{CA} of design A collapse: $P(H>40) = \Phi\ [(\ln 40-\ln 30)/0.2] = \Phi\ (z=1.43) = 0.076$

P_{IA} of design A intact: $P(H<40) = 1- P(H>40) = 0.924$

Similarly,

P_{CB} of design B collapse: $P(H>44) = \Phi\ [(\ln 44-\ln 30)/0.2] = \Phi\ (z=1.915) = 0.028$

P_{IB} of design B intact: $P(H<44) = 1- P(H>44) = 0.972$

If it is further assumed that average range of fatalities for design A collapsing is (10, 5) and for design B is (10, 3) and, (0, 0) for structure remaining intact for both cases, then the expected utility based on work by Ang(1990) for both cases are calculated as shown.

$$E[U_A] = \Sigma (U_{Ai} * P_{Ai}) = [u_{CA} * P_{CA} + u_{IA} * P_{IA}]$$

$$E[U_B] = \Sigma (U_{Bi} * P_{Bi}) = [u_{CB} * P_{CB} + u_{IB} * P_{IB}]$$

where, $u_{CA} = E[1\text{-}.004\ X_{AC} – 0.005\ E(N^2{}_{AC})]$

and, $u_{CB} = E[1\text{-}.004\ X_{AB} – 0.005\ E(N^2{}_{AB})]$

$$E[X_{AC}] = 60mil + 10mil = 70mil$$

$$E[N^2{}_{AC}] = E[N_{AC}]^2 + Var(N_{AC}) = 10^2 + 5^2 = 125$$

$$E[X_{BC}] = 65mil + 12mil = 77mil$$

$$E[N^2{}_{BC}] = E[N_{BC}]^2 + Var(N_{BC}) = 10^2 + 3^2 = 109$$

Hence, $E[U_A] = 0.895$ and $E[U_B] = 0.929$

From the results of the example, design B is chosen because it provides the greatest expected utility and is the best risky option of choice. However, it is interesting to note from this example that it is not always sufficient to estimate expected monetary values by placing some weight to account for societal loss. Modeling societal losses to be included in EUT is more complex. Hence emphasis must be placed in developing better workable models for utilizing intangibles based on societal risks for decision making. Furthermore, more studies need to be done in order to merge the criterion for societal risk along with the expected monetary loss based on societal risk perception (or risk aversion).

4.3.2. Example to illustrate the use of game theory

Fig. 41 shows the illustrative game for understanding the concepts of game theory in application to Wimbledon tennis final match. This is an extended schematization of the simple example of tennis match provided by Dixit and Skeath (2004). If the outcome of the Wimbledon final match is to be determined the strengths and weaknesses of all the players are to be assessed against each other as per the schedule of play. As the matches progress only the best players would advance further towards to the final match.

Each match in itself would consist of sets and each set has its game points. The outcome of each match played between two players at a time can be estimated based on track record of the individual players and assessing the pair-wise interaction of the players at each game on to each sets and ultimately to winning each match. As the best players advance towards playing the final match, the number of players also decreases in number. Only one player will ultimately win the Wimbledon match. When there are many players in the initial matches prior to the quarter finals, all players can essentially be grouped as those with exceptional players who are top seeded in world tennis ranking based on previous wins and individual histories. Thus one can estimate that most likely the top seed players might enter the quarter finals. The entire process can be modelled utilizing game theory model to choose a favourite player to win the Wimbledon finals.

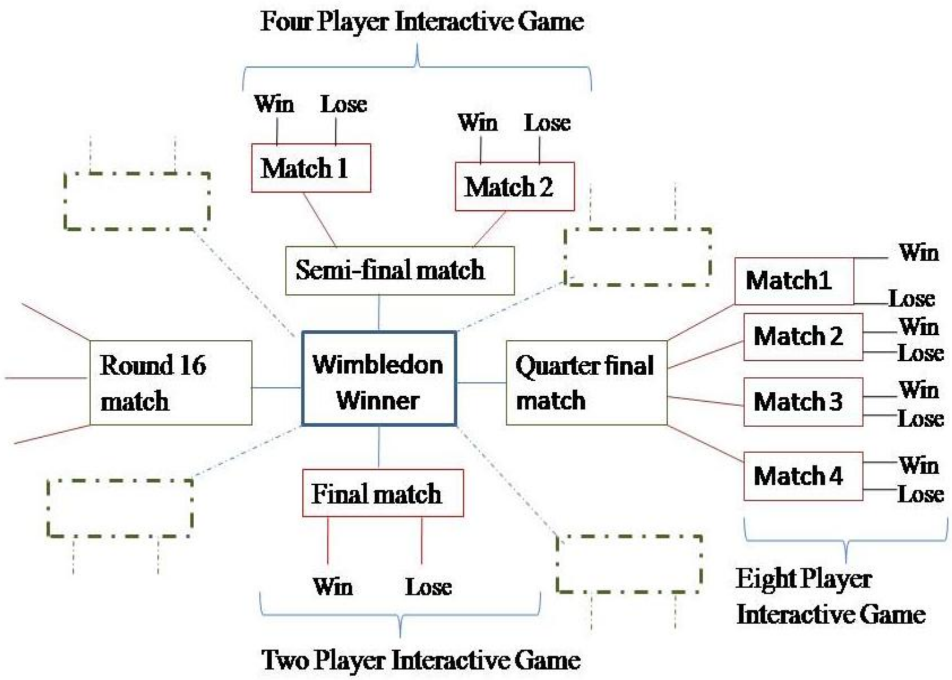


Figure 41. Utilizing game theory principles to solve a complex tennis match

Analogously, different attributes that constitute the operation of the complex plants and historical incidents or near-misses could be accounted for based on probability and consequence assessments for different deviating scenarios that have the capacity to cause major incidents. Based on reliability data of safety systems and the cost of reducing risks, the best option or the most preferred option could be chosen for optimum solution for abating the risk loss and adopting appropriate safety measures.

Similar to the principles of winning the tennis final, the same pattern can be adopted to consider strategic interactions of process operations by modeling them as adversarial risk games. This pattern would be science based because of quantitative risk analysis and *VaR* measures. Utilizing game theory principles to understand the complex chemical portfolio strategic interactions is schematized in Fig. 42.

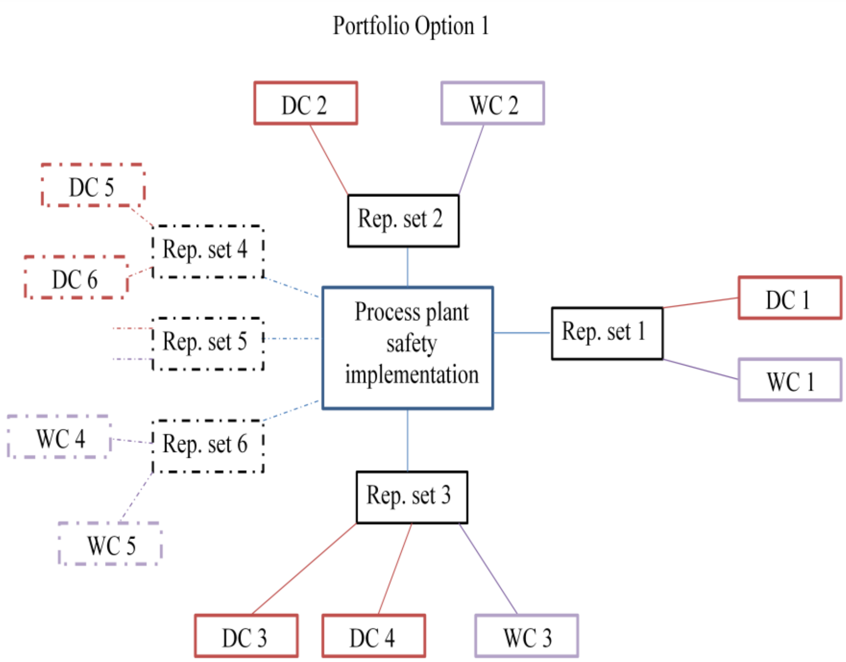


Figure 42. Utilizing game theory principles to understand the complex chemical portfolio strategic interactions

A recent report by the World Economic Forum (2010) provides a map on the interaction of different countries from an economic perspective and for understanding systematic vulnerabilities for the purpose of managing risks. Borrowing this idea, the interaction of different operations and the key parameters for decision making in the chemical process industry, a risk interconnection map could be developed for individual portfolios. This would provide information about real values of losses (for both tangible and intangible assets) for trading-off between risky scenario versus the dollar amount needed to be spent to mitigate the risk for process safety. A conceptual risk interconnection map portraying some possible representative sets for choosing most preferred risk option is provided in Fig. 43.

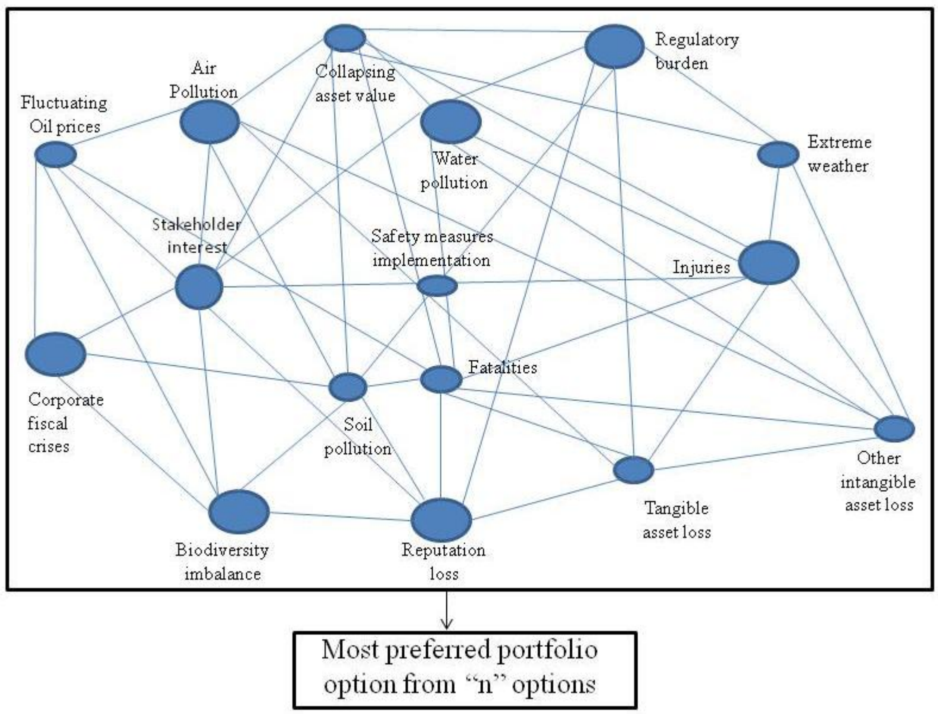


Figure 43. Illustrative risk interconnection map for chemical process industry

The final desired result from performing calculations based on game theory principles, including the different competing alternatives, is to generate the best response curves. Fig. 44 shows an example best response curve for two alternatives which is the loss to the company if the quantified process risk is realized into a catastrophic incident and the cost for mitigating the potential risks in form of safety cost. The ideal solution of the best response curve would be the Nash equilibrium point, which should be further studied to be properly utilized in the chemical process industry.

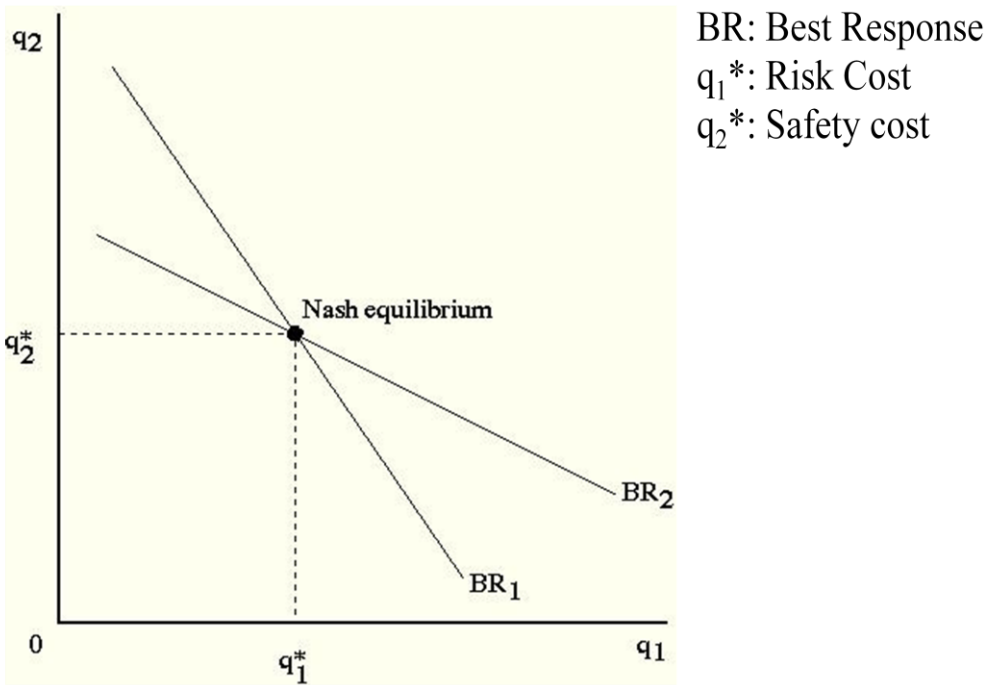


Figure 44. Nash equilibrium approach for the solution of adversarial game in chemical process industry

In decision making using EUT, the real decision scenarios problems are characterized by many attributes and placing values on all the attributes is very difficult. Hence, reaching the maximum of the overall utility model considering all attributes is demanding. Hence, trade-offs must be assessed by properly constructing the one dimensional expected monetary value function and combine that with systematic pattern of values assigned to all other attributes and then comparing the utilities (Keeney &

Raiffa, 1976). In order to study utility functions in chemical process industries, systematic methods must be developed to obtain patterns which can be utilized to understand effects of attributes such as societal risks, environmental damage, company risk acceptability and public risk tolerance. Therefore, game theory principles can be useful for understanding of the strategic interactions between different attributes. Much research is needed towards this endeavour and, to include decision making models in simulation and consequence modelling software packages. Once this pattern is set, it will be very useful for effectively mitigating risks in the process industry.

5. CONCLUSIONS

This section provides the overview of the research along with specific conclusions based on the results from case study as well as general conclusions from the overall study from the proposed novel research methodology. Based on the conclusions suitable future work is also proposed in this section.

5.1. Research Conclusions

From this study we conclude that the comprehensive judgments of all the risks and losses for the business decision making should entail the analysis of the overall results of all possible incident scenarios. *VaR* is most suitable as an overall measure for many scenarios and large number of portfolio assets. The proposed novel methodology aids in better understanding the risk and decision making for an entire portfolio along with the inclusion of societal impact.

Prediction of tangible and intangible risks and their inclusion in the economic analysis is significantly important while making business decisions or choosing between competing alternatives for production and safety. Cost benefit analysis supports sound decision making for larger portfolio investments. The background, the theory and methodology and the economic analysis are proposed. QRA and *VaR* as a combined quantitative analysis tool is stated as the bridge between engineers who quantify the risks and the management who make business decisions based on the estimated risks (Fang, Ford and Mannan, 2004). The current work builds on the work done by Fang et al., (2004), which proposes the combination of LOPA and QRA for improved risk-informed decision making.

The comprehensive judgments of all the risks and losses for the business decision making should entail the analysis of the overall results of all possible incident scenarios of a portfolio. Besides estimating the harm to people using *FN*-curves, graphically representing the monetized asset damage losses also aids in decision making to judge business prospects. Hence, *F$*-curves are constructed analogous to *FN*-curves, by constructing curves of cumulative frequency vs. monetary damage. Finally, these information add value in identifying the most serious types of incidents, the critical equipment in need of safety measures and selecting of the most preferred option among different design alternatives.

Prediction of tangible and intangible risks and their inclusion in the economic analysis is significantly important while making business decisions or choosing between competing (or conflicting) alternatives for saving costs, improving safety, increasing production and enhancing the life cycle of processes and plant assets. In this research, the importance of studying major incidents and monetizing the assets are stressed, the methodology for making business decisions from the economic analysis is developed and the methodology is demonstrated by applying it on case studies. For this purpose, credible scenarios and their incident outcome frequencies were first developed. The quantified portfolio risks were classified as tangible risks and intangible risks. The tangible risks were monetized and the expected loss using *VaR* were calculated. The *VaR* values and the economic losses enabled concluding that the column, full bore line rupture and the reboiler are the critical assets for risk mitigation in the plant. Societal Risk model were developed to account for intangible risk. *FN*-curve and *F$*-curve were generated according to the consequences of the potential scenario risks.

Societal Impact by incidents increases sharply with the total number of victims and the devastation of the plant. Societal or group risk curve provides a measure of this disruption (*i.e.*, societal impact). A suitable representation of societal risk is *FN*-curves (Evans and Verlander, 1997). Hirst (1998) has referred to *FN*-curves as important for the assessment of risks to populations from hazardous installations. *FN*-curve is the frequency of exceedance curve which is plotted with the values of the cumulative frequencies, *F* versus N or more fatalities (HSE, 2003). *FN*-curves are valuable tools that also outline certain tolerability of risks as satisfactory or unsatisfactory. The criterion for tolerability is based on the perception of risk.

The application of UK-HSE criterion lines provide additional guidelines for decision making along with the consideration of economic asset losses. *FN*-curves and *F$*-curves can be correlated and this would be very beneficial for understanding the trends in historical accidents in the U.S. chemical process industry. Continuous risk estimation could provide more refined values for decision making. Plant specific information of availability of equipment could better predict losses in terms of accounting for repeated occurrence of low and medium incidents in one year.

The *FN*-curves and *F$*-curves were utilized to predict the expected number of fatalities per year values for incidents. Once the suitable safety measures are adopted, the *VaR* value can be recalculated to analyze the benefits (if any) of adopting certain safety or mitigation strategies. Finally, *FN*-curves and *F$*-curves were drawn for the entire portfolio and their trends compared. Based on this study it can be concluded that *FN*-curves and *F$*-curves can be collated. This would be useful to generate *FN*-curves and *F$*-curves for all U.S. major incidents and world-wide catastrophes, to estimate the frequencies of occurrence of the historical incidents and understand the general profile of the historical catastrophic incidents.

In this work, the two databases namely the EPA-RMP and the HSEES databases having different criteria for reporting were studied. A total of 2,623 RMP data points for a period of 1994 to 2009 and approximately 33,000 HSEES data points for a period of 1996 to 2004, were analyzed to understand the number of incidents reported annually and the type of incidents reported along with their consequences and their initiating causes for failure. The different types of consequences were utilized for the generation of the safety pyramids similar to the one proposed by Heinrich. Safety pyramids were also generated for consequences resulting from the different initiating causes for failure leading to incidents as reported in the HSEES. Pair-wise correlation between the consequences and multiple regression analysis were performed to understand the existence of relationships between the different tiers (consequences) of the safety pyramids.

The analysis from the database information will provide valuable insight to measure the proportions between fatalities, major injuries, minor incidents, equipment damage, societal losses (societal risks), evacuations and shelter-in-place. If appropriate risk mitigation measures for improving safety are adopted based on the low consequence societal losses such as evacuations, the chances for reducing societal risks with greater consequences can be improved because it provides the necessary tools for monitoring accident consequences in plants. The safety pyramids generated could be effectively utilized by companies to prevent major incident consequences as it provides a measure of historical incident consequences in the process industry. From this study it can be concluded that there is a statistical relationship between the different consequence tiers of the safety pyramid. Additionally, there is a relationship between different tiers of consequences based on HSEES database study. Further, for both the databases the ratio between the different tiers is different from the ratio proposed by Heinrich. This could be because of the criterion for reporting in the RMP database and because of newer types of processes in the chemical industry than when safety pyramid ratios were first proposed.

The accident ratios along with information about the low consequences or the "near misses" at the base of the triangles offer preventive opportunities for improving safety in order to prevent low incident consequences from escalating to more serious consequences such as fatality and major injury. Furthermore, facilities and regulatory agencies tracking the different consequences could utilize the regression equations to estimate the potential for more serious accident consequences by studying the low risk incidents or low severity of consequences. RMP data analyses could specifically be utilized by all facilities covered under the RMP rule as well as particularly by the petroleum industry. The HSEES database analyses could be utilized in general by all chemical facilities and particularly those housing hazardous substances.

In the presence of newer more complex processes emerging, newer risks could surface, making studies such as this, invaluable to learn more about the chemical industry incidents and seek incentives to better understand the profile of incidents. While this work is comprehensive and provides information about the trends in process operations in both chemical and petroleum industry, the following limitations exist:

(i) More number of years of data are needed from both databases in order to establish the industry trends more concretely. This study was limited to about 15 year data from RMP database and 8 year data from HSEES database.

(ii) The detailed description of the type of equipment that actually failed along with further information about the mode of failure of the equipment are not provided in either database. This valuable information, if solicited, can provide information for improving process safety, for increasing equipment reliability and for more precisely conducting accident investigations.

(iii) HSEES data does not have the actual number of people sheltered-in-place as is the case in RMP in addition to the number of evacuees. The actual near-miss information in facilities is also unavailable from both databases. If near-miss information are collected, the entire safety pyramid proposed by Heinrich can be compared and more complete accident investigation would be made possible, which could significantly aid in preventing future incidents.

(iv) The actual number of employees working in a facility and the number of hours worked are not provided in either database. This information along with more accurate description of the incidents and the description of the initiating cause of failure, could be useful to generate true group risk curves such as *FN*-curves like the ones generated by UK HSE or the Dutch TNO. True *FN*-curves would enable management and regulators to more completely understand the actual societal risk trends of US facilities.

From database mining it can be seen that there is a need for initiating better reporting of incidents along with more incident description by the companies to regulatory agencies. Common knowledge sharing of incidents and their resulting consequences throughout the US process industry could benefit the facilities to establish better emergency preparedness measures and employ appropriate training of plant workers and local emergency responders. Monitoring of incident root causes and investigating the causes for near-misses alike can help improve the safety program of facilities and process industry. Government agencies can use this information to regulate certain types of chemical processing and hence promote safer work environments in process industry.

In this work the importance of utilizing decision analysis techniques and game theory in the chemical process industry has been emphasized and a conceptual framework is provided to arrive at decision analysis based on quantitative risk analysis for improving safety and preventing major catastrophes. Given the different contributing factors present during decision making and the vast amount of information with which to make less subjective decisions, reaching the maximum of the overall utility model considering all attributes is a daunting task. Other industries are effectively utilizing decision making analysis techniques. Much research is needed towards this endeavour in the chemical process industry. Nevertheless, decision theory, concepts of expected utility theory and game theory principles can be utilized for providing decision makers with the effective tools to choose the most preferred risk option from conflicting portfolio options.

Despite the limitations, this work lays the groundwork for harnessing databases to understanding profile of incidents and also for generating societal risk information as lagging metrics to be included along with leading indicators to form risk metrics for risk decision making in the chemical process industry.

5.2. Future Work

(i) An important factor to consider in the research is the domino effect. Domino effect in chemical process industry refers to the damage or failure of equipment and its resultant effect because of the generated static overpressure and radiant heat energy. Structural damage and subsequent loss of containment leading to possible explosion could exacerbate the societal consequences both within and outside the plant facility. The resulting economic loss due to accounting of the domino effect damage could be varying from losses estimated otherwise.

(ii) Continuous risk estimation could provide more refined values for decision making. Plant specific information of availability of equipment could better predict losses in terms of accounting for repeated occurrence of low and medium consequence incidents in one year.

(iii) Include market fluctuation values to estimate the *VaR* to include actual market fluctuations and how loss of production because of major catastrophes could also affect the maximum expected losses in addition to plant asset values.

(iv) The company tolerability criteria and the societal risk aversion should be correlated to understand the relationship which could help estimate the risk acceptability in US process industries.

(v) *FN*-curves and *F$*-curves can be correlated to estimate frequency of occurrences of major historical incidents and then generate *FN*-curves for those incidents, which would be very useful for process industry worldwide.

(vi) The concepts of decision analyses present here can be further studied to be applied in a chemical process industry setting to enable better decision making for improving safety.

(vii) More information about US hazardous chemical incidents and near-misses is needed to be collected in order to generate true *FN*-curves based on information about the actual number of facilities in HSEES and the actual number of employees working in the facilities where incidents occur. Better information reporting and collection is required for understanding the incident trends in process industries. Incident reporting around the world must be more transparent for more in-depth information about incidents.

(viii) Software currently utilized for designing and optimizing plant operations should be embedded with economic evaluation capacity and decision analyses information as guidelines for choosing optimum solutions for complex processes or portfolios.

(ix) Much research is needed in developing workable models for using decision theory principles of expected utility theory and game theory in the chemical process industry setting.

(x) Better sensitivity analysis methods must be developed for ensuring that the "most preferred" portfolio option chosen is indeed the best possible risk trade-off between production and process safety in consideration of intangible assets.

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Journal articles

- K. P. Prem, D. Ng, H. J. Pasman, M.Sawyer, Y. Guo & M. S. Mannan, "Risk measures constituting risk metrics for improving decision making in the chemical process industry: *Value-at-Risk"*, Journal of Loss Prevention in the Process Industry, 2010.
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