Universitetet i Stavanger

FACULTY OF SCIENCE AND TECHNOLOGY

MASTER'S THESIS

Study program/specialization: MSc in Risk Management / Reliability & Resilience Engineering	Spring semester, 2019 Open
Author: **Malik Mohsin Abbas**	(signature of the author)
Program coordinator: Prof. Terje Aven Supervisor(s): Professor. Terje Aven, External: Bjarte Haegland (TechnipFMC)	
Title of master's thesis: Nexus between Risk and Resilience: A review of recent research on integrated conceptualization and characterization and presentation of its new application	
Credits: 30	
Keywords: Resilience, Risk, Uncertainty, Strength of Knowledge, Safety Management	'Number of pages: 63 Stavanger, 15.06 .2019 date/year

Title page for Master's Thesis

Faculty of Science and Technology

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- MASTER THESIS -

NEXUS BETWEEN RISK AND RESILIENCE:

A review of recent research on integrated conceptualization and characterization and presentation of its new application

Written by:

Malik Mohsin Abbas

Supervised by:

Professor. Terje Aven

University of Stavanger

Faculty of Science and Technology

Department of Safety, Economics, and Panning

Spring, 2019

ABSTRACT

This thesis reviews recent research on the nexus between risk and resilience. This research relates to conceptualization and characterization of risk and resilience, with implications for risk and resilience analysis and management. The review highlights the presentation of a framework developed for the integrated understanding and study of risk and resilience. It points to a development discussed in the literature showing separate camps for risk and resilience analysis and management, and how this development can be confronted.

The thesis also presents and discusses a new application of this framework, starting from a deterministic model of resilience studied in the literature. By adding uncertainty to the model, new insights are provided. The uncertainty is described through probabilities as well as judgments of the strength of knowledge supporting these probabilities. A simple example from an offshore industry is used to illustrate the application.

Key Words: Risk, Resilience, Uncertainty, Strength of Knowledge, Safety Management.

ACKNOWLEDGEMENT

This thesis is written and submitted as a fulfillment of the requirements for a MSc degree in Risk Management with specialization in Reliability and Resilience Engineering at the University of Stavanger (UiS), Norway. The work has been carried out from February 1st till June 15th, 2019.

All praises are to be for Almighty ALLAH, the most merciful and kind and peace be upon His last messenger Muhammad (PBUH), his pure descendants (Twelve Imams) and family. I am grateful to Almighty ALLAH for His countless blessings and giving me health and strength to write this thesis and complete this master's program.

I want to take this opportunity to express my sincere gratitude to my supervisor Professor Terje Aven for his patience, constructive criticism, red teaming, and showing me the right path throughout the thesis. He was always available to me for guidance and prompt feedback despite his busy schedule. I am incredibly thankful and indebted to him for sharing his knowledge and expertise in the field of risk, resilience, and literature writing. Without his support, this thesis was not possible. It has been a pleasure and an honor!

I would also like to thank my external thesis guide Bjarte Haegland from TechnipFMC for proofreading and sharing his honest and illuminating views related to improving the readability of the thesis.

Lastly, I would like to thank my parents, family, and friends for their constant prayers and support during this journey.

Mohsin Abbas
15.06.2019

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ACRONYMS

A= events

A’= specific events

C= consequence

C’= specified consequence

K= knowledge

P= probability

Q= measure of uncertainty

SoK= strength of knowledge

SRA= Society for Risk Analysis

U = uncertainty

X = system state

Y= resilience

CHAPTER 1

INTRODUCTION

1.1 Background

To monitor and govern the safety of complex systems, safety regulations are formulated, and different approaches are used mainly characterized as engineering risk assessment approach and sociotechnical approach (Aven & Ylönen, 2018). Engineering risk assessment approach is to a large extent built on probability-based risk perspective, to describe the system through static models such as fault tree, event tree, etc., quantifying risk and evaluating it by some predefine risk acceptance criteria (Kaplan & Garrick, 1981). Whereas, the sociotechnical perspective point towards the limitations of risk assessment and argues that some of the critical aspects of safety such as human-machine interaction and system dynamics are not adequately considered in traditional risk assessment approaches (Aven & Ylönen, 2018). Besides that, there is always a possibility of surprise. Therefore, there is a need for more robust and resilient systems which brings the resilience perspective into play. The essence of resilience management is to deal with unforeseen events and surprises (Aven, 2017; Aven, 2018a). The focus of the resilience is more towards the recovery while that of probabilistic risk assessments is on failures. Aven (2018a) points towards the fact that a growing separation trend has been observed in the literature, with the risk scientist working on risk and developing their concepts and tools neglecting the resilience science to a large extent in their research work and vice versa. However, in the recent years, the risk as a science has developed; highlighting the uncertainties and knowledge dimension with emphasis on the need of looking beyond probability and expected values (Aven, 2008; Aven, 2104; Aven, 2015). Lately, scientists are also talking about interaction and dependencies between risk and resilience's and their linkage (Aven & Thekdi, 2018) and have argued that neither risk nor resilience can be appropriately managed without considering each other (Aven, 2017; Aven, 2018a; Aven & Thekdi, 2018). Aven & Thekdi (2018) has developed a framework that links resilience both at a generic and an applied level, allowing for a unifying conceptualization and characterization of risk illustrating the nexus between risk and resilience.

Noticing the importance of this recent development with having significant implications on the future of risk and resilience analysis and management (Aven, 2018) has led to the selection, review and application of this topic.

1.2 Purpose

The purpose of the thesis is to review the current knowledge about the link between risk and resilience and present a new application of recent unifying conceptualization and characterization of risk and resilience for better resilience and safety management of complex systems, in particular for offshore petroleum activities.

1.3 Approach

The objectives of the thesis are achieved by:

- Reviewing the scientific literature.
- Brainstorming and knowledge gained from risk management courses at the University of Stavanger, UiS.
- Valuable inputs, guidance, and red-teaming sessions provided by professor Terje Aven.

1.4 Structure of the thesis

From this point forward thesis is organized in the following way:

- In Chapter 2, the current knowledge on risk, resilience and their linkage has been reviewed as mentioned in the purpose.
- In Chapter 3, a brief overview of risk strategies used in resilience analysis and vice versa concerning recent advancements in risk and resilience sciences are presented.

- In Chapter 4, we propose an extension of the deterministic resilience model using the characterization discussed in chapter 3, which includes an assessment of the strength of knowledge. An illustrative example is also provided.

- In Chapter 5, further discussion is made on the importance and use of risk-based strategies in conjunction with resilience analysis.

- Finally, in the last Chapter 6, some conclusions are drawn.

CHAPTER 2

REVIEW OF RISK, RESILIENCE AND THEIR LINKAGE

In this chapter, the current knowledge on risk, resilience and their linkage has been reviewed as mentioned in the purpose. The episode contains:

- A brief overview of the risk concepts and risk management are provided in section 2.1.
- Resilience concepts, its main principles, and a brief overview of resilience assessment approaches are presented in section 2.2.
- The linkage between risk and resilience is elaborated and discussed in 2.3.

2.1 Risk

Risk is a word we hear almost on a daily basis. We hear it in the media, from politicians, engineers, doctors, economists and other members of the society. We listen to words such as climate change risk, economic risks, health risks, risk of losing a job, risk of explosions, the risk to critical infrastructures, risk of terrorist attacks, etc. But the question is; what do we mean by "risk"? What does the term "risk" imply and how is this term understood by a different segment of societies?

If we review the literature starting from the year 1700 to this point in time, we will not find an agreed definition of the risk concept. Some relevant descriptions listed by Aven and Renn (2010) in their book "*Risk Management and Governance*" (Aven & Renn, 2010) along with the source reference of these definitions in parenthesis are (Aven & Renn, 2010, p.2):

1. "Risk is equal to the expected loss (Willis, 2007).
2. Risk is equal to the expected disutility (Campbell, 2005).
3. Risk is the probability of an adverse outcome (Graham & Weiner, 1995).
4. Risk is a measure of the probability and severity of adverse effect (Lowrance, 1976).

5. Risk is the combination of probability and extent of consequences (Ale, 2002).

6. Risk is equal to the triplet (s_i, p_i, c_i), where s_i is the i^{th} scenario, p_i is the probability of that scenario, and c_i is the consequence of the ith scenario, i=1, 2,…., N) (Kaplan & Garrick, 1981).

7. Risk equal to the combination of events/consequences and associated uncertainties (A, C, U), where A=event, C= consequences, U= associated uncertainties (Aven, 2008).

8. Risk refers to the uncertainty of outcome, of actions and events (Cabinet Office, 2002).

9. Risk is a situation or event where something of human value (including humans themselves) is at stake and where the outcome is uncertain (Rosa, 1998).

10. Risk is the effect of uncertainty on objectives (ISO, 2009)"

From these definitions, we can see that the world of risk is developed around words like "probability", "expected loss", "consequences" and "uncertainty". Based on these, Aven (2012) masterfully summarized the six developments paths in the risk concept, as shown in the figure below (2012, p.40):

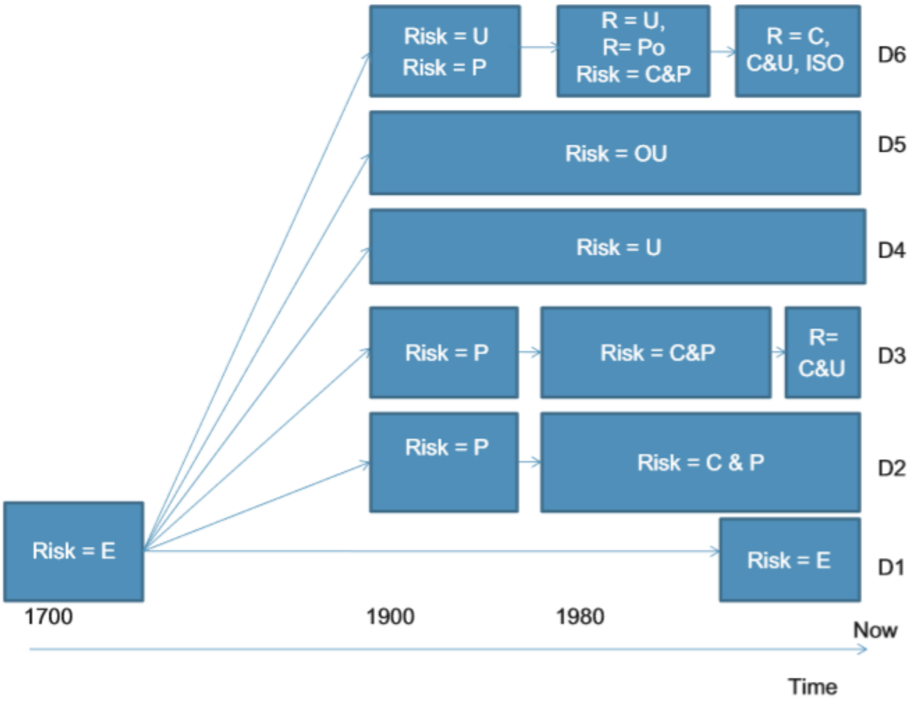

Figure_1 Six thought constructed development paths of Risk Concept (Aven, 2012, p.40)

In short, by looking at the definitions and development paths mentioned above, the risk can be broadly categorized into two main groups:

2.1.1 Traditional risk perspective

In this perspective, the probability is the main component of risk where risk is seen as an answer to three questions (Kaplan & Garrick, 1981, p.11-27):

(1) what can go wrong,

(2) how likely it is,

(3) and what will be the consequences?

This perspective is often referred to as the probability base risk perspective. In traditional risk perspective, the risk is defined as a probability of adverse outcome expressing stochastic uncertainty. This probability is unknown and is estimated using data related to similar situations. Schematically probability base risk perspective can be written as (Kaplan & Garrick, 1981, p.11-27):

$$(C, P) \text{ or } (A, C, P) \tag{1}$$

where,

A=event

C= consequences

P= related probabilities

This perspective has mostly been used in industry for more than 30 years and still being used. However, lately, the risk scientists found this perspective to be too narrow, mainly due to the following reasons (Aven & Ylönen, 2016, p.170):

- Assumptions hide a critical aspect of risk and uncertainty.
- Two or more probabilities can be the same, but the knowledge behind it could be weak and strong.
- Probabilities are based on historical data and models.
- Surprises can occur relative to probabilities.
- Probability is just one of many tools to describe uncertainties.

The arguments above lead to the replacement of probability with uncertainty in the risk concept.

2.1.2 Uncertainty base risk perspective

In this perspective, uncertainty is the main component, and probability is seen as one of the tools to describe uncertainty. Risk is defined as a two-dimension combination of consequences and uncertainties (Aven, 2015, p.13):

$$(C, U) \text{ or } (A, C, U) \tag{2}$$

where,

A=event

C= consequences

U= associated uncertainties

There is an offshore installation and looking into the future there will be consequence C such as: leakage, fire, successful operations, failure etc. but right now we do not know what these consequences will be. We are uncertain U about the consequences and event, so we face risk.

This risk is then described as (Aven, 2015, p.14):

$$(A', C', Q, K) \tag{3}$$

where,

A' = specified events,

C' = specified consequences such as fatalities, production loss and environmental consequences

Q = measurement of uncertainty such as probability and the strength of knowledge etc.

K = Knowledge (data, expert statements, models) on which these C' and Q' are based on.

Schematically above-mentioned risk concept and description can be shown as below:

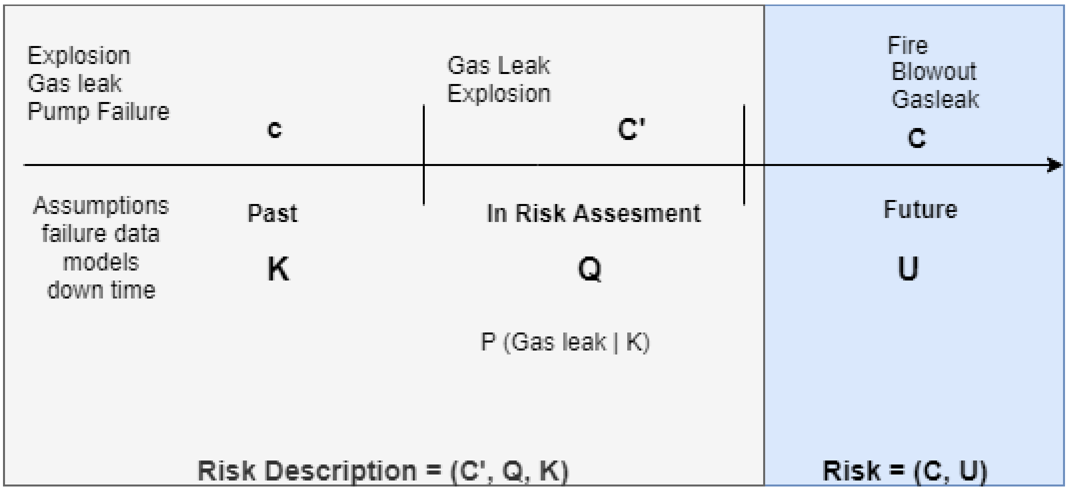

Figure_2 A schematic illustration of uncertainty-based risk concept and description adapted from (Aven, 2015)

2.1.3 Risk management process and strategies

Risk assessments are used to support decision making related to safety management by providing the decision maker insights related to different alternatives, acceptance of risk, implementing risk measures, etc. The two main pillars of risk management are (Aven, 2016, p.6):

1. Risk management strategies,
2. The framework of the risk management process.

Klinke & Renn (2002) presented three risk management strategies mainly characterized as:

1. risk-based,
2. cautionary/precaution based,
3. and discourse based.

According to Klinke & Renn (2002), risk-based strategies argue that policies to treat risks should be designed in the proportion of risk, which is the combination of probability and consequences. The cautionary/precautionary based strategies focus on robustness /resilience and argue that instead of trying to estimate the likelihood of an adverse event, one should observe caution by implementing the measures to increase robustness or by not starting the activity. The discourse bases strategy addresses the ambiguity. It focuses on resolving risk issues through deliberation, involvements of affected people, and discussing the differences (2002).

In line with different frameworks (e.g., ISO, 2009; Tehler, 2015; Aven, 2015), the risk assessment process, primary steps can be described as follow (Aven, 2016, p.6):

1. Establishing the context, for example, to express values, define the purpose, set goals, etc.
2. System description, for example, structural/functionals modes for describing the current situation

3. Identification of events/hazards/opportunities which can affect the current state using FMECA, HAZOP, HAZID, workshops, etc.
4. Developing scenarios that could lead to these events and analyzing their effects using methods such as Fault tree, Event tree, etc.
5. Likelihood and Consequences, make judgments about the possibility and consequences of different risk scenarios using qualitative or quantitative methods
6. Establish risk picture: how high or low is the risk in the system.
7. Risk evaluation is the risk acceptable or measures needed.
8. Risk treatment.

The above steps are schematically presented as follow (Tehler, 2015, p. 25):

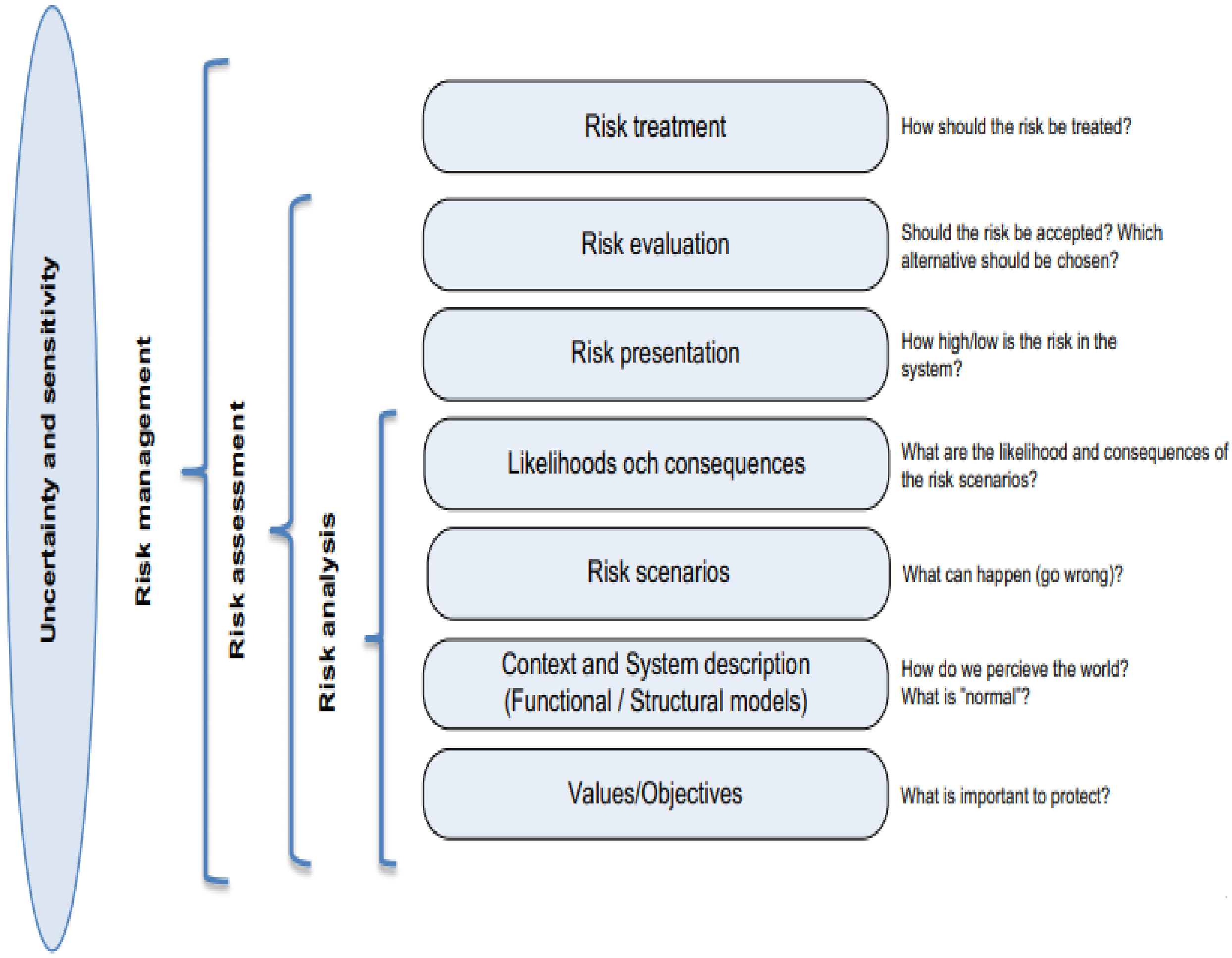

Figure_3 Main levels of Risk Management framework (Tehler, 2015, p.25)

2.2 Resilience:

The term resilience has been first derived from the Latin word “resilire”, which means to “bounce back” (Hosseini, Barker, & Ramirez-Marquez 2016).

According to SRA (2015), resilience is defined as:

“The ability of the system to sustain or restore its basic functionality following a risk source or an event (even unknown)” (SRA, 2015).

The National Academy of Sciences (NAS) defined disaster resilience as:

“The ability to plan and prepare for, absorb, recover from, and adapt to adverse events” (NAS, 2012).

In the engineering context, Hollangel (2014) defined resilience as:

“The intrinsic ability of a system to adjust its functioning before, during, or following changes and disturbances so that it can sustain required operations under both expected and unexpected conditions” (Hollangel, 2014, p.222).

Resilience has been used in a wide variety of domains and sciences such as materials, ecosystems, psychology, business, engineering (Tredgold, 1818; Holling, 2013; Tisseron, 2007; Hamel & Valinkangas, 2003; Hollnagel, Paries, Woods, & Wreathall 2011.) in its own way. The study of the description of resilience from these references show that resilience can be understood as (Hollnagel, 2014):

- An intrinsic property of the material that can withstand abrupt load and shocks without breaking as a static system.

- A property of an ecological system where it can absorb changes and system can work under these new changes or variables but does not return to the original position. Hence a living or dynamic mode.

- As a property of the psychological system where a system not only absorbs the changes but also reflect and respond to these changes and anticipate starting something new of these changes.

- The inherent ability of the system to absorb, respond, anticipate and return to its original position before, during or after the events which can occur both expectedly and unexpectedly.

The above definitions exhibit more or less the same concepts summarizing resilience as a combination of four abilities (Steen & Aven, 2011, p.293):

1. to respond to both expected and unexpected hazards flexibly,
2. to monitor current state, performance and address critical,
3. anticipate threat and opportunities,
4. learn from past data experiences.

These four abilities are interdependent and are often referred to as "four cornerstones of resilience," as illustrated in the figure below (Hollangel, 2014):

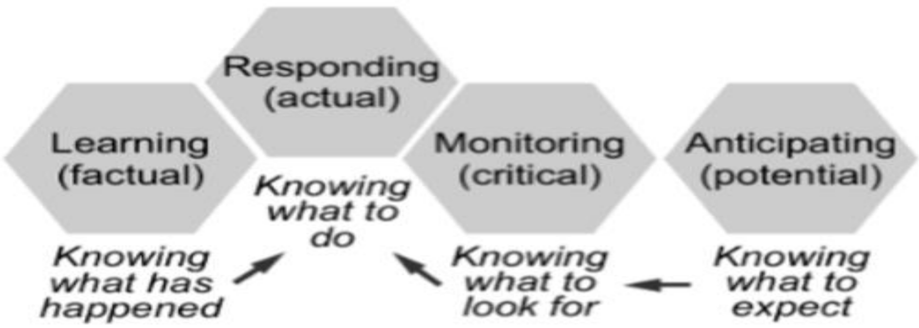

Figure _4 The four cornerstones of resilience (Hollangel, 2014)

(i) Knowing what to do (to respond and adjust operation during the regular and irregular disturbance).

(ii) Knowing what has happened (to learn from past data, experience, successes as well as failures).

(iii) Knowing what to look for (to monitor which can become a potential threat or risk in near feature).

(iv) Knowing what to expect (to anticipate threats, developments, opportunities, changes, etc.).

2.2.1 Resilience assessment approaches:

The review of resilience assessment approaches is primarily based on the work done by Hosseini et al. (2016). Literature shows that resilience assessment approaches can be broadly classified into two primary schemes with subcategories, as shown below in the figure (Hosseini et al. 2016, p.51):

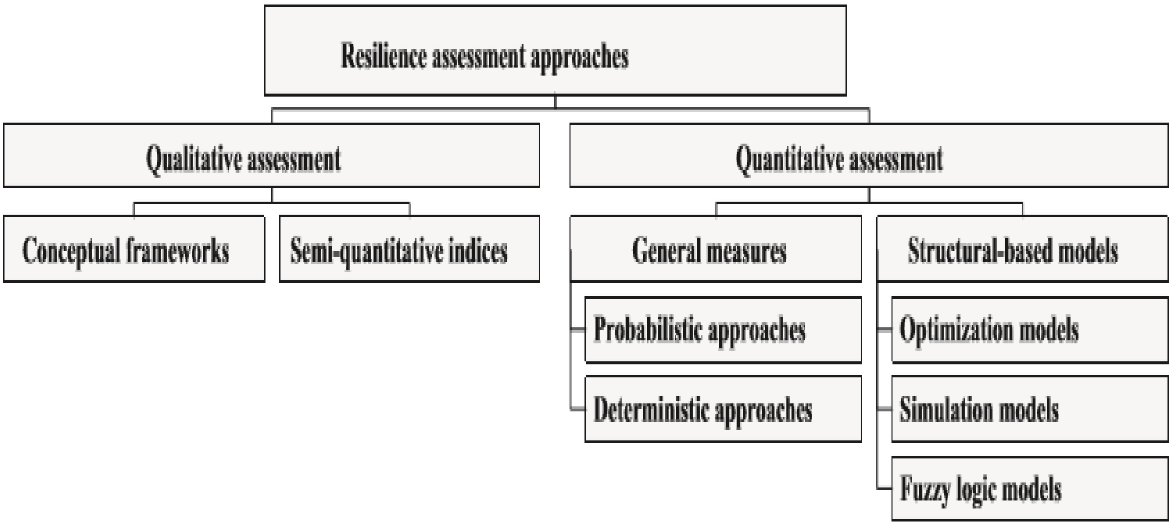

Figure_5 Classification scheme of resilience assessment approaches (Hosseini et al., 2016, p.51)

The qualitative assessment approach is further subdivided into two categories referred to as (Hosseini et al. 2016, p.51):

1. Conceptual framework and
2. Semiquantitative indices.

The conceptual frameworks provide the best practices, indicators, attributes and guidelines for the system resilience. Compliance with these attributes or methods helps in evaluating the system resilience (e.g., Alliance, 2007; Vugrin, Warren & Ehlen, 2010; Kahan, Allen & George, 2009). The semiquantitative indices assess different qualitative aspects such as redundancy, resourcefulness, robustness, adeptness, etc. of resilience, based on expert's opinions on the scale from 0-10 or percentage scale from 0-100 (e.g., Cutter, Berry, Burton, Evans, Tate & Webb, 2008; Shirali, Motamedzade, Mohammadfam, Ebrahimipour & Moghimbeigi, 2012).

The quantitative assessment approaches are also divided into two categories (Hosseini et al., 2016, p.51):

1. General measures and
2. Structural based models.

General measures asses the resilience of system quantitatively by measuring the performance of the system before and after disruption irrespective of the structure of the system. This assessment could be either based on a deterministic approach (e.g., Bruneau, Chang, Eguchi, Lee, O'Rourke & Reinhorn, 2003; Henry & Ramirez-Marquez, 2011) which does not incorporate uncertainty, probability of disruption or on probabilistic approach (e.g., Youn, Byeng & Pingfeng, 2011), which includes the likelihood associated with the system behavior. Both these approaches can address the dynamic (time-dependent) and static (time-independent) performance of the system. The structural based models analyze the system behavior and characteristic with the use of modeling and simulation to examine the effect of structure on system resilience (e.g., Muller,2012; Albores & Shaw, 2008; Azadeh, Salehi, Arvan,&Dolatkhah,2014).

2.3 Nexus between risk and resilience

To simplify the nomenclature, the term "risk analysis" as described by SRA (2015) is referred to as "risk assessment, risk characterization, risk communication, risk management, and policy relating to risk, in the context of risks which are a concern for individuals, public and private sector organizations, and society at a local, regional, national, or global level" in line with the norms of Society of Risk Analysis (SRA, 2015; Aven 2018a, p.2).

Similarly, the term "resilience analysis" as described by SRA (2015) is used in broad sense that incorporates "resilience assessment, resilience characterization, resilience communication, resilience management and policy relating to resilience, in the context of resilience which are a concern for individuals, public and private sector organizations, and society at a local, regional, national, or global level" (SRA, 2015; Aven, 2018a, p.2).

As mentioned earlier in the introduction, the use of risk analysis has traditionally been the dominant approach in safety management and decision making. These approaches are to a large extent built on probability-based risk perspective, to describe the system through static models such as fault tree, event tree, etc., quantifying risk and evaluating it by some predefined acceptance criteria (Kaplan & Garrick, 1981). Over the last few decades, the field of resilience analysis has developed as an alternate approach for the safety management of complex system mainly due to limitations of probabilistic risk assessment to deal with some essential aspects of safety such as human-machine interaction, uncertainties, and surprises (Aven, 2018a). The added value that resilience analysis brings compared to the traditional risk perspective is its ability to confront uncertain and black swan types of event. However, in the recent years, the risk as a science has developed highlighting the uncertainties and knowledge dimension with emphasis on the need of looking beyond probability and expected values prompting the scientists to talk about interaction and dependencies between risk, resilience and their linkage (Aven & Thekdi, 2018).

The study of literature shows that there is a variety school of thoughts present in the scientific community having a different opinion on the relationship between risk and resilience. Some are on the point of view that these two fields are entirely different, some find them complementary to each other, some see resilience as a part of risk while others find risk as part of resilience (see Park, J., Seager, T., Rao, P., Convertino, M., & Linkov, I., 2013; Linkov, I., Trump, B. D., & Fox-Lent, C., 2016; Aven, 2017; Aven, 2018a; Aven & Thekdi, 2018).

For example, Park et al. (2013) argues that traditional risk analysis sees engineering systems as a "problem" to be solved, where failure need to minimize while in contrast to it, resilience engineering looks at the engineering system as a “process” that demands continuous management because the terms keep on changing, failures occurs, so the engineering systems need to be adaptive and responsive to the changes. The other difference, Park et al. (2013) identifies, is the issue of “incompleteness.” In traditional risk analysis, the focus is on the identified hazards and determining probabilities, neglecting the inherent uncertainty and realization of incompleteness. He argues that the low probability events even if they have high consequences are ignored either on assumptions or due to cost constraints whereas the resilience embraces incompleteness and the inherent uncertainty of complex system with a focus on more flexible and adaptative strategies. The probabilistic risk assessment focuses on the in the incremental evolution due to the demand of governmental regulations hindering the creativity and adaptation, whereas the resilience emphasis on innovation and flexibility (Park et al. 2013).

Despite these differences, traditional risk and resilience analysis have some similarities that links them to each other to some extent (Aven, 2011; Linkov et al. 2016). For example, Linkov et al. (2016) say that the risk and resilience analysis is grounded in a similar philosophically ethos of (Linkov et al. 2016, p.3):

1. evading hazardous consequences of bad things happening and
2. reviewing systems fragility and suggesting measures that could best mitigate or resolve such weakness.

Linkov et al. 2016 have the point of view that risk is a driving force for both the field with the overall aim of mitigating the adverse effects of a hazardous event as much as possible. He further links the traditional risk and resilience analysis by arguing that practitioners of both sciences are required to identify and categorize the hazardous events that could generate adverse outcomes to humans, the environment, or society in general (i.e., environment, infrastructure, life, health, etc.), and consequently develop and suggest countermeasures to confront such threats/event. Another common feature exhibited by both risk and resilience analysis is that both the risk and resilience analysis allow the use of both quantitative and qualitative data and assessments, making them flexible for a broader range of applications. This could be from well-known threats to highly uncertain events through the utilization of expert's subjective knowledge where quantitative data is limited or unavailable (Linkov et al. 2016; Aven, 2011).

The comparison between traditional risk analysis and resilience analysis is summarized in the table below (Park et al. 2013, p.360):

Table_1 Comparison between conventional risk analysis and resilience analysis (Park et al.2013, p.360)

Risk	**Resilience**
Prevention of failure proceeds from premises that hazards are identifiable	Preparation for the unexpected, adaptation to the changes,
Minimizing failure probability	Minimizing the failure consequences
Protection	Recovery
Assumptions based (transforms Low probability events into premise)	Recognizes incompleteness, Acknowledgement of unknown
Incremental evolution of prior design	Anticipate, adapt, innovate
Actions according to the predefined plan, standards (By the books)	Varies from place to place condition to condition
Probability, scenario, and cost-effective based	Possible consequence analysis of involving situations with unidentified causes

However, in literature, we also see perspectives acknowledging the necessity of integrating risk and resilience sciences while calling for the usage of risk analysis in conjunction to resilience analysis and vice versa (Aven & Thekdi, 2018; Aven, 2017). They are of the point of view that risk and resilience are closely linked to each other and have argued that neither risk nor resilience can be adequately managed without considering each other (Aven, 2017; Aven, 2018a; Aven & Thekdi, 2018). These perspectives are based on a broad understanding of risk and resilience, in which risk and resilience are seen as a science, and uncertainty is the main component of risk. For example, Aven (2017) argued that resilience analysis needs to be supplemented with some risk assessment, primarily qualitative focusing on the strength of knowledge considerations. Aven (2017) suggested using such assessments in conjunction with resilience analysis; as such assessments address the potential occurrence of an event. He showed that through such analysis one might be able to reveal the new cause-effect relationship leading to the identification of potentially unexpected and unknown threats, which will lead to the development of better strategies to meet these events. The second point highlighted by Aven (2017) for the need of unifying risk and resilience, is the issue of scarce resources. He argued that by uniting risk and resilience, one would be able to utilize the resources more efficiently, risk assessment could be used to prioritize the areas where one wants to improve resilience (Aven 2017). The rationale behind this is further discussed in chapter 3.

In short, the different perspectives found in the literature on risk and resilience can be broadly categorized into two main groups (Aven, 2018a):

1. A different school of thought based on traditional risk perspective.
2. Unified school of thought based on the uncertainty-based risk perspective.

Schematically the strength of linkage based on these perspectives is shown as below (Aven, 2018a, p.3):

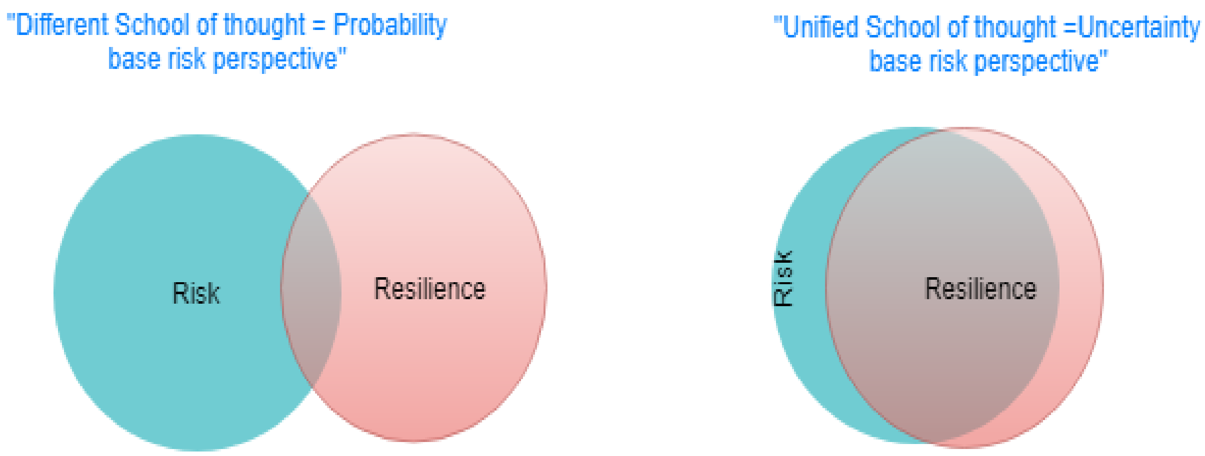

Figure_6 Schematic illustration of linkage between risk and resilience based on different risk perspectives (Adapted from Aven, 2018a, p.3)

2.3.1 Conceptual Linkage

Risk analysis science has two primary knowledge generating fields described as (SRA, 2017 Aven, 2018c, p.2415):

1. Applied risk analysis (A): “Risk knowledge related to an activity (interpreted in a broad sense also covering natural phenomena) in the real world, for example, the use of a medical drug, the operation of an offshore installation, or the climate” (SRA, 2017; Aven, 2018c, p.2415).

2. Generic risk analysis (B): “Knowledge on concepts, theories, frameworks, approaches, principles, methods, and models to understand, assess, characterize, communicate, and (in abroad sense) manage risk” (SRA, 2017; Aven, 2018c, p.2415).

Similarly, we can say that the resilience analysis also has the two knowledge generating fields same as a risk by replacing the word “risk” with “resilience” in the above definitions.

In the (A) type, the focus is usually on finding the answers to questions like: What can go wrong? What will be the impact of this action? What does the data show? What will be the effect of this, and how can it go wrong? How can we improve the tools? How to make this better? What are the uncertainties? etc., whereas the (B) type is about knowledge generation related to core concepts and conceptual research in risk and resilience analysis (SRA, 2017; Aven, 2018c, p.2415).

The question that arises here is to where to study the nexus between risk and resilience? What shall be the practical approach? How to integrate and measure the strength of linkage? Shall we focus on the (A) type knowledge generation, or shall the focus be on (B) type? According to SRA (2017), the main goal of (A) research is to generate knowledge about a specific activity such as new product under development, medical drug, etc. While the (B) research focuses on improving the definitions and core concepts knowledge generation relevant for different applications (see SRA, 2017; Aven, 2108c, p.2415). The “unified approach” stimulates the integrative thinking for developing a suitable concept of risk and resilience to meet the need of a unified risk-resilience approach. In the above discussion on the concepts of risk and resilience, we can see that there are several different definitions of risk and resilience, which can be considered as creating tension. However, integrative thinking makes the scientist see beyond these definitions. It utilizes different ideas to achieve a new and better understanding, for the opening of new horizons (Aven, 2018b). Our aim and interest here are not to research about truth claims as in (A) but to review the concepts that support the integrated risk-resilience approach (Aven, 2018b). Therefore, when studying the nexus between risk and resilience analysis, Aven (2018a) suggested that it would be useful to look them at the generic level and how they are defined as it encompasses the elemental notions, concepts, and principles of relevant field and science, rather than dwelling into the applied analysis which is guided by generic research (Aven,2018a) .

Based on the above discussion, it is more fruitful to further look into the linkage between risk and resilience at a generic level according to the two main risk perspectives. As described earlier, in uncertainty base perspective, the risk is defined as two dimensions combination of (Aven, 2018a):

1. The consequences of activity about something that human values (e.g., life, environment, economy).

2. Uncertainties U (what will be the consequences?).

In short, the risk is written as (C, U) or (A, C, U). This can schematically be written as (Aven & Thekdi, 2018, p.5):

$$"Risk\ = (A, C, U) = \ (A, U)\ +\ (C, U \mid A)" \qquad (5)$$

$$= \text{“}occurrence\ of\ events, and\ associated\ uncertainties\text{”}$$

$$+$$

$$\text{“}consequences\ given\ events, and\ associated\ uncertainties"$$

The "+" sign here is not to be interpreted as mathematical summation but to be as a symbol of the combination of the two components. The term $(C, U|A)$ exhibits the important aspect of resilience, which is in line with the SRA, 2015 resilience definition "as the ability of the system to maintain or restore its functionally given one or more events "A" occur, whether these events are known or unknown"(SRA, 2015). If for example C are related to a number of fatalities given an event A (explosion) has occur in relation to the maintenance of offshore facility then the term $(C, U|A)$ expresses this number and uncertainty. This link can be clearly observed when the consequences are defined in terms of system performance as for example, looking into the future an event may disrupt the system causing its performance output "O" to jump above or below a reference level (expressed in terms of an objective, target value, or the current state). There are uncertainties associated with both the occurrence of these events and the actual performance output (Aven & Thekdi, 2018). Likewise, (C, U|A) can be characterized in the form of $(C', Q, K|A)$, where C' are the specific consequences such as (production loss, downtime, fatalities etc.) while, Q is a measure of uncertainty e.g. probability, strength of knowledge (SoK) and K is knowledge (Aven & Flage, 2017). This characterization allows for more unifying approaches and provides means to measure system resilience and characterize associated uncertainties in a suitable way which was not possible in the case of probability base risk perspective. In short, the term (C, U|A) exhibits the important aspect of resilience and can be understood as the "resilience induced conditional risk" or "lack of resilience-induced conditional risk", given the occurrence of A (Aven & Thekdi, 2018, p.5). Hence linking resilience closely to uncertainty-based risk perspective in which resilience analysis can be seen as part of risk analysis (Aven & Thekdi, 2018, Aven, 2018a).

Likewise, to show the lack of conceptual linkage between risk and resilience according to the "different school of thought/probability base risk perspective," we return to the general definition of probability-based risk perspective in which probability is the main component of risk. This can be schematically written as (Aven, 2018a, p.4):

$$\text{"}Risk\ = (A, C, P) = \ (A, P)\ +\ (C, P \mid A)\text{"} \tag{4}$$

$$=\ \text{“}occurrence\ of\ events, and\ associated\ probabilities\text{”}$$

$$+$$

$$\text{“}consequences\ given\ event\ and\ related\ probabilities\text{"}$$

As Aven (2018a) suggested, we can see that this representation does not provide a meaningful way of linking risk and resilience, as probabilities offer little information about events which are not known. Moreover, it does not give a meaningful scheme of characterizing resilience. Also, the uncertainties are not adequately taken into consideration in this scheme, making it challenging to link risk and resilience in this perspective (Aven, 2018a, p.4).

CHAPTER 3

HOW RISK ASSESSMENT SUPPORTS RESILIENCE ANALYSIS

Both risk assessment and resilience analysis can be performed independently and separately from each other. However, the recent advancement in the risk science has allowed for the possibility of integration and using both risk and resilience analysis in conjunction with each other for better safety management of a complex system. The main focus in this chapter and of the thesis is on the use of risk assessment in conjunction with resilience analysis, but for completion, a brief description of resilience-based strategies used in risk analysis is also provided.

3.1 *Resilience based strategies in risk analysis*

Resilience and resilience-based strategies are an integral part of risk science (Renn, 2008). The study of the latest risk management and principles shows that resilience is a vital strategy for handling risk (Renn, 2008). Klinke & Renn (2002) presented three risk management strategies mainly characterized as:

(1) risk-based,
(2) cautionary/precaution based, and
(3) discourse based.

The cautionary/precautionary based and discourse-based strategies are built on the fact of realization of importance to address uncertainties and surprises which are otherwise not considered in traditional risk assessment approaches. The cautionary/precautionary based strategies focus on robustness/resilience and argue that instead of trying to estimate the probability of an adverse event, one should observe caution by implementing the measures to increase robustness or by not starting the activity. The cautionary principle is used for all types of uncertainties and ambiguities, while the precautionary principle is applied in the case of scientific uncertainties (Aven & Renn, 2018; Aven & Thekdi, 2018). The discourse bases strategy discusses the ambiguity and focuses on resolving the risk issues through deliberation, involvements of affected people, and addressing the differences (Klinke & Renn, 2002).

3.2 *Risk assessment as an aid to resilience analysis*

Resilience management can be performed without consideration of risk analysis. One can increase the resilience of the system by implementing emergency preparedness system, redundant systems, barriers, etc. or boost the immune system of the body using multivitamins and through exercise. However, if we ponder over it, we will realize the need of risk consideration in conjunction with resilience analysis based on the following reasons (Aven & Thekdi, 2018):

Firstly, Aven (2017) highlighted the need for risk considerations in resilience analysis. He argued that by addressing the potential occurrence of an event and using risk assessment in conjunction to resilience analysis, one might be able to identify the new cause-effect relationship, leading to the recognition of potentially unexpected and unknown events which will lead to the development of better strategies to meet these events. It would not be fruitful to only rely on resilience-based strategies for the safety management of offshore installations without studying why certain failure occurs.

The second issue, where the risk assessment supports resilience analysis is an inefficient use of resources. As the resources are scarce, and one always wants to utilize the resources efficiently, risk assessment can be used to prioritize the areas where one wants to improve resilience (Aven, 2017). For example, let us envision an offshore installation. The management has decided to increase the resilience of the facility. The biggest challenge one face is to answer the question, where to enhance the resilience? Where is the improvement of the resilience needed? And to what event does resilience relate to? One can perform and propose the measure to increase the resilience of the system without identifying specific events by implementing emergency preparedness system, redundant systems, barriers, etc. But considering risk and identifying some event will lead to better resilience management and efficient use of resources. For example, an analyst did the resilience analysis and found that in case of a gas leak, a system is resilient as it can recover to its normal functioning state, while in case of an oil spill the system is not resilient as it takes a long time to recover. Based on this, one can focus more on implementing the measures to prevent and recover from an oil spill then on a gas leak.

However, by looking at the likelihood of both the events we may end up with different recommendations, for example, the possibility of gas leakage is very high (0.9999) while the risk analysis shows that occurrence of an oil spill is improbable (0.0001). Then the system will rarely go into a failure state, so the system resilience is high. Although we can still implement measure to further strengthen the resilience of a facility in case of an oil spill, but its impact on the overall risk will be quite marginal, resulting in inefficient use of resources. Aven (2017) highlighted the fact that some type of risk assessment approaches can strengthen resilience analysis. These approaches are mostly broad qualitative kind of risk assessment focusing on the strength of knowledge related to the occurrence of events, recovery process and corresponding uncertainty and is more suitable as compared to the traditional risk assessment approaches (Aven, 2017; Aven & Thekdi, 2018). These assessments support resilience analysis and provide insights about (Aven, 2017, p.540):

- Judgments about the events that can occur.
- Separating known, unknown and surprising events and assessing their probabilities where found meaningful.
- Trying to reveal unknown and surprising events.
- Assessing the strength of knowledge and identifying knowledge gaps.
- Identifying erroneous assumptions.

As discussed, the recent advancement in the risk science has allowed for both the conceptualizing and characterization of resilience similarly to risk as illustrated by Aven and Thekdi (2018) as:

$$Risk = (A, U) + (C, U \mid A)$$

$$= \text{“}occurrence\ of\ events, and\ associated\ uncertainties\text{”}$$
$$+$$
$$\text{“}consequences\ given\ events, and\ associated\ uncertainties\text{”}\ (resilience)$$

This can be further observed when we see resilience in close relation to system performance. As an example, let us consider a system working at desired performance level L. In the future an event A may causes the system to "jump" to a disruptive state below L, in response a recovery process comes into play enabling system recovery and causing the system to bounce back to L or better. The consequence C then expresses the time it takes to recover, that is, return to a desired state L or better. Then risk can be seen as (C, U), the risk of going into disruptive state and downtime time in the period considered, and resilience by (C, U | A), the recovery time given the occurrence of the event A, and associated uncertainties (Aven, 2018). According to the basic resilience form defined in terms of system recovery at time t to the loss suffered by the system at some previous point in time t_d the system resilience Y can be expressed as (Henry & Ramirez-Marquez, 2011, p.116) :

$$Y = \frac{Recovery(t)}{Loss\ (t_d)} \tag{6}$$

At the time of the analysis, the ratio of recovery to loss "Y" in unknown. To predict Y, we develop a model of the system under study, linking Y and some underlying set of explanatory variables $X = (X1, X2, \ldots)$ such as system lifetimes, restoration times, flow rate etc., depending on the system under study. Using the model f, the ratio performance recovery to loss Y is predicted as:

$$Y = \frac{Recovery(t)}{Loss\ (t_d)} = f(X) \tag{7}$$

There are uncertainties related to both X and Y. There is uncertainty about performance lost/disruptive state. There is uncertainty about which state the system will go into following an event. For example, following a gas leak, a system can go into different disruptive states. A detected gas leak will result in different degradation level as compared to undetected gas. Likewise, an ignited gas will cause much more disruption than the unignited one. There is uncertainty about the recovered state. There is a possibility that the system will return to its desired performance level from the gas leak, but not from the explosion, there may also be a possibility that a system takes more time to recover from a terrorist attack than from cyber malfunctioning. To describe this uncertainty, we may use subjective probabilities, imprecise probabilities, etc. We write:

$$P\ (Y|K),\ \ E\ (Y|K),\ \ etc\ .$$

As mentioned earlier, to describe the uncertainty related to Y and X different subjective probabilities, imprecise probabilities, etc. are used which are conditional on background knowledge. There is uncertainty concerning background knowledge on which these models and judgments are based (Bjerga, Aven & Zio, 2012). Therefore, we need to assess the strength of knowledge (SoK) about different assignments and judgments we made earlier using the criteria described by Aven and Flage (2017, p.7z). According to this criterion, the strength of knowledge is characterized as:

Table_2 SoK score assessment & Interpretation (Aven & Flage,2017, p.7z)

Score & interpretation
Weak: If one or more of the following are true: - Assumptions made represents strong simplifications. - Data is nonexistent or highly unreliable. - Strong disagreement among experts. - The phenomena involved are poorly understood, or models give a poor prediction. ***Strong:*** If all of the following are true: - The assumption made is reasonable. - A large amount of data and reliable information is available. - There is broad agreement among experts. - The phenomena involved are well understood, or models included give the right prediction. ***Medium:*** If conditions met are in between the Strong and Weak.

Based on the above discussion, the system resilience can be determined as:

$$P(Y) + SoK, E(Y) + SoK, etc.$$

The application and use of these approaches are further presented and discussed in the next chapter by applying it on deterministic resilience model presented by Henry and Ramirez-Marquez (2011).

CHAPTER 4

APPLICATION: AN EXTENSION OF DETERMINISTIC RESILIENCE MODEL

In this chapter, we are going to present the application of the above-mentioned risk assessment approach supporting resilience analysis. Here resilience is defined in line with the SRA (2015) definition of resilience, which states that "Resilience is the ability of the system to sustain or restore its basic functionality following a risk source or an event (even unknown)" (SRA, 2015).

The application presented in this section is an extension of the deterministic model presented by Henry and Ramirez-Marquez (2011). It is extended by incorporating risk considerations mentioned in chapter 3.

4.1 *Application*

Henry and Ramirez-Marquez (2011) presented a conceptual model describing system performance and state transition to study system resilience, as illustrated in the figure below. Initially, the system is in a healthy (normal) state S_o. At some time t_e in the future, an event occurs which initiates system disruption causing a system transition from the normal state to disruptive state S_d. In response, a recovery process comes into play enabling system recovery and causing the system to bounce back to a recovered state S_f. Depending upon the degree of resilience of the system, the recovered state S_f could be the same as a normal state S_f or different.

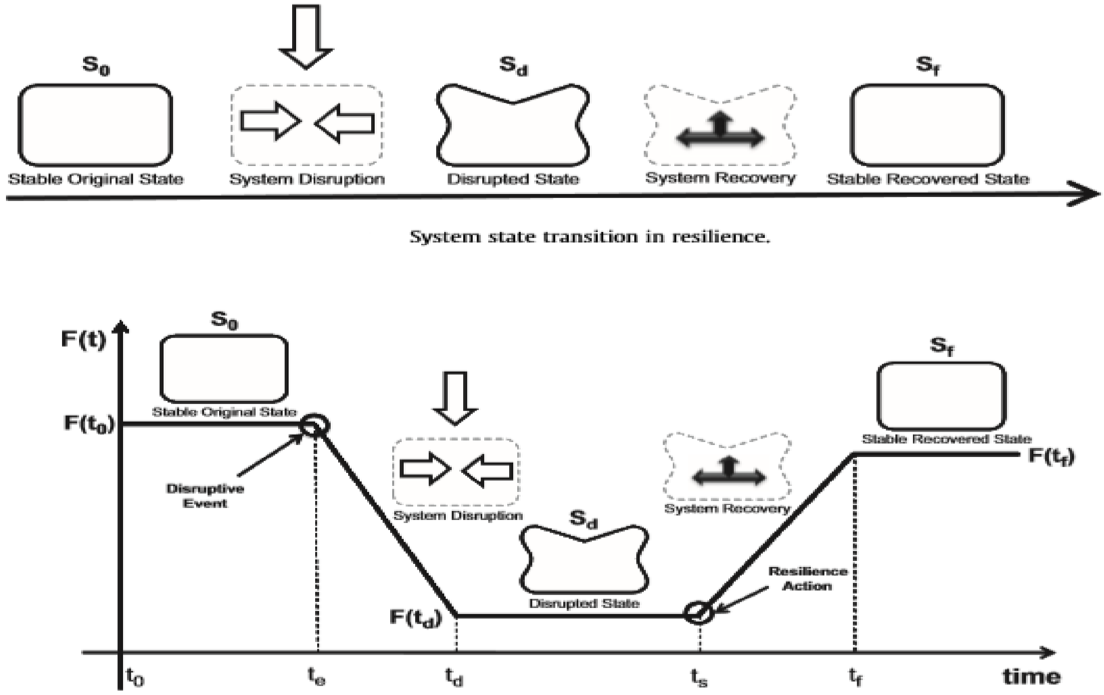

Figure_7 System performance and state transition to describe resilience (Henry & Ramirez-Marquez, 2011, p.117)

According to the basic resilience form defined in terms of system recovery at time t to the loss suffered by the system at some previous point in time t_d the system resilience Y can be expressed as (Henry & Ramirez-Marquez, 2011) :

$$Y = \frac{Recovery(t)}{Loss\ (t_d)}$$

We can see that system resilience is closely linked to system performance and state transition. Let ωt_o is the system performance at the time t_o corresponding to the stable state S_0. The system performance will remain at this level until time t_e at which disruptive event occurs causing degradation in the system performance level, resulting in system transition from the normal state to disruptive state. The corresponding system performance value at this point is represented by ωt_d which is lower than ωt_o .After this recovery actions come into play initiating system recovery from disruptive state to recovered state, causing an increase in system performance value from ωt_d to ωt_f at time t_f. This value could be the same as ωt_o or not, depending upon the degree of resilience. Based on this, the system resilience can be determined as (Henry & Ramirez-Marquez, 2011, p.118):

$$Y(t|e^j) = \frac{\omega(t|e^j) - \omega(t_d|e^j)}{\omega(t_0) - \omega(t_d|e^j)} \quad (8)$$

In the above equation (8) the numerator of this metric implies recovery up to time t, while the denominator refers to the total loss due to disruption e^j.

where,

ωt= Performance of the system at time t.
e^j = disruptive event
t_d = time till where effects of the disruptive event remains

4.1.1 *Uncertainty considerations in conjunction with deterministic resilience metric*

From the above, we see that system resilience is quantified as a function of system performance at different times. However, there is uncertainty about system delivery function corresponding to a disrupted state. There is also uncertainty about the restoration process, recovered state and time. Lastly, there is uncertainty about which state a system will go into following an event which is not represented by this metric. For example, following a gas leak, a system can go into different disruptive states. A detected gas leak will result in different degradation levels as compared to undetected gas. Likewise, an ignited gas will cause much more disruption than the unignited one. One can argue here about improving resilience concerning the worst-case scenario without considering the likelihood of different states in which system can jump, but we are led to a discussion of scarce resources. Using likelihood judgments in conjunction with this resilience metric will result in efficient use of resources. There is a possibility that a gas leakage rarely ignites, or a system rarely goes to the worst disrupted state, so spending resources on improving resilience here will have quite a negligible impact on the overall risk resulting in inefficient use of resources.

To quantify system delivery function, the recovery process, and corresponding resilience, several judgments, parameters, and models had to be used. We know that models are the simplification of the real world/system and there is always a possibility of model error and model uncertainty. How big or significant this error is, depends upon the background knowledge and on which these models and judgments are based (Bjerga et al., 2012). Therefore, there is a need to assess the strength of knowledge concerning different subjective choices made about the system delivery function and recovery process using the criteria described by Aven and Flage (2017). There could be weak assumptions, poor models, or fewer data to predict the system delivery function or disruptive state, leading to inaccurate or uncertain resilience assessment.

The other reason for incorporating the strength of knowledge assessment is that there could be a situation in which system resilience concerning two disruptive events could turn out to be the same. But in one case the knowledge on which this is based could be weak while on the other it could be strong, which is not reflected by these metrics, for example:
Resilience in case of the terrorist attack at t_f:

$$Y\big(t_f|e^j = terrorist\ attack\big)|K = \frac{\omega(t_f|e^j) - \omega(t_d|e^j)}{\omega(t_0) - \omega(t_d|e^j)}$$

$$Y\big(t_f|e^j\big)|K = 0.8 \quad Weak$$

Similarly, resilience in case of a gas leak is:

$$Y\big(t_f|e^j = gas\ leak\big)|K = 0.8 \quad Strong$$

However, in case of a gas leak, assessments are based on strong knowledge as a large amount of data is available, the phenomenon is well understood, and there is broad agreement among experts, while in case of a terrorist attack the knowledge is weak as the phenomenon is poorly understood with more considerable variation. In such cases, one can give less weight to resilience metric with inadequate knowledge and focus more on strengthening the system resilience in case of a terrorist attack than on a gas leak, which was otherwise neglected.

The above arguments support for an extension of the deterministic model to include uncertainties and incorporating the risk assessments approached described in chapter 3, as shown below:

Figure_8 Uncertainty considerations in conjunction with deterministic resilience metric

4.2 Example

Let us consider an offshore gas processing facility. The primary function of the processing facility is to process a certain amount of gas in a specified period of time. For a system to be sufficiently resilient, it must be able to sustain/restore the processing of the required amount gas in a specified period of time following an event. The management has decided to perform the resilience analysis of the installation and to do that a team has been formed to assess the degree of resilience of a facility.

4.2.1 System delivery function

In our case, we considered the system resilience in terms of the processing capacity facility which is assumed to be 15 m^3/s, i.e., for the system to be termed as sufficiently resilient, it must be able to restore or sustain the processing capacity of 15 m^3/s following an event.

$$\omega t_0 = 15\ m^3/s$$

4.2.2 Disruptive Event

The disruptive event considered here is the gas leak. At some time, t_d in the future, a leakage happened on the installation. As a result, the system can go into different disruptive states. A detected gas leak will result in a system degradation performance value of for example say $\omega(t_d|e^j) = 10$ refer to as state 1. If it is undetected but not ignited then the system will be degraded to an assumed performance value of $\omega(t_d|e^j) = 5$ refer to as state 2. An ignited gas leak which is extinguished will push the system into a disruptive state with the assumed delivery function of $\omega(t_d|e^j) = 0$ refer to as state 3.

4.2.3 Resilience Evaluation

After the recovery process is modeled. The system delivery function values are assumed, and system resilience is evaluated using equation (8) and is shown in the table as below:

Table_3 System Resilience Evaluation

	t_0	t_d	t_f	$Y(t_f\|e^j)$
$\omega(t\|e^j = Gas\ leak)$	15	0	5	0.3
		10	12	0.4
		5	15	1

For detail calculations please see appendix.

4.2.4 Likelihood considerations

From the above, we can see that a system is quite resilient when its performance level is degraded to a value of 5 while when it is degraded to a value of 0 or 10, the system is not resilient at a time t_f. One can argue here about implementing measures to improve resilience without considering the likelihood of different states and system resilience, but we are led to a discussion of scarce resources and more risk informed decision making to support resilience management.

Table_4 Likelihood of System Resilience

	t_0	t_d	t_f	$Y(t_f\|e^j)$	$P(Y(t_f\|e^j)\|K)$
$\omega(t\|e^j = Gas\ leak)$	15	0	5	0.3	0.01
		10	12	0.4	0.1
		5	15	1	0.89

By looking at the subjective likelihoods, one can conclude that the system is resilient in case of a gas leak at the time t_f as the system resilience is quite high as it will rarely go into state 3. Although we can still implement measure to further strengthen the resilience of a facility in case of a gas leak but its impact on the overall risk will be quite marginal resulting in inefficient use of resources.

4.2.5 SoK Assessment

Until now, we have made choices related to the system value, time, and corresponding states to calculate system resilience. As described earlier, models are the simplification of the real world/system, and there is uncertainty related to background knowledge on which these models and judgments are based (Bjerga et al., 2012). Therefore, we need to assess the strength of knowledge concerning different choices and decisions made earlier using the criteria described by Aven and Flage (2017).

The main aim of such risk and uncertainty considerations is to challenge the accuracy and reliability of current beliefs and judgments. To do this, we start by identifying the key assumptions/factors relevant to resilience evaluations and likelihood judgments. Then we assess the strength of knowledge and perform the sensitivity analysis concerning those assumptions/factors whose SoK is characterized as weak or medium and see how this choice impacts the initial resilience assessment. For example, let system resilience was evaluated at the time $t_f = 5$ as follow:

$$Y\left(t_f = 5|e^j\right)|K = \frac{\omega(t_f|e^j) - \omega(t_d|e^j)}{\omega(t_0) - \omega(t_d|e^j)}$$

$$\rightarrow Y\left(t_f|e^j\right)|K = \frac{12-0}{15-0}$$

$$Y\left(t_f = 5|e^j\right)|K = 0.8$$

The analysis is made on several assumptions. We asses SoK about the assumptions made. We start by identifying essential assumptions.

<u>*Assumptions:*</u>

1. Extreme Weather conditions are not being taken into consideration.
2. Restoration time for all components is assumed to be uniformly distributed.
3. Spare parts available on site.

Now we assess the SoK about assumptions identified based on the criteria described by Aven and Flage, (2017). The SoK is determined to be strong for two (2) and three (3), as it meets the criteria, while the SoK for one (1) is assessed to be weak as there was disagreement among experts and this assumption was seemed to be too simplified. After the SOK consideration, we perform the sensitivity analysis related to each of these choices and judgment and see how this choice impacts the original resilience assessment at $t_f = 5$. The sensitivity analysis with respect to the first assumption is done as follow:

$$Y\left(t_f = 5|e^j\right)|K = \frac{\omega(t_f|e^j) - \omega(t_d|e^j)}{\omega(t_0) - \omega(t_d|e^j)}$$

$$\rightarrow Y\left(t_f = 5|e^j\right)|K = \frac{10 - 0}{15 - 0}$$

$$Y\left(t_f = 5|e^j\right)|\, K = 0.66$$

Similarly, for the rest of assumptions, sensitivity analyses are performed the same as above. The deviation from the initial assessment results is characterized into three categories:

1. Low (Negligible/minor changes in the result).
2. Medium (Moderate changes).
3. High (significate changes).

The results are tabulated as in Table_4. The factor having low SoK and having a high degree of sensitivity is categorized as important while the one having high SoK and low sensitivity is classified as least important.

Table_5 Importance Assessment

Assumptions No.	**SoK**	**Degree of Sensitivity**	**Importance**
1.	Weak	High	1
2.	Strong	Low	3
3.	Strong	Medium	2

The results are graphically illustrated as:

Figure_9 Importance assessment adapted from (Bjørnsen, Jensen & Aven, 2018)

The factor having a significant effect on initial resilience assessment is characterized as important and needed to be further considered for evaluation and developing strategies. Thus, by focusing on the background knowledge and supporting this resilience metric by the strength of knowledge assessment, one may identify erroneous assumption and gain new knowledge resulting in the establishment of the more affluent knowledge base. Thus, presenting a clearer picture and improved basis for the decision maker to make decisions.

4.2.6 Management Review and decision

Finally, the results from the assessment are presented to the management for review and decision making as the analysis does not automatically give decision but supports decision making. Besides that, there is a broader picture that needs to be seen and the management has to look into the broader perspective in terms of strategic, cost limitations and other factors, etc. which the analysis team may not be aware of.

CHAPTER 5

DISCUSSION

Above we have illustrated and presented an application of how some types of risk assessments approaches to strengthen the resilience of the complex systems. One of the main goals of this thesis has been to utilize the recent integrated conceptualization and characterization framework provided by Aven & Thekdi (2018) and Aven (2018a) with already available resilience models in the literature for analyzing system resilience of complex systems, and to show how this characterization framework contributes to a better understanding of the system resilience. In this regard, the part of the work done, especially the application chapter (chapter 4) in this thesis can be seen as addressing these challenges. One such problem is the unavailability of reliable prognosis models, hence making it challenging to determine required measures to ensure the desired performance level of the system. By adding semi-quantitative types of uncertainty judgments to deterministic resilience models, a broader and richer knowledge basis is established for understanding resilience (ratio of recovery to loss) and suggesting measures to strengthen the system resilience. The central idea is that judgments made in the analysis might be based on imperfect knowledge, which needs to be reflected in the study, and when presented to the decision maker for a clear picture. To cater to this, we have incorporated additional steps of including semi-quantitative risk assessments, highlighting knowledge aspects in conjunction with deterministic resilience model. This step aimed to identify and assess the knowledge supporting the modeling choices and judgments related to states, system performance, recovery, and loss variation in the system. Using such assessment in conjunction with resilience analysis broadened the basis for identifying events and proposed preventive and rehabilitation measures, as we not only consider the current knowledge beliefs but also dwell into and investigate the possible deviations and consequences if current judgments and opinions turned out to be wrong or inaccurate. As a result, this inquisition could lead to the identification and possibility of events and consequence, resulting in the development of robust strategies against them which otherwise would have been overlooked due to weak knowledge or low judged probability based on current knowledge and beliefs.

In the suggested extension of the model, we have included both strength of knowledge (SoK) assessment and an importance assessment. Assessing the importance, as well as the uncertainty and sensitivity, allow the possibility of generating multiple models, states, etc. for which new measures and strategies can be developed. However, finding and identifying robust measures that are at least equally efficient for the initial models as well as for the new ones would be challenging. This challenge has not been addressed in this work as it was not in the scope of the thesis and may be considered as a limitation. However, the proposed approach can be seen as a starting point which can be built upon further and form the basis for the identification of such robust measures. Another drawback is that it increases the workload. There are a variety of modeling and simulation tools available, but still, the workload is increased. The extent to which risk and uncertainty considerations are to be included is value decision depending upon the scope, time, and resources available.

This kind of assessment described can be performed by the same team which has done the initial analysis or by a second team, often called as a “red team.” This red team will challenge the basis, criteria, assumption, results of the study initially done. The aim of “red teaming” is same as of qualitative risk assessment type explained, i.e., to reveal and identify possible (Aven 2017, p.540):

- Knowledge Gaps.
- Potential surprising events, especially unknown-known and low judged probability events.
- New cause-effect relation.
- Erroneous assumptions.

However, the added value the new team refer to as “red team ” (Aven, 2014) bring in is that this new team will have different a perspective, a different set of knowledge which will broaden the perspectives and enrich the knowledge base, resulting in the possible revelations of potential surprise, plus it also plays the role of quality checking.

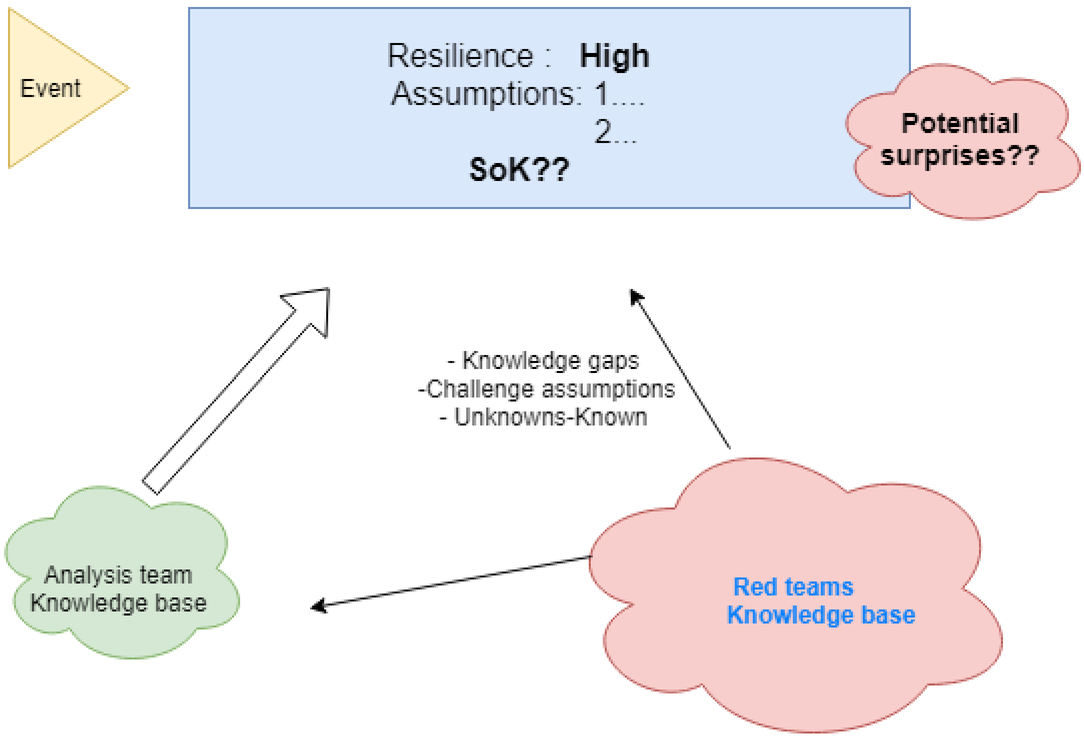

Figure_10 Challenging current analysis and strength of knowledge by red team adapted from (Bjerga, 2017)

5.1 *Consideration of processes to highlight potential surprises for improved resilience assessment*

The type of risk assessments proposed in conjunction with resilience analysis can also be of value for considering the overall processes to highlight potential surprises. For example, Bjerga & Aven (2016) and Aven (2017) shed light on this by presenting a security case (A terrorist attack on the BP-Equinor-Algerian Sonatrach facility in Algeria (Amenas)). On the 16th of January 2013, a terrorist attack occurred on the facility, resulting in the loss of 40 precious lives. Before investing in this project, Equinor (Statoil back then) conducted an assessment and found the security to be satisfactory. Their assessment was based on the assumption that the Algerian army will protect the complex as past data has shown the efficiency of the military. However, it turned out that the military did not respond as it was thought to do. Aven (2017) pointed to the fact that the phenomenon of the terrorist attack was not correctly understood by the analysis team as a large number of attackers attacked the facility forming a weak knowledge base for decision making. The system was not resilient in this case as a large number of people died. The likelihood and judgments can be made based on current knowledge, but about the basic understanding of the phenomenon and process under study, we should relate this to what degree the aspect, risk source/agents, their capacity and intention is known and understood (Aven, 2017). The critical point here is about proper analysis and characterization of risk and resilience analysis. As pointed out by Aven (2017), it is not about saying that the implementation of the current approach would have resulted in a different outcome, instead it is about arguing that the use of integrated risk-resilience characterization framework would have provided a structured way for what to address by conceptualizing the thinking, processes and focusing on potential surprises relevant to current knowledge and beliefs which could have resulted in better outcomes if implemented (Aven, 2017). In this way, considerations of risk and uncertainty are not only beneficial when considering system states and performance, but also when considering processes to highlight potential surprises to strengthen system resilience.

5.2 *Risk consideration in conjunction with probabilistic resilience approaches and metrics*

In the current work, we presented an extension of the deterministic resilience model presented by Henry and Ramirez-Marquez (2011) to include uncertainties and risk considerations. However, the study of the literature (for example see Hosseini et al. 2016) shows that probabilistic approaches and metrics have also been developed to asses system resilience incorporating uncertainties and the probability of disruption and restorations. For example, Youn et al. (2011) describe the resilience metric as (Hosseini et al. 2016, p.56):

“Sum of passive survival rate (reliability) and proactive survival rate (restoration) following a disruption” (Youn et al., 2011; Hosseini et al. 2016, p.56).

$$\Psi(resilience) = R(reliability) + \rho\,(restoration) \tag{9}$$

Here Youn et al. (2011) calculates restoration as the joint probability distribution of a system failure event, E_{sf} a correct diagnosis event, E_{cd}, a correct prognosis event, E_{cp}, and a successful recovery action event, E_{mr}

(10)

$$\rho = P\left(E_{mr} \middle| E_{cp} E_{cd} E_{sf}\right) * \ P\left(E_{cp} \middle| E_{cd} E_{sf}\right) * \ P\left(E_{cd} \middle| E_{sf}\right) * \ \ P(E_{sf})$$

Another probabilistic metric described in the literature in line with Hashimoto et al. (1982) is the (Aven, 2017, p.538):

“Probability of the system working in normal working state at time “t+1” if the system has jumped to a disruptive state at some previous time “t” i.e.

$$P(X_{t+1} = \ 3 \ | X_t = 2 \ or \ 1 \ ) \tag{11}$$

where,

X = system state
3 = Normal functioning state
2,1 = Different disruptive states

In the above approaches (for example equation 9,10,11), uncertainty has been described using the probabilities. However, Aven (2015, 2017) has drawn our attention to the drawbacks of using probabilities to express uncertainties. He argued that these probabilities could be either frequentist or subjective. The frequentist probabilities present the fraction of times a system is in a normal function state “3” if a large population of similar situations is considered. These probabilities are always unknown, and One has to estimate these probabilities using some models which again lead our discussion to model uncertainty (Bjerga et al., 2012) and SoK assessments (Aven & Flage, 2017). The other difficulty pointed out by Aven (2015) is in the availability and construction of massive population of similar events as in most of the cases the situations are unique, as the case of the previously mentioned BP-Equinor-Algerian Sonatrach security case (Bjerga & Aven, 2016). In such instances, frequentist probabilities are difficult to conceptually define where the situation cannot be repeated over and over again, estimating such probabilities is also a challenge which brings the subjective probabilities into play. The subjective probabilities express the assessor uncertainty or degree of belief, and this degree of belief is the same as drawing a random red ball from an urn containing a total of ten balls out of which nine are red, and one is blue (Aven, 2008). However, these subjective probabilities also have some limitations and depend upon background, which needs to be highlighted as describes in chapter 3 of this thesis (see Aven, 2008; Aven, 2015). Therefore, these probabilistic approaches and metrics need to be supplemented by the strength of knowledge assessment, as suggested by Aven (2017).

The key idea is that probabilistic resilience metric caters for expressing and describing uncertainty using either subjective or frequentist probability, but they have some limitations representing system resilience. The recent advancement in the risk science has allowed the possibility of addressing these limitations by incorporating and using qualitative assessments (SoK assessments) as illustrated in chapter 3 and chapter 4 and highlighted by Aven (2017).

CHAPTER 6

CONCLUSIONS

The review has shown that resilience analysis and management have been developed as an alternate approach for the safety management of complex systems, mainly due to the limitations of traditional risk analysis and management approach to deal with some crucial aspects of safety such as human-machine interaction, uncertainties, and surprises. The essence of resilience analysis and management is in on recovery and ability to confront surprises and black swan types of events. Two schools of thoughts are being observed in the scientific literature on the nexus between risk and resilience. The first is based on traditional risk perspective (A, C, P) (referred as “different school of thought”) alienating the risk and resilience science with limited risk-resilience linkage at the applied and generic level. The second school of thought is based on uncertainty-based risk perspective (A, C, U) (referred as “Unified school of thought”) concatenating risk and resilience science with strong conceptual and applied linkage. Here, the scientists and author are of the point of view that neither risk nor resilience can be properly analyzed and managed without each other. This is the right approach and need to be pursued further, as suggested by Aven (2018a).

In the unified framework, risk assessments are mainly qualitative, highlighting the strength of knowledge is an integral component of resilience analysis and management. These assessments establish a more fruitful knowledge basis for decision making and ensure the right overall focus. It allows for efficient use of resources by asking the right questions concerning threats/hazards and opportunities, revealing new cause-effect relationships resulting in the identification of the potentially surprising and unknown events, leading to the development of better resilience and safety management strategies for a complex system, in particular for offshore petroleum activities.

6.1 Possible future work

Unifying approach and concepts reviewed in this thesis provides a platform and basis for further research and development of integrated risk-resilience frameworks and tools both at a generic and an applied level. The extension of the deterministic resilience model presented in this thesis is just one of many applications area of the risk-resilience approach. Such approaches can be applied to other resilience models and metrics. Safety regulations and regime may also be possibly revisited based on these ideas.

APPENDIX

System resilience calculation:

The system resilience "Y" value in "Table_3" is calculated using equation (8) i.e.

$$Y\left(t_f|e^j\right)|K = \frac{\omega(t_f|e^j) - \omega(t_d|e^j)}{\omega(t_0) - \omega(t_d|e^j)}$$

The system initial state "t_o" performance value "$\omega(t_0)$" is assumed to be 15 m^3/s. Total three transitions are assumed from "initial state" to "disruptive state t_d" with the performance values "$\omega\left(t_d\middle|e^j\right)$" assumed to be at 0,10 and 5 m^3/s respectively. Likewise, the transitions from respective disruptive state to the recovered state with the performance value "$\omega(t_f|e^j)$" are assumed to be 5, 12 and 15 m^3/s respectively.

Therefore,

for $\omega(\boldsymbol{t_0}) = \mathbf{15},\ \omega(\boldsymbol{t_d}|\boldsymbol{e^j}) = \mathbf{0}\ \boldsymbol{and}\ \omega\left(\boldsymbol{t_f}\middle|\boldsymbol{e^j}\right) = \mathbf{5}\ \ \boldsymbol{we\ calculate}$:

$$System\ Resilience = \ Y\left(t_f|e^j\right)|K = \frac{\omega(t_f|e^j) - \omega(t_d|e^j)}{\omega(t_0) - \omega(t_d|e^j)}$$

$$\rightarrow Y\left(t_f = 5|e^j\right)|K = \frac{5-0}{15-0}$$

$$\rightarrow Y\left(t_f = 5|e^j\right)|K = 0.3$$

For $\omega(\boldsymbol{t_0}) = \mathbf{15},\ \omega(\boldsymbol{t_d}|\boldsymbol{e^j}) = \mathbf{10}\ \boldsymbol{and}\ \omega\left(\boldsymbol{t_f}\middle|\boldsymbol{e^j}\right) = \mathbf{12}$:

$$System\ Resilience = \ Y\left(t_f|e^j\right)|K = \frac{\omega(t_f|e^j) - \omega(t_d|e^j)}{\omega(t_0) - \omega(t_d|e^j)}$$

$$\rightarrow Y\left(t_f = 12|e^j\right)|K = \frac{12-10}{15-10}$$

$$\rightarrow Y\left(t_f = 12|e^j\right)|K = 0.4$$

And for $\omega(\boldsymbol{t_0}) = \mathbf{15},\ \omega(\boldsymbol{t_d}|\boldsymbol{e^j}) = \mathbf{5}\ \boldsymbol{and}\ \omega\left(\boldsymbol{t_f}|\boldsymbol{e^j}\right) = \mathbf{15}$:

$$System\ Resilience = \ Y\left(t_f|e^j\right)|K = \frac{\omega(t_f|e^j) - \omega(t_d|e^j)}{\omega(t_0) - \omega(t_d|e^j)}$$

$$\rightarrow Y\left(t_f = 15|e^j\right)|K = \frac{15 - 5}{15 - 5}$$

$$\rightarrow Y\left(t_f = 15|e^j\right)|K = 1$$

These final values of “Y” are inserted and shown in “Table_3”.

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