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Abstract

The risk matrix (RM) is a widely espoused approach to assess and analyze risks in the oil & gas (O&G) industry. RMs have been implemented throughout that industry and are extensively used in risk-management contexts. This is evidenced by numerous SPE papers documenting RMs as the primary risk management tool. Yet, despite this extensive use, the key question remains to be addressed: Does the use of RMs guide us to make optimal (or even better) risk-management decisions?

We have reviewed 30 SPE papers as well as several risk-management standards that illustrate and discuss the use of RMs in a variety of risk-management contexts, including HSE, financial, and inspection. These papers promote the use of RMs as a "best practice." Unfortunately, they do not discuss alternative methods or the pros and cons of using RMs.

The perceived benefit of the RM is its intuitive appeal and simplicity. RMs are supposedly easy to construct, easy to explain, and easy to score. They even might appear authoritative and intellectually rigorous. Yet, the development of RMs has taken place completely isolated from academic research in decision making and risk management. This paper discusses and illustrates how RMs produce arbitrary decisions and risk-management actions. These problems cannot be overcome because they are inherent in the structure of RMs. In their place, we recommend that O&G professionals rely on risk- and decision-analytic methods that rest on over 300 years of scientific thought and testing.

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List of Abbreviations

API	American Petroleum Institute
DA	Decision Analysis
HSE	Health, Safety and Environment
IT	Information Technology
ISO	International Organization for Standardization
MCS	Monte Carlo Simulation
NORSOK	Norske Sokkel Standard
O&G	Oil and Gas
PCE	Pressure Control Equipment
PWD	Pressure-While Drilling
RMs	Risk Matrices
SME	Subject Matter Expert
SPE	Society of Petroleum Engineers

Chapter 1 – Introduction

In the oil & gas (O&G) industry, risk-intensive decisions are made daily. In their attempt to implement a sound and effective risk-management culture, many companies use risk-matrices (RMs)[1] and specify this in "best practice" documents. Furthermore, RMs are recommended in numerous international and national standards such as ISO,[2] NORSOK,[3] and API.[4] The popularity of RMs has been attributed in part to their visually appeal which is claimed to improve communications.

Despite these claimed advantages, we are not aware of any published scientific studies demonstrating that RMs improve risk-management decisions.[5] However, several studies indicate the opposite, that RMs are conceptually and fundamentally flawed. For example, Cox et al. (2005) derived and discussed several fundamental flaws introduced through the qualitative scoring system that is often used in RMs. Cox (2008) provided further examples of these flaws and presented a set of rules that RMs must obey if they are to be logically consistent. Hubbard (2009) provided compelling arguments for why, in most cases, the use of RMs results in unclear information flow and sub-optimal risk management decisions.

The objectives of this thesis are to:

- summarize the known flaws of RMs;
- identify several new problems with RMs;
- demonstrate that a sample of SPE papers, which either demonstrate or recommend the use of risk matrices, include these flaws and problems;

[1] Sometimes called a Probability-Impact Matrix (PIM)
[2] ISO: International Organization for Standardization, the world largest developer of voluntary International Standards
[3] API: American Petroleum Institute, which establishes standards for petroleum industry activities in the US
[4] NORSOK: produces standards for petroleum industry activities in Norway
[5] Clearly, using RMs to analyze and manage risks is better than doing nothing. Indeed, any approach that generates some discussion of the risks in a particular activity will be helpful.

- summarize the current effort to fix RMs; and
- demonstrate decision analysis (DA) as a possible alternative to RMs.

Following this introduction the remainder of this thesis is organized thus.

- Chapter 2 introduces a description of RMs, and includes a discussion about current practices and standards for risk management, followed by an example.
- In chapter 3, we illustrate the flaws and dangers resulting from the use of RMs.
- Chapter 4 describes the approaches used to fix the known flaws of RMs, including their limitations.
- In chapter 5, we demonstrate and provide evidence that decision analysis is a better alternative to RMs.
- Finally, in chapter 6, we provide a summary and a discussion of the earlier chapters and answer the question of whether the use of RMs guides us to make optimal (or even better) risk-management decisions.

A substantial part of this thesis (Chapters 2 and 3) are drawn from the SPE paper (SPE 166269-MS), which written for Annual Technical Conference and Exhibition (ATCE) 2013 with the same title. This paper was written by the author of the present work, together with the supervisor of this thesis and another co-author (Philip Thomas, Reidar Bratvold and Eric Bickel). Thus, there are a number of similarities that can be noted between the two documents.

Chapter 2 – Risk Matrices: a Short Introduction

2. Basic Knowledge of Risk Matrices

Risk matrices (RMs) are the most popular risk-assessment/risk-management methodology employed across many industries, including the oil and gas (O&G) industry, information technology (IT) industry and many research organizations. RMs don't require complicated input data, thus, making it convenient and intuitive for its users. In addition, RMs provide a graphical output that enables the risk analyst to easily communicate the risk assessment result to the stake holders and shareholders. However, despite the popularity of RMs, neither its accuracy nor its reliability has been rigorously assessed or reported in the published literature.

2.1 Terminology

Discussions about RMs require a brief discussion about associated terminology. If risk managers are to communicate effectively with each other as well as with other stakeholders, it is important that they use a common language. Moreover, because risk management draws on and interacts with so many other fields—including decision analysis, geoscience, engineering, economics and statistics—that share many of the same concepts, it would be a confusing to use different terminology for these shared concepts. The goal of any risk management exercise is to improve communication and understanding of the risk factors, and achieve clarity on optimal risk mitigation actions. This will be achieved only with a clear definition of the central terms used in risk management. These include 'risk', 'uncertainty', 'probability', 'consequence', 'opportunity' and 'outcome'. The following definitions are used in risk management and management science in general. The definition in this section has been drawn from work by Hubbard (2009), Clemen (2001) and Bratvold and Begg (2010).

***Risk*.** Within the context of RMs, 'risk' is defined as consequence multiplied by probability. Risk has a negative connotation, and by 'risk management' we implicitly mean the mitigation of downside possibilities. This notion of risk is focused on downside loss rather than upside gain. Probability multiplied by consequence yields the expected downside consequence or the expected loss. Purveyors of RMs refer to expected downside consequences as ‘risk’, but we will use the more precise term ‘expected loss’ (EL).

***Uncertainty*.** Uncertainty is a subjective aspect of our state of knowledge. Examples of uncertain quantities are future events (e.g., the price of gas on a given future date) or current states of nature [e.g. original oil in place (OOIP) for a given well or field]. To quantify uncertainty, we must identify the range of states in which an uncertain quantity may take and associate probabilities with those states. There is no single, ‘correct’ uncertainty for a given event—the uncertainty represents the lack of knowledge of the person or people involved.

***Probability*.** A probability is a number between 0 and 1 that express our degree of belief that an outcome will occur. In the context of most events in risk management, a probability does not describe a characteristic of the physical world that we can discern through repeated experiments. The probability is the quantification of our belief about some uncertainty of a future event. In a case where our belief is driven by historical data, probability is frequently referred as likelihood.

***Consequence*.** A consequence is the value or score estimated for a given outcome. For example, if the outcome is ‘blow out’, the consequence could be estimated to be $250 million.

***Outcome*.** An outcome is a possibility resulting from a combination of decisions and uncertainties. An outcome must be both clear and useful for analyses[6].

[6]Howard (2007) introduced the notion of a clairvoyant—a person who can answer any question accurately, including questions about the future, but who possesses no particular expertise or analytical capability. Using this notion, we can say a clear outcome is one that passes the clarity test: a mental exercise to determine whether the clairvoyant can immediately answer a question or whether the clairvoyant needs to know other things first. “Spot price of oil on August 24, 2022,” does not pass the test because it needs further specification of the classification (e.g. Brent, WTI) and it also may need the time of that specific day. “Technical success” needs to be defined to pass the clarity test. Terms frequently used in developing RMs such as ‘moderate’, ‘severe’, ‘frequent’ and ‘seldom’ do not pass the clarity test.

***Opportunity*.** Opportunity is a desirable consequence of uncertainty. For example, 'the oil-in-place is 30% higher than expected'.

2.2 What is a Risk Matrix

An RM is a graphical presentation of the likelihood, or probability, of an outcome and the consequence should that outcome occur. Consequences are often defined in monetary terms. RMs, as their name implies, tend to be focused on outcomes that could result in a loss, rather than gain. The purported objective of the RM is to prioritize risks and risk-mitigation actions.

Pritchard et al. (2010) gave an example of using RMs to assess the risk of a drilling hazard. This paper was one of three in a special issue of World Oil devoted to advances in drilling. Pritchard et al. (2010) note the example as a "typical industry risk assessment matrix." We have adopted this example as **Figure 1** and use it to explain the flaws inherent in RMs.

Probability	P - Rating	P - Indices						
> 40%	6	Likely						
20% < p <= 40%	5	Occasional				Severe Losses		
10% < p <= 20%	4	Seldom						
5% < p <= 10%	3	Unlikely					Well Control	
1% < p <= 5%	2	Remote						Blowout
<=1%	1	Rare						
Consequence Rating Consequence Indices Consequence Cost			1 Incidental <=$100K	2 Minor $100K - $250K	3 Moderate $250K - $1MM	4 Major $1MM - $5MM	5 Severe $5MM - $20MM	6 Catastrophic >$20MM

Figure 1 — A risk matrix modified from Pritchard *et al.* (2010)

The consequences and probabilities in an RM are expressed as a range. For example the first consequence category might be "<$100K," the second might be "$100K–$250K," and so on. The first probability range might be "<=1%," the second might be between 1% and 5%, and so on. A verbal label and a score are also assigned to each range. (Some RMs use these instead of a quantitative range.) For example, probabilities from 10% and 20% might be labeled as "Seldom" and assigned a score of 4. Probabilities greater than 40% might be termed "Likely" and given a score of 6. Consequences from $5 million to $20 million might be termed "Severe" and given a score of 5; losses above $20 million might be labeled as "Catastrophic" and given a score of 6.

Such an RM would treat losses of $50 billion (on the scale of BP's losses stemming from the Macondo blowout) or $20 million in the same way, despite their being three orders of magnitude distinct. Because there is no scientific method of designing the ranges used in an RM, many practitioners simply use the ranges specified in their company's best practice documents. In fact, as we will show below, differently shaped regions can alter risk rankings.

The cells in RMs are generally colored green, yellow, and red. Green means "acceptable," yellow stands for "monitor, reduce if possible," and red is "unacceptable, mitigation required." le. Previous work has detailed the way in which the colors *must* be assigned if one seeks consistency in the ranking of risks. Most of the SPE papers we examined failed to assign colors in a logically consistent way. For example, some of the cells designated as red were "less risky" than some of the cells that were designated as yellow.

2.3 Case Example to Demonstrate the Use of Risk Matrices

The problem context presented in Pritchard et al. (2010) is the loss of fluid while drilling in a particular section of a well. There is then a need to identify the possible outcomes and consequences arising from this event and to prioritize these risks. Three possible downside outcomes were identified: *severe losses* of drilling fluid, *well control* issues, and *blowout*.[7] Once the possible outcomes were defined, Pritchard et al. (2010) specified their probabilities and the range of possible consequences, both of which are given in **Table 1**.[8] Once the assessment of consequence and probability[9] was complete, the outcome was plotted in the RM (see **Figure 1)** to determine whether the risk of an outcome fell into a green, yellow, or red region. Thus, well control and blowout fell in the yellow region, whereas severe losses was red. Hence, in the parlance of RMs, the

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[7] The outcomes are assumed to be independent, which might not be correct. For example, a blowout implies loss of well control.

[8] The probabilities in this case example are taken from Pritchard et al. (2010), and the consequences come from reconversion of the consequence scores into their definition as presented in Pritchard et al. (2010).

[9] The probabilities not need sum to 1, as the events are assumed to be mutually exclusive but not collectively exhaustive.

possibility of severe losses is "riskier" than either well control or blowout and should therefore be prioritized over these other two concerns.

Table 1 — Drilling case example

Event : Fluid losses happens in hole section (12-14 in)		
Outcome	**Consequence (Million US$)**	**Probability**
Severe Losses	1-5	40%
Well Control	5-20	10%
Blowout	>20	5%

Figure 1 indicates the score associated with each range. Pritchard et al. (2010) assumed that cells along a diagonal with slope of -1 have the same risk. Thus, they considered blowout and well control to have the same degree of risk. Poedjono et al. (2009) and Dethlefs & Chastain (2011) also documented the use of RMs in a drilling context, but they used the more common practice of multiplying the probability and consequence scores to obtain a "risk score" for each outcome. **Table 2** shows the results of applying this procedure to the Pritchard et al. (2010) example. There appears to be no mathematical theory that would allow the multiplication of scores, a practice that seems to be an attempt to mimic the calculation of expected loss, in which case monetary consequence would be multiplied, or "risked," by the likelihood of its occurrence. Based on these results, actions to mitigate severe losses will be prioritized while blowout will be addressed only after the other two possible outcomes have been addressed.

Table 2 — Risk ranking results

Outcome	Risk Score	Rank
Severe Losses	20	1
Well Control	15	2
Blowout	12	3

Before concluding this section, we explain how and why we slightly modified the RM used by Pritchard et al. (2010). First, they used a decreasing score scale rather than the increasing scale which is more commonly used. As we will show later, the choice between an ascending or descending scale in our analysis can alter the prioritization. Second, they did not use mutually exclusive categories. Specifically, they used categories of $1 million to $5 million and $2 million to $20 million. This is clearly problematic for an outcome of, say, $3 million. Similarly, there was an overlap in their probability ranges of 0% to 1% and 0% to 5% which means that the ranges were not mutually exclusive.

2.4 Current Practices and Standards

RMs are considered to be versatile enough to be used to analyze and prioritize risks in many settings. A number of international standards support its role in risk assessment, and many companies consider RMs to be a "best practice." In this section, we illustrate a common RM-analysis approach. We then summarize how some central risk management standards view the use of RMs.

2.4.1 Common Industry Practices

In order to use the RM for risk prioritization and communication, several steps must be carried out. Clare and Armstrong (2006) presented a common risk evaluation process for the O&G industry, where they used RMs as a risk-evaluation tool. The work process they used is shown in **Figure 2**.

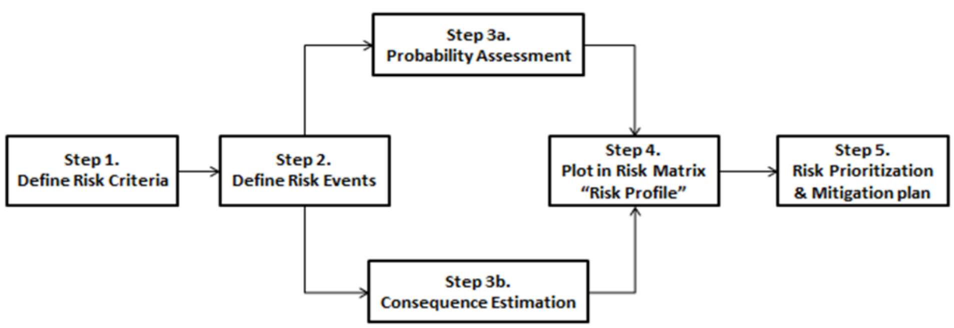

Figure 2 — Common workflow for analyzing risks using RMs

Step 1 – Define Risk Criteria. This step determines the size of the RM and its number of colors. Although there is no technical reason for it, RMs are generally square. The most common size is five rows by five columns (i.e., a 5 × 5 matrix), but some companies use a 3 × 3 matrix, others an 8 × 8 matrix. Some companies choose to include more colors than the standard red, yellow, and green in their RMs.

Step 2 – Define Risk Events. This step identifies the risk events. For example, drilling a particular hole-section is the event for which we are going to identify all the possible downside outcomes.

Step 3 – Consequence Estimation and Probability Assessment. This step estimates the consequence range of each outcome identified in Step 2 and assigns probabilities to each outcome. For example, the outcome of severe losses is registered, and the expected financial consequence is estimated to be from $1 million to $5 million. The chance of this occurring is estimated to be 40%. Using the RM in **Figure 1**, this equates to a probability score of 5 ("Occasional") and a consequence score of 4 ("Major").

Step 4 – Risk Profile. This step positions each identified downside outcome in a cell in the RM.

Step 5 – Rank and Prioritize. This step ranks and prioritizes the outcomes according to their risk score. Most companies use a risk management policy where all outcomes in the red area are "unacceptable" and thus must be mitigated.

The results of Steps 2–5 are often collectively called a "risk register," and the information required is usually collected in a joint meeting with the key stakeholders from the operating company, service companies, partners, and others.

2.4.2 Standards

Among the standards that are commonly used in the O&G industry are API, NORSOK, and ISO. All of these standards recommend RMs as an element of risk management. This section summarizes how each of these standards supports RMs.

API. API (2009) recommends RMs customarily for its risk-based inspection (RBI) technology. Risk-based inspection is a method to optimize inspection planning by generating a risk ranking for equipment and processes and, thus, prioritization for inspection of the right equipment at the right time. API (API RP 581) specifies how to calculate the likelihoods and consequences to be used in the RMs. The specification is a function of the equipment that is being analyzed. The probability and consequence of a failure is calculated using several factors. API asserts that “Presenting the results in a risk matrix is an effective way of showing the distribution of risks for different components in a process unit without numerical values.”

NORSOK. The NORSOK (2002) standards were developed by the Norwegian petroleum industry to “ensure adequate safety, value adding and cost effectiveness for petroleum industry developments and operations. Furthermore, NORSOK standards are as far as possible intended to replace oil company specifications and serve as references in the authority’s regulations.” NORSOK recommends the use of RMs for most of their risk-analysis illustrations. The RMs used by NORSOK are less rigid than those of API-RBI, since the NORSOK RMs can be customized for many problem contexts (the RM template is not standardized). NORSOK S-012, an HSE document related to the construction of petroleum infrastructure, uses an RM that has three consequence axes—occupational injury, environment, and material/production cost—with a single probability axis for all three consequence axes.

ISO. The ISO (2009) standard influences risk management practices not only in the O&G industry but in many others. In ISO 31000, the RM is known as a Probability/Consequence Matrix. Also in ISO 31000 is a table that summarizes the applicability of tools used for risk assessment. ISO claims that the RM is a “strongly applicable” tool for risk identification and risk analysis and is “applicable” for risk evaluation. As with the NORSOK standard, ISO does not standardize the number of colors, the coloring scheme (risk acceptance determination), or the size of range for each category. ISO praises RMs for their convenience, ease of use, and quick results. However, ISO also lists limitations of RMs, including some of their inconsistencies, to which we now turn.

Chapter 3 – Risk Matrices: Flaws and Dangers

3. Deficiencies of Risk Matrices

Several flaws are inherent to RMs. Some of them can be corrected, while others seem more problematic. For example, we will show that the ranking produced by a RM depends upon arbitrary choices regarding its design, such as whether one chooses to use an increasing or decreasing scale for the scores. As we discuss these flaws, we also survey the SPE literature to identify the extent to which these mistakes are being made in practical applications.

To locate SPE papers that address or demonstrate the use of RMs, we searched the OnePetro database using the terms “Risk Matrix” and “Risk Matrices.” This returned 527 papers. Then, we removed 120 papers published prior to the year 2000, to make sure our study is focused upon current practice. We next reviewed the remaining 407 papers and selected those that promote the use of RMs as a “best practice” and actually demonstrate RMs in the paper; leaving 68 papers. We further eliminated papers that presented the same example. In total, we considered a set of 30 papers covering a variety of practice areas (e.g., HSE, hazard analysis, and inspection). We believe that this sampling of papers presents the current RM practice in the O&G industry. We did not find any SPE papers documenting the known pitfalls of using RMs. The 30 papers we consider in this paper are given in the Appendix.

3.1 Known Deficiencies of Risk Matrices

Several deficiencies of RMs have been identified by other authors.

3.1.1 Risk Acceptance Inconsistency

RMs are used to identify, rank, and prioritize possible outcomes so that scarce resources can be directed towards the most beneficial areas. Thus, RMs must reliably categorize the possible outcomes into green, yellow and red regions. Cox (2008) suggested we should conform to three axioms and one rule when designing RMs in order to ensure that the EL in the green region is consistently smaller than the EL in the red region. Cox (2008) also clarifies that the main purpose of yellow region is to separates the green region and red region in the RMs; not to categorize the outcomes. He argues that the RM is inconsistent if the EL in the yellow region can be larger than in any of the red cells or lower than in any of the green cells. Nevertheless, the practice in O&G is to use the yellow region to denote an outcome with a medium risk. Every single SPE paper I reviewed employs this practice and also violates at least one of the axioms or the rule proposed by Cox (2008) leading to inconsistencies in the RMs.

Figure 3 shows an example RM with many outcomes. This example shows that there are two groups of outcomes. The first group is the outcome with medium-high probability and medium-high consequence (e.g., severe losses, well control issues) and the second group is outcome with the low probability but very high consequence (e.g., blowout). In **Figure 3**, the first group of outcome is illustrated in the red cells while the second group is on the yellow cell. The numbers shown in some of the cells represent the probability, consequence and EL, respectively, where EL is calculated as probability multiplied by consequence. This example shows the inconsistency between EL and color practice in RM where all outcomes in the red cells have less EL compared to the outcome in the yellow cell. Assuming that we wish to rank outcomes based on expected loss, we would prioritize the outcome in the yellow cell compared with the outcomes in the red cells which is the opposite of the ranking provided by the color region in RM. Clearly, using the RM would in this case lead us to focus our risk mitigation actions on the outcome does not have the highest EL. This type of structure is evident in 8 of the papers reviewed.

Probability	P - Rating	P - Indices						
> 40%	6	Likely			(45%, 1, 0.45)	(45%, 3, 1.35)	(45%, 15, 6.75)	(45%, 25, 11.25)
20% < p <= 40%	5	Occasional				(25%, 3, 0.75)	(25%, 15, 3.75)	(25%, 25, 6.25)
10% < p <= 20%	4	Seldom					(15%, 15, 2.25)	(15%, 25, 3.75)
5% < p <= 10%	3	Unlikely						(10%, 25, 15.5)
1% < p <= 5%	2	Remote						(5%, 250, 12.5)
<=1%	1	Rare						
Consequence Rating			1	2	3	4	5	6
Consequence Indices			Incidental	Minor	Moderate	Major	Severe	Catastrophic
Consequence cost			<=$100K	$100K - $250K	$250K - $1MM	$1MM - $5MM	$5MM - $20MM	>$20MM

Figure 3 — Risk acceptance inconsistency in RMs.

3.1.2 Range Compression

Cox (2008) described range compression in RMs as a flaw that “assigns identical ratings to quantitatively very different risk.” Hubbard (2009) also focused extensively on this problem.

Range compression is unavoidable when consequences and probabilities are converted into scores. The distance between risks in the RM using scores (mimicking expected-loss calculation) does not reflect the actual distance between risks (that is, the difference in their expected-loss).

In our case example shown in **Figure 1**, blowout and well control are considered to have the same risk (both are yellow). However, this occurs only because of the ranges that were used and the arbitrary decision to have the “catastrophic” category include all consequences above $20 million. **Figure 4** more accurately represents these outcomes. A blowout could be many orders of magnitude worse than a loss of well control. Yet, the RM does not emphasize this in a way that we think is likely to lead to high-quality risk mitigation actions. To the contrary, the sense that we get from **Figure 1** is that a blowout is not significantly different (if any different) from a loss in well control—they are both “yellow” risks after all. Using the scoring mechanism embedded in RMs compress the range of outcomes and, thus, miscommunicates the relative magnitude of both consequences and probabilities. The failure of the RM to convey this distinction seems to undermine its commonly stated benefit of improved communication. This example demonstrates the range compression inherent in RMs, which necessarily affected all of the surveyed SPE papers. The next section will introduce the “Lie Factor” that we use to quantify the degree of range compression.

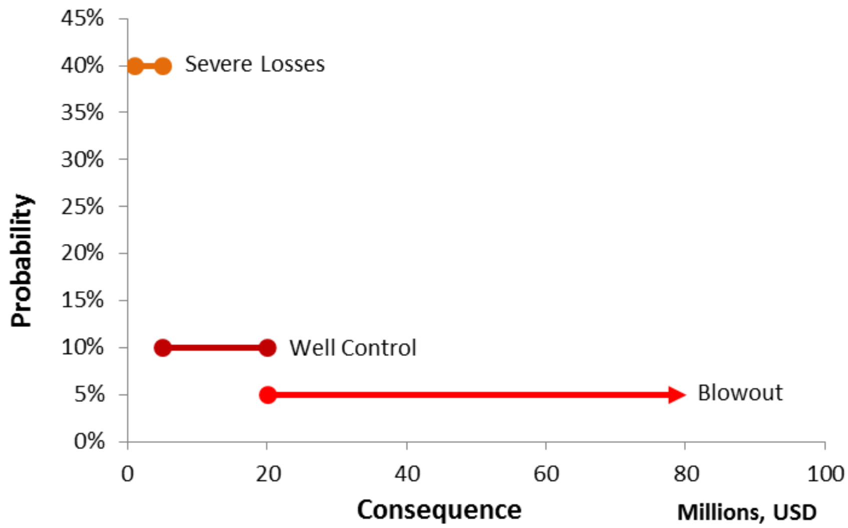

Figure 4 — Plot of probabilities and consequences value of the outcomes in the case example.

3.1.3 Centering Bias

Centering bias refers to the tendency of people to avoid extreme values or statements when presented with a choice. For example, if a score range is from 1 to 5, most people will select a value from 2 to 4. Hubbard (2009) analyzed this in the case of information technology projects. He found that 75% of the chosen scores were either 3 or 4. This further compacts the scale of RMs, exacerbating range compression. Smith et al. (2008) came to the same conclusions from investigating risk management in the airline industry.

Is this bias also affecting risk management decisions in the O&G industry? Unfortunately there is no open-source O&G database that can be used to address this. However, six of the reviewed SPE papers presented their data in sufficient detail to investigate whether the centering bias seems to be occurring. Each of the six papers uses an RM with more than 15 outcomes. **Figure 5** shows the percentage of the outcomes that fell into the middle consequence and probability scores. For example, paper SPE 142854 used a 5 × 5 RM, hence the probability ratings ranged from 1 to 5. Of its 24 outcomes, 18 have a probability rating of 2, 3, or 4 (which we will denote as "centered"), and the remaining 6 outcomes have a probability rating of 5. Hence, 75% of the probability scores were centered.

For the six papers combined, 77% of the probability scores were centered, which confirms Hubbard (2009). However, only 62% of the consequence scores were centered, which is less than that found in Hubbard (2009). A closer inspection shows that in four out of the six papers, 90% of either probability or consequence scores were centered.

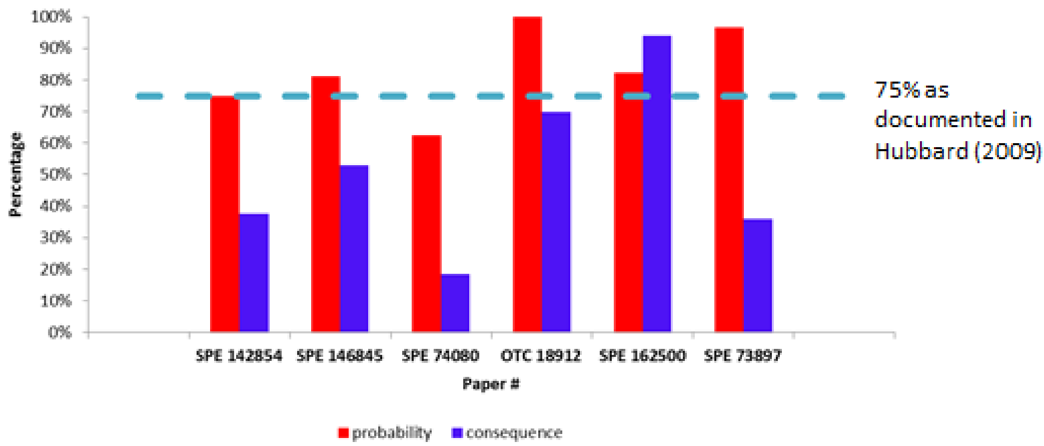

Figure 5 — Centering bias evidence in SPE papers.

3.1.4 Category Definition Bias

Budescu (2009) concluded that providing guidelines on probability values and phrases is not helping the probability assessments. For example, when guidelines specified that "very likely" should indicate a probability greater than 0.9, study participants still assigned probabilities in the 0.43 to 0.99 range when they encountered the phrase "very likely." He argued that this creates "illusion of communication" rather than real communication. If a specific definition of scores or categories is not effective in helping experts be consistent in their communication, then using only qualitative definitions would likely result in even more confusion. Windschitl & Weber (1990) showed that the interpretation of phrases conveying a probability depends on context and personal preferences (e.g., perception of the consequence value). Although most research on this topic has focused on probability-related words, consequence-related words such as "severe," "major," or "catastrophic" would also seem likely to foster confusion and miscommunication.

We reviewed the 30 SPE papers on the scoring method used. The papers were then classified into qualitative, semi-qualitative, and quantitative categories.[10] Most of the scores (97%) were qualitative or semi-qualitative. Yet, these papers included no discussion indicating that the authors are aware of Category Definition Bias or any suggestions for how it might be counteracted.

Category Definition Bias is also clearly seen between papers. For example, SPE 142854 considered “Improbable” as “virtually improbable and unrealistic.” In contrast, SPE 158114 defined “Improbable” as “would require a rare combination of factors to cause an incident.” These definitions clearly have different meanings, which will lead to inconsistent risk assessments. This bias is also seen in the quantitative RMs. SPE 127254 categorized “Frequent” as “more than 1 occurrence per year,” but SPE 162500 categorized “Frequent” as “more than 1 occurrence in 10 years.” This clearly shows inconsistency between members of the same industry. **Table 3** summarizes the variations in definitions within the same indices in some of the SPE papers surveyed.

[10]Qualitative refers to RMs in which none of the definitions of probability and consequence categories provide numerical values. Quantitative refers to RMs whose definitions of all probability and consequence categories provide numerical values. Semi-quantitative refers to RMs in which some of the definitions of probability and consequence categories provide numerical values.

Table 3 — Category Definition Bias evidences in SPE papers.

Paper	Index	Index Definition	Quantitative Measures
SPE - 146845	Frequent	Several times a year in one location	occurence > 1/year
SPE - 127254	Frequent	Expected to occur several times during lifespan of a unit	occurence > 1/year
SPE - 162500	Frequent	Happens Several times per year in same location or operation	occurrence > 0.1/year
SPE - 123457	Frequent	Has occurred in the organization in the last 12 months	-
SPE - 61149	Frequent	Possibility of repeated incidents	-
SPE - 146845	Probable	Several times per year in a company	1/year > occcurence > 0.1/year
SPE - 127254	Probable	Expected to occur more than once during lifespan of a unit	1/year > occcurence > 0.03/year
SPE - 162500	Probable	Happens Several times per year in specific group company	0.1/year > occcurence > 0.01/year
SPE - 123457	Probable	Has occurred in the organization in the last 5 years or has occurred in the industry in the last 2 years	-
SPE - 158115	Probable	Not certain, but additional factor(s) likely result in incident	-
SPE - 61149	Probable	Possibility of isolated incident	-

Given these gross inconsistencies, how can we accept the claim that RMs improve communication? As we show here, RMs that are actually being used in the industry are likely to foster miscommunication and misunderstanding, rather than improve it. This miscommunication will result in misallocation of resources and the acceptance of sub-optimal levels of risk.

3.2 Identification of New Deficiencies

This section discusses three RM flaws that had not been previously identified. We demonstrate that these flaws cannot be overcome and that RMs will likely produce arbitrary recommendations.

3.2.1 Ranking is Arbitrary

***Ranking Reversal*.**

Lacking standards for how to use scores in RMs, two common practices have evolved: ascending scores or descending scores. The example in **Figure 1** uses ascending scores, in which a higher score indicates a higher probability or more serious consequence. Using descending scores, a lower score indicates a higher probability or more serious consequence. These practices are contrasted in **Figure 6.**

Probability	P - Rating Descending	P - Rating Ascending	P - Indices						
> 40%	1	6	Likely						
20% < p <= 40%	2	5	Occasional				Severe Losses		
10% < p <= 20%	3	4	Seldom						
5% < p <= 10%	4	3	Unlikely					Well Control	
1% < p <= 5%	5	2	Remote						Blowout
<=1%	6	1	Rare						
Consequence Rating Ascending				1	2	3	4	5	6
Consequence Rating Descending				6	5	4	3	2	1
Consequence Indices				Incidental	Minor	Moderate	Major	Severe	Catastrophic
Consequence Cost				<=$100K	$100K - $250K	$250K - $1MM	$1MM - $5MM	$5MM - $20MM	>$20MM

Figure 6 — RMs with two different scoring systems.

A glance at **Figure 6** might give the impression that ascending or descending scores would produce the same risk-ranking of outcomes. However, **Table 4** shows for each ordering, the resulting risk scores and ranking of the outcomes shown in **Figure 6**. Using ascending scores, severe losses will be prioritized for risk mitigation. However, using the descending scores, blowout will be prioritized for risk mitigation.

Table 4 — Risk prioritization from different practices.

Ascending			Descending		
Outcome	**Risk Score**	**Rank**	**Outcome**	**Risk Score**	**Rank**
Severe Losses	20	1	Severe Losses	6	2
Well Control	15	2	Well Control	8	3
Blowout	12	3	Blowout	5	1

The typical industry RM given in Pritchard et al. (2010) used descending ordering. However, both ascending and descending scoring systems have been cited in the SPE literature. In the 30 SPE papers surveyed, five uses the descending scoring system, and the rest use ascending. This behavior demonstrates that RM rankings are arbitrary; whether something is ranked first or last, for example, depends on whether or not one creates an increasing or a decreasing scale. How can a methodology that exhibits such a gross deficiency be considered an industry best practice? Would such a method stand up to scrutiny in a court of law? Imagine an engineer defending their risk management plan by noting it was developed using an RM, when the lawyer points out that simply changing the scale would have resulted in a different plan. What other best practices do engineers use that produces different designs simply by changing the scale or the units?

Instability due to Categorization.

RMs categorize consequence and probability values. Yet, there are no well-established rules for how to do the categorization. Morgan et al. (2000) recommended testing different categories, as no single category breakdown is suitable for every consequence variable and probability within a given situation.

Following this recommendation, we tried to find the best categories for the RM in **Figure 1** by examining the sensitivity of the risk ranking to changes in category definitions. To ease this analysis, we introduced a multiplier n that determines the range for each category. We retained ranges for the first category for both consequence and probability. For the categories that are not at the endpoints of the axes, n will determine the start-value and end-value of the range. For example, with n = 2, the second probability category in **Figure 1** has a value range from 0.01 to 0.02 (0.01 to 0.01 × n). For the category at the end of the axis, n will affect only the start value of the range, which must not exceed 1 for probability axis and must not exceed $20 million for the consequence axis. **Table 5** and **Table 6** show the probability and consequence ranges, respectively, for n = 2 or n = 3.

Table 5 — Probability range on different multiplier, n.

	***n* = 2**		***n* = 3**	
Equation	**rating**	**probability**	**rating**	**probability**
$0.01 \cdot n^4 < p \le 1$	6	0.16 < p <= 1	6	0.81 < p <= 1
$0.01 \cdot n^3 < p \le 0.01 \cdot n^4$	5	0.08 < p <= 0.16	5	0.27 < p <= 0.81
$0.01 \cdot n^2 < p \le 0.01 \cdot n^3$	4	0.04 < p <= 0.08	4	0.09 < p <= 0.27
$0.01 \cdot n < p \le 0.01 \cdot n^2$	3	0.02 < p <= 0.04	3	0.03 < p <= 0.09
$0.01 < p \le 0.01 \cdot n$	2	0.01 < p <= 0.02	2	0.01 < p <= 0.03
$p \le 0.01$	1	<= 0.01	1	<= 0.01

Table 6 — Consequence range on different multiplier, n.

	***n* = 2**		***n* = 3**	
Equation	**rating**	**consequence (MM US$)**	**rating**	**consequence (MM US$)**
$100 \cdot n^4 < cons$	6	1.6 < cons	6	8.1 < cons
$100 \cdot n^3 < cons \le 100 \cdot n^4$	5	0.8 < cons <= 1.6	5	2.7 < cons <= 8.1
$100 \cdot n^2 < cons \le 100 \cdot n^3$	4	0.4 < cons <= 0.8	4	0.9 < cons <= 2.7
$100 \cdot n < cons \le 100 \cdot n^2$	3	0.2 < cons <= 0.4	3	0.3 < cons <= 0.9
$100 < cons \le 100 \cdot n$	2	0.1 < cons <= 0.2	2	0.1 < cons <= 0.3
$cons \le 100$	1	<= 0.1	1	<= 0.1

We can vary the multiplier and observe the effect on risk ranking for both ascending and descending scores. Since **Table 1** gives the consequence value in ranges, we use the mid-point[11] consequence value within the range for each outcome, as shown in **Table 7**. Given a single consequence value for each outcome, the categorization instability analysis can be carried out. **Figure 7** and **Figure 8** show how the risk ranking is affected by change in *n*.

Table 7 — Case for Categorization Instability Analysis.

Outcome	Consequence (Million US$)	Probability
Severe Losses	3	40%
Well Control	12.5	10%
Blowout	50	5%

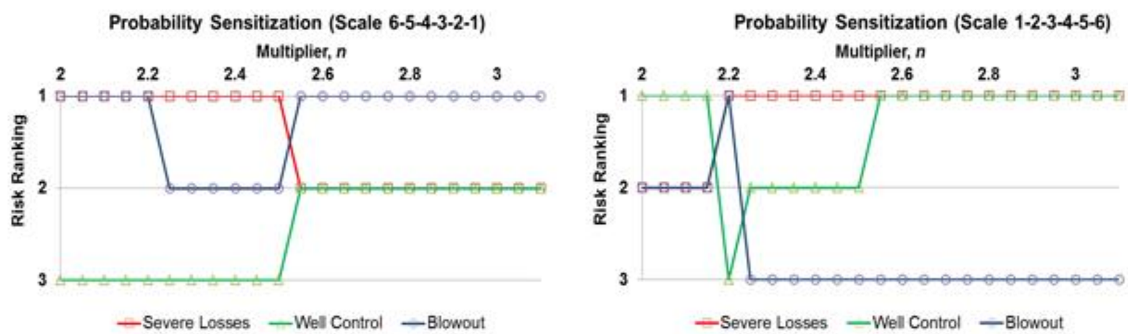

Figure 7 — Sensitivity of risk prioritization to probability categorization.

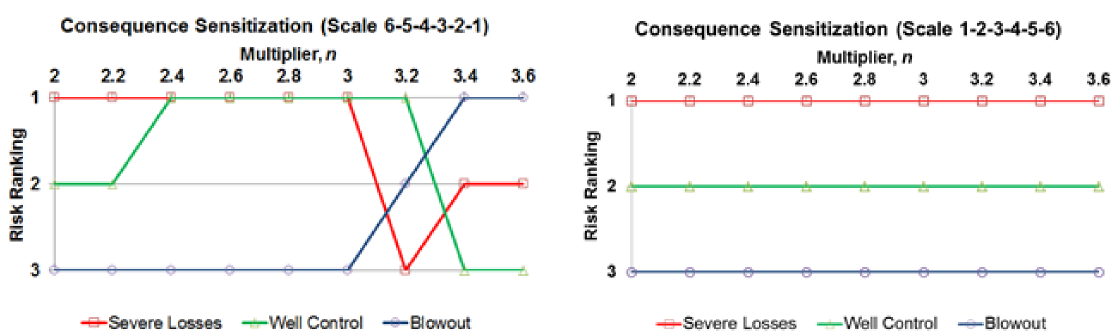

Figure 8 — Sensitivity of risk prioritization to consequence categorization.

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[11]For the practicality of the analysis, we assume that for blowout consequence, the ratio of the range's high-value to low-value is the same as for category 5 (high-value = 4 × low-value). Thus, the range is \$20 million to \$80 million, and the middle value is \$50 million. No matter which value is chosen to represent the high-end consequence, the instability remains and is equally severe.

These figures indicate that except where consequence is in ascending order, the risk-prioritization is a function of *n*. This is problematic since the resulting risk ranking is unstable in the sense that a small change in the choice of ranges can lead to a large change in risk prioritization. Thus, we again see that the guidance provided by RMs is arbitrary and hardly appears to be a beacon of clarity.

For each SPE paper that used at least one quantitative scale, **Table 8** shows percentage of the domain for categories 1 through 4, category 5 having been excluded because it was often unbounded. The left-hand table is for the probability, and the right-hand table is for the consequence. For example, the probability categories for SPE 142854, in ascending order, cover 0.001%, 0.1%, 0.9%, and 99% of the domain. The consequence categories for SPE 142854, in ascending order, cover 0.1%, 0.9%, 9%, and 90% of the domain.

That categories cover different amounts of the total range is clearly a significant distortion. In addition to this, the size of the categories varies widely across papers. For example, in the papers we surveyed, category 3 on the likelihood axis spans 0.9% to 18% of the total range. Given that the risk ranking resulting from a RM is so sensitive to the choice of category range sizes, this choice should be a based on the nature of the problem at hand and should receive significant attention in the construction of the RM. This does not appear to be the case in the papers we have surveyed.

Table 8 — Percentages of total range for each rating.

Frequency		
Paper number	**Rating**	**Percentage of range**
SPE - 127254	1	0.95%
SPE - 127254	2	0.02%
SPE - 127254	3	2.36%
SPE - 127254	4	96.67%
SPE - 142854	1	0.001%
SPE - 142854	2	0.10%
SPE - 142854	3	0.90%
SPE - 142854	4	99.00%
SPE - 98852	1	0.04%
SPE - 98852	2	1.96%
SPE - 98852	3	18.00%
SPE - 98852	4	80.00%
SPE-162500	1	0.09%
SPE-162500	2	0.90%
SPE-162500	3	9.00%
SPE-162500	4	90.00%

Consequence		
Paper number	**Rating**	**Percentage of range**
SPE - 142854	1	0.10%
SPE - 142854	2	0.90%
SPE - 142854	3	9.00%
SPE - 142854	4	90.00%
SPE - 98423	1	1.00%
SPE - 98424	2	4.00%
SPE - 98425	3	15.00%
SPE - 98426	4	80.00%

3.2.2 Relative Distance is Distorted

Lie Factor. According to **Table 7,** the consequence of blowout is 4 times that of well control (50/12.5). However, the ratio of their scores in the RM is only 1.2 (6/5). The difference in how risk is portrayed in the RM versus the expected values can be quantified using the *lie factor*.

The lie factor (LF) was coined by Tufte (2001, 2006) to describe graphical representations of data that deviate from the principle that "the representation of numbers, as physically measured on the surface of the graphic itself, should be directly proportional to the quantities represented" (Tufte, 2006). This maxim seems intuitive. Yet, it is difficult to apply to data that follow an exponential relationship, for example. Such cases often use log plots, in which the same transformation is applied to all the data. However, as shown below, RMs distort the information they convey at different rates within the same graphic.

Slightly modifying Tufte's (2006) definition, we define lie factor as

$$LF_m = \frac{\Delta V_m}{\Delta S_m}, (1)$$

where,

$$\Delta V_m = \frac{|V_{m+1} - V_m|}{V_m} \quad \text{and} \quad \Delta S = \frac{|S_{m+1} - S_m|}{S_m}$$

The LF is thus calculated as the change in value (of probability or consequence) over the *m* and *m+1* categories divided by the change in score over the *m* and *m+1* categories. In calculating the LF, we use the mid-point across the value and probability ranges within each category.

From **Figure 1**, the score of the consequence axis at m = 3 is S = 3 and at m = 4 is S = 4. Using the mid-point value for each category, LF_3=11.4=(|3000-625|/625)/(|4-3|/3). The interpretation of this is that the increase in the underlying consequence values is 11.4 times larger than an increase in the score.

None of the 30 papers reviewed included enough quantitative information for the LF to be calculated. We define the LF for an RM as the average of the LFs for all categories. An alternative definition might be, the maximum LF for any category. **Table 9** shows the result of our average LF calculation.

All nine papers have an LF greater than one along at least one axis. SPE 142854, for example, has an LF of 96 on the consequence axis and 5,935 on the probability axis.

Many proponents of RMs extol their visual appeal and resulting alignment and clarity in understanding and communication. However, the commonly used scoring system distorts the scales and removes the proportionality in the input data. How can it be argued that a method that distorts the information underlying an engineering decision in non-uniform and in uncontrolled ways is an industry best practice? The burden of proof is squarely on the shoulders of those who would recommend the use of such methods to prove that these obvious inconsistencies do not impair decision making, much less *improve it*, as is often claimed.

Table 9 — Lie Factor for 9 SPE papers.

	Average of each category	
Paper Number	***Lie Factor* of Consequence**	***Lie Factor* of Probability**
SPE 142854	96	5935
SPE 86838	30	-
SPE 98852	745	245
SPE 121094	5	-
SPE 74080	94	-
SPE 123861	28	113
SPE 162500	85	389
SPE 98423	16	-
IPTC - 14946	1	3

Chapter 4 – Partial Fixes for Risk Matrices

4. Partial Fixes for Risk Matrices

Despite all the identified flaws, RMs are still regarded by the O&G industry as the best available tool for risk assessment and evaluation. Because they are specified in industry standards, RMs have often been designated a 'best practice', which helps account for their popularity and persistence. Because of this, many fixes have been proposed for RMs. In this section we address sets of axioms, new definitions and new algorithms, and will reveal their limitations.

4.1 Minimum Consistency Theorem

Cox (2008) introduced three axioms and one rule to create RMs that reliably categorize the outcomes that has low risk into the green region and the outcomes that have high risk into the red region. The three axioms and one rule are the

- weak consistency axiom;
- between-ness axiom;
- consistent coloring axiom; and the
- three color only rule.

The three axioms will be explained using the RM in **Figure 9**. In **Figure 9**, probability and consequence rating are treated as utility values, ranging from 0 to 1. Colors designate the three risk regions. The three numbered cells designate the outcomes that will be referred to below.

probability score	probability range					
1	0.8 < p <= 1					
2	0.6 < p <= 0.8					
3	0.4 < p <= 0.6				3 (0.41, 0.61)	
4	0.2 < p <= 0.4			2 (0.39, 0.59)		1 (0.21, 0.81)
5	0 <= p <= 0.2					
consequence range		0 <= x <= 0.2	0.2 < x <= 0.4	0.4 < x <= 0.6	0.6 < x <= 0.8	0.8 < x <= 1
consequence score		1	2	3	4	5

Figure 9 — A 5 × 5 RM to explain the minimum consistency theorem

***Weak Consistency*.** Weak consistency requires RMs to have all risks with low quantitative value positioned in the low qualitative risk region (green), and all risks with high quantitative value in the high qualitative risk region (red). For example, in **Figure 9**, the probability/consequence pair for outcome 1 is (0.21, 0.81) and for outcome 2 is (0.39, 0.59). These yield risk values for of 0.17 and 0.23, respectively. However, outcome 1 has the lower risk value, even though it is located in the red region and outcome 2 is located in the green region. This violates the axiom of weak consistency.

***Between-ness*.** Between-ness requires an RM to prohibit an outcome to change from the green region directly to the red region due to small changes in probability and consequence. In **Figure 9**, Outcome 2 has probability/consequence values of (0.39, 0.59), which places it in the green region. If the probability and consequence of outcome 2 were increased by 0.01, outcome 2 would still be in the same cell. However, if the probability and consequence of outcome 2 were increased by 0.02 instead, to (0.41, 0.61), outcome 2 would move to the cell designated as outcome 3, which is in the red region. Thus, the RM in **Figure 9** violates the requirement for between-ness.

***Consistent Coloring*.** Consistent coloring requires that all cells that intersect or are below the 'green' iso-risk contour[12] be green, and that all cells that intersect or are above the 'red' iso risk contour be red. Yellow cells must either intersect neither iso-contour or intersect both iso-contours. The consistent coloring axiom is best explained by example. Given a plot of probability and consequence with uniform[13] categories along both axes, The RM can be designed by (1) choosing the risk acceptance according to our preference, (2) creating the iso-risk contour using the selected risk acceptance, (3) and color each cell according to which iso-contour line(s) it intersects. However, this coloring process will not be perfect, since the iso-risk contour is concave and therefore will not be presented perfectly by the vertical and horizontal lines that make up grid in RMs. Also, the remaining two axioms would also need to be fulfilled.

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[12] Iso-risk contour line is the continuous line that describes an equal risk along the probability and consequence axis. It is built by a set of consequence and probability value that yield the same risk.
[13]Uniform means that each category along the probability axis and the consequence axis uses the same-sized range, as shown in **Figure 9.**

Three Color Only Rule. Cox (2008) argued that RM with too many colors gives spurious resolution and therefore, it is not possible to have an RM with more than three colors that follows the three axioms. An RM that has more than three colors will have inconsistencies between the color that denotes a medium-low risk, and the color that denotes the highest risk. The derivation of this rule is outside the scope of this thesis, but Cox (2008) present the scientific proof of three color only rule.

Corollary of Minimum Consistency Theorem. The following corollary to the minimum consistency theorem is valuable for RM design. Given a uniform interval of probability and consequence in terms of its utility value, regardless of the size of the RM, the top-most right cell must be red, and the top-most left cell and the bottom right cell must be green. This causes the 3 × 3 RM to have only one possible coloring configuration. For a 4 × 4 RM, even though several color configurations are possible, only one useful[14] color configuration exists. Both coloring configurations are shown in **Figure 10** and **11** For 5 × 5 RMs, many color configurations are possible, depending on the objectives and the risk acceptance criteria, but they still need to adhere to the minimum consistency theorem.

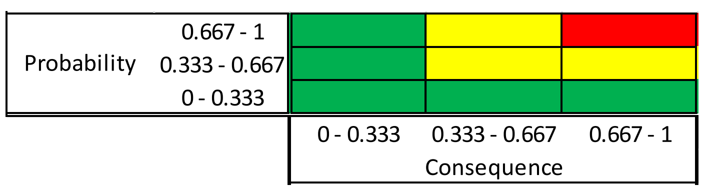

Figure 10 — A 3 × 3 RM with color configuration mandated by the corollary to Cox's axioms

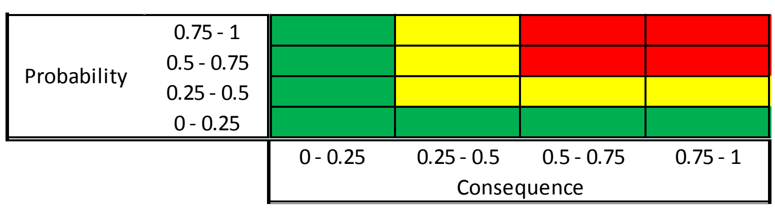

Figure 11 — A 4 × 4 RM with color configuration mandated by the corollary to Cox's axioms

[14]Useful RM is defined as an RM that is able to differentiate between an outcome with low risk (green) and an outcome with high risk (red) (keeping in mind that the risk for the yellow region is unknown).

Mathematical Notation. The set of equations that expresses the three axioms depends on the chosen RM size. This thesis will present the mathematical notation for RMs up to 5 × 5, since the notation for RMs larger than 5 × 5 will be similar to that for a 5 × 5 RM.

The set of equations for 3 × 3 RMs and 4 × 4 RMs is shown in Eq. 2.

$$\begin{aligned}
&\arg\min_{x,y} N_y(x,y) = \left\{ x \mid \forall y : R_g < R_r \right\} \\
&R_{g_{i+1,j+1}} \neq \text{Red and } R_{g_{i+1,j-1}} \neq \text{Red and } R_{g_{i-1,j+1}} \neq \text{Red and } R_{g_{i-1,j-1}} \neq \text{Red} \\
&R_x = P\big(u(x)\big) \cdot u(x) \\
&R_y = P\big(u(y)\big) \cdot u(y)
\end{aligned}, \quad (2)$$

For an RM to be useful, the number of yellow cells, N_y has to be minimized under the condition that the green iso-risk contour line with risk equal to *x* has less risk than the red iso-risk contour line with risk equal to *y*. Furthermore, no red cells may share a border with a green cell.

This set of equations can be satisfied by only one coloring configuration for 3 × 3 RMs and one for 4 × 4 RMs. *This means that the risk acceptance is predetermined and does not provide any latitude for a preference of the decision maker*.

For 5 × 5 RMs the set of equations is shown in Eq. 3.

$$\begin{aligned}
&\begin{bmatrix}
N_y(x,y) = \left\{ x \mid \forall y : R_g < R_r \right\} \\
N_g(x,y) = \left\{ x \mid \forall y : R_g < R_r \right\} \\
N_r(x,y) = \left\{ x \mid \forall y : R_g < R_r \right\} \\
R_{g_{i+1,j+1}} \neq \text{Red and } R_{g_{i+1,j-1}} \neq \text{Red and } R_{g_{i-1,j+1}} \neq \text{Red and } R_{g_{i-1,j-1}} \neq \text{Red}
\end{bmatrix}_{\text{max distinction}} \\
&R_x = P\big(u(x)\big) \cdot u(x) \\
&R_y = P\big(u(y)\big) \cdot u(y)
\end{aligned}, \quad (3)$$

The numbers of yellow, green and red cells, N_g, N_y and N_r, are defined by choosing the iso-risk contour line under the condition that every possible green iso-risk contour line with risk x has less risk value than the chosen red iso-risk contour line with risk y, which yields the maximum distinction[15].

Discussion of the Method. The minimum consistency theorem with the three axioms and one rule do indeed increase the consistency among RMs. However, this theorem does not take into account our preference by constraining the coloring options in our RMs. The inability to designate the top left cell or bottom right cell as red reduces the flexibility in defining our preference. This makes RMs that are built using minimum consistency theorem too rigid for a proper risk assessment.

4.2 Risk Aversion Coefficient

The definition of risk as a product of probability and consequences is seen by some RM practitioners as incomplete. Therefore, some RM practitioners have extended the conventional definition of risk to include a risk aversion coefficient, *n*, with $1 \leq n \leq$ to 2, as shown in Eq. 4.

$$risk = probability \times consequence^n \text{ , (4)}$$

The risk aversion coefficient allows greater weight to be placed on the consequence, as the coefficient approaches 2. A comparison between the conventional definition of risk and the augmented definition of Eq. 4 is shown in **Figure 12**. This figure shows that the augmented definition of risk increases the number of red cells by shifting the iso-risk contour line to the left (shown by the movement from the green line to the red line).

[15]The definition of maximum distinction is depends on the objective of the RM itself: sometimes we want to differentiate certain outcomes rather than obtain the maximum number of differences between the outcomes.

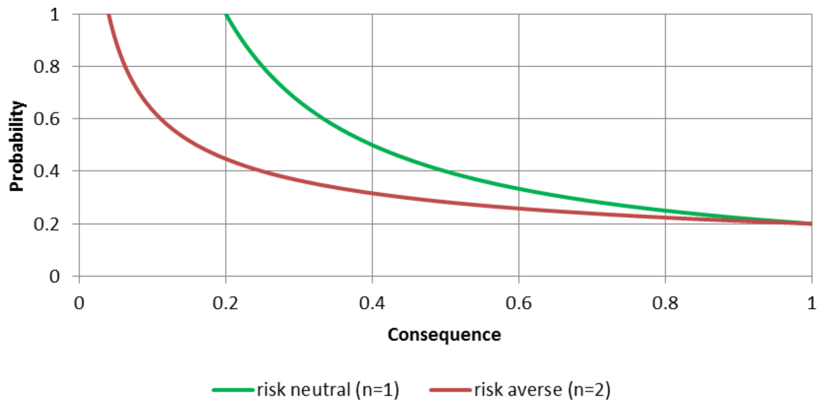

Figure 12 — Comparison of risk definitions

This augmented definition can be analyzed using the Arrow-Pratt measure of absolute risk aversion, defined as:

$$A(R) = -\frac{R'(c)}{R''(c)}, \quad (5)$$

where $R'(c)$ is the first derivative of the risk definition, and $R''(c)$ is the second derivative of the risk definition. Using this equation on both the conventional risk definition and the augmented definition of risk will indicate whether Eq. 4 is a valid function.

For the conventional risk definition,

$$u(c) = p \times c$$
$$u'(c) = 1$$
$$u''(c) = 0$$
$$A(R_1) = -\frac{u''(c)}{u'(c)} = \frac{0}{1} = 0$$

and for the augmented risk definition,

$$u(c) = p \times c^n$$

$$A(R_2) = -\frac{u''(c)}{u'(c)}$$

$$u'(c) = p \times nc^{n-1}$$

$$u''(c) = (n-1)\left(p \times nc^{n-2}\right)$$

$$A(R_2) = -\frac{u''(c)}{u'(c)} = -\frac{\cancel{p} \times \cancel{n}c^{n-1}}{(n-1)\left(\cancel{p} \times \cancel{n}c^{n-2}\right)}$$

$$A(R_2) = -\frac{c^{n-1}}{(n-1)\left(c^{n-2}\right)} = -\frac{\left(c^{n-1}\right)\left(c^{2-n}\right)}{(n-1)} = -\frac{c}{n-1}$$

Because $1 \le n \le 2$ then $A(R_2) < A(R_1)$, hence Eq. 4 will always be more risk averse than the conventional risk definition (Eq. 1). Therefore, Eq. 4 is a valid definition of risk aversion.

However, when we apply Eq. 4 to RMs, it increases their inconsistent coloring. This effect is illustrated in **Figure 13** where outcome A is positioned in a red cell and outcome B positioned in a green cell. Risk values A and B can be calculated by multiplying the middle values in their respective probability and consequence ranges using Eq. 4. As *n* increases, an increase in the difference between the risk values A and B will be taken as indicating an increase in inconsistency in the RM, and a decrease in the difference would indicate a decrease in inconsistency.

Probability	Rating	Indices						
> 40%	6	Likely			A			
20-40%	5	Occasional						
10-20%	4	Seldom						
5-10%	3	Unlikely						
<5%	2	Remote				B		
<1%	1	Rare						
Consequence Rating			1	2	3	4	5	6
Consequence Indices			Incidental	Minor	Moderate	Major	Severe	Catastrophic
Consequence cost			$100K	$100K - $250K	$250K - $1M	$1M - $5M	$5M - $20M	>$20M

Figure 13 — An RM to illustrate risk aversion coefficient effect on risk inconsistency

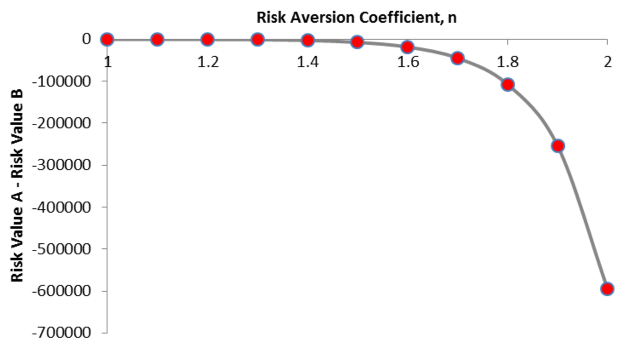

Figure 14 — Risk value difference of risk A and risk B with varying risk aversion coefficient

Figure 14 shows that increasing the risk aversion coefficient increased the absolute value of the difference between the risk of outcome A and that of outcome B, thus, indicates that the risk aversion coefficient increases the inconsistency of an RM.

Discussion of the Method. At first glance, the risk aversion coefficient as defined in this section seems logical. However, applying this definition to an RM violated Eq. 4, and hence, produced larger inconsistencies for RMs.

4.3 Cost Function Minimization

The minimization of cost function is adapted from Huber *et al.* (2008), as a means to optimally design RMs. It uses an algorithm that was developed to minimize the cost function in binary RMs, which have only two risk regions, 'low' and 'high', as shown in **Figure 15**.

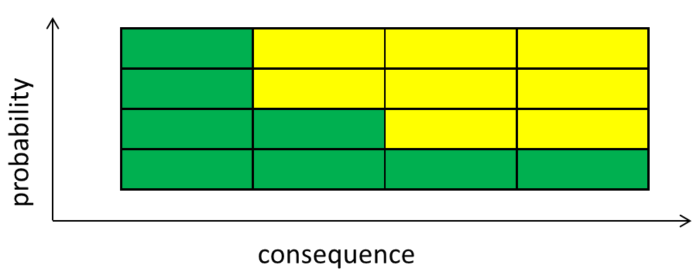

Figure 15 — A binary RM

Figure 16 illustrates how the cost function is perceived in binary RM. The process starts with the uncolored cell which being cut by an iso-risk contour line, resulting in two coloring possibilities for the cell: it is either green (low risk) or yellow (high risk). If we choose yellow as the color of the cell, the bottom left corner of the cell will incur the biggest cost. If we color the cell green, the top right corner of the cell will incur the biggest cost. Learning from this, cost can be intuitively explained as a function of probability, *p*, consequence, *c*, and decision, *d* of which color is used for the cell ($Cost(p, c, d)$).

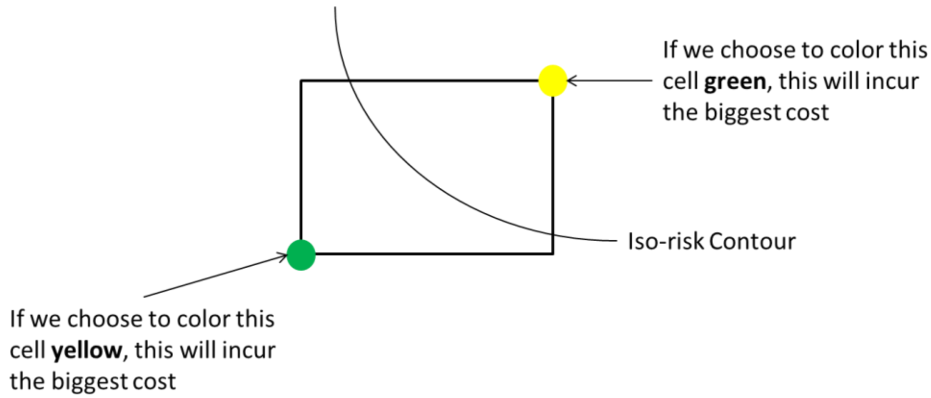

Figure 16 — Iso-risk contour line cut the cell in an RM, giving the cell two coloring choices

There are two views to describe the cost of the cells; it can be described as 'minimax' view or 'expected cost' view. These two views have two different cost functions. Both of them calculate the difference of R_{cell}, the risk value of the chosen RM color which equals to the risk values of iso-risk contour line and $R_{\text{p,c}}$ is the risk with probability *p*, and consequence, *c* in the cell that should designated the opposite color of the cell.

Minimax View. Eq. 10 shows the cost function for minimax view that describes cost as the *worst cost* that can happen in a cell. Thus, the objective here is to minimize the maximum cost of categorization in the cell. Hence, it's called minimax.

$$Cost(p,c,d) = \max\left[\left(R_{cell} - R_{p,c}\right)^2\right]. \quad (6)$$

Expected Cost View. The expected cost view describes cost function as the *total cost* of the cell when the whole cell is categorized into one color, thus, integration of the difference between risks over the cell is needed. In **Figure 16**, if the cell is colored green, then we have to integrate the difference of a risk above the iso-risk line curve to the top right edge of the cell (R1 = risk of the cell and R2 = maximum risk that can be described by the category of the cell), and if the cell is colored yellow, we have to integrate over from the bottom left edge of the cell, to the iso-risk line curve (R1 = minimum risk that can be described on the cell to R2 = risk value that described by the cell). The equation of expected cost view is described in Eq. 7.

$$Cost(p,c,d) = \int_{R1}^{R2} \left(R_{cell} - R_{p,c} \right)^2 dR \;. \;(7)$$

Since only two color possibilities exist for the cell (owing to binary RMs), both views decoupled the choosing breakpoint (categorization) issue and coloring option issue, which makes it easier. Therefore, the goal is to determine the categorization for the set of probability ranges and consequence ranges that incur the minimum cost, but this depends on how the cost is viewed.

There are two algorithms for this minimization. The first algorithm is called a strip-sweep algorithm, which moves the categorization of the cell to incur the minimum risk. The second method is called a zig-zag algorithm, which cuts the iso-risk contour line into segmented probability and consequence categories.

***Strip-Sweep Algorithm*.** The strip-sweep algorithm moves the boundary in the category to achieve the minimum cost. **Figure 17** represents how the strip-sweep algorithm works. Imagine there is one big cell that passes through by the iso-risk contour line and slices this big cell into two cells which have to be designated by two different colors. The adjustment can be done by choosing where to cut the cells (moving y_2 upwards or downwards) which determine the size of the two cells. The color assignment to these two cells is done with the objective of minimizing the cost of the big cell.

On the left side of the picture, the cell above y_2 has no cost at all since it is fully placed above the iso-risk contour line. Thus, the cell can be described using a single color. However, on the same picture, the cost incurred in the bottom cell is large, owing to the iso-contour line that cuts right at the center of the cell. Thus, we need to find the boundary of the probability that gives the minimum sum of the cost for these two cells. In **Figure 17**, it achieved by pulling the y_2 boundary slightly downwards (right side of the picture).

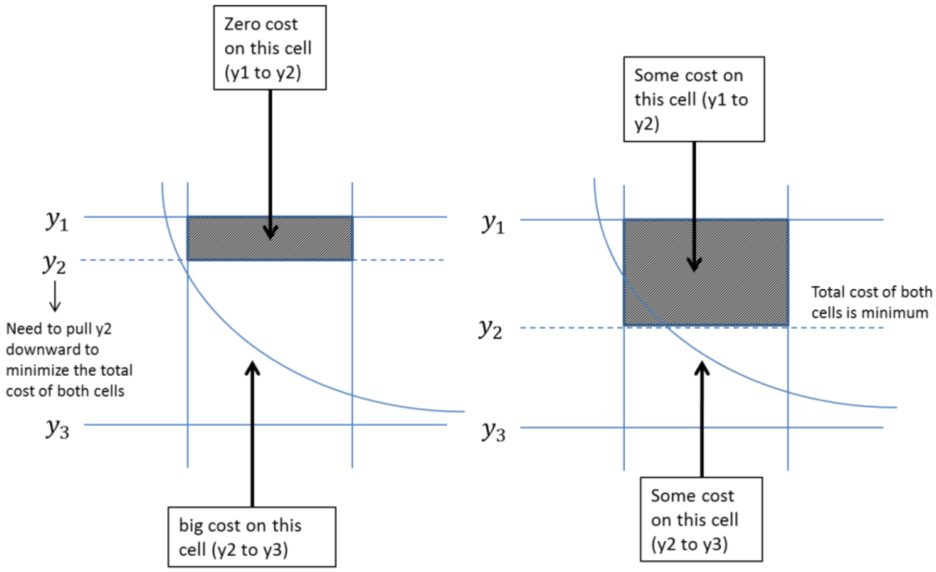

Figure 17 — A picture illustrating the strip-sweep algorithm

Zig-Zag Algorithm. The zig-zag algorithm works similarly to the bisection method for moment matching. In **Figure 18**, imagine we can draw a line that cuts and categorizes the iso-risk contour line. The algorithm start this cutting line from the top left of the figure, moving downward until it cut the iso-risk contour line, then move to the right until equal areas is achieved, then repeat. The goal is to find a set of range for probability axis (y) and consequence axis (x) that minimizes the cost. This algorithm will produce sets of equations which can be optimized numerically. This makes it implementation highly convenient.

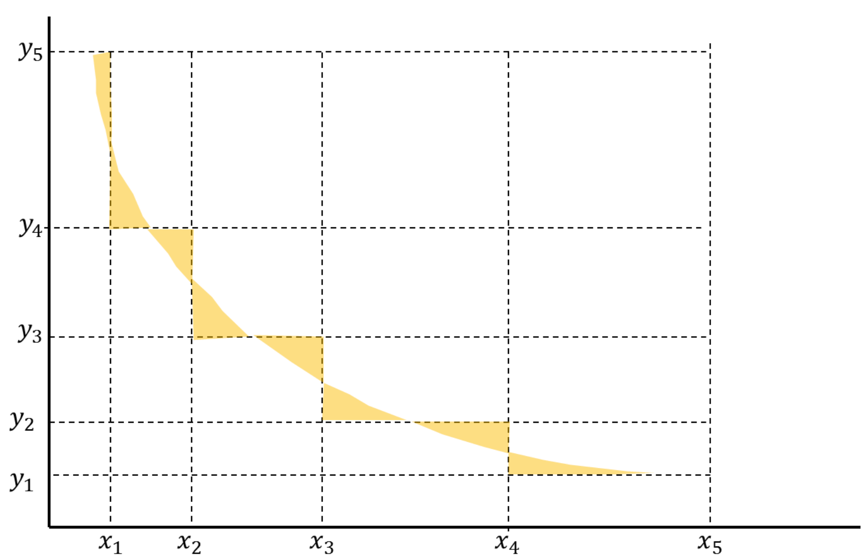

Figure 18 — A picture of a zig-zag algorithm

Discussion of the method. Even though minimization of the cost function seems a promising to fix for RMs, the results of this algorithm has not been encouraging for the following reasons. First, these algorithms are difficult to implement when we deal with an RM that has more than two colors. Minimization algorithm on binary RMs deal only with one cost function, thus, there are no interaction between two differing cost functions. However, when an RM is not binary, the change of range in probability or consequence leads to the interaction between two or more differing cost functions, making numerical solution imprecise.

Second, if only a binary RM is needed, or assumes the interaction between two or more differing cost functions is handled well, a zero cost is practically impossible to achieve, except there is infinite number of categories.

Cost minimization is numerically extensive, yet still gives inexact result. Considering the effort needed to implement these algorithms and the imprecise results of the algorithms, this is not an optimal solution to be implemented to get a consistent, yet useful, RM.

4.4 Summary of the (Partial) Solutions

RMs are prone to conceptual errors and flaws, and since RMs are common in many industries, many researchers and academics have tried to find solutions to fix the conceptual errors and flaws already noted. However, despite the numerous and extensive efforts made, the results of these fixes are not promising.

The minimum consistency theorem gives a set of axioms and a rule, adding constraints in addition to our preferences, which makes the resulting RMs too rigid to describe our preference.

Risk aversion coefficients are indeed analytically correct in describing aversion towards high consequence events, yet fail to fix RMs owing to categorization within RMs: indeed, they can increase inconsistency within RMs.

Cost functions are numerically extensive and require huge investments for implementation while still failing to produce promising results.

Solutions for RMs are not easily formulated, thus, the use of solutions other than RMs is recommended. There exists another method that is as practical as RMs, which gives us clarity to view the problems, hence, become a good basis for risk management exercises. we will introduce one of these solutions in the next chapter.

Chapter 5 – Alternative Solutions: Decision Analysis

5. Decision Analysis

Ron Howard, one of the founding-fathers of decision science, coined the term ‘decision analysis (DA)’ as a “systematic procedure for transforming opaque decision problems into transparent decision problems by a sequence of transparent steps” in Howard (1966). Since DA requires us to think probabilistically, it captures the essence of risk management. Hence, it makes DA suitable as an alternative for RMs. In addition to consistency, DA provides sets of thoughtful academically developed tools that are practical enough to be used in the real world. In this section we will solve the case example using DA to illustrate that unlike RMs, the analysis resulting from DA brings clarity to help the decision maker.

5.1 Principles of Decision Analysis — In a Glance

The goals of employing DA are to achieve clarity of the problem and to guide us towards making good decisions. A ‘good decision’ is defined as “an action we take that is logically consistent with our objectives, the alternatives we perceive, the information we have, and the preferences we feel”. Since we live in an uncertain world, making a good decision doesn’t always lead to a good outcome, but it definitely increases the chance of good outcome.

There are numerous important principles of DA, but only the ones that are most relevant for this thesis that will be discussed. High level model of decision-making methodology as described by Bratvold and Beggs (2010) is the model that is used throughout this thesis (shown in **Figure 19)**. Consideration of using the model is because its implementation which supports the common O&G risk management practices where the risk analysts report the result of the analysis to their immediate supervisor. The model mainly consists of three steps.

Step 1 - Structuring / Framing. This step ensures the right people are treating the right problem and from the right perspective. Decision hierarchy and value tree diagrams are often used in this step.

Step 2 - Modeling / Evaluating. This step builds models which incorporate all the main elements of the decision problems and solve it. This step is very important to create understanding and insights of the analyst. The model is also used to communicate quantitative results to the shareholders. Decision trees and influence diagrams will be used to model the case example.

Steps 3 - Assessing and Deciding. This step makes sure that the models built in step two is robust. This is done by testing them and making different sets of scenarios from the models. Sensitivity analysis is incorporated into this step and Monte Carlo simulation is used to get the effect of value distribution for the case example risk assessments.

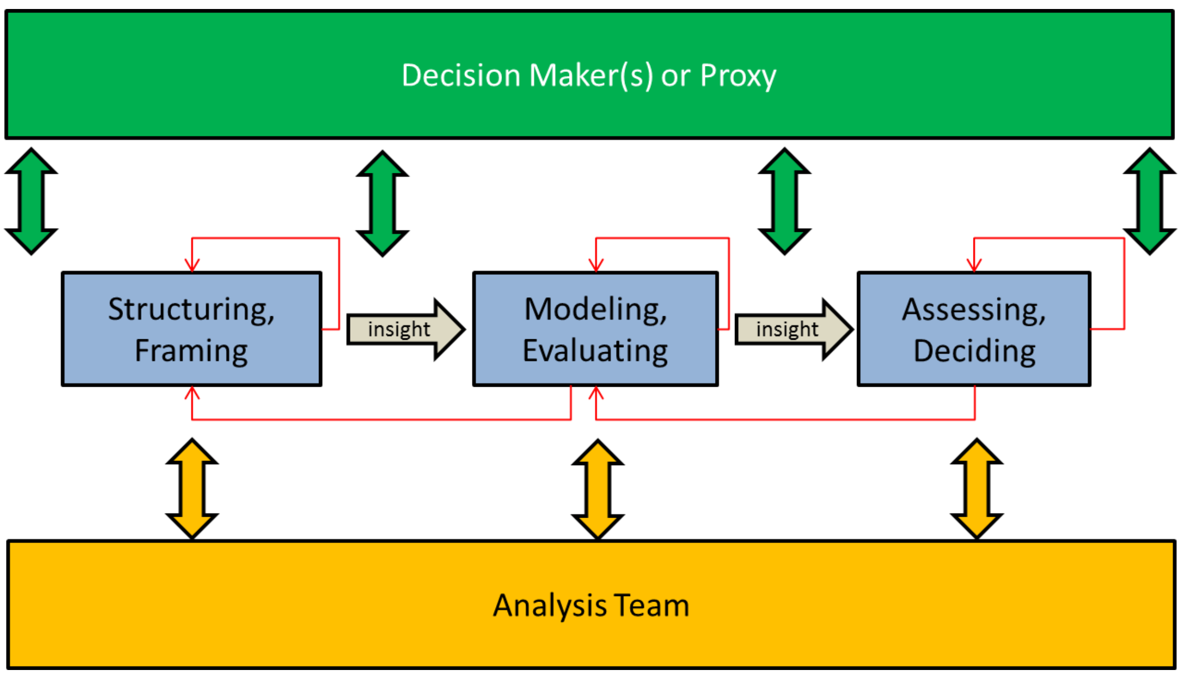

Figure 19 — High level modeling methodology

5.2 Solving the Case Example with Decision Analysis

Let's recall our example in section 2.3:

- to evaluate the risk of possible outcomes if there has been fluid loss in a hole in section 4;

- there are three possible outcomes identified by the expert with their associated consequences and probabilities;
- the goal is to do the risk prioritization, thus, a risk ranking. From there, the mitigation plan that optimally allocates our resources based on the risk prioritization result can be created.

5.2.1 Framing

As described previously, the objective of framing is to make sure we are dealing with the right problem with the right people from the right perspective. There are three important decision elements that are considered when framing every decision case: objectives, alternatives and information. This thesis only discusses the framing parts briefly and limited to that are particular to the case examples. For further information see work by Bratvold and Beggs (2010).

Pritchard *et al.* (2010) used a frame that had an objective to minimize the drilling risk by making risk prioritization. Since the resources for risk mitigation are limited, they wanted to rank the identified risks and mitigate the most ‘important’ risk. Using this risk ranking result, they would like to develop a mitigation plan that enables them to make a good decision for the drilling operation. For the sake of justifiable comparison between RM and DA, This thesis will assume a similar frame for solving the case example with DA. While for the case of choosing between two mitigation plans, different frame for DA will be introduced.

There is a significant difference of how RM and DA view the risk tolerance. In RM, the risk tolerance is denotes by its coloring practice. However, in DA, the concept of risk tolerance is more into its utility of the value. And as shown by Leach (2010), in O&G industry, the best results are achieved using risk neutral attitude. Risk neutral assumption will leads to the decision making that are based on the highest/lowest expected monetary value. In the case of risk management, the decision with lowest sum of the expected loss and implementation cost will be chosen. This thesis assumes risk neutrality as a risk attitude to complete all remaining calculations.

5.2.2 Modeling

In this thesis, decision trees and influence diagram is used to model the problems. Decision trees provide good structures to calculate the expected downside consequence. In addition, using an RM as it is completed by Pritchard *et al.* (2010) would restrict us to model any dependence between outcomes, since an RM has a built in assumption of independence. By using DA, the dependence can be modeled using the conditional probabilities. However, dependence in the models will make a decision tree grow fast and become decision forest, which could be difficult to build.

This decision forest problem can be alleviated with an influence diagram, which compresses the information that a decision tree provides while present the inter-dependency between variables.

This section will start with an independent model to lay the basic structure to solve the problem. Next, the independent model is expanded by taking into account the dependence between outcomes.

Independent Model

Figure 20 shows a decision tree with no dependence taken into account. It shows a clear structure for risk prioritization. Square nodes represent the decision that will be taken: circle nodes represent the uncertainty of the outcome with its associated probability. Thus, the risk or expected loss is calculated by the product of probability and consequence which can be ranked for the risk prioritization purposes. **Figure 20** shows the decision tree analysis using the values as expressed as the single most likely value for each consequence as used in section 3.2.1. The number and in this step have no meaning. It is intended purely to give a proper structure for the problem solving exercise.

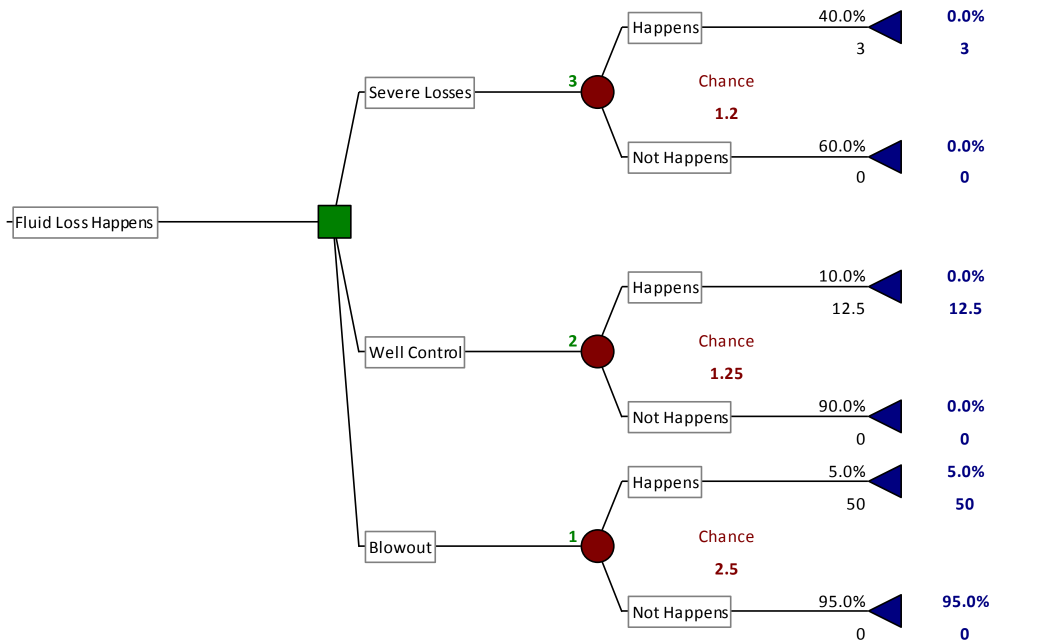

Figure 20 — A decision tree for the case example (no dependence was taken into account)

Dependence Model

In many cases, however, not taking dependence into account is perilous. Dependence gives a holistic view about the problems which leads to the right perspective to prioritize risks. For example, when *severe losses* happen, it will obviously increase the chance of both *well control* and *blowout*. As noted previously, dependence is not easy to model using decision trees as it will soon grow to become a decision forest. For example, if there are three outcomes that are inter-dependent and each outcome has two consequences and probabilities, then there will be eight end points ($\text{consequences}^{\text{outcome}} = 2^3$) for each branch, and since each branch modeled each outcome, there will be 24 end-points ($\text{consequences}^{\text{outcomes}} \times \text{outcomes}$) on the decision tree. An influence diagram is needed to compress this information.

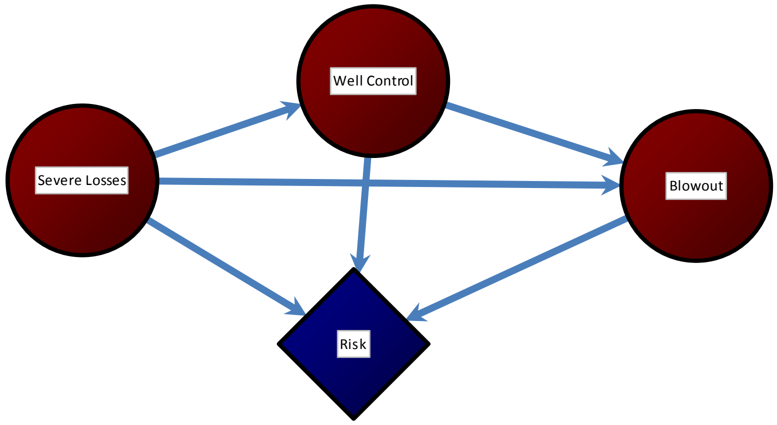

Figure 21 — An influence diagram with *severe losses* as the conditional outcome

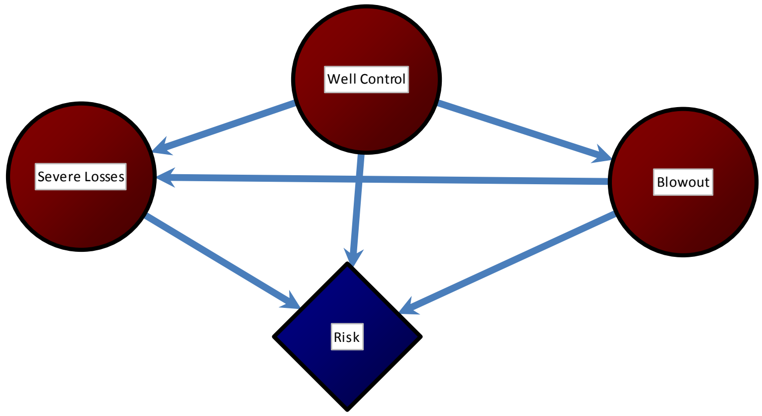

Figure 22 — An influence diagram with *well control* as the conditional outcome

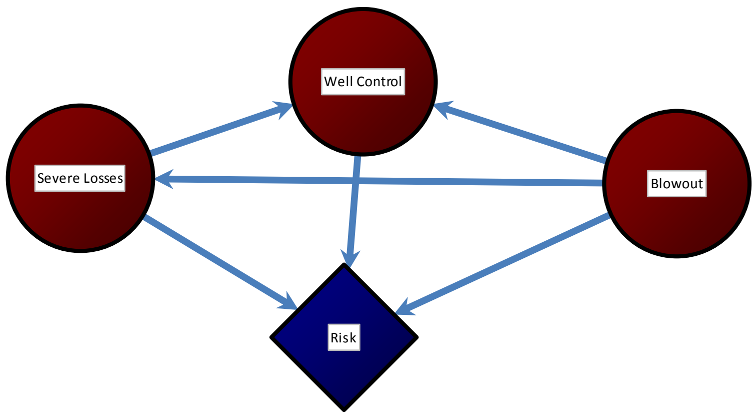

Figure 23 — An influence diagram with *blowout* as the conditional outcome

Since each outcome is interdependent, each conditional outcome we choose to mitigate has two possible representative structures. Hence, there are six (P_2^3) possible influence diagrams to represent dependence in our example. For example, when *severe losses* happened, then the next possible outcome is *well control* or *blowout***.** The best way to choose between these two structures is to get the most logic influence diagram according to the SME. The three influence diagrams that the SME chose is shown above. An influence diagram in **Figure 21** will become the branch to calculate the risk for *severe losses*, influence diagram in **Figure 22** will become the branch to calculate the risk for *well control* and **Figure 23** will become the branch to calculate the risk for *blowout***.** Arrows in this case refer to the dependencies between each risk (dependence is not equal to causality). Further information is documented in work by Howard and Matheson (2005).

The influence diagram then can be converted into decision trees. However, structure of the decision tree resulting from the conversion process has to be modified to give the right structure. In this case, the branch of the tree after the *blowout* occurs will be omitted since after the *blowout* has happened, the well will be shut down and be killed, thus, leaving no chance of *severe losses* or *well control* to happen.

Probability	
P(S)	0.4
P(S|B')	0.4
P(S|B'W')	0.4
P(W)	0.1
P(W|S)	0.1
P(W|S')	0.1
P(W|S'B')	0.1
P(W|SB')	0.1
P(B)	0.05
P(B|SW)	0.1
P(B|S'W')	0.05
P(B|S'W)	0.1
P(B|W)	0.1
P(B|W')	0.05
P(B|SW')	0.1

Consequence (in Million USD)	
severe losses	3
well control	12.5
blowout	50

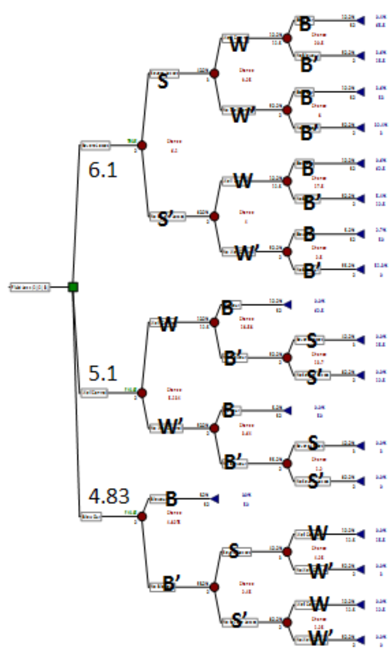

Figure 24 — A decision tree that includes dependence

After the modification, the decision trees becoming structure as shown in **Figure 24**. This model assumes that the dependence affects only the probability of the outcome while the consequence stays the same. The list in in **Figure 24** shows the conditional probability of the outcome with 'B' denotes *blowout*, 'S' denotes *severe losses* and 'W' denotes *well control*. Henceforth, P(B|S'W) means the probability of *blowout* given *severe losses* do not happen and *well control* issues happened (shown in **Figure 24** as 10%). The probability and consequence value in this step is arbitrary since our goal is just to get the right model for our problem.

The numbers will be taken care in the next step by doing sensitivity analysis that can capture the whole risk distribution, encapsulating a full range of consequence and probability values.

5.2.3 Assessing and Deciding

To assess the model, we used Monte Carlo simulation (MCS) to capture the wide distribution of risk values. MCS uses a random number generator and the associated distribution of probability and consequence to capture the risk values. **Figure 25** shows the proposed framework to calculate the risks distribution of the outcomes with 10000 iterations.

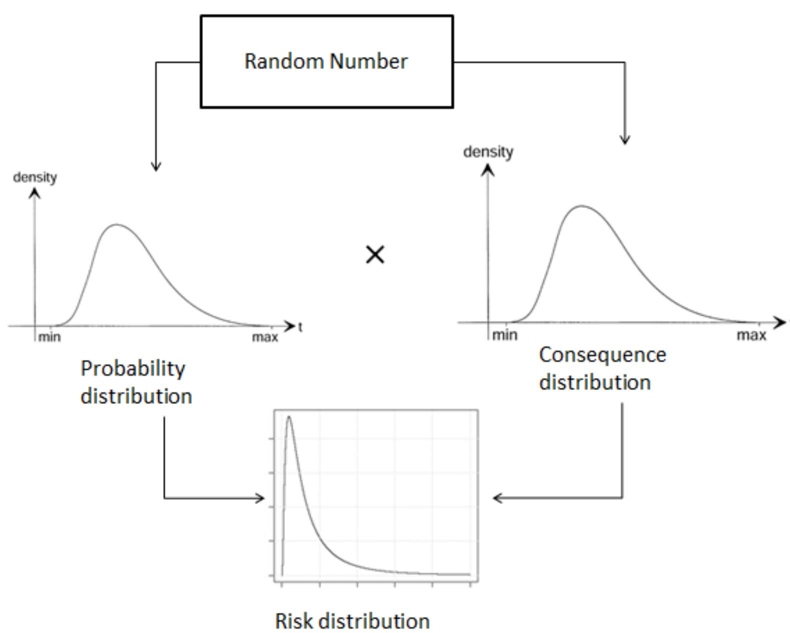

Figure 25 — A Monte Carlo simulation framework for our case example

Figure 25 shows the probability and the consequence that treated as a disjointed variable. This means there are two types of uncertainties: first, the probability that either the outcome is going to happen/not happen; second, if the outcome has happened, the probability distribution has to be used to describe the range of consequences in monetary value that might happen. To avoid the double counting of the first uncertainty, we have to use the bounded[16] distribution such as there is no consequences distribution that contains 0. **Figure 26** shows the influence diagram of how MCS is implemented for the case example.

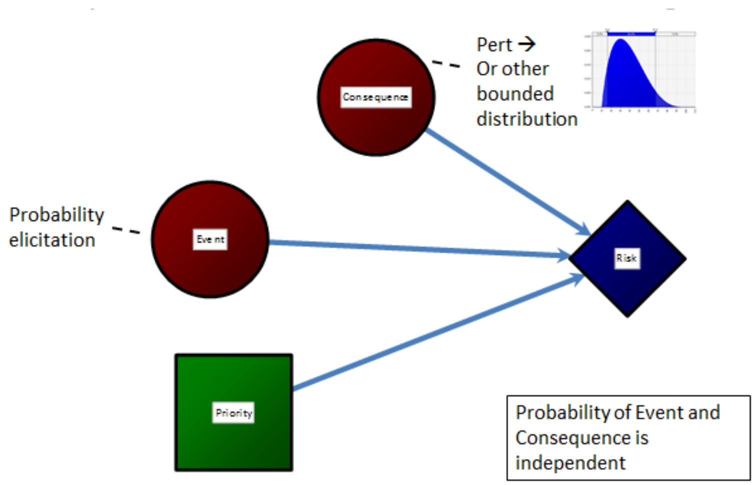

Figure 26 — A Monte Carlo simulation model for the case example

To get a better view of a relative magnitude for each risk, rank function is incorporated which allows the calculation of expected rank for each risk. This idea is very similar to a counting approach to get the probability value. **Figure 27** shows the workflow involved to include the rank function in MCS. It starts with generation of risks distribution using MCS, then the rank function is used to generate the distribution of the ranks, then we convert the frequency values of those ranks into the probability. This probability and rank values then can be converted into the expected rank value to prioritize our risks using Eq.8. The closer the expected rank value is to 1, the more it has to be prioritized.

[16] Bounded here means contain minimum and maximum value. In our case, the most important thing is the minimum > 0 to avoid double counting of the "not happened" outcome.

$$E(rank) = \sum_{i=1}^{n} P(i) \times R(i)\,. \quad (8)$$

By using this approach the relative magnitude of risk is scalable from one risk to another, thus, giving us the appropriate comparison between each risk. From this the prioritization can be appropriately conducted. Another advantage of this method is that it is easy to implement for numerous risks; making this method a suitable alternative for RMs.

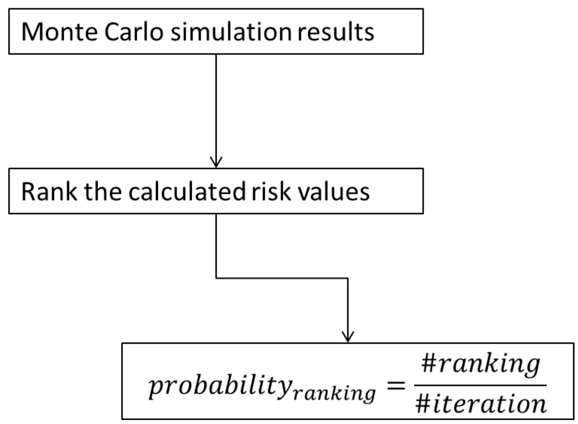

Figure 27 — Workflow for risk ranking using rank function and Monte Carlo simulation

Assessing—Independent Model

SME's judgment is needed to codify the input data for MCS. The input data will determine the type of distribution and range of values associated with each case. To solve the case example, we use a PERT distribution as input data in probability and consequence as elicited from the SME. **Table 10** shows the input data for the non-dependence case as elicited from the SME taken from Pritchard *et al.* (2010), with the assumption of *blowout* consequence values the same as in section 3.2.1.

Table 10 — Non-dependence case, SME's judgment

	Distribution type	min	mode	max
P(S)	PERT	0.05	0.4	0.45
P(W)	PERT	0.05	0.1	0.3
P(B)	PERT	0.00001	0.05	0.07
Consequence Severe Losses	PERT	1	3	5
Consequence Well Control	PERT	5	12.5	20
Consequence Blow Out	PERT	20	50	80

MCS is using this input data to produce the risks distribution for each outcome. The risks distribution for each outcome and their metrics such as the minimum, mean, maximum is shown in **Figure 28**, **29** and **30.** If it is decided to prioritize based on the risk mean values, then the *blowout* becomes the first priority since it gives the highest mean risk value for our operations. It then follows that *well control* becomes second priority, and *severe losses* become the last priority. Since the shape of each resulting distribution is log normal due to central limit theorem, using only the mean values could lead us astray. The better way of doing the prioritization is by using the distribution of rank function.

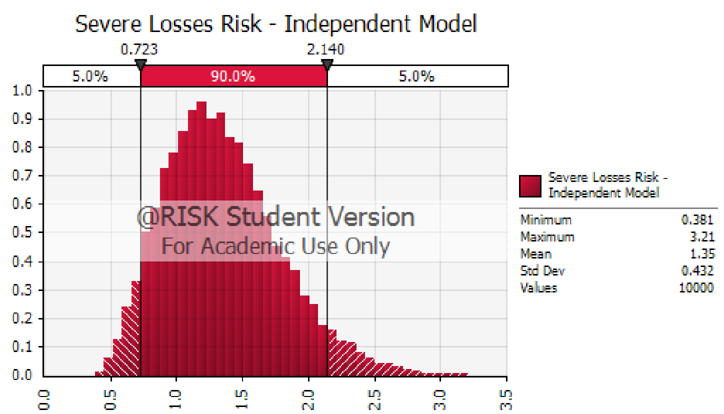

Figure 28 — *Severe losses* risk distribution - non dependence model

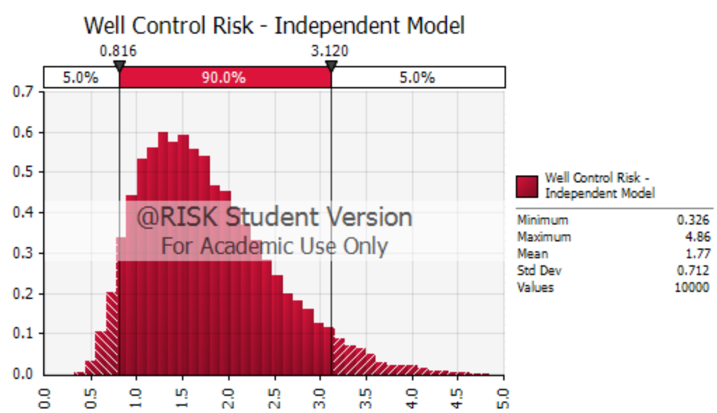

Figure 29 — *Well control* risk distribution - non dependence model

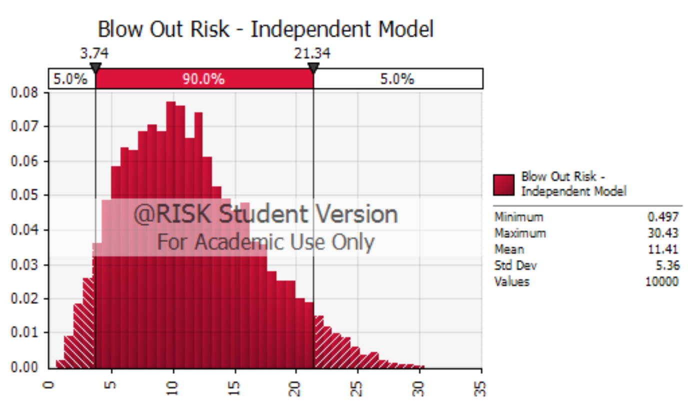

Figure 30 — *Blowout* risk distribution - non dependence model

Figure 31 shows the results of MCS which incorporate the rank function and conversion of the frequency into the probability for each outcome. It shows *blowout* has a 99.07% chance if becoming the first priority, a 0.77% chance of becoming the second priority, and a 0.16% of becoming the third priority. These values then can be converted into expected rank value for each outcome using Eq. 8 as shown in **Table 11**.

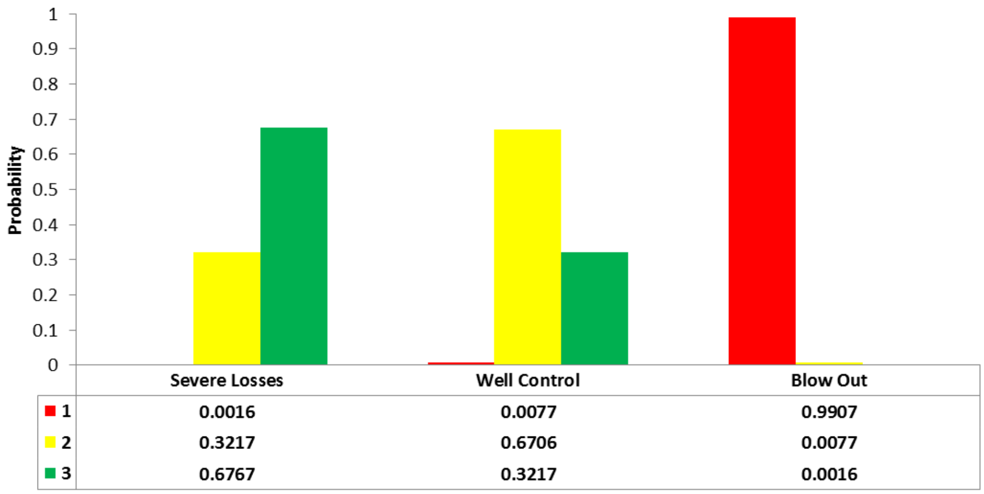

Figure 31 — Rank distribution for each risk – non dependence model.

Table 11 — Expected rank values for the case example – non dependence model

	Expected Rank
Severe Losses	2.68
Well Control	2.31
Blow Out	1.01

Keep in mind that these results do not include dependence in the model. As noted previously, dependence is of great importance, and must be accounted for. Thus, a dependence model is needed before the decision is made.

Assessing and Deciding—Dependent Model

The dependence model needs considerably greater input data for us to run a Monte Carlo simulation. **Table 12** lists all the input data that are used to run the MCS for the dependence model. These input data come from SME's judgment.

Table 12 — A Monte Carlo simulation input data for dependence model

	Distribution Type	Min	Most Likely	Max
P(S)	PERT	0.01	0.4	0.45
P(S|B')	PERT	0.01	0.4	0.45
P(S|B'W')	PERT	0.01	0.4	0.45
P(S|B'W)	PERT	0.01	0.4	0.45
P(W)	PERT	0.01	0.1	0.2
P(W|S)	PERT	0.01	0.1	0.25
P(W|S')	PERT	0.01	0.1	0.2
P(W|S'B')	PERT	0.01	0.1	0.2
P(W|SB')	PERT	0.01	0.1	0.25
P(B)	PERT	0.0001	0.05	0.07
P(B|SW)	PERT	0.01	0.1	0.5
P(B|S'W')	PERT	0.0001	0.05	0.07
P(B|S'W)	PERT	0.01	0.3	0.5
P(B|W)	PERT	0.01	0.3	0.5
P(B|W')	PERT	0.0001	0.05	0.07
P(B|SW')	PERT	0.0005	0.05	0.07
Consequence Severe Losses	PERT	1	3	5
Consequence Well Control	PERT	5	12.5	20
Consequence Blowout	PERT	20	50	80

* all consequence value in Million USD

One question that might arise from the SME's judgment concerning the value of P(B|SW), which is smaller than the value of P(B|W). It stems from the fact that if *well control* issues happen because of the *severe losses*, it is easier to control since the source of a problem is known. Further, if *well control* issues is happened without any *severe losses* occurring, it might become more difficult to prevent, thus, more likely to become a *blowout*.

To get the risks distribution for each outcome, the MCS is incorporated into the decision trees in **Figure 24**. It yields the risks distribution for each outcome as shown in **Figure 32**, **33** and **34**.

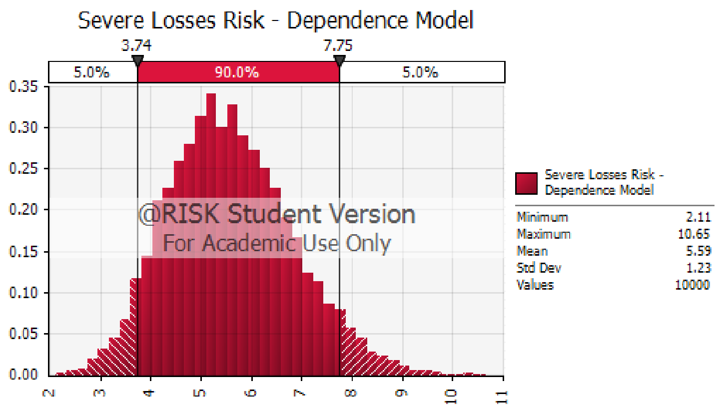

Figure 32 — *Severe losses* risk distribution - dependence model

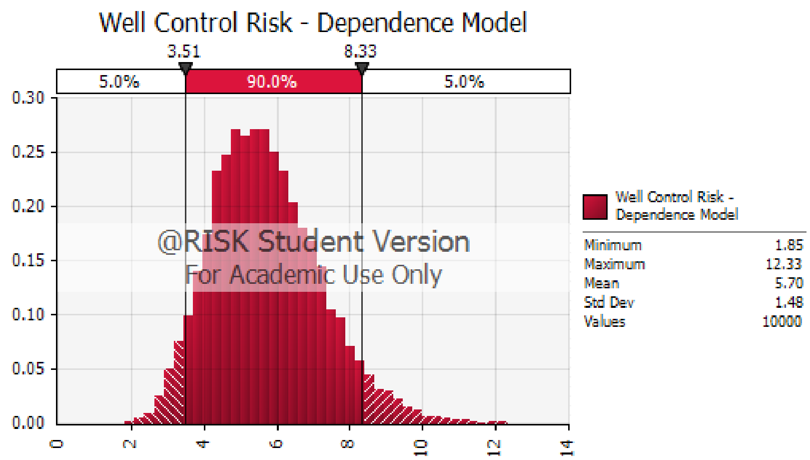

Figure 33 — *Well control* risk distribution - dependence model

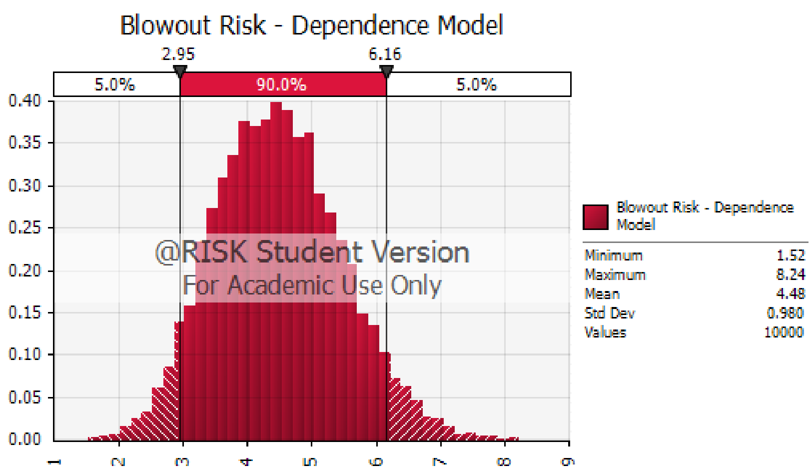

Figure 34 — *Blowout* risk distribution - dependence model

When we include dependence, the result is very different from the non-dependence model. **Figure 35** shows that *well control* has the biggest chance of becoming first priority. This prioritization is aligned with what we observe, since *well control* always happens before *blowout*. Even though *severe losses* is increasing the chance of *well control* issues, there are many other different ways to experience *well control* issues, such as encountering the abnormal pressure zones or problems in pressure control equipment. Further, if we resolve these issues through good *well control* mitigation, we will never reach *blowout*, which gives large consequences compared with the other two risks.

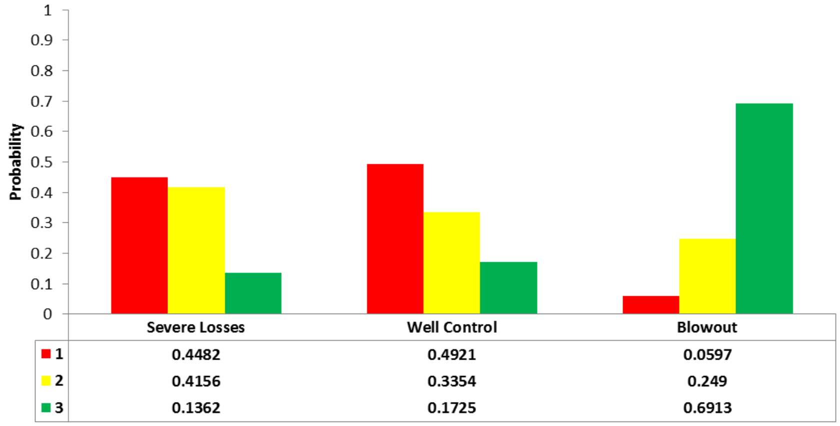

Figure 35 —- Rank distribution for each risk – dependence model.

As shown in **Table 13**, the expected rank value confirmed the previous finding. It is clearly seen that the *well control* is the prioritized outcome, but since the rank is very close with the *severe losses*, it could be concluded that in order to get maximum risk reduction, the mitigation plan has to be directed to reduce risks from both outcomes.

Table 13 — Expected rank values for the case example – dependence model

	Rank Expected Value
Severe Losses	1.688
Well Control	1.6804
Blowout	2.6316

5.3 Choosing between Mitigation Plans

The result from risk ranking is then used as a basis to create a mitigation plan that is geared towards the prioritized risk. Using the risk ranking results enables the SME to identify two possible mitigation plans. The first mitigation plan proposed is 'pressure-while drilling (PWD)' technique, which allows the control of the bottom-hole pressure in real time manner, leading to a decrease in the chance of the three outcomes. The second mitigation plan is to 'use better pressure control equipment (PCE)' in addition to the PWD techniques. This second mitigation plan will lead to the reduction of the most likely value in *well control* issues and *blowout* probabilities. This is possible because the PCE has a better equipment grade and better control at the surface, which further increases the safety of the well.

The caveat for the PWD + PCE is its cost, which is much higher than PWD only. Here, SME's estimation is being used again, in this context to quantify the residual probabilities after the mitigation has been implemented. It is common to have a reduced probability of the outcome happening when the mitigation is in place, although it has no effect in altering the consequences. A comparison of both mitigation plans is given in **Table 14** and **15**.

- **Pressure-while drilling (PWD)**

Table 14 — Pressure-while drilling: SME's estimation

Cost of PWD : 0.5 Million USD	Distribution Type	Min	Most Likely	Max
P(S)	PERT	0.005	0.2	0.225
P(S|B'W)	PERT	0.005	0.2	0.225
P(W)	PERT	0.001	0.01	0.02
P(W|S)	PERT	0.001	0.01	0.025
P(B)	PERT	0.002	0.01	0.1
P(B|SW)	PERT	0.00002	0.01	0.015
P(B|W)	PERT	0.00002	0.01	0.015
P(B|SW')	PERT	0.002	0.02	0.05

Consequence Severe Losses	PERT	1	3	5
Consequence Well Control	PERT	5	12.5	20
Consequence Blowout	PERT	20	50	80

* all consequence value in Million USD

- **Pressure-While Drilling + better Pressure Control Equipment (PWD + PCE)**

Table 15 — Pressure-while drilling + better PCE: SME's estimation

Cost of PWD + PCE : 0.75 Million USD	Distribution Type	Min	Most Likely	Max
P(S)	PERT	0.005	0.2	0.225
P(S|B'W)	PERT	0.005	0.2	0.225
P(W)	PERT	0.0001	0.005	0.02
P(W|S)	PERT	0.0001	0.005	0.025
P(B)	PERT	0.002	0.005	0.1
P(B|SW)	PERT	0.00002	0.005	0.015
P(B|W)	PERT	0.00002	0.005	0.015
P(B|SW')	PERT	0.002	0.01	0.05

Consequence Severe Losses	PERT	1	3	5
Consequence Well Control	PERT	5	12.5	20
Consequence Blowout	PERT	20	50	80

* all consequence value in Million USD

Given these probability and consequence values from SME, DA or RMs can be used to decide which mitigation plan is the best. Obviously, the most effective mitigation plan should achieve the minimum risk at minimum cost. This will be the objective of our analysis.

In this thesis, the analysis to choose between these mitigation plans will be conducted using RMs and DA. The resulting analysis can then be compared to determine which one gives greater clarity to the decision-making process.

5.3.1 Mitigation Plan Analysis with Risk Matrices

In RMs, to choose between mitigation plans, the risk score reductions that would result from implementation of each plan have to be calculated. Just like in the example case, all the values that are used for the analysis in the RM are the most likely or middle value. Before the risk score reduction for each mitigation plan can be calculated, the RM has to be used to identify whether there is an outcome in the red region of the RM. If an outcome in the red region exists, the mitigation plan will be automatically disqualified. Using the RM for our case example, we can see that both mitigation plans have outcomes within green or yellow region (as shown in **Figure 36**), which means they both qualify for inclusion in the next step.

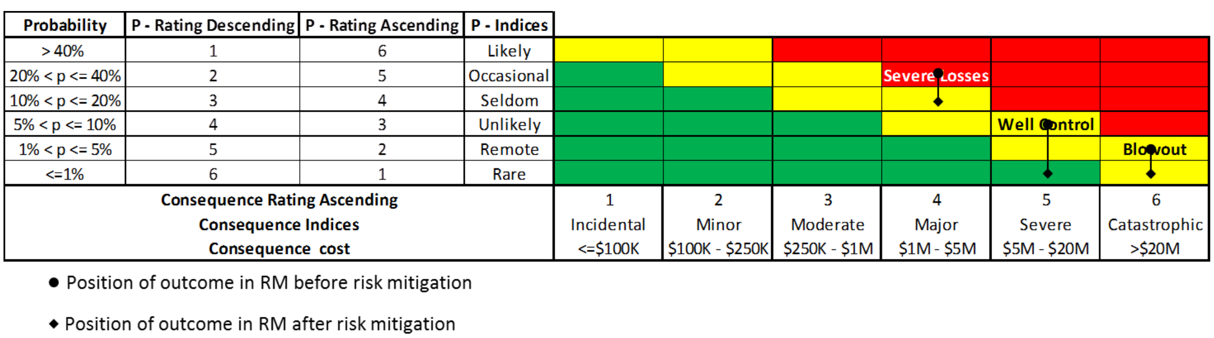

Figure 36 — An RM for both mitigation plans (both of them produced the same RM)

The next step is to calculate the risk score reduction for each plan. The risk score reduction can be calculated by measuring the difference in risk scores from before and after implementation of the mitigation plan. The cost per unit risk score reduction then can be calculated by dividing the cost of mitigation plan with the total risk reduction from all outcomes. The result of the analysis is shown in **Table 16**.

Table 16 — Comparison of between mitigation plans in the RM

Mitigation Plan	Cost (MM US$)	Outcome	Before Mitigation Risk Score	After Mitigation Risk Score	Risk Score Reduction	(Cost MM US$ / 1 unit risk reduction score)
PWD Only	0.5	Severe Losses	20	16	-4	0.025
		Well Control	15	5	-10	
		Blowout	12	6	-6	
PWD + Better PCE	0.75	Severe Losses	20	16	-4	0.0375
		Well Control	15	5	-10	
		Blowout	12	6	-6	

The results in **Table 16** show that the mitigation plan with minimum cost is PWD only, and the calculated risk score reduction shows that the PWD + better PCE has no benefit in terms of additional safety. That is, better PCE perceived as no additional value in terms of safety. This result from the RM analysis should be compared with results from the decision analysis method.

5.3.2 Mitigation Plan Analysis with Decision Analysis

To analyze the risk mitigation plan using DA, the analysis has to be done with the same framework as provided in **Figure 19**. In this case, we don't need to generate the alternatives since they are given ('PWD' or 'PWD + better PCE'). The objectives are cost and safety: our preference is to minimize risk to be as low as possible, but with minimum cost and risk neutral assumption for the risk attitude.

The structure used to perform the analysis for the two mitigation plans is shown in **Figure 37** where there are two branches, separating out from the decision node. One of them represents PWD and another represents PWD + better PCE. By calculating the expected loss + cost for each branch, we can work out the expected value. The smallest expected value between two decision branches represents the one that will incur the minimum downside risk.

However, an uncertainty analysis has to be incorporated into the model. For this, a Monte Carlo simulation was used. The Monte Carlo simulation gives a holistic view between two alternatives, and thus, we can choose accordingly.

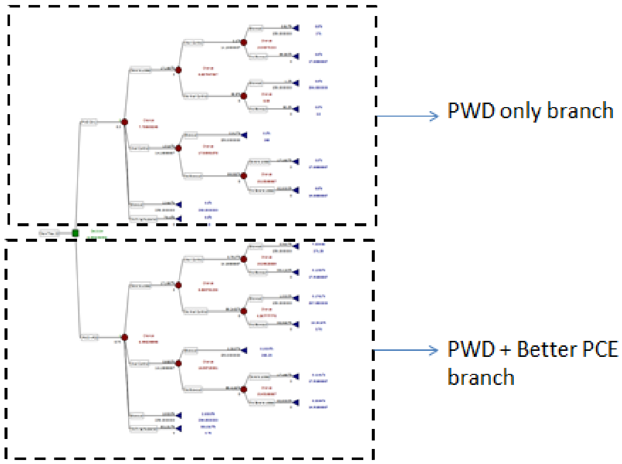

Figure 37 — A decision tree for 'PWD' and 'PWD + better PCE'

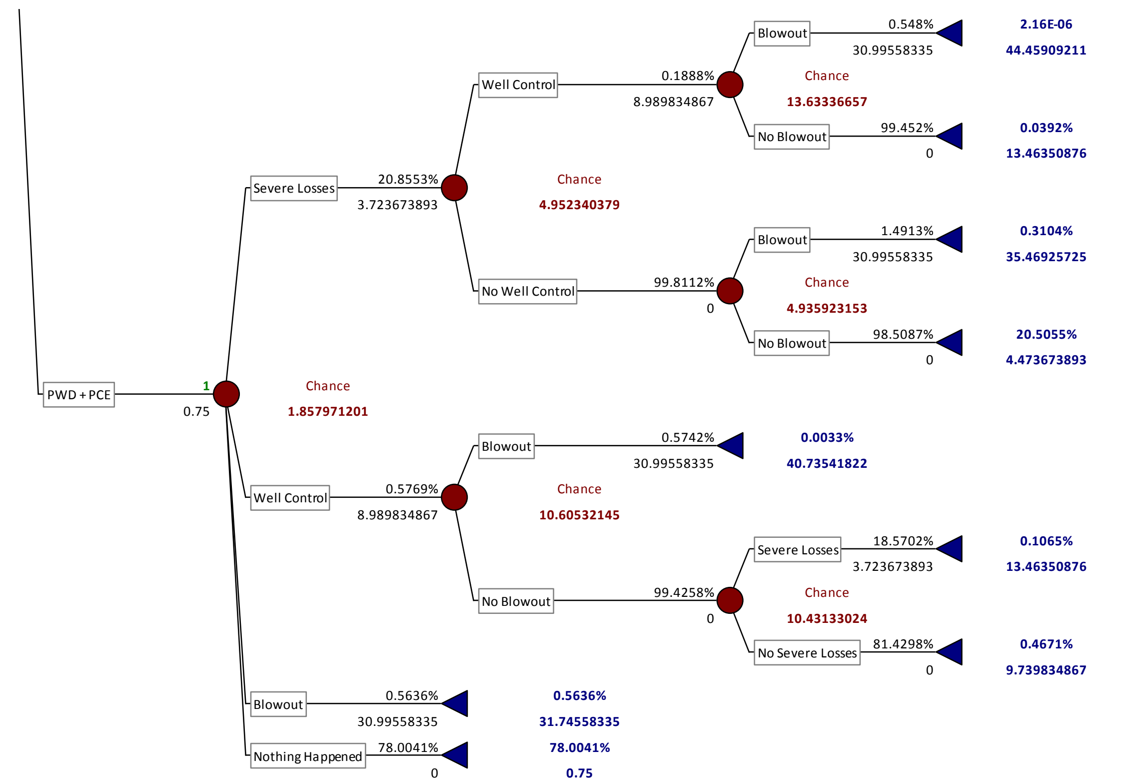

Figure 38 — PWD + PCE branch (the PWD only branch will have the same form)

Figure 38 shows a structure that is different from the prioritization case. In the prioritization case, the outcomes are prioritized by the expected loss for each outcome. In the mitigation case, it is needed to assume that the events presented are not collectively exhaustive but mutually exclusive. Therefore, the probability of all outcomes needed to sum to one by introducing a new outcome called 'nothing happened'. Thus, the fluid losses may lead to four possible outcomes: *severe losses*, *blowout* and *well control* or *nothing happened*.

MCS is then incorporated into **Figure 37**. The results are **Figure 39** which shows the distribution of expected consequences for PWD + better PCE and **Figure 40** which shows the distribution of expected consequences for PWD only. From here, a comparison between the two mitigation plans can be made. The results of the distributions are in favor towards PWD + better PCE since it achieved lower maximum, mean and standard deviations compared to PWD only.

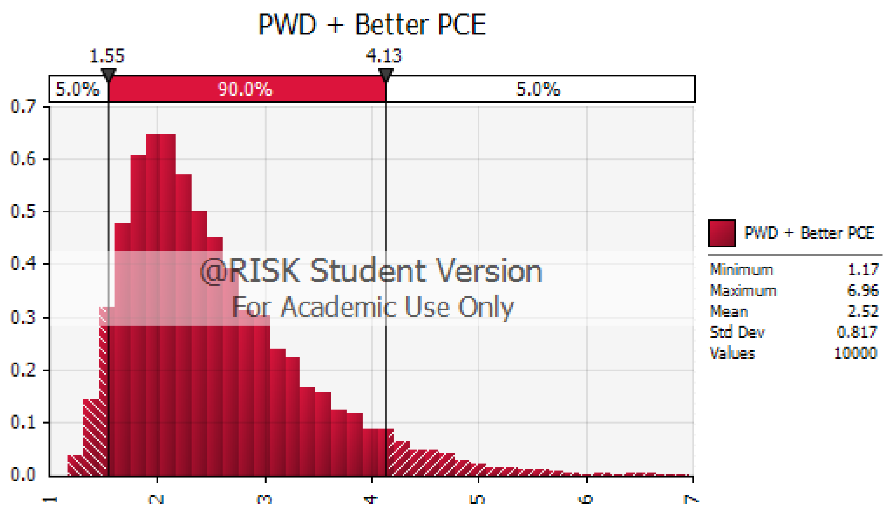

Figure 39 — Distribution of expected loss for PWD + better PCE

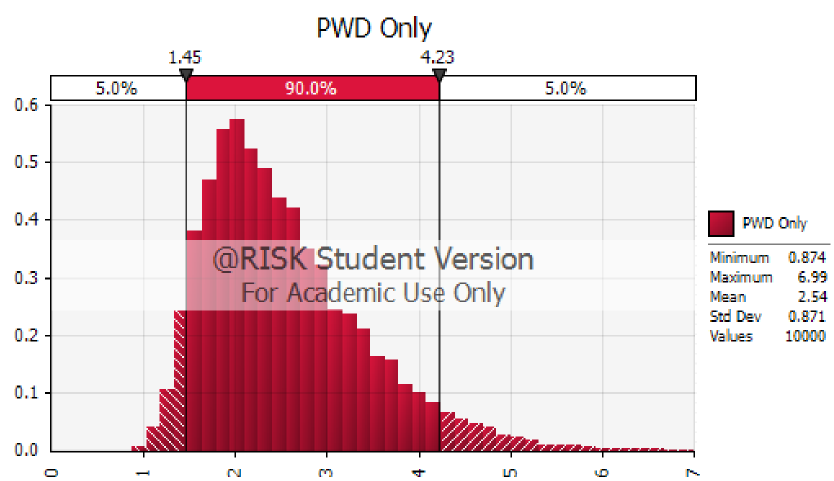

Figure 40 — Distribution of expected loss for PWD only

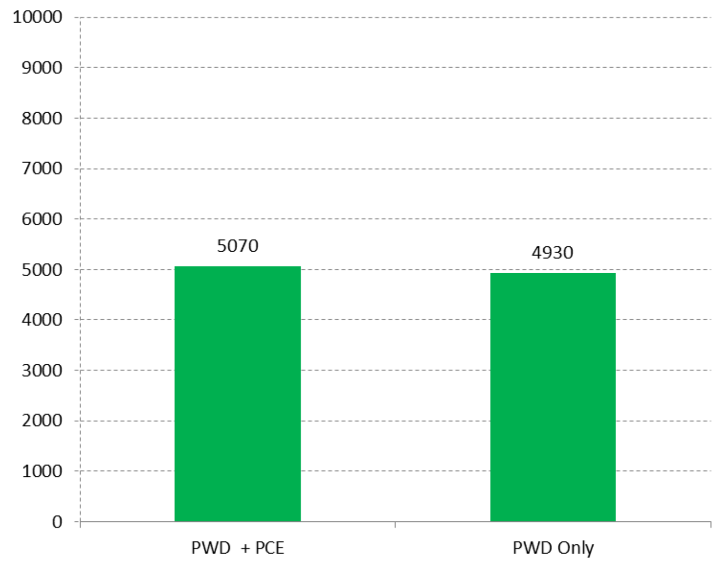

Figure 41 — Numbers chosen as an optimal solution in a MCS for both plans

Figure 41 shows that the PWD + better PCE is chosen as optimal solution in 5070 out of 10,000 iterations. This confirms the previous finding where PWD + better PCE is a better alternative than PWD only.

5.3 Comparison of RM and DA in Choosing Risk Mitigation Plan

The analysis using DA shows that PWD + better PCE is a better alternative than PWD only, whereas the analysis by RM shows that PWD only is a better alternative. This contrast in the decision is caused by the RM that is inherently flawed. Specifically for this case example, it is the range compression bias which obscured RM decision making process. The RM assigned the same score to very different probability/consequence values. Thus, the decision suggested by the RM leads us to the possibility of choosing an inferior alternative. This issue can be alleviated with DA method that doesn’t compress the actual values into arbitrary scores and won’t introduce arbitrary risk acceptance or coloring which leads to confusion.

5.4 Discussion

This thesis has presented a method with DA principles as an alternative for RMs. Unlike RMs, DA brings clarity about the problems under investigation with minimal (if any) conceptual biases or errors. Instead of presenting a deterministic view of a problem(s), DA provides a holistic view that allows for good risk prioritization.

Furthermore, DA gives us the ability to model the problems with more realistic features, such as dependence and sensitivity analysis. These realistic features cannot be included in RMs since they rely on a grid- and category-based assessment.

Many people find it challenging, at least initially, to deal with good decision making requirements. For many, it is difficult to be clear about their preferences, objectives, alternatives, and to become a probability assessor.

Using RMs gives the impression of scientific and intellectual rigor, without dealing with good decision making requirements. Instead because of their inherent flaws and errors they could lead us to inferior decisions. The only way to consistently making a good decision is to work through what is perceived to be the hard part of good decision making requirements.

The DA method is a tool that requires us to have a good decision making requirements. Using it for the first time may not always be easy, but the more experience we gain in using it, the easier it becomes to implement, until we see they are just as convenient as RMs. Furthermore, the DA method is easily scalable to the problems with more variables/risks. It's a tool that requires practice in using it, but certainly is better than RMs.

Chapter 6 – Discussion and Conclusions

Risk matrices (RMs) are among the most commonly used tools for risk prioritization and management in the O&G industry. RMs are recommended by several influential standardization bodies, and our literature search found more than 100 papers in the OnePetro database that document the application of RMs in a risk-management context. However, we are not aware of any published empirical evidence showing that they actually help in managing risk or improve decision outcomes.

In this thesis, we have illustrated and discussed inherent flaws in RMs and their potential impact on risk prioritization and mitigation. Inherent dangers such as risk acceptance inconsistency, range compression, centering bias, and category definition bias were introduced and discussed by Cox et al. (2005), Cox (2008), Hubbard (2009) and Smith et al. (2009). We addressed several previously undocumented RM flaws: ranking reversal, instability resulting from categorization differences, and the lie factor. These flaws cannot be corrected and are inherent to the design and use of RMs. The ranking produced by RMs was shown to be unduly influenced by their design, which is ultimately arbitrary. No guidance exists regarding these design parameters because there is very little to say. A tool that produces arbitrary recommendations in an area as important as risk management in O&G should not be considered an industry best practice.

There are undoubtedly O&G professionals who recognize and understand the inherent inaccuracy of RMs and take steps to avoid these dangers, to the extent this is even possible. However, we suspect that this does not apply to the majority of O&G professionals who develop or use RMs, based on the literature review and extensive data gathering conducted for this paper.

We hope that this thesis increases awareness of the inherent flaws in RMs and that risk professionals in the O&G industry are prompted to move away from RMs and use more consistent risk-management approaches.

It may be true that using RMs to analyze and manage risks is better than doing nothing (even that may be debatable). Indeed, any approach that generates some discussion of the risks in a particular activity will be helpful. The fact that these flaws have not been raised before is evidence of the fact that RMs obscure rather than enlighten communication. Instead of RMs, the O&G industry should rely on risk- and decision-analytic procedures that rest on over three-hundred years of *scientific* development and understanding.

This thesis has illustrated a decision analysis procedure that can act as a guide in solving risk management issues. Decision analysis-based methods provide clarity and can be appropriately implemented in O&G the industry. It may seem harder initially to implement than RMs since DA requires the users to deal with good decision making requirements such as defining preferences and objectives, generating alternatives, seeking more information, assessing probabilities. However, once the user is accustomed to these procedures, they will notice that the results from DAs are much clearer and cleaner in practice than RMs.

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Appendix: 30 Selected SPE Papers and Their Flaws

Table 17 — 30 SPE papers and (some of) their inherent flaws.

Paper	Year	Author(s)	Risk acceptance Inconsistency	Category definition bias	Centering bias	Scoring System
Corrosion 2000	2000	Reynold, John T.	y	y	Not available	Ascending
SPE 61149	2000	Piper and Carlon	y	y	Not available	Descending
SPE 66516	2001	Berg, F.R.	y	y	Not available	Ascending
SPE 73892	2002	Mcculloch.	y	y	Not available	-
SPE 73897	2002	Smith et al.	y	y	y	Ascending
SPE 74080	2002	Zainuddin et al.	y	y	y	Descending
SPE 85299	2003	Coakley et al.	y	y	Not available	Ascending
SPE 86838	2004	Theriau et al.	y	y	Not available	Descending
SPE 98566	2006	Campbell and Tate	y	y	Not available	Ascending
SPE 98852	2006	Alkendi	y	y	Not available	Ascending
SPE 98679	2006	Clare and Armstrong	y	y	Not available	Ascending
SPE 98423	2006	Valeur and Clowers	y	y	Not available	Ascending
SPE 108279	2007	Poedjono et al.	y	y	Not available	Ascending
SPE 108853	2007	Mcdermott	y	y	Not available	Ascending
SPE 105319	2007	Samad et al.	y	y	Not available	Ascending
OTC 18912	2007	Truchon et al.	y	y	y	Descending
SPE 111549	2008	Kinsella et al.	y	y	Not available	Ascending
SPE 121094	2009	Poedjono et al.	y	y	Not available	Ascending
SPE 123457	2009	Lee	y	y	Not available	Ascending
SPE 123861	2009	Leistad and Bradley	y	no	Not available	Ascending
SPE 111769	2009	Jones and Bruney	y	y	Not available	Descending
SPE 137630	2010	Samad et al.	y	y	Not available	Ascending
SPE 127254	2010	Neves Da Silva et al.	y	y	Not available	Ascending
IPTC 14434	2011	Al-Mitin et al.	y	y	Not available	Ascending
IPTC 14946	2011	Areeniyom	y	y	Not available	Ascending
SPE 142854	2011	Dethlefs and Chastain	y	y	y	Ascending
SPE 146845	2011	Petrone et al.	y	y	y	Ascending
SPE 158114	2012	Bower-White	y	y	Not available	Ascending
SPE 162500	2012	Bensahraoui and Macwan	y	y	y	Ascending
SPE 161547	2012	Duguay et al.	y	y	Not available	Ascending