TOWARDS IMPROVED DECISION SUPPORT IN FINANCIAL SECTOR OPERATIONAL RISK ANALYSIS

Lappeenranta–Lahti University of Technology LUT

Master's Programme in Business Analytics, Business Administration

Master's thesis

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Examiner(s): Post-doctoral researcher, Mariia Kozlova, D.Sc. (Econ&BA)

University lecturer, Roman Stepanov, Ph.D.

ABSTRACT

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As all organizations seek to achieve their objectives, they make decisions under uncertainty and attempt to understand what might happen, both on positive and negative, as much as possible for their benefit. Risk management is part of the uncertainty identification and reduction, thus being an important part of decision-making. Thus, risk management should provide useful support to decisions to create value in taking actions to achieve objectives.

However, over last few decades risk management has suffered from oversimplification to make it accessible to wider audience. This has led to models that have been developed outside of mathematics and decision analysis, and thus they are not considered useful or improving decision-making under uncertainty. Operational risk is one part of wider risk management and should also provide useful insight into decision making with information created via useful models. However, unlike other financial sector's risk classes like credit risk, operational risk does not have consensus how to build models for its analysis.

The purpose of this thesis was to assess prevalent model of operational risk analysis and how modelling approach should be improved to support decision making. Via design science research, qualitative and quantitative modelling of the decision situation was done with influence diagrams, bowties, and Monte Carlo simulation. Related risks were quantified with Monte Carlo simulation to present their uncertain effect on the decision objective. The study shows that applied methods are better in operational risk analysis than prevalently used risk matrix. Another contribution is that it was shown that risk matrix is not risk analysis, but classification. Lastly, it was shown that there seems to be no consensus on what operational risk analysis model should consist of. All in all, the study contributed to financial sector operational risk analysis by providing a practical blueprint with steps towards better decision support with useful models.

Table of contents

1 Introduction

Organizations of all size make decisions under uncertainty (e.g., Kahneman, Slovic & Tversky, 1982; Keeney, 1992; Kahneman, 2011; MIT, 2015; Howard & Abbas, 2016) to achieve desired objectives and in knowledge economy one has better opportunity to get advantage with capacity to make better judgments and choices (e.g., Schoemaker & Tetlock, 2017). These uncertainties, including both positive opportunity and negative risk, arise from different areas relevant to the decision at hand and details about these uncertainties need to be informative for the decision maker to support the decisions in adequate manner. Uncertainty can be described in different ways in different contexts, and there are several approaches how it is done. Therefore, one should select a useful model to be used in each context.

This is true also for financial sector in which operational risk, mainly as negative aspect of uncertainty, has been on the side of credit and market risk until the era of digitalization. Digitalization is one reason there exist increased uncertainties, such as cyber-attacks, on business operations over the last few decades (e.g., Grimwade, 2022; Peters, Shevchenko, Hassani & Chapelle, 2016). However, there are no clear guidelines what constitutes standardized models for operational risk analysis to be used in different areas, such as European Banking Authority's (hereafter EBA) capital requirement regulation (hereafter CRR) (e.g., Peters et al., 2016; Zhu et. al., 2019) and business decision-making.

Thus, simple risk analysis models, like risk matrix, seem to have become prevalent in certain geographies also in financial sector's operational risk analysis, but which are severely flawed (e.g., Cox, 2008; Hubbard, 2010; Ball & Watt, 2013; Ale, Burnap & Slater, 2014; Hubbard & Evans, 2010; Thomas, Bratvold & Bickel, 2013). There seems to be only studies showing how to apply risk matrix, and these tend to ignore the studied flaws, (e.g., Arnetz, Hamblin, Ager, Aranyos, Upfal, Luborksy, Russel & Essenmacher, 2014; Marin-Garcia, Chavez-Burbano, Guerra, Rabadan & Perez-Jimenez, 2017; Qazi & Dikmen, 2021; Kadkhodaei & Ghasemi, 2022), but no studies showing that risk matrix works as intended. And even those kinds of studies attempt to alleviate the identified flaws with quantitative approaches (e.g., Ni, 2010; Levine, 2012; Duijm, 2015; Ruan, Yin & Frangopol, 2015; Hsu, Huang & Tseng, 2016; Qazi & Pervaiz, 2018; Peña, Bonet, Lochmuller, Chiclana & Gongora, 2018).

The previous studies on financial sector operational risk, such as McCormack (2014), Peters et. al. (2016), and Zhu, Li, and Wu (2019), have mainly shown what features a model should have and not comparative analysis to prevalent models. The studies show mathematical proof to Loss Distribution Approaches (hereafter LDA), and other studies (e.g., Vukovic, 2015) show also practical coding implementation. Thus, author attempted to replicate ways to do the development towards improved decision support in operational risk analysis via practical examples. The methodology used was design science research with its problem-solving approach. The aim to achieve was to examine what is needed from an operational risk analysis model to adequately inform decision-making of relevant uncertainties, and how the model meets requirements from authorities, research, and literature. Qualitative and quantitative approaches were applied to decision situation's risk modelling to approximate real life situation.

As a results, the study showed that solutions from decision analysis and analytics can provide better models for operational risk analysis, as demonstrated with practical case studies based in previous research and literature. Applying probabilistic model, MCS, and approaches closely related to it, author was able to demonstrate that they provide a useful way to analyse operational risk and this finding is in line with existing research, literature, and practice. The results indicate that financial organisations would benefit from moving towards more useful operational risk analysis models that can be used also outside of operational risk context.

The thesis is structured as follows: first, the rest of this chapter describes the background and motivation, objectives and scope, research problem and questions, as well as central concepts used in the thesis. Chapter two reviews the theoretical background and its literature on models used in operational risk analysis. Chapter three describes the research methodology used in this thesis. Chapter four describes the construction of the thesis artefact for the support of financial sector operational risk analysis and decision making. Chapter five presents the discussion on the thesis findings and results as well as limitations and future research possibilities.

1.1 Background and motivation

Over the last about fifteen years one could have read in financial news that errors, such as inappropriate correlations, on models and lack of management of model risk have been argued to be one reason for the great financial crisis of 2008. Model risk partially overlap with operational risk, which includes the risk related to lack of due diligence in task in which it should be easy to define as good as possible execution. Thus, as in model risk definition, one should commit oneself to find models giving values as correct as possible. (E.g., Morini, 2011)

At the time of writing, author works in financial sector and identified a need for improvement in operational risk analysis methods used in financial sector, because there seems to be gaps in financial institutions on what constitutes as an adequate internal model for operational risk analysis. Authorities, such as EBA, give some guidelines on operational risk modelling e.g., via CRR (EBA, 2018) and the model requirements increase, e.g., towards advanced measurement approach (AMA) (EBA, 2018) existing at the time of writing. However, Basel Committee on Banking Supervision (hereafter BCBS) seems to be removing AMA model and propose only one standardized measurement approach (hereafter SMA), but this is argued by e.g., Zhu et al. (2019) and Peters et al. (2016) not to be reasonable.

Another perspective to the problem at hand is that prevalent model used in operational risk analysis is developed outside of decision analysis and mathematics to e.g., bring risk analysis closer and more understandable to wider audiences, and that has oversimplified the methods, making those inadequate to support decision-making (e.g., Cox, 2008; Hubbard, 2010; Ale, Burnap, & Slater, 2014; Hubbard & Evans, 2010; Thomas, Bratvold, & Bickel, 2013). With this background, the motivation and need for the research is evident and studied further in this thesis.

1.2 Objectives and scope

The main objective of this thesis is to assess operational risk analysis models, human judgment, one prevalent, and one probabilistic, on their utility in decision support and what is required from them to be adequate in financial sector operational risk analysis. The adequacy is assessed against requirements derived from authoritative (mainly EBA, 2018) material, literature, and practice. Along the main objective practical comparison is attempted and how an organization can implement these improvements.

Therefore, with design science research the objective is to do an artefact for the thesis as a demonstration (blueprint) towards better models for operational risk analysis and how they can support decision making. The artefact attempts to cover mainly model-specific topics and provide practical approaches to their implementation.

The scope of this thesis is limited to operational risk analysis and its models, as well as their implementation to some extent. The scope touches relevant areas, such as administrative and technical side of implementation on general level. However, even the scope of this work is financial sector, the motivation for improvement is connected to other areas as well, such as public sector or security management in which author has worked as well.

1.3 Research problem and questions

The research problem of the thesis revolves around the domain of decision-making under uncertainty (e.g., Kahneman et al., 1982; Kahneman, 2011; MIT, 2015) and how the uncertainty is measured in financial sector operational risk analysis. Currently a prevalent model is not considered adequate, based on research (chapter 2.3) conducted during previous few decades. Therefore, more useful models are needed to support business decisions.

On the other hand, there seems to be gaps on consensus what useful enough internal model is, so comparative analysis is done between human judgment, prevalent and probabilistic approaches how they can aid in uncertainty analysis. Therefore, the main research question for the thesis is “What is needed from an operational risk analysis (internal) model to adequately inform decision-making of relevant uncertainties?” and as a support question “what is needed from an internal model to meet requirements derived from authoritative sources, literature and practice?”.

1.4 Central concepts

This chapter describes the central concepts used in this thesis. Considering the literature and work life there seems to be several interpretations regarding used terminology in risk management domain, especially about what risk means. The detailed definitions can be found below.

Decision-making

Decision-making in this thesis means to achieve clarity of thought and action in making any decision on which one focuses one's attention (Howard & Abbas, 2016). A deciding agent is entity that operates in an environment, and they can be different entities, such as people, robots, and software (decision support systems). These agents choose actions through decision making to achieve their objectives over time (MIT, 2015). In this thesis decision-making and decision makers are referred mainly to people, who are supported with decision support systems and models.

Decision

A decision is a choice between two or more alternatives that involves allocation of resources. Decision must not be confused with an outcome, which can be bad due to uncertainty even decision is considered good (Howard & Abbas, 2016). Decision quality is achieved understanding following main elements of a decision (adapted from Howard & Abbas, 2016; Spetzler et al., 2016; Keeney, 1992):

1. Decision maker and decision
2. Objective/values
3. A (right) frame
4. (Right) Alternatives to choose from
5. Preferences
6. (Right) Information
7. Logic/reasoning by which the decision is made.

Uncertainty

One of the main challenges in decision making is uncertainty and it is inseparable part of decisions (Howard & Abbas, 2016). In literature uncertainty is separated into different types of uncertainty, aleatoric and epistemic. Aleatoric uncertainty is randomness inherent in a certain process and which is not possible to be reduced, whereas epistemic related to lack of knowledge that could be reduced, in theory, by acquiring more information (e.g., Padilla, Kay & Hullman, 2021).

Uncertainty in this thesis is the lack of complete certainty, or the existence of more than on possibility; The true value, positive or negative, is unknown. This includes discrete and continuous values and can be measured by assigning probabilities to various outcomes. (Hubbard, 2010).

Risk

Concept of risk and its word is considered confusing even among risk management professionals and nowadays sometimes considered as both positive and negative thing (e.g., ISO31000 (ISO, 2018)), but these are already covered with "uncertainty" (definition above) (e.g., Hubbard, 2010). Risk here is a state of uncertainty with possibilities involving some negative outcome, such as loss, injury, or other undesirable outcome with a range of possible values. The definition for operational risk is in line with this as it is generally considered or classified only as negative outcome(s) resulting from processes, people and systems or from external events (e.g., Naim & Condamin, 2019). The key in this thesis is how to describe visually the uncertainty of the negative values of range outcomes.

Risk perception

Risk perception refers to individual perspective how risks and uncertainties are seen and responded to. Various factors might bias risk judgment. For example, how risks are expressed can have a major impact on perceptions and behaviour. (Kahneman et al., 1982)

Risk analysis methods

Risk analysis methods have been developed since about 17th century and have been adopted in various industries for different applications. Hubbard (2010) has stated that we always use some method in risk analysis and describes the partial map of risk analysis methods, in no specific order, summarized as follows:

- Expert intuition. This is the baseline for methods and for another method to add value, it should be better than expert intuition. Expert intuition, or unaided human judgment, is examined in chapter 2.2.
- Expert audit. Like expert intuition, but more systematic, e.g., with checklists.
- Simple stratification methods. Rating scales like "green-yellow-red" or "low-medium-high" with variations. These can be assessed for likelihood and consequence on two-dimensional heatmap, which in this thesis is also the risk matrix.
    - Risk matrix in this thesis is a 5x5 matrix with ordinal scales 1-5 and verbal scales for levels, as well as multiplication of levels to get a risk score between 1-25 with colouring between green-yellow-orange-red, 1 to 25 respectively. More detailed information can be found in chapter 2.3.
- Weighted scores. Different variables are on some scale and are multiplied by some weight to get a weighted risk score. The numerical weight may vary based on for example handled hazardous material with regards to personnel safety.
- Traditional financial analysis (deterministic modelling without probabilities). For example, risk is expressed as discount rate or scenarios, such as best and worst case.
- Calculus of preferences. Not strictly risk analysis but are sometimes used to evaluate decisions based on their risks. Methods include e.g., multi attribute utility theory (MAUT) and multi-criteria decision-making (MCDM).
- Probabilistic models. Chances of various losses and their amounts are computed mathematically. This includes methods like probabilistic risk analysis (e.g., Bedford & Cooke, 2011) used in engineering, finance, and insurance. in this thesis Monte Carlo Simulation (hereafter MCS) is included. More detailed information can be found in chapter 2.4.

Model risk

Derived from Morini (2011), model risk is related to the concept of models not being able to approximate reality or examined phenomena. One should steer to create and use models that provide values that are as correct as possible. Model risk can be considered as one form of epistemic uncertainty, i.e., lack of knowledge of model specifics and could be reduced with more information.

2 Theoretical background

This chapter describes the theoretical background of this research and covers literature regarding different models mainly used in operational risk analysis. Based on author's studies and experience on the topic literature was chosen, spanning from about 1970's to today, to get as comprehensive view as possible of prevalent risk analysis approaches and their requirements. The literature was retrieved from author's personal library as well as via Google, Google Scholar, and university databases. The rest of this chapter is structured as follows.

First, the general criteria and requirements are derived from authoritative sources, namely EBA's (EBA, 2018) AMA criteria, as well as from literature, such as Peters et al. (2016) and practice, mainly Vose (2022). Second, the analysis baseline, unaided human judgment, is described to examine its performance, and to which the other models are compared. Third, a widely used risk analysis model in risk management, namely risk matrix, is described with its attributes. Then probabilistic or statistical model, namely simulation, is described with its attributes. Then these approaches and their performance is discussed. Lastly, summary of the theoretical background and models is described and how to proceed towards operational risk analysis approach improvement and development through used research method.

2.1 Risk analysis model requirements

EBA (2018) CRR describes rules concerning requirements for supervised institutions under directive 2013/36/EU for e.g., own funds requirements, including operational risk. Requirements for operational risk are described in Title III (EBA, 2018) with different approaches. Basel II accord outlines three approaches, Basic Indicator Approach (hereafter BIA), Standardized Approach (hereafter TSA), and Advanced Measurement Approach (AMA), to operational risk capital reserve calculations with increasing requirements (e.g., Naim & Condamin, 2019).

BIA (title III, chapter 2) is basically backwards looking model that examines institution's historical incidents rather than future risks. The own fund requirement for BIA is 15% of the average of three years of relevant indicator described in article 316, i.e., indicator is sum of elements that is positive, mainly gross income, described in article 316 (EBA, 2018). Thus, there is no requirements for operational risk analysis method, but it is a conservative amount of capital from institution's income and assumes e.g., that operational risk amount increases as an institution increases in size.

TSA (title III, chapter 3) increases the requirements (appendix 1) and decomposition on details into business lines and their funds. Calculation for operational risk in institution shall consist of average of three years of sum of annual funds across all business lines. The funds for each business line are a product of provided beta factor and the relevant indicator for the business line. Then average over previous three years is sum of the elements. There is an alternative TSA described in article 319 with lighter division in business lines, with other conditions.

Examining the TSA criteria (appendix 1), differentiating from BIA, TSA has requirement (a) for operational risk assessment and management system, most likely referring to administrative task rather than to specific risk analysis methods, i.e., institution can choose the used risk analysis models. Institution shall identify exposures and track negative outcomes but does not indicate how this shall be done. Lastly, independent review shall assess the previous requirements, but does not distinguish what "necessary knowledge" is. (EBA, 2018)

Then (b) requires operational risk assessment to be integrated to management processes, which is important, but does not describe how and with what methods. With regards to risk profile, there is no indication how this should be done. Lastly, (c) describes reporting and controls, but not telling what that constitutes of (EBA, 2018). These are somewhat relevant requirements in general, but from modelling perspective e.g., Peters et al. (2016) describe new proposed Standard Measurement Approach's (SME) weaknesses, such as instability, risk insensitivity, and super-additivity. These can be damaging for an institution and do not necessarily reflect true capital requirement (e.g., Zhu, 2019). Therefore, BIA and TSA are easy to use, implement and follow as minimum, but may result inaccurate capital requirements with unnecessarily conservative reserves, capital because e.g., they have not been calibrated since 2004. Also, BIA and TSA are basically backwards looking, i.e., consider only historical losses and income. (e.g., Peters, 2016)

Moving to AMA model one can see from appendix 1 that with just model specific AMA requirements the number of criteria increases considerably from BIA and TSA. However, one could argue that these requirements should apply to risk analysis models to some extent regardless of the capital approach. On the qualitative requirements, regarding internal validation process, used models should be back tested and validated against reality (e.g., Hubbard 2010; Morini, 2011) so that one can have sufficient certainty that these models work and provide good enough information to decision making. Concerning validation, also data flows and processes related to risk analysis system should be transparent and available to e.g., auditors and authorities for assessment. (EBA, 2018)

Moving to quantitative requirements (article 322), (2a) states that calculations should comprise both expected loss and unexpected loss in business practices. This indicates that calculations should have a probability distribution of the losses describing the body (expected loss) and the rest towards tail (unexpected loss). With regards to tail, the calculation should capture also severe tail events, achieving soundness standard comparable to 99,9% confidence interval (hereafter CI) over one year (EBA, 2018). Also, in Finland, Finnish Financial Supervisory Authority (FIN-FSA) (Finanssivalvonta, 2023) has created a regulations and guidelines document (Finanssivalvonta, 2014) for management of operational risk in supervised entities of financial sector, which states that a financial institution must prepare for rarely materializing severe risk events, i.e., tail events.

Also, (2c) states that major drivers of risk affecting the distribution's tail shall be included, which indicates some form of causal analysis (e.g., Pearl & McKenzie, 2018) or sensitivity analysis (e.g., Vose, 2008). Among AMA modelling loss distribution approach (hereafter LDA) is mostly utilized, consisting of annual frequency and severities for operational risk losses (e.g., Peters et al., 2016; Zhu et al., 2019; Naim & Condamin, 2019).

What comes to data and its sources (2b), internal and external data, scenarios, business environment factors, as well as controls should be part of risk analysis. However, there is no mentioning of data quality, which is important for model inputs. On the other hand, it is stated (2e) that measurement system shall be internally consistent and avoid double counting of assessments or controls, and 3 (a & f) require long enough period of historical data and relevance, as well as 4 (a) require usage of relevant external data on low probability-high impact scenarios, indicating that data quality and management should be appropriately done. Lastly, regarding the process (2d) it is stated that institutions may recognize correlations in operational risk losses, i.e., it is not mandatory. But if correlations are included, the system must be sound, implemented with integrity, and consider the uncertainty around correlation estimates, as well as validate correlation assumptions with appropriate techniques. (EBA, 2018)

5 requires the usage of scenario analysis of expert opinion (e.g., Vose, 2008) along with external data (4a) with regards to high severity events. Over time these scenarios should be back tested against the actual loss experience (3a, 3f, 6d) to ensure their accuracy (EBA, 2018; also e.g., EBA, 2021). It should be noted that these scenarios should also cover a range of impacts in different relevant variables, and not just single point estimates.

Lastly, regarding business environment and control factors (6a,6c), the assessment methodology should include their key factors that change risk profile, which indicates again of causal analysis (e.g., Pearl & McKenzie, 2018) or sensitivity analysis (e.g., Vose, 2008, 5.3), as well as some distribution approach to describe the profile. This should also involve human experience and expert judgment (6b).

Concluding the authoritative requirements, the following table (table 1) contains the requirements for an improved risk analysis model. The requirements combine some of the features examined above and may have some overlap with other requirements examined below the table.

Table 1. EBA requirements for an operational risk analysis model. (EBA, 2018)

ID	EBA requirements (EBA, 2018)	Author’s comment
R1	Internal validation of models (back testing is done appropriately against historical data)	Assumption here is that this refers to back testing of the models against the actual experienced losses and other relevant data.
R2	Data flow and process (data and process elements can be linked to model)	Assumption here is some form of administrative and architectural or technical description of the used data.
R3	Model captures risk profile: 1. Expected losses 2. Unexpected losses 3. Tail(s) and drivers 4. 99,9 % Confidence interval	Assumption here is that the model captures the required features appropriately.

R4	Model can include correlations	Emphasis on ”can”, as correlation is not required and requires acceptance to be included. However, correlations should be possible to do with a used method, if needed in a risk analysis model.
R5	Internally consistent and avoid the multiple counting of qualitative assessments or risk mitigation techniques	This leans more towards process side of risk assessment, but e.g., aggregation should be done appropriately.
R6	Internal and external data can show improvement in model analysis results	Assumption here is that one can see change in results when more information is given, i.e., uncertainty is reduced.
R7	Model shows key driving factors and their influence on risk profile	Assumption here is that one can identify what are the main factors for a risk as well as what factors/risks influence the risk profile.
R8	Model can include sensitivity analysis to assess sensitivity of risk estimates to changes in risk factors and weight of these factors.	These are related to business environment and internal controls but should also cover factors in risk analysis model.

What comes to research, for example Peters et. al., (2016) described some standardization requirements for a model and state that like any other scientific domain, operational risk modelling is no different when it comes to creating a statistical modelling framework. They argue that the change towards single SMA includes several problems, and recommend standardizing AMA model, with several recommendations, rather than removing it as SMA cannot be considered a suitable alternative to AMA. Thus, their recommendations are summarized as following table 2.

Table 2. Literature standardization for an operational risk analysis model.

ID	Standard (Peters et al., 2016)	Author’s comment
L1	Different risks can be appropriately aggregated from business lines to institution level	Standardization recommendation 1. Connected to EBA requirement 5. Model can do appropriate aggregation of risks.
L2	Model is flexible and can use different distributions for risk probability/frequency and severity (and possible regression component)	Standardization recommendation 2 and 3. Model can express different risk features, such as a single probability (Bernoulli) or frequency (Poisson), and different impact distributions based on data and assumptions.
L3	The models can be fitted to risks (data)	Standardization recommendation 4. Model can appropriately utilize past data in its analysis.
L4	Institution can choose between Bayesian and frequentist models	Standardization recommendation 5.
L5	Models can be calibrated to loss experience	Standardization recommendation 6. Model is and can be back tested and performs well.

From practical point of view e.g., Vose (2022) examined financial sector and what requirements there are with regards to operational risk analysis. Even the examined financial sector requirements were for larger banks, one can use the stated questions to assess what risk analysis can tell with different models. The questions are as summarized as following table 3.

Table 3. Practical questions for an operational risk analysis model (Vose, 2022).

ID	Question (Vose, 2022)	Author's comment
P1	What is our overall risk exposure/profile?	Relates to aggregation requirement in EBA ID5 and literature ID1.
P2	Which are the top risks?	This requires some clarification as this can mean top as in biggest or which risk drive the examined phenomena, where is the most uncertainty, and so forth. Nevertheless, this requires from a risk model to be able to do e.g., sensitivity analysis to the top risks (EBA requirement ID8).
P3	Where to spend risk treatment money efficiently?	One should be able to assess control effectiveness on risk and its profile, so one can compare what are efficient risk treatment strategies and see how they impact risk profile.
P4	Are we taking too much risk?	One must be able to know the risk profile holistically to assess this (EBA requirement ID3 and literature ID1).
P5	Where is risk concentrated?	Related to question 1 and risk profile that should show expected losses e.g., in business lines. (EBA requirement ID3 and literature ID1).
P6	How much insurance should we buy?	Related to question 1 and 3, and EBA requirement 3, i.e., one should know the risk profile and tails to which and how much insurance is appropriate.
P7	How much capital reserve do we need?	This relates to all EBA requirements and literature questions.

2.2 Unaided human judgment model

Inherent beliefs have major effect on the many human decisions on probability of uncertain events, which are usually expressed with phrases like "I ponder that…" or "chances are…" or "it is unlikely that…" or similar qualitative manner. Beliefs can be expressed in numerical manner as odds or subjective probabilities between 0-1 (or 0-100%). Thus, predictions can be given in categorical and numerical form. Categorical form is nominal, e.g., winner of election or person's future occupation. Numerical form consists of e.g., future monetary value of a stock or a student's grade point average. (Kahneman et. al., 1982)

In (operational) risk assessment humans tend to assess risks' probability and impact with vague language, such as "likely" and "very high", respectively. One reason is that mathematical probability theory is less intuitive or less known to most (e.g., Kahneman et. al., 1982), and is more abstract than everyday tasks, such as assessing how much groceries cost. (Hubbard, 2010)

Expressing subjective likelihoods is like assessing physical quantities, such as distance or size, and are founded on restricted set of data, which is examined via heuristic principles. People count on these heuristics assumptions that make a task of assessing likelihoods from more complex thinking into simpler mental operations. These heuristics are useful for a human to function but can lead to severe and systemic errors. Relying on these heuristics used in different scenarios tend to lead to common biases that are found in intuitive judgment of probability and impact (Kahneman et al., 1982; Fox & Clemens, 2005; Kahneman, 2011).

These heuristics and biases are thoroughly collected and described by Kahneman et al. (1982), and since about 1970's the literature in field of judgment and decision making on the biases and their effect on decision-making has increased and broadened steadily. Kahneman (2011) made these research results mainstream with his book "Thinking fast and slow", which describes the human thinking systems, fast 1 and slow 2, and their pros and cons. Since the identification of these biases their impact has been a focus of reduction with varying degree of success. (Kahneman et al., 1982; Kahneman, 2011)

In operational risk analysis and assessment experts are more relied on than for example in credit risk analysis, which has more structured data and suitable models that can utilize that data. Someone who is deemed to be an expert in a topic at hand is asked to provide risks with their probability or frequency and impact, directly or indirectly (Hubbard, 2010). Expert judgment techniques, such as quantification of their uncertainty (e.g., Merkhofer, 1987), are used in situations in which e.g., observations on phenomena are low to quantify a model with “real data”. Experts’ judgment “data” can be used to refine estimates from possibly available “real data” per model requirements. Also, expert judgment can be used to estimate model parameter uncertainties, and experts’ experience is seen as valuable input when “real data” is scarce or not available. (Bedford & Cooke, 2011)

Choosing experts to be used in predictions can be a major challenge. It is advantageous to use diverse group of experts to cover all facets of thought on examined phenomena to e.g., utilize wisdom of crowds (e.g., Surowiecki, 2005; Tetlock & Gardner, 2015), i.e., group’s combined predictions are sometimes better than single person’s prediction. However, this requires persons in groups have some knowledge on the topic at hand and sometimes knowledgeable persons are excluded. (Bedford & Cooke, 2011)

Nowadays computational power of computers is phenomenal and can e.g., retrieve data and make computations somewhat effortlessly. Unlike machines, human mind is not a computer-like system and in most cases cannot retrieve personal memories (historical data) accurately and make complex statistical computations. Therefore, one should know and assess the performance of a human expert in this task of making judgments. For example, in different domains measurement instruments are calibrated and used, so that a user knows that they measure accurately and precisely enough the examined phenomena and what is the measurement error, such as inconsistency, and over- or underestimation (Hubbard, 2010). However, it is not natural to humans to group events by their probability and follow the proportion of events that occur among each group to discover how one’s predictions come true (Kahneman et al., 1982).

Thus, human mind resorts to the heuristics described above that are sufficient for variety of situations in everyday life. However, as thinking and decision situations grow more complex, associated biases affect judgment in undesired manner. With respect to assessing risks biases are not often considered and because people are not aware of them, their effect is not mitigated and models that increase their effect are used. Also, models that outperform human judgment on various tasks are not used to mitigate the biases (e.g., Hubbard, 2010; Hubbard & Seiersen, 2016; Bedford & Cooke, 2011).

2.3 Risk matrix model

Risk matrix, or probability impact matrix or heatmap, has become one of the most popular, if not the most popular, method for risk assessment over the last about forty years (e.g., Clemens et al., 2005; Jordan, Mitterhofer & Jorgensen, 2018). One origin of risk matrix seems to be in security domain and author was able to find literature of the risk matrix predecessor from atomic operational safety (Johnson, 1973), information/data security (Courtney, 1977) and from United States military standard on system safety program requirements from 1984 (Department of defence, 1984). The standard describes an example hazard risk assessment matrix as shown in figure 1 below.

FREQUENCY OF OCCURRENCE	HAZARD CATEGORIES I CATASTROPHIC	II CRITICAL	III MARGINAL	IV NEGLIGIBLE
(A) FREQUENT	1A	2A	3A	4A
(B) PROBABLE	1B	2B	3R	4B
(C) OCCASIONAL	1C	2C	3C	4C
(D) REMOTE	1D	2D	3D	4D
(E) IMPROBABLE	1E	2E	3E	4E

Hazard Risk Index	Suggested Criteria
1A, 1B, 1C, 2A, 2B, 3A	Unacceptable
1D, 2C, 2D, 3B, 3C	Undesirable (MA decision required)
1E, 2E, 3D, 3E, 4A, 4B	Acceptable with review by MA
4C, 4D, 4E	Acceptable without review

Figure 1. Risk matrix from United States military standard on system safety program (Department of defence, 1984).

The model above is almost the same as nowadays, but with slightly different scaling (5x4) and scale names (roman numbers for impact and alphabets for frequency). The risk scores are classified with combination of the scale levels, which is like multiplication that is used nowadays with numerical scales. On the other hand, Courtney (1977) describes an 8x7 matrix seen below (figure 2) with scales for probability and impact with x times per day/year and with monetary values, respectively, using factors of 10 for both scales.

Values of p

	1	2	3	4	5	6	7	8
1					$300	$ 3K	$ 30K	$300K
2				$300	3K	30K	300K	3M
3			$300	3K	30K	300K	3M	30M
4		$300	3K	30K	300K	3M	30M	300M
5	$300	3K	30K	300K	3M	30M	300M	
6	3K	30K	300K	3M	30M	300M		
7	30K	300K	3M	30M	300M			

Values of E $/year

Figure 3—Determination of Annualized Risk, E.

Figure 2. Risk matrix from Courtney (1977).

One can see that the US military version of risk matrix has also some criteria for risk appetite, which is also a concept in risk management (e.g., Ale et al., 2014). Courtney's (1977) version does not have the appetite, but still addresses risk tolerance, which is another related concept. Johnson (1973) (figure 3) specifically refers to risk tolerance in the paper for atomic energy commission.

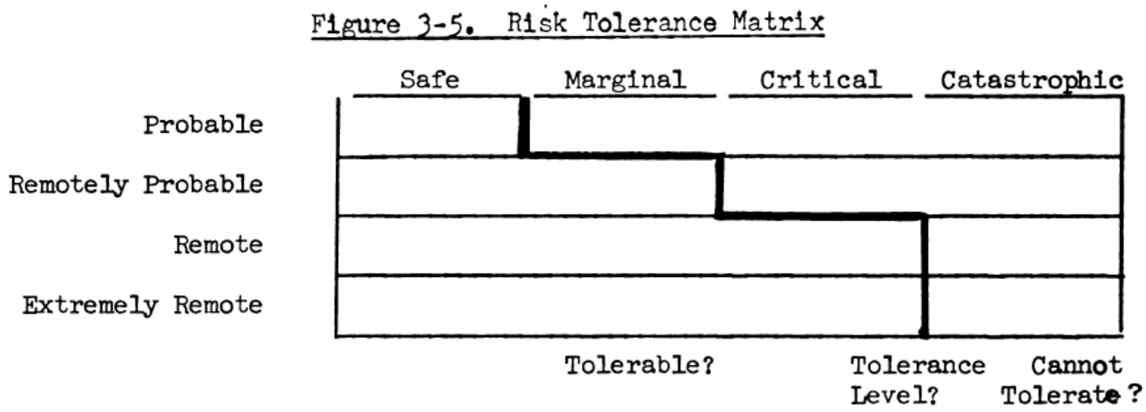


Figure 3. Risk tolerance matrix from Johnson (1973).

Overall, the described models look much alike and do not differ much from modern versions of risk matrix. Thus, since its inception risk matrix has been structurally more or less the same and mainly colouring has come along over time (e.g., Clemens, 1995). Next, one version of the prevalent modern risk matrix is described.

Risk matrix falls into "scoring method" category that uses ordinal scales for probability and impact, i.e., scales that indicate relative order of the examined properties of a risk. The scales can be just textual, such as low-medium-high, or numerical, e.g., between 1-5. With numerical scales, these scales are then multiplied with each other to get an overall risk score for each risk. These scores in turn are plotted in a matrix, or heatmap (e.g., Jordan et. al., 2018), visualization that indicates the classification, with relevant colouring with respect to level of importance, of the risk after its assessment (e.g., Cox, 2008; Hubbard, 2010; Thomas et al., 2015).

The impact of negative consequences is often described with monetary values or intervals for each level of impact scale, i.e., for 1 the loss range is from 0€ to 100000 €, for 2 from 100000€ to 500000€, and so forth. For the probability scale percentages can be similarly added for each level of the scale, but in practice this is rare (e.g., Hubbard, 2010; Thomas et al, 2015; Cox, 2008; Vose, 2022).

From structural point of view the above is enough to construct a risk matrix. For each level of the scales for probability and impact one can create linguistic description what each level means in practice. For example, “likely” can be described as follows: “risk is almost sure to happen in the examined period of time”. For impact the description for “critical” can be: “risk causes one or more severe injuries or deaths”. Sometimes risk score colours (classes) have descriptions on their importance to aid e.g., in risk handling, such as mitigation or acceptance. These are created mainly to aid the assessment of risks in business units outside or risk function. (e.g., Hubbard, 2010; Ale et al., 2014)

Risk matrix and its features described above looks, at the time of writing, something like figure 4 below that is derived from literature and author’s experience with the method and tools that use risk matrix. The white cells and the heatmap are usually included in a risk matrix in one form or another. Variance in features can be found in e.g., scales’ range (3x3,4x4, 4x5…) or risk score class colouring (e.g., Ball & Watt, 2013). The grey cells describe the probability scale percentages, which are rarely used.

	80-100 %	Very likely	5	5	10	15	20	25
	60-80 %	Likely	4	4	8	12	16	20
Probability	40-60 %	Possible	3	3	6	9	12	15
	20-40 %	Unlikely	2	2	4	6	8	10
	0-20 %	Very unlikely	1	1	2	3	4	5
				1	2	3	4	5
				Negligible	Minor	Moderate	Significant	Critical
				0-100 000 €	100000-200000€	200000-500000€	500000-1000 000 €	1000 000 – inf €
						Impact		

Figure 4. Risk matrix derived from literature (e.g., Vose, 2008; Hubbard, 2010) and author’s experience at the time of writing.

2.3.1 Advantages

Risk matrix does not require any special training or research to be used, so anyone can create similar scoring method for anything following general guidelines found in various, mainly non-academic sources (e.g., Hubbard, 2010). It is simple and easy to make, explain and use, and argued to be potentially valuable when one cannot use specific assessment methods and data is not available. Thus, it seems to promote conversation on different risks among people with various background, especially without risk management background.

The main advantage of risk matrices is to set risk priorities and guide resource allocation to take care of the most highly scored risks first and then descending towards lower risk score, which are then at acceptable level. I.e., it seems to show a way for actions with classified and ranked items within. It is also promoted by many parties that can be seen as authorities, which seems to indicate that it is advantageous for an organization to use risk matrix, because authorities promote and accept it (e.g., Cox, 2008; Ball & Watt, 2013; Ale et al., 2014; Thomas et al., 2015; Dujim, 2015; Pykhova, 2021).

2.3.2 Challenges

The description in risk matrix introduction might indicate that there is some structured and validated theory behind risk matrix, but there seems to be no empirically tested theory like in probability theory or decision analysis methods. Thomas et al. (2015), for example, kept a presentation on pitfalls of Heat Maps in strategic decision group (SDG, 2017; also e.g., Hubbard & Seiersen, 2016) and stated, with empty slide, that there is no theory for a risk matrix and that it has been developed in isolation from science and practice of decision making under uncertainty, which has been a field of research for a long time (e.g., Kahneman et al., 1982; MIT, 2015). They also state there is no best practice suggestions to address pressing questions how to create risk matrix and it features, which is in line with e.g., Hubbard (2010) and Cox (2008) that anyone can make one in different ways.

Anthony Cox (2008) has probably done the most extensive study on risk matrix and its flaws that are also brought together with other observations by e.g., Hubbard (2010) and Thomas et al. (2015), Hubbard and Seiersen (2016), as well as many others such as Ball and Watt (2013), Ale et al. (2014), and Dujim (2015). Also, Courtney (1977) already then stated that matrix ratings do not provide meaningful parameter for guidance and should coexist with risk analysis techniques that quantify losses in currency. Therefore, below is described some of the several disadvantages of risk matrix found in literature and practice.

Risk matrix relies mainly on expert input and different experts interpret the used linguistic scale descriptions differently. For example, for probability scale figure 4 above showed different words for each level and as stated, sometimes specific percentual probabilities are added to indicate the meaning of a given word, e.g., “very likely” is “more than 90%” or “90-100%”. This is intended to clarify the meaning of the scale level, but instead users interpret the linguistic levels differently anyway, even with additional description what the verbal level means. I.e., verbal scales add imprecision and error themselves, even they are claimed to be more useful than specific percentual probabilities, leading to false agreement what level risk is. (e.g., Granger & Henrion, 1990; Budescu et al., 2009; Hubbard, 2010; Hubbard & Evans, 2010; Ball & Watt, 2013; Moors, Kieruj & Vermund, 2014; Dujim, 2015; Hubbard & Seiersen, 2016)

As an example, for linguistic interpretation YouGov (2018) studied how people perceive various positive and negative verbal descriptions. Figure 5 below shows that respondents interpret the different verbal adjectives very differently, even in the extreme cases. The average has somewhat narrow distribution around the given scale average (5), even though it is also often misused (see Savage, 2012; Savage, 2022), but otherwise there is lots of ambiguity around different adjectives. This is the same for ordinal scale level names in risk matrix described above. (e.g., Budescu, 2009; Keeney, 1992)

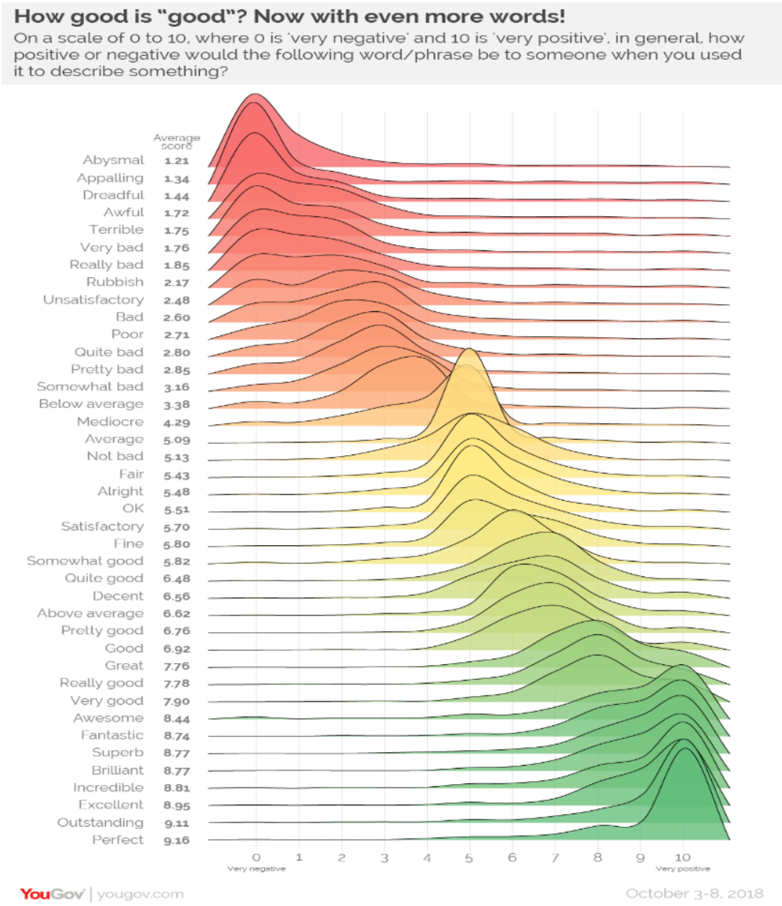


Figure 5. Response distributions on different adjectives (YouGov, 2018).

This ambiguity described above is significant especially for the impact of risk as the impact can be from a range and not a single point (e.g., Ale et al., 2014). For example, a denial of service (DoS) attack can be e.g., from 2 minutes to 2000 minutes with current controls, or anything between or outside that range, affecting organization in various ways. Assessors may agree on this range but with risk matrix are forced to classify the risk with verbal scale, and depending on assessor's risk perception (e.g., Kahneman et al., 1982; Cox, 2008; Ale et al., 2014) one can think risk impact is minor but another might see risk as significant.

Even assessors would agree on risk score level, the agreement can be an illusion, because higher loss ranges are used by people tolerant to risk, whereas lower loss ranges are used by people averse to risk, leading to miscommunication (e.g., Hubbard, 2010; Budescu et al., 2009). Also, as e.g., Ball & Watt (2013) and Dujim (2015) bring up, it is ambiguous whether the scores refer to each individual loss or averaged loss over some time, or worst case, and so forth. I.e., It is not clear what measure (figure 6 below) of range of impacts is used when assessing impact and into what class of impact the assessed value falls into.

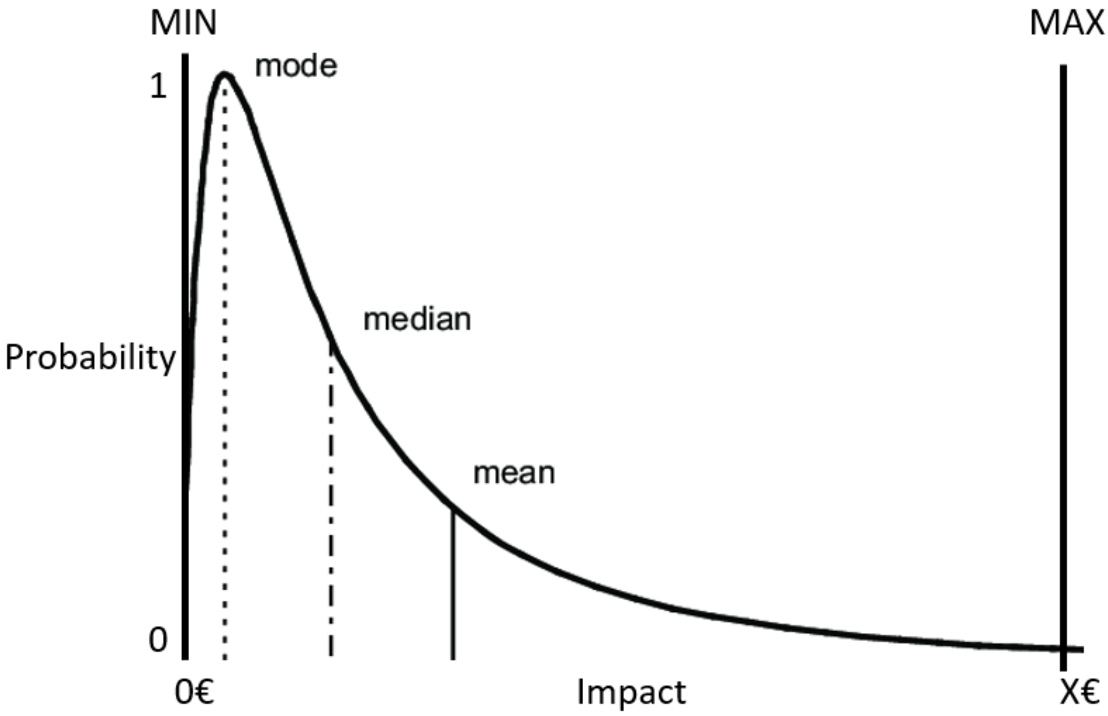


Figure 6. Sample loss distribution of a negative risk with statistical measures. (Adapted from Quirk, 2006).

As impacts are distributions in quantitative and qualitative sense, one cannot use a single risk matrix to different types of impacts, such as environment, health, or economic domains. Thus, these frequently called dimensions should have their own risk matrix, but from practical point of view they would have the same limitations inherent in risk matrix. Also, one cannot aggregate qualitative ranks of risks from risk matrix as it does not cover the whole risk profile of single or multiple risks (e.g., Hubbard, 2010; Dujim, 2015; Naim & Condamin, 2019).

Moving to the numerical side of risk matrix, as above figure 6 above shows the impact is a range with probability distribution, which shows the uncertainty around the magnitude of the impact. However, risk matrix classes or categories are not probability distributions, and thus cannot be considered an appropriate way to visualize and deal with uncertainty (e.g., Dujim, 2015). Risk matrix is a deterministic single point estimation of individual events that does not consider uncertainty and has fixed categories with no indication how to handle varying impact ranges. I.e., it only considers if one event happens, but does not consider the even not happening, i.e., zero probability.

Also, one cannot do arithmetic, such as multiplication or addition, with ordinal scales, but only indicate comparative rank or order (>, <, =), i.e., there is no similar calculation as with actual values, such as money. However, almost all scoring methods use addition or multiplication with risk matrix. The risk matrix scoring version examined in this thesis is multiplicative, risk score = probability level * impact level, as can be seen in figure 4 in chapter 2.3 (e.g., Hubbard, 2010; Ball & Watt, 2013; Ale et al., 2014; Dujim, 2015; Hubbard & Seiersen, 2016; Naim & Condamin, 2019). Multiplying the scales provide risk score between 1-25, but the formula skips risk score levels such as 7 or 11, even they are “included” in the colouring of the risk score levels. Thus, the levels for probability, impact and their product of risk score compress actual values into a pre-specified score, leading to range compression (Cox, 2008).

Range compression happens when factors are multiplied together like in risk matrix. For example, probability range does not have percentages, but when it does the levels put together different probabilities, such as 0 to 20%. For the impact the different is even more extreme as the levels tend to increase non-linearly and specially the highest level of risk impact is usually “above value x”, i.e., as in figure 4 above the significant level is 1 million euros or above, so in the same level can be risks with impact 1 million, 10 million and 100 million euros. Combining the previous together one gets very different risks in same risk score class. For example, with probability level 1 and impact level significant, the previous 1-, 10- and 100-million-euro losses would be categorized the same. They are also in green area, which is usually “acceptable”. Thus, one cannot discriminate among different risks, and this is critical to the allocation of resources to address these risks, which is also dependent on given budget (e.g., Cox, 2008; Hubbard, 2010; Ni et al., 2010; Ball & Watt, 2013; Hubbard & Seiersen, 2016)

Vose (2022) showed that risk matrix classes overlap each other when using multiplicative scoring to classify the risk into coloured classes. I.e., from figure 7 (figure’s upper limit is set to 1 million, even technically the highest impact usually is above X, so tends to infinity, even not specified) below one can that a risk that is classified into a lower-level class can be larger than a risk in a class above, and vice versa. This is also shown by Cox (2008), who also state that a 5x5 matrix can be consistent with presented requirements by only having exactly three colour categories, which is violated in practice and creates more ranking reversal errors. Also, Proto, Recchia, Dryhurst and Freeman (2023) argue that risk matrices should avoid colours altogether as the colouring might influence decision making in unintended manner.

Thus, one does not have any sense of ranking when colouring risks, which is claimed to be one of the main advantages of the risk matrix to get a high-level understanding of risk priorities. As Vose (2022) states, what is the point of using misleading scoring, when it is almost the only thing that is considered as an advantage for risk matrix? (Vose, 2022; Cox, 2008).

Risk score with % probability	Min	Max	Range
Dark green	0	40000	40000
Light green	0	200000	200000
Yellow	40000	400000	360000
Orange	120000	600000	480000
Red	400000	1 000 000	600000

Probability	80-100 %	Very likely	5	5	10	15	20	25
	60-80 %	Likely	4	4	8	12	16	20
	40-60 %	Possible	3	3	6	9	12	15
	20-40 %	Unlikely	2	2	4	6	8	10
	0-20 %	Very unlikely	1	1	2	3	4	5
				1	2	3	4	5
				Negligible	Minor	Moderate	Significant	Critical
				0-100 000 €	100000-200000€	200000-500000€	500000-1000 000 €	1000 000 – inf €
						Impact		

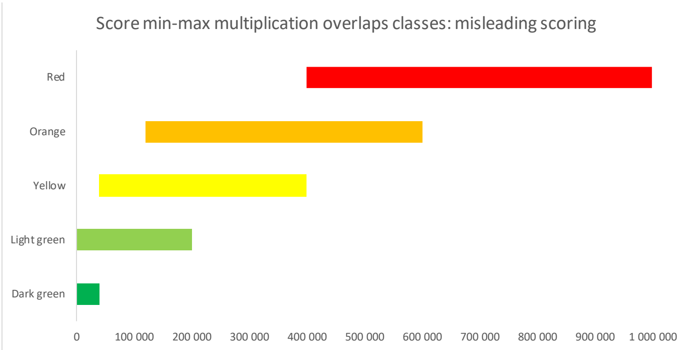


Figure 7. Risk matrix class ranges from minimum and maximum values derived from figure 4 above. (Adapted from Vose (2022)).

Smith's (2009) study on the risk matrix input bias shows also that matrix scales cause even more compression as people preferably chooses values in centre of the scale, or more precisely 3 or 4, which is shown also by Hubbard (2010), and Hubbard and Seiersen (2016). As one can see from figure 7 above, yellow and orange classes overlap a lot, which indicates that as multiples of 3 and 4 are used the most, one cannot really know whether the category is yellow or orange, or separate 3x4 and 4x3 from risk matrix classification.

Correlation (e.g., Vose, 2008) among risks is significant in risk analysis but ignored in scoring models like risk matrix. I.e., risk matrix presumes that risks are independent, when they might not be. This leads to assessing risks wrong as one cannot results of combined risks (e.g., Hubbard, 2010; Hubbard & Seiersen, 2016). Cox (2008) also show that for risks with negatively correlated frequency and impact, the results from risk matrix are "worse than useless", leading to worse than random decisions.

As e.g., Ball & Watt (2013) and Dujim (2015) state, the claimed advantages, mainly simplicity and understandability/transparency, described earlier supporting the use of risk matrix seem to be false based on the arguments described above. It is not a simple tool and its structure, which has not changed much over time, seems to make it an invalid tool that goes against deeper thinking, which it should improve.

To conclude, in practice risk matrix is shown to make decisions worse than just using unaided human judgment, or just flipping a fair coin, as there is no empirical evidence that matrix improves decisions and related risk analysis. Thus, risk matrix fails to remove and address known errors in in subjective unaided human judgment, and is not even aware of the related psychology, such as risk perception and cognitive biases (e.g., Kahneman et al. 1982; Cox, 2008; Hubbard, 2010; Ball & Watt, 2013; Hubbard & Seiersen, 2016).

2.4 Probabilistic model

Loss Distribution Approach (LDA) seems to be one of the most recognized ways to model operational risk in financial sector, especially for capital requirements for banks still using AMA model. The LDA approach is based on statistical model that includes loss frequency distribution and loss impact distribution. The key is to model future risks and their losses by finding fitting distributions to past losses to approximate future losses (e.g., Peters et al., 2016; Hartini, Hartoyo & Sasongko, 2018; Zhu et al., 2019; Naim & Condamin, 2019).

From technical point of view, total loss exposure for an organization based on LDA is equal to the sum of the amount of individually assessed losses. The individual losses are derived from number of losses (random variable) with assumed probability distribution and amount of losses (random variable) with assumed probability distribution. In practice, loss calculation is done via simulation with each run consisting of sampling the number of losses, loss amounts, and addition of the total loss amounts. Figure 8 below describes this process. (e.g., Peters et al., 2016; Naim & Condamin, 2019).

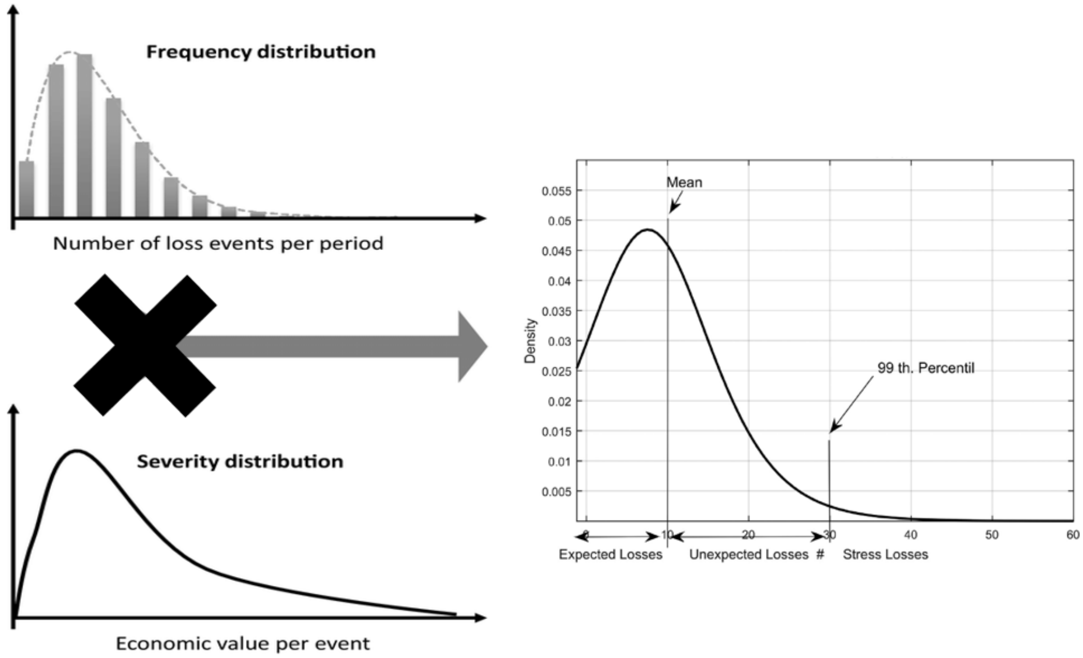


Figure 8. LDA calculation approach (adapted from Bettanti & Lanati, 2021; Naim & Condamin, 2019; Peña et. al., (2018)).

Based on literature, there are various quantitative models to be used in operational risk analysis, but one the most common approaches for seems to be Monte Carlo simulation (hereafter MCS), which is much like LDA described above. Stanislaw Ulam and Nicholas Metropolis, as well as Enrico Fermi separately, developed modelling with randomly generated neutrons for Manhattan project, and used computers developed by John von Neumann. (e.g., Hubbard, 2010; Brandimarte, 2014)

After World War 2, MCS has been used in different applications, such as Probabilistic Risk Analysis (PRA) for nuclear power safety, developed by Norman C. Rasmussen. PRA usage and MCS with it had more and more application areas in nuclear safety and is still indispensable part of risk analysis in the field. Other fields using MCS include e.g., decision-theory, decision analysis, economics, operations research, oil & gas, analytics, data science, insurance, among others. (e.g., Hubbard, 2010; Vose, 2008: Bedford & Cooke, 2011; Brandimarte, 2014)

MCS is often associated with a process of modelling and simulating a system and its randomness with several scenarios. Generated scenarios are examined via relevant statistics to assess the performance of the model with regards to e.g., decision policy (Brandimarte, 2014). These systems can be visualized qualitatively with e.g., influence diagrams (e.g., Howard & Abbas, 2016) or partially, like risks, with bowties (e.g., Grimwade, 2022).

MCS is a method to create probability distributions from random samples to create large amounts of scenarios, or iterations, of examined phenomena. Sampling is done via probability distribution’s shape that illustrates the likelihood of plausible values. Considering an uncertain input variable x the cumulative distribution function (CDF) F(x) provides likelihood P that the variable X will be less than or equal to x as follows: (Vose, 2008)

$F(x) = P(X \leq x)$

Where F(x) ranges from 0 to 1. In reverse direction, i.e., what is the value of F(x) for a given value of x? Inverse function G(F(x)) is as follows:

$G(F(x)) = x$

The inverse function G(F(x)) is used in the generation of random samples from each distribution in a risk analysis model (e.g., Vose, 2008). For operational risk, MCS can be used to calculate the final annual loss distribution like e.g., Zhu et al. (2014) indicate below (figure 9), and which is also in line with LDA. The model also shows Value-at-Risk (VaR), which a standard, yet criticised, measure in financial risk and measures the magnitude of operational risk. VaR indicates that at some confidence percentage, such as 99,9% for AMA model, one is sure that one does not lose more than distribution value at 99,9 percentile in future.

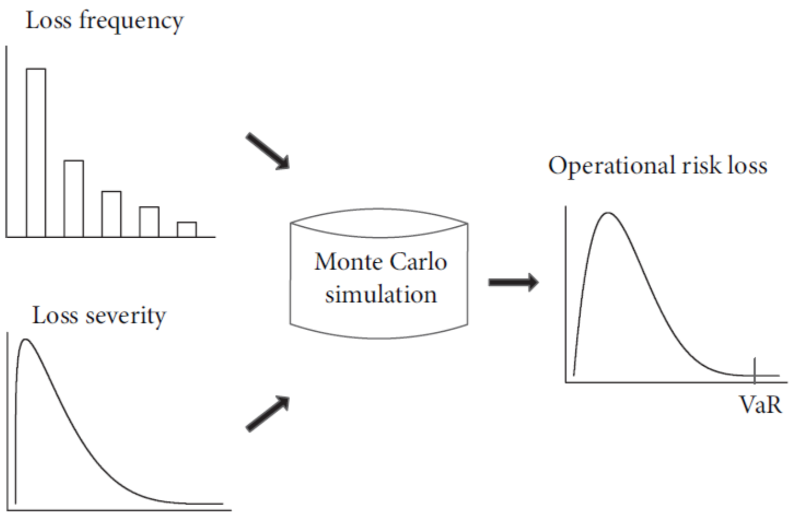


Figure 9. Annual loss distribution with LDA using MCS and showing Value-at-Risk (adapted from Zhu et al., 2014).

2.4.1 Advantages

MCS offers advantages in various ways and is widely recognized as a valid technique in different fields, providing useful and acceptable results. It is useful to examine system and its parts, as well as how they behave alone and in unison, affecting the system output(s). The distributions in a model do not have to be strictly approximated, which offers freedom around their use. Correlations and interdependencies can be modelled, which are important part of risk analysis. MCS also allows sensitivity analysis to examine model sensitivity per different variables and their varying values.

Mathematical foundation of MCS is rather simple yet solid, and more complex mathematics can be included if needed. Computer does the hard work of determining model's outcome distribution. Model behaviour can be investigated and dealt with accordingly. Changes to models can be made to e.g., improve or fix it, and results can be compared with previous models (e.g., Vose, 2008; Hubbard, 2010).

2.4.2 Challenges

Naim and Condamin (2019) seem to have made recent study on operational risk analysis models in banking sector and have presented several challenges in it. Quantitative models seem to be inspired from market and credit risk models but are poorly translated into operational risk. Also, they argue that quantitative models are dominated by data-driven models. Thus, the challenge is that there is no structural assumption on operational risk distributions and in operational risk the important events are rare, so one does not have the data for the data-driven models. I.e., there is not built a reliable theory of the underlying phenomena. This has led to e.g., possible misinterpretation to model past losses and to game the used models to reduce required capital.

Naim and Condamin (2019) state further general assumptions for LDA models, namely individual losses follow the same distribution, and the losses are independent of each other. Also, the loss distribution is independent of the distribution of number of losses. They argue that these assumptions can be violated in several situations. However, this is the line with the EBA (2018) requirement that correlation is not required, but must have authoritative acceptance, if included in risk modelling. Thus, on one hand one should follow regulation, which, on the other hand, might not be a reasonable guideline.

For frequency, the assumption on distribution seems acceptable and at least theoretically a Poisson distribution could be justified for approximation, but in practice does not seem to account observed variance in number of events. However, regarding impact the solution is not as straightforward, even theoretically. Several different distributions for impact are provided in literature (e.g., Vose, 2008; Hubbard, 2010; Institute of risk management, 2015; Hubbard & Seiersen, 2016) and there seems to be no consensus which to use and to which risks. In practice, lognormal distribution is the most used for impact because e.g., of its features and ease of use (e.g., Vose, 2008; Peters et al, 2016; Naim & Condamin, 2019)

LDA seems to be mainly concerned about the tail of the distribution, or low probability-high impact events, especially concerning capital requirements. I.e., theoretical loss distribution is dependent on large losses that are supposed to be examined in distribution tails. The reserved capital is dependent on the tail, which is also indicated by EBA (2018) requirements to have 99.9% CI on distribution and describe the tails adequately, as well as the driving factors for tails. This may be seen as a prohibitive requirement, because e.g., historical data does not necessarily indicate rare and highly impactful events. (Naim & Condamin, 2019)

The previous disadvantages are mainly directed to the LDA models that are used in e.g., AMA banks. Because the LDA models are concerned to be too complex, not comparable, and unstable, they are argued to be unsuitable for risk analysis. That has led to situation where regulator proposed in 2016 to replace the AMA model with a revised SMA (EUR-LEX, 2021), which gets rid of internal model for capital calculation, but keeps internal modelling possibility for internal capital adequacy assessment process (ICAAP). I.e., there are several changes from regulations' perspective, which may cause confusion in banks using different models. (e.g., Zhu et al., 2019; Peters et al., 2016; Naim & Condamin, 2019; Grimwade, 2022)

What comes to quantitative modelling, in this case MCS, literature describes other challenges as well. Randomness of MCS sampling can over- and under sample from different distribution parts and thus it cannot duplicate as real as possible distribution shape unless large enough number of iterations is done (e.g., Vose, 2008; Hubbard, 2010). An inappropriate model is used for uncertainty via e.g., unrealistic probability distribution. Modelling errors, such as errors in estimates or assumptions or in their input, can lead to unreliable results. Computer or the software within can be faulty, which can lead to wrong outcomes, even modelling would be correct (e.g., Brandimarte, 2014). To conclude, it is easy to make and run a bad MCS models and as described above there are several reasons for this.

2.5 Discussion of risk analysis approaches

To compare models their features can be examined against authoritative requirements, as described in chapter 2, but there exists some general ordering already. For example, e.g., Hubbard (2010) has defined a risk management success-failure spectrum that includes the models described in chapter 2. The spectrum levels are described in general with some characteristics for models in each category. These levels are described as follows:

1. **Best**. Numeric methods to create simulations. Inputs are proven via statistical methods. Scepticism of any model and checks against reality for improvement.
2. **Better**. Numeric methods that use at least some proven components.
3. **Baseline**. Unaided human judgment without formal risk management.
4. **Worse**. Some scoring/classification methods or misused numeric methods. However, not relied on by (business) decision-makers. Maybe no worse than baseline but wasted resources.
5. **Worst**. Ineffective methods are used with confidence even they add error to analysis. No objective and measurable proof to help baseline human judgment. Far worse than doing nothing (baseline) in addition to wasted resources. One reason for bad decisions.

As Hubbard (2010) states, the baseline is intuition or unaided human judgment, and it is not the worst approach to risk analysis. If one considers the unaided human judgment described in chapter 2.2, we all use human judgment in everyday life and can perform in reasonable manner most of the time. We all are forecasters and utilize this e.g., in planning of daily situations, such as commute to work on time, what to eat, how to exercise, and the effect of decision we make on the previous (e.g., Tetlock & Gardner, 2015; Kahneman et al., 1982). The previous situations contain various uncertainties, and we think about them and respond to them differently, if we can and want to. For example, travel time to work depends on transportation model, whether it is personal of public, other commuters, road conditions or other constructions on way to work, traffic lights, and so forth.

The objective with regards to getting to work is arrival on time, and we assess the effect of the uncertainties above on that objective without any structured risk analysis method. The measure used is time and we assess the travel time to work via different scenarios with different outcomes. Thinking the major, or at least thought as major, variables in work commute we approximate the travel time usually to some single point, e.g., twenty minutes, and as time goes by, we get experience on the variance in the travel time and can test our mental model accuracy and assumptions. Through different realized scenarios more accurate approximation is possible of travel time in different weather seasons and other varying factors, just like in simulation.

The mental operation above is called simulation heuristic by Kahneman et al. (1982) that operates like running of an actual simulation model. As described above, one can determine some starting conditions for a "run" of travel time and change variable values to produce different outcomes. These outcomes of the mental simulation are generated like statistical model can be assessed by Monte Carlo techniques, and results are used to judge whether real system could produce them. Human mind can also think counterfactual scenarios, i.e., how things could have been after the fact, if some or all things regarding the event were different (Kahneman et al., 1982; Pearl & McKenzie, 2018). A computer cannot perfectly mimic human mind and its useful aspects, such as the counterfactual thinking (e.g., Pearl & McKenzie, 2018), at least at the time of writing this study (e.g., Cicurel & Nicolelis, 2015).

One can see above the connection between mental model, or unaided human judgment, and probabilistic method of MCS, indicating that creating mentally range of scenarios of examined phenomena is useful. However, like any other heuristic mental simulation is subject to characteristic errors and biases (Kahneman et al., 1982). Similar comparison seems not to be done in literature between risk matrix and mental models, i.e., that risk matrix is a proven model and mentally similar thinking would be useful. Risk matrix directs assessor to create a single scenario of a risk, even theoretically one can make different scenarios of the same risk and classify them into different heatmap positions, but in practice this is not done. And if this would be done, it creates large number of unnecessary items in a risk storage.

Even human cognitive maps of causal structures were perfect, learning of complex systems would still be difficult. Trying to model these kinds of complex systems require tasks that exceeds human cognitive capabilities, except perhaps for mathematical savants. Many of us are unable to make reasonable inferences about complex system dynamics despite given perfect and complete knowledge of the system structure. For example, people cannot mentally simulate even the simplest feedback system, which is first-order linear positive feedback loop, such as compounding of interest or population growth. Thus, perfect mental models without simulation capability yield little insight. (Sternman, 2000)

Having discussed the risk analysis baseline of unaided human judgment, it is useful to some extent in our lives and probably e.g., in small and micro companies it is possibly a good enough mode to do risk analysis as baseline with other financial methods required for a company to operate. However, for a larger organization such as a financial institution the results of risk analysis should outperform unaided human judgment at predicting the likelihood or frequency and impact of various events to e.g., better assess the required capital reserves and aid decision making also in other areas, such as investment process. Tetlock and Gardner (2015), however, argue that forecasting accuracy is seldom determined after the fact and is almost never done with sufficient regularity that conclusions can be drawn. This may be one reason that models like risk matrix are used, because their accuracy is not determined, even literature referred here indicate that it is not a usefully accurate model.

Moving to risk matrix, it belongs to the Hubbard (2010) spectrum level 4 and 5 as per level descriptions and as examined literature in chapter 2.3. Therefore, it seems to be one of the worst (operational) risk analysis models that exist. Author also argues that risk matrix is not even a risk analysis model, but classification model, because it is like, but different from, e.g., multivariate classification, clustering, and learning with correct classes as described by Cox (2008).

Classification models mentioned above are used in analytics and deemed useful in suitable application areas. However, risk matrix classes for each risk are derived from external risk analysis, after which assessor checks corresponding colour class or category in risk matrix. The previous is illustrated on general level in figure 10 below with the figures described in chapter 2.

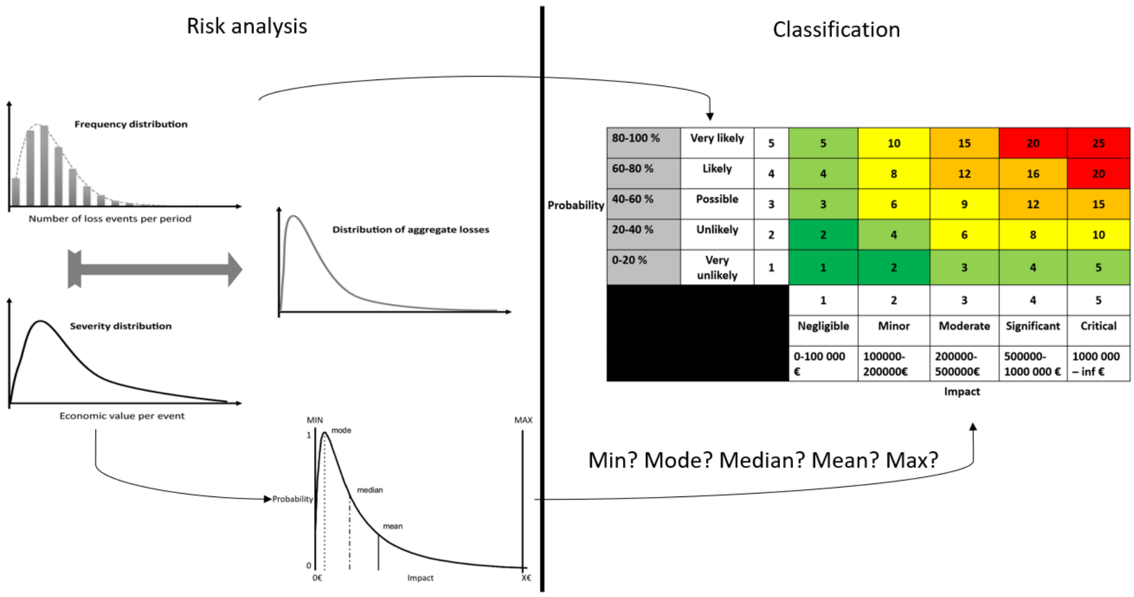


Figure 10. Risk analysis versus classification with risk matrix.

With regards to usage of risk matrix the above figure 10 is not correct on the risk analysis side, because such LDA or simulation analysis seems not to be done where risk matrix is used, at least from author's experience. It could be done, but then risk matrix's flaws ruin the otherwise useful analysis, because e.g., on impact side range compression forces the use of one distribution measure as point estimate (e.g., Vose, 2008) between min-max to be used, and there is no consensus what measure should be used in risk matrix classification. On the probability side risk matrix considers only risk's probability of happening once and not frequency. Thus, especially on the impact side the full risk profile loses most of its usefulness, if one distribution measure is used in risk matrix analysis.

As an example of poor risk matrix classification, one can think about risks with maximum impact: Very likely and negligible impact, and very unlikely and critical impact. These are classified with 5x1 and 1x5 multiplication, and the risk score/class is the same (5), which might indicate that they both are on acceptable level, whereas in practice the one with critical impact probably is not acceptable. Cox (2008) and others provide more detailed examples how very different risks are plotted into same category and how risk matrix leads to suboptimal resource allocation.

As the description on risk matrix indicates, one cannot derive quantitative outputs from risk matrix, when it is a qualitative presentation. Thus, one might as well bite the bullet and scrap risk matrix and use proven quantitative models in the first place (e.g., Hubbard, 2010; Ale et al., 2014). With the examples from literature and practice it seems to be reasonable to conclude that risk matrix is not a suitable method for (operational) risk analysis, or even risk classification.

What comes to MCS, it has its own flaws described in chapter 2.4. Another argued disadvantage is the tools used for simulations, but nowadays the hardware and software can do complex simulations with enough iterations in reasonable time. Even native Excel can do most cases and is available for wide audience. Also, commercial, and free software is available to do MCS and can automate many tasks of MCS. (e.g., Hubbard, 2010; Vose, 2008; SAS, 2008).

Recent analysis on MCS in operational risk analysis, e.g., Naim & Condamin (2019), argue that LDA is not an adept risk analysis method, at least as internal risk model, because e.g., the idea behind it is that potential future losses can be derived from historical losses by fitting a distribution to frequency and impacts. However, they propose as an alternative a structured scenario assessment, in which has three measurements – Exposure, occurrence, and impact. This model can e.g., create a distribution of possible losses, and uses MCS for each variable for exposure, occurrence, or impact. After the simulation, one can use the model for capital calculation.

As one can see, above would be in line with Peters et. al. (2016) who also propose the use of MCS to get good enough accuracy with 10^7 iteration years. Naim & Condamin (2019) also propose use of Bayesian networks developed in late 1980’s by Judea Pearl (see also Pearl & McKenzie, 2016) to create better results than limited expert intuition and their ineptitude to comprehend uncertainty in decision-making. Bayesian networks are causal models and e.g., Pearl and McKenzie (2016) describe these as well. Also, influence diagrams are similar, and they are used in decision analysis (e.g., Morgan & Henrion, 1990; Howard & Abbas, 2016; Spetzler et al. 2016). Then the Bayesian network simulates the model like MCS to get approximation of results. For example, regulatory capital for operational risk is then calculated as the 99,9% value at risk (VaR), which is the quantile of the distribution for losses over predefined amount of time, such as next year of analysis. (Vose, 2008; Peters et. al., 2016)

Bayesian networks or MCS are not deterministic, unlike risk matrix is, but probabilistic and tolerate error (e.g., Naim & Condamin, 2019). I.e., They do not provide crisp results or decisions, but range of uncertain outcomes or conclusions. And if the facts contradict the results, one can challenge and reject the quantitative model based on data or expert judgment. This seems not to be done with risk matrix in practice, and it cannot really be compared with these kinds of transparent models.

Inputs into the described risk analysis models rely on faulty human inputs. However, with e.g., calibration of experts, one can reduce the biases in human judgment to provide reasonable information to unaided human analysis scenarios and more advanced models, like MCS (e.g., Kahneman et al., 1982; Camarer, 1991; Fox & Clemens, 2005; Vose, 2008; Hubbard, 2010; Bedford & Cooke, 2011; Tetlock & Gardner, 2015; Chang, Chen, Mellers & Tetlock, 2016). However, risk matrix uses vague, mostly non-numerical terms that do not benefit from calibration, because risk matrix classifies the risks per pre-determined criteria, and e.g., described range compression brings together in same category risks with different profile. (e.g., Keeney, 1992; Morgan & Henrion, 1990)

What comes to modelling approaches, there is debate between qualitative and quantitative approaches to risk analysis, usually qualitative referring to risk matrix and quantitative to models like MCS. However, this dichotomy is not necessary as one can use qualitative modelling, such as influence diagrams (e.g., Howard & Abbas, 2015) or causal loop diagrams (system dynamics) (Sternman, 2000) or Bayesian networks (Naim & Condamin, 2019), to understand the examined decision situation and its system, and then use quantitative models, such as MCS to see how uncertainty affects the decision situation and its objectives (also e.g., Granger & Henrion, 1990; Risk academy, 2019). There are also domain specific models for operational risk, such as FAIR (Factor Analysis for Information Risk) for information security (Freund & Jones, 2015).

Graphical illustration, like influence diagram (figure 11), of a decision problem reveal how information and decisions coordinate through intermediate effects and how they affect the value of some target key figure. The key figures vary depending on business case, but with regards to operational risk the figure could be e.g., a service up time of a banking process. The qualitative model shows assumptions about the system and its parts and should capture the essence of the decision situation in an abstract form to give a big picture (e.g., Vose, 2008; Brown, 2018; Lumina decision systems, 2023). This does not require quantitative risk analysis expertise from business subject matter experts, but they can provide a better foundation for the decision analysis, and for the uncertainty analysis within via graphical illustration. Also, then the risk analyst also knows better the examined phenomena and how assumptions and node connections should be included and handled.

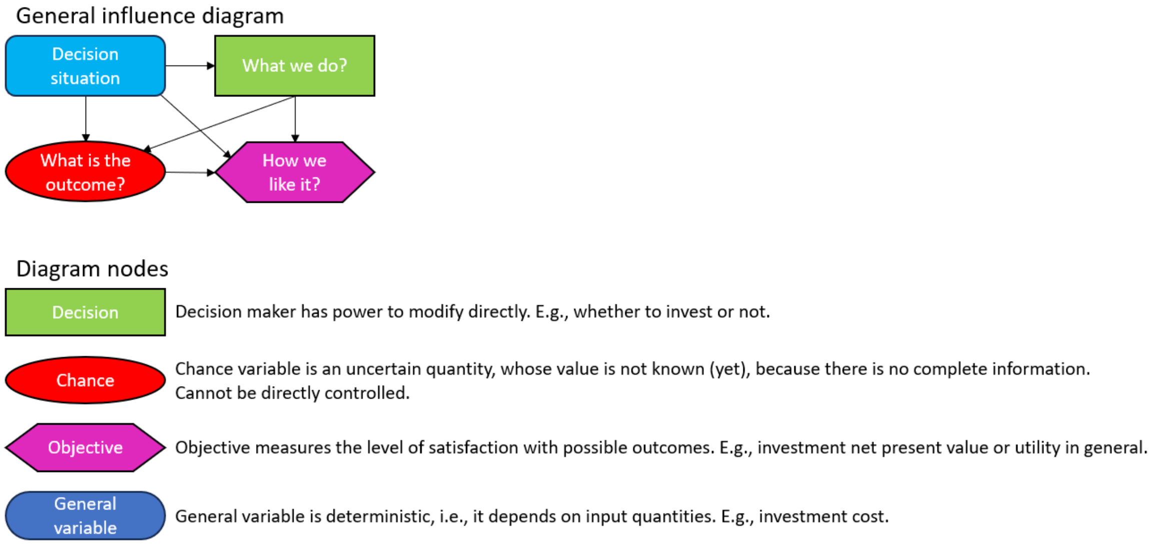


Figure 11. Influence diagram and node descriptions. (Adapted from Granger & Henrion, 1990; Lumina decision systems, 2023; Cox, Popken & Sun, 2018)

Influence diagram describes a larger decision system, but e.g., a bowtie (figure 12 below) can describe a singular event with its drivers, outcomes, and controls (e.g., ISO, 2019). This could be the chance node in the influence diagram, describing the uncertain impact of the risk event to the objective (node) in business context. For example, a net banking process could have an objective of 100% uptime and a denial-of-service (DoS) attack can have varying consequences on the objective. A financial institution then can think about controls, such as internet service provider (ISP) blocking net traffic, and how much they are willing to pay for the service to keep the risk impacts on acceptable level. Also, the consequences can vary from time to money to reputation, all of which could be measured.

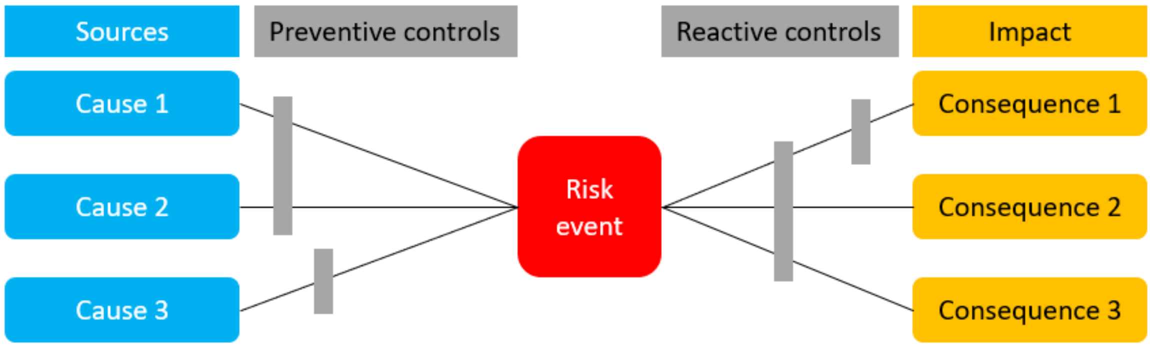


Figure 12. Bowtie. (Modified from ISO, 2019; Cox, Popken & Sun, 2018)

Understanding in qualitative sense about the decision problem and variables, such as risks, in the decision system one has clearer picture of the whole, rather than just thinking about risks in isolation. Having the decision problem modelled and collected needed information, one can continue to build the actual model. With regards to risk events, one can model their uncertainties with different approaches. Instead of using qualitative scales like in risk matrix, one should learn to subjectively assess actual quantities for probability or frequency and impact, usually in money, which are relevant in financial sector for e.g., capital calculations (e.g., Peters et. al., 2016).

Having discussed the various aspects of the used and examined risk analysis models, appendix 2 examines the model features that fulfil, or not, the model requirements described in chapter 2.1. Using a crisp qualitative scale, in credit rate sense and not risk matrix, models' features are commented by author to reflect the how models' theoretical and practical implementation meet the defined requirements. As one can see, based on examined theory risk matrix does not really meet any of the requirements set by authorities, literature, and practice. The comparison to the defined requirements reflects Hubbard's (2010) general risk analysis models' success-failure spectrum and seems to indicate that risk matrix is not useful neither for capital calculations nor decision support.

Human judgment, as the baseline, seems to meet the requirements better than risk matrix, which also in line with Hubbard's (2010) spectrum. However, as decision situations grow more complex and more variables and their interactions come along, human judgment cannot perform alone. This is where MCS, or similar model, can aid human judgment and MCS meets the requirements described in chapter 2.1. One could argue that this analysis is biased and does not reflect e.g., risk matrix usage as discussion aid, but by studying used references one can see that the examined models are in similar order of usefulness. The most important thing to note here is that no model is perfect, but some are measurably more useful than others. With this discussion in mind and as a background, it is time to move onto the design of the improvement of operational risk analysis approach to better support decision making.

2.6 Summary of the theoretical background

The previous chapters described on general level some of the most common risk analysis models used in operational risk analysis and one can see that they are quite diverse. Their features were described based on the available literature, at the time of the writing, but did not delve into related yet relevant common or model-specific areas to stay within research scope. All these models are argued to have several common and individual advantages and challenges, and these should be available especially to a decision-maker that makes decisions based on the provided operational risk analysis insight.

“All models are wrong, but some are useful” is often attributed to a statistician George Box and indicates that one should aim to use useful models for a given decision situation. Also, all risk models, such as MCS, are just tools to aid in decision making (e.g., Brandimarte, 2014). And one always uses some model in (operational) risk analysis whether it is a mental model or some structured model, such as risk matrix or MCS described above (e.g., Hubbard, 2010). Therefore, it is advisable to know the models, as well as their advantages and challenges, used in operational risk analysis and choose the most useful model for each situation. The next chapter describes the research methodology used in in the following chapters of this research.

3 Research design

This chapter describes the research method used in this research and the reasoning for its use. First, the approach is explained and then Design Science Research Process (hereafter DSRP) is described in detail. Empirical parts of this research are conducted and examined in chapter four.

3.1 Research approach

Author attempts to use Design Science Research Method (DSRM) (Peffers, Tuunanen, Rothenberger & Chatterjee, 2007) in qualitative (Hirsjärvi, Remes & Saja-vaara, 2009) sense in attempt to identify what qualities are needed for operational risk analysis, i.e., what models should have (Gregor, 2006; Hevner, March, Park & Ram, 2004). Thus, the approach is more prescriptive in nature for artefact construction, even descriptive aspects are included where necessary. The created constructs can be solutions to understand a research problem or to business needs, which are the objective also in this thesis. Therefore, as DSRM is inherently a “problem-solving process”, it was chosen to be used in this thesis. (Peffers et. al., 2007; Hevner et. al., 2004)

The research problem of this thesis with its objectives and motivation forms the beginning of the DSRP. The background and its literature describe the starting point from which the thesis proceeds towards design science blueprint development. Empirical part will demonstrate how an organization can implement the improvements and the resulting plan (blueprint) would be the final artefact for the DSRP and the thesis. (Peffers et. al., 2007; Hevner et. al., 2004)

Peffers et. al. (2007) describe several rules that should be followed in DSRP, and the most important rule is that the created artefact addresses the defined problem at hand. Utility, quality, and efficacy of the artefact should be evaluated, and research must attempt to make verifiable contribution. Artefact development should be derived from extant literature and knowledge to provide a useful solution. Also, the results should be distributed to appropriate audiences, which in this thesis are interested parties in financial sector operational risk. (Peffers et. al., 2007.)

3.2 Design science research process

Peffers et. al. (2007) built a process (figure 13) for DSR that would provide a common framework for carrying out design science research. The process includes six phases that author followed in this research, beginning with problem centred approach, and thus the process started with problem and motivation phase. However, even the process is described in sequential order, it is not mandatory to be followed from phase 1 onwards, but as the figure 13 indicates there are several entry points into the process depending on research approach.

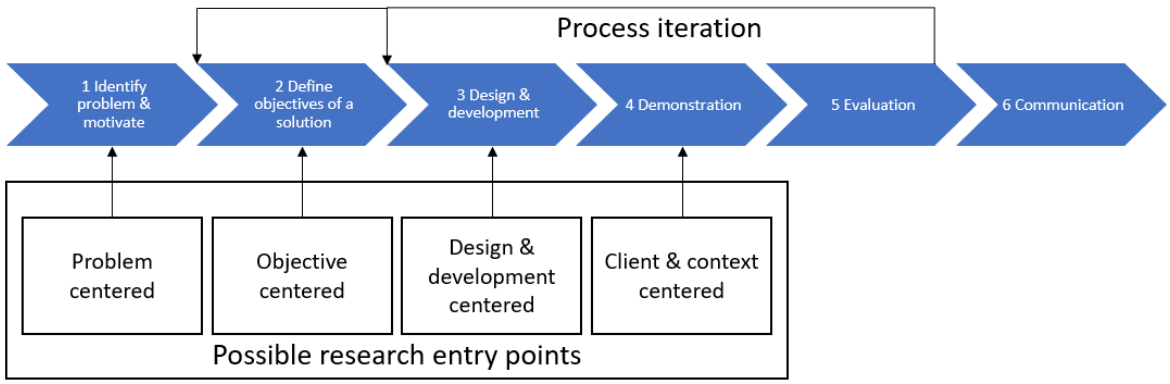


Figure 13. DSR process (adapted from Peffers et al., 2007).

Problem identification and motivation defines the research problem and justifies the value of the constructed solution. Justification for this solution, i.e., thesis artefact, attempts to motivate both author and the audience to pursue a solution with acceptable results. This phase also helps to understand author's reasoning and understanding of the defined problem at hand. Details of the research problem, background and its motivation can be found in chapters 1 and 4.1. (Peffers et. al., 2007)

Next step of the process is to define objectives for the constructed solution, and these should be inferred from the problem definition and literature of what is possible and feasible. Problem and literature are described in chapters 1 and 2. Objectives can be both quantitative and qualitative, and author aimed for both, meaning that examined models are compared quantitatively against the defined requirements, and qualitative objectives are features in both administrative and technical implementation of solutions. (Peffers et. al., 2007)

The third phase, design and development (chapter 4.2), is the core of DSR process, in which the goal is to create a useful artefact that can be e.g., constructs, models, methods, or instantiations. The contribution of the research should be embedded in designed artefact(s). I.e., this phase determines the desired functionalities, architecture, and creation of the actual artefact. (Peffers et. al., 2007; Hevner et. al. 2004)

The fourth phase in the process is the demonstration of the use of the artefact to prove that the idea works, or not, to solve the defined problem. This could involve e.g., experimentation, simulation, case study, or other suitable activity. Author uses experimentation of the designed models, meaning how they can be used and how the perform against the defined requirements and decision support (chapter 4.3). (Peffers et. al., 2007)

Then the constructed artefacts are evaluated, with measurement, against the literature and requirements to assess whether it needs refinement or not to solve the research problem. The evaluation should compare the set objectives to actual results from the demonstration e.g., with quantitative performance measures. When the evaluation is done, it must be decided whether to iterate back to previous phases or continue to the last phase of communication, which in this research is the final thesis. (Peffers et. al., 2007)

Finally, the last phase of the process is communication, which includes the description of previous steps, i.e., the constructed artefact, its utility and novelty, rigor of its design, as well as its effectiveness. The research can also be communicated to both technical and management-oriented audiences. This thesis serves as the communication to wider audience via thesis publication channel (Peffers et. al., 2007; Hevner et. al., 2004)

The problem-centred approach described above was a justified and logical choice as it fits to the previously described research problem and its background. The DSRP with its artefact would answer to the gaps in work life how to practically implement the improved analysis of operational risk to support decision making. The next chapter describes in detail the construction of the artefact blueprint for operational risk analysis approach.

4 Operational risk analysis approach blueprint

This chapter describes the process of the development of the DSRP artefact, i.e., a blueprint for operational risk analysis approach for a financial organization. DSR process' each phase is gone through and advancing towards a final artefact is described. The chapter finalizes with results and evaluation of the designed artefact.

4.1 Problem and objectives

Easy solutions to problems of model uncertainty do not exist. Simplifications and assumptions that affect the models and their results must be identified and presented to the readers, so that they can have appropriate enough confidence in the model. It is better that the model creator points out the weaknesses of a model, so that decision-makers are aware of them and can take them into account. (Vose, 2008)

As can be seen from theoretical background, it seems evident what sufficient risk analysis model look like, but regulatory changes may create confusion what models can be used and what for. Even literature (e.g., Peters et al., 2016) have shown how to create models for capital calculations, as IRM (2015) state, the objective should be to create useful business tool for wider purposes, such as supporting decision-making in various domains, rather than just a restricted model for operational risk regulatory capital calculation.

However, this is not the case in practice as prevalent model, risk matrix, is used only for operational risk analysis, and does not really help in business decisions towards objectives. Therefore, based on the presented literature and practical problems, author identified the need for and importance of research around operational risk analysis models that support better business decisions, not necessarily limited to operational risk.

To conclude, the main goal regarding the blueprint is to investigate how a described operational risk analysis model can help to support business decisions as well as possible. As described in the model requirements (chapter 2.1), there are several requirements for models from regulation, literature, and practice. Thus, author attempts to create a blueprint that reflects the requirements and how it should be done in practice with appropriate solutions. The objective is to create as exhaustive blueprint as possible towards an operational risk analysis design that would help in decision-making. Next chapter describes the design and development of the blueprint.

4.2 Design and development

This chapter describes the creation of the blueprint based on the problem and objectives defined above. The design and development of the blueprint is discussed and how it is based on extant literature, practice, and author's experience. Both qualitative and quantitative methods are applied for a simple decision situation with its risks and an objective. Decision analysis process is followed on general level, and in qualitative modelling methods are influence diagram for the decision situation and bowtie-model for the individual risks related to the decision problem.

The following chapters are separated into methodology and tools, as well as process, architecture, and model(s), with the emphasis on the models that are the main topic within the scope of this study. Process chapter describes on general level when and where operational risk analysis should be done. Architecture chapter describes technical side of the operational risk analysis and one possibility to be implemented to support used risk analysis models. Last chapter on models describe the model used and how these all can support in decision making.

4.2.1 Methodology and tools

Quantitative methods applied in demonstration (chapter 4.3) include MCS and sensitivity analysis with Simulation Decomposition (hereafter SimDec) (Kozlova & Yeomans, 2022; Kozlova, Moss, Yeomans, & Caers, J. 2023; Kozlova, Moss, Roy, Alam, & Yeomans, (forthcoming)) with related concepts mentioned in model requirements (chapter 2.1). Demonstration is carried out with created data and different methods, e.g., data visualizations, are used. The main output of the design and development would be the DSR artefact, i.e., operational risk analysis model and its code, that attempts to fulfil the set model requirements as well as possible.

MCS is applied on the decision situation and its risks described (chapter 4.2.3 and appendices 4 and 6). In forecasted losses it is assumed that possible controls are in place for each risk, and not described in detail, but only the frequency and impacts are described via probability distributions. I.e., so called inherent risk without controls is not considered, because it is a problematic concept and not much used in practice. The model attempts to forecast risks' future loss distributions in monetary terms and how their combined losses affect the monetary business objective.

The (initial) parameters for each risk using lognormal-Poisson process based on the created data and qualitative model (chapter 4.2.3) are implemented in Excel and R (chapter 4.3.2 and appendices 3-5). Number of simulation iterations, 10000, for deriving the distribution of random parameter values was chose to get better approximation results, even about 3000 iterations would yield useful enough results. Computationally even larger iterations are possible to get more accurate results. Then the models generate distributions of random values for each risk, and risks' values are then added to get the overall risk profile, or total loss distribution, of all risks (risk profiles: appendix 3). Risk aggregation is done as follows:

1. Random number for each risk frequency is calculated with 10000 iterations.
2. Random number for each risk impact is calculated with 10000 iterations.
3. Annual (one iteration) total loss is product of frequency and impact of each risk for each iteration.
4. Total loss distribution is created from the 10000 iterations or annual states of world.

In addition to MCS, SimDec is utilized for further uncertainty analysis and sensitivity analysis. SimDec uses global, variance-based sensitivity analysis, which is different from one-at-a-time sensitivity analysis, such as spider diagrams or tornado diagrams usually used, which do not consider joint impacts of variables that are changing simultaneously. SimDec improves expressing the cause-effect relations between multiple variable combinations and their effect on the output. It consists of grouping approach and visualization, where algorithm creates scenarios for grouping by partitioning selected input variables, here risks, into states. Then algorithm maps the scenarios to every simulation run to create association of output value with respective multi-variable scenario. Probability or frequency distribution of the output histogram is color-coded per output value-scenario association. The process goes as described in figure 14:

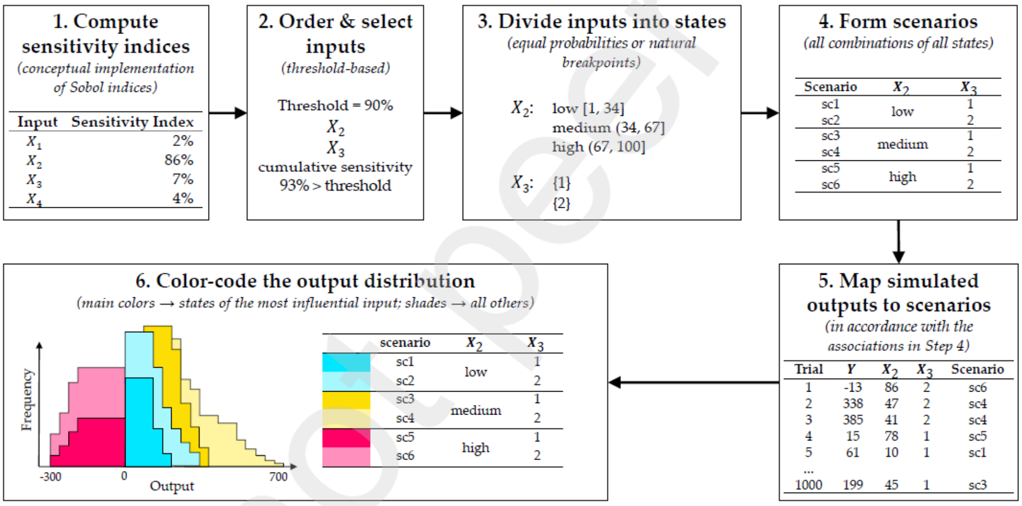


Figure 14. SimDec algorithm process. (Kozlova, Moss, Yeomans, & Caers, 2023)

With regards to tools used in risk analysis, the qualitative model is possible in various solutions, even basic Excel. Excel add-ons, such as @Risk (Lumivero, 2023), make the analysis more streamlined, but it is possible to use some coding language, such as R or Python. Also, there are some commercial solutions on the market that provide quantitative analysis, such as Archer insight (Archer IRM, 2023) that uses bowtie for modelling and simulation, or Analytica (Lumina decision systems, 2023) that uses influence diagrams for modelling and simulation. For the sake of availability for any organization, not just financial institution, author utilizes Excel and R in the demonstration.

4.2.2 Process

Risk management or assessment process generally follows phases described in ISO 31000 (figure 15), in which the method of identifying, analysing, and treating risks is shown (ISO, 2018). As can be seen from the figure 15 below, the process (right) is, or should be, closely connected to principles (top) and overall framework (left). However, in practice they are quite separated and e.g., there is not much if any integration of risk analysis into business processes, but risk management/assessment process is bolt on exercise that business is forced to do by risk management function.

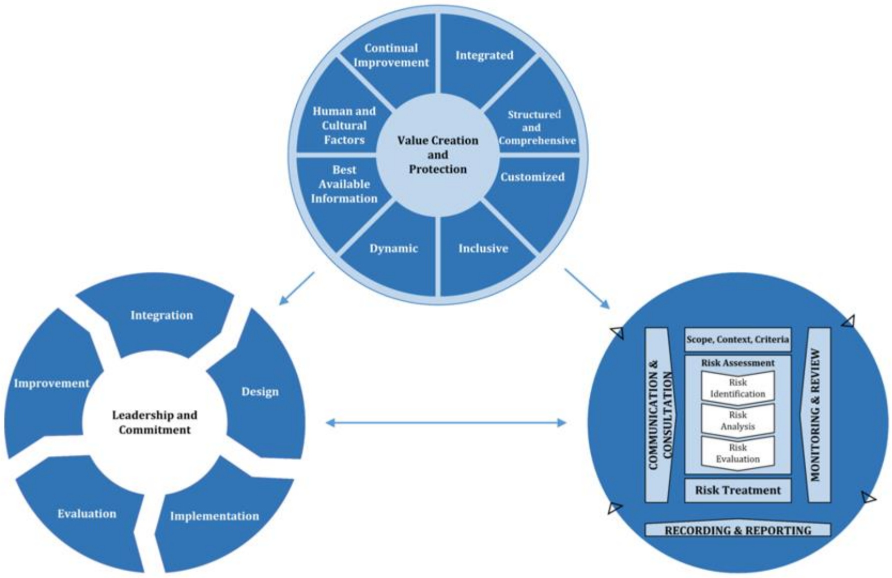


Figure 15. ISO 31000 principles, framework, and process. (Modified from ISO, 2018)

The ISO31000 process is argued to be continuous or iterative as described by the arrows around the process circle, but in practice the RCSA tends to be an annual exercise and not a dynamic part of business processes and decision making. Thus, the business is forced to do an excessive and possibly large assessment once a year, making the available information older and older the further time goes by after the exercise, making the analysis more and more outdated and useless in later decisions as the world changes. I.e., business does an exercise separated from business that does not help in business decision making, as the prevalent model seems to be risk matrix.

Regarding to best available information, e.g., EBA guideline on internal governance (EBA, 2021) state that risk management function of a financial institution should review risk outcomes against previous estimates, which is back testing described in chapter 2.1 requirements, to assess and improve the accuracy and effectiveness or risk management process. However, in practice this kind of back testing or other improvement seems to be not done, at least on operational risk analysis.

Based on the previous discussion and theory, it would be advisable to improve decision making processes and integrate (operational) risk analysis into them. Decision analysis (see e.g., Granger & Henrion, 1990; Howard & Abbas, 2016; Spetzler et al., 2015) has included uncertainty analysis decision making frameworks (see chapter 1.4 decision definition) a long time and following these principles one would improve not only the decision-making process, but also reduce also operational risks in the decision-making process itself. Granger and Henrion (1990) describe that to decision analysis many analysts use linear approach, which is like the ISO 31000 risk assessment process. However, Granger and Henrion (1990) view a process of analysis (figure 16) as a process of learning and discovery, which is iterative and refines previous steps when needed.

In figure 16 below, uncertainty analysis is just one part of decision analysis. One should have an appropriate frame define to solve an actual problem and collect relevant information to make model of the problem at hand. Then one can add and assess uncertainties, such as operational risk events that affect e.g., banking processes. Having this kind of decision-making process in place one goes iteratively towards clarity of thought and action and can include relevant uncertainties into decisions. Vose (2008) describes a similar risk analysis process that iterates between decision-maker and (risk/decision) analyst for decision situation and its risk management. Further analysis of the process is outside of the scope of this study.

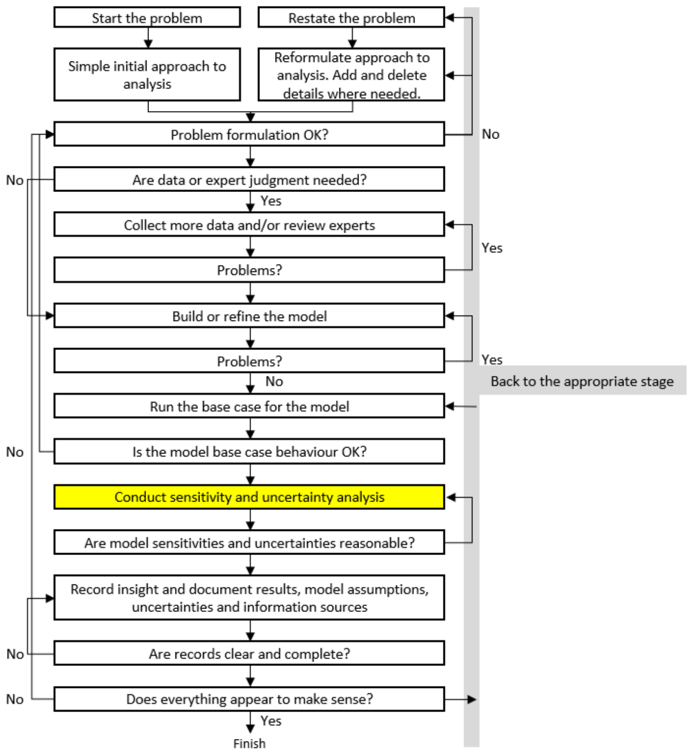


Figure 16. Good, iterative policy analysis. Uncertainty analysis highlighted. (Modified from Granger & Henrion, 1990)

4.2.3 Architecture

Since financial organizations tend to be larger and have analytics functions available, they seem to be using analytics' solutions like SAS (SAS, 2023) for various tasks, including risk analysis. SAS (2008) published a paper on LDA for operational risk economic capital analysis, showing that operational risk analysis is possible also via analytics' solutions in an appropriate manner. Other solutions, such as R or Python coding languages, would yield similar benefits as SAS, and can also be used in other decision situations, and not only for risk analysis, unlike GRC software and the like that tend to be restricted to risk matrix. Thus, utilizing internal analytics would be beneficial for a financial organization aiming to improve and integrate operational risk analysis into business and decision making.

With regards to data, as described in model requirements (chapter 2.1), a financial institution should use internal data, external data, scenarios, and business environment factors as input into risk analysis models, where available. However, also data quality is important, because if data validation and cleaning is not done properly, then the analysis result is garbage in and garbage out, which is true for any model used. Internal data quality validation can be conducted by analytics to e.g., treat missing data table values, but also business is responsible for validation as the data to date warehouses can be taken from business processes. External data, such as ORX (ORX, 2023) or Verizon data breach investigation report (Verizon, 2023), validation can be problematic as one does not have control over it, so one must critically examine the external data whether it can be used. Expert judgment, often used in creating scenarios, can be improved to some extent with calibration training (e.g., Kahneman et. al., 1982; Hubbard, 2010; Chang et. al., 2016) that reduces biases, such as over-confidence, in the analysis of measurements at hand.

Figure 17 below shows a high-level illustration of technical architecture that could be built by e.g., in-house analytics/IT based on the operational risk analysis requirements. Data sources provide data that is stored in some form of general data warehousing solution, from which data is used for different purposes. Risk analysis engine would do include models used in analysis that uses the data and yield model outputs that can be moved to storage and intelligence platform. For reporting, some form of business intelligence solution can provide insight for business and ideally possibility for business to interact with the risk analysis models. Further analysis of the technical architecture is outside of the scope of this study.

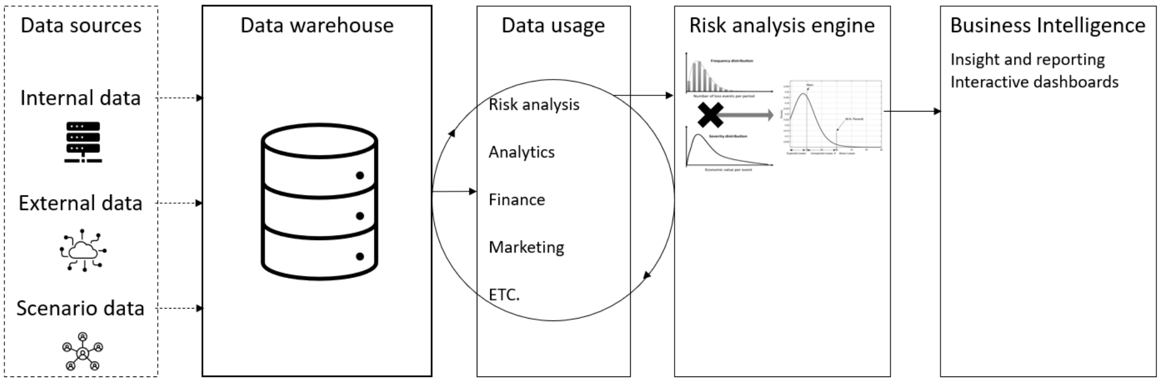


Figure 17. technical architecture illustration for risk analysis and its data. (Modified from Hartini et. al., 2018; Bettanti & Lanani, 2021)

4.2.4 Modelling and data

This chapter describes a base case with qualitative model with influence diagram and bowtie to better understand the examined decision situation, its system, and related parameters, namely risks. As described about decision analysis process (chapter 4.2.1), author starts with the decision situation or problem statement with some objective(s). If the frame of the decision is done inappropriately or totally wrong, later analysis, such as quantitative, attempts to solve a wrong problem bringing useless results, and most likely wastes resources. Formulating the problem appropriately further needs are identified, such as need for data or expert judgment, to build a suitable model for the decision situation.

Figure 18 below shows and outlines a simple decision situation, examined in this study, with influence diagram with related risks. Risks' individual assessment was done via bowtie that includes different impacts and ranges of their consequences that affect the objective. In operational risk the event types are about e.g., internal or external fraud, employment practices and safety, business practices, damage to assets, business disruption, and process management. In this case, various qualitative elements were not described, but mainly the quantitative analysis, which can be applied to different types of risks according to their nature. Risks' impact values are negative monetary range, and for operational risk the probability or frequency varies depending on the individual risk scenario as applied via replicated example and its data.

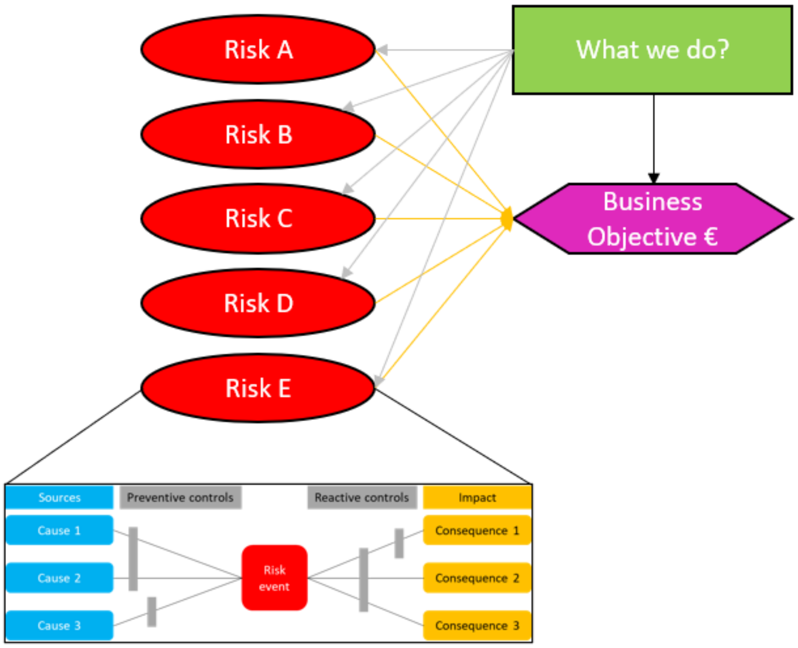


Figure 18. Decision situation and related risks that have monetary consequences on business objective in euros.

Understanding the above helps a decision maker to consider what to think and do about the objective, related risks, and their perception to these risks, so that further (quantitative) analysis has a solid decision problem formulation. In this decision situation, the objective can be operational risk capital reserve or other business objective in monetary terms, and risks' individual and total profiles affect the business objective.

With this kind of a qualitative model, it is possible include and indicate qualitatively e.g., directional, or causal relations and correlations between model parameters and assumptions within, but correlation is not required as described. When the base case model is ready it is tested to ensure it works as intended, i.e., it makes sense e.g., regarding risk event profiles. This ensures appropriate further analysis and when thinking about parameter values with varying uncertainty and possible sensitivities.

Having identified and listed the uncertainties, in this case negative risk events, it must be considered over which period risk event(s) can materialize and make assumptions about parameters, namely probability or frequency and impact. Usually this is one year or 12 months, but this depends on the examined system and risk frequencies as well as defined risk analysis workflow. Nevertheless, the time frame must be framed as anything is possible in infinite time. For each risk a probability or frequency is determined for the occurrence, and these can be modelled with Bernoulli or Poisson distributions, respectively, but Poisson is applied in this study (appendix 3).

Poisson is chosen for the demonstration as it is prevalent in literature and practice. Poisson distribution is used if the event is assumed to happen more than once in time period, as an average value. For example, Poisson's average events happening can be described as, e.g., "over 12 months event happens on average 4 times". This base case uses example data, in which the frequencies are very low, which suits for operational risks happening rarely, but possibly having possibly severe impacts, such as penalties from banking authorities.

Poisson probability mass function:

$F(x)= (e^{-\lambda t}(\lambda t)^{x})/x!$

Where λt distribution models the number of occurrences of and even in time t with expected rate λ average events per period t. e is Euler's number ~2.718 and ! factorial function. λt is mean and variance.

Regarding impacts, they are expressed with ranges of monetary values. An event happening on average 4 times in 12 months could have an impact could be from assumed minimum 100 000€ to assumed maximum 1 000 000€, with 99% CI. I.e., There is still chance that the impact could be lower than minimum or higher than maximum. Using ranges represents our uncertainty around the impact rather than presenting unrealistically precise single point estimates. Then MCS is used to create an approximate impact distribution with selected distribution type. Lognormal is chosen for the demonstration for its prevalent usage and features, such as long tail and left bound to zero as negative losses cannot be negative. As the parameters for impact distribution are average and mean, they can be derived from the min and max values, and/or as times goes by from average of historical loss events, as imaginary data is used in this study.

Lognormal probability density function:

$F(x) = 1/(x\ sqrt(2\pi\sigma^2))\ exp[-(ln[x]-\mu^2)/2\sigma^2]$

Where μ is $ln(\mu^2/(sqrt(\sigma^2+\mu^2)))$ and σ is $sqrt(ln((\sigma^2+\mu^2)/\mu^2))$. Where μ is mean and σ is variance.

After the previous information, including assumptions, is collected, and documented in appropriate data storage (see chapter 4.2.2), it should be checked whether the approximations about uncertainties and sensitivities are reasonable. Data and expert judgment should be considered, if needed. In practice, internal data and external data, such as ORX or FIN FSA, could be used to reduce the uncertainty around estimates to get more accurate forecasts. Also, calibrated experts can provide input to model, if needed and available. Overall, one validates and monitors the approximations about parameters, so that the approximation error(s) do not spoil the initial analysis performed. This is not done in this study, because of the nature of the thesis.

In this study sample data was created with available tools and was used in the demonstration to show how the applied models and its parameters work. I.e., real data was not used, even though it would be available for a private person through FIN-FSA data from financial institutions or from relevant general sources, such as ORX. However, lack of real data is often the case in real operational risk analysis because e.g., available data points do not exist, especially for technology related risks that evolve so rapidly or are exploitable zero-day vulnerabilities that have not existed before. Thus, similar conditions as here are possible in real life decision situation but does not mean these models cannot be used. Next the demonstration phase attempts to show with quantitative examples how proposed approach works, or not, to solve the defined decision situation. Appendix 3 describes the risk parameters and used tools, Excel, and R (appendices 3-5), and their usage.

4.3 Demonstration

This chapter describes the demonstration of the quantitative approach, with uncertainty and sensitivity analysis, of the qualitative model described in previous chapter. Experimentation of the models is done with the created imaginary data and its variations. Models' performance, possible modifications, and other improvements are explained. Lastly, analysis of the model is done against the earlier defined requirements.

4.3.1 Base case simulation model in Excel

Model parameters were described earlier (chapter 4.2.4) on general level and specific values are shown in figure 19 below, which shows replicated AMA model calculation in native Excel and its formulas (Stachanov Holding B.V., 2021). Figure 19 below illustrates the MCS parameters for frequency and impact (top left yellow and green) that are partly derived from made-up data and its natural logarithms (right side red cells). There is random results for 10000 trials, one per Excel row, for frequency and impact (blue and orange ranges, respectively), as well as total losses and its summary statistics (pale yellow ranges). One should note that image (figure 19) is one random run and values are subject to change every time spreadsheet file is refreshed (e.g., by pressing F9), so results are different, e.g., in following R analysis that has set a seed for random numbers to get same results in different model runs.

The Excel model uses the described Poisson distribution for frequency and lognormal distribution for impact. In Excel Poisson distribution is done with inverse Binomial formula and lognormal distribution with inverse lognormal formula. Poisson uses the average value for risk event happening over time and lognormal uses the logs, derived from made-up data, on mean and standard deviation. These are then summed to total annual losses for each trial with Excel's sumproduct-function that multiplies the frequencies of each risk with respective impacts. As a result, the distribution of total losses was simulated of the five risks (A-E) for 10 000 possible future combinations, of which about 29% resulted in zero losses and maximum total losses about 20 M€.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	Risk	A	B	C	D	E						Monte carlo simulation results			"Actual" observed losses for each risk in millions				
2	Frequency per year	0,25	0,2	0,1	0,05	0,01						Count total losses	10000		A	B	C	D	E
3	Trials binomial	10000	10000	10000	10000	10000						Count zero losses	2841		1,25	2,10	3,00	2,10	1,40
4	p value binomial	0,000025	0,00002	0,00001	0,000005	0,000001	=F2/F3					Max losses (M€)	19,471		1,30	2,50	3,50	2,10	1,40
5	Input lognormal mean	0,40	0,95	1,14	0,85	0,46	=AVERAGE(S15:S24)					Percentile 99,9% (M€)	14,681		1,80	2,70	3,40	2,00	1,80
6	Input lognormal standard deviatior	0,16	0,14	0,10	0,28	0,17	=STDEV.S(S15:S24)								1,80	3,10	3,00	3,10	1,80
7															1,20	2,00	3,00	1,20	1,50
8	Monte Carlo simulation	Frequency of loss events (Poisson)				=BINOM.INV(B3;B4;RAND())	Impact of loss events (M€)			=LOGNORM.INV(RAND();B5;B6)		Total annual losses (M€)			1,70	2,50	3,00	2,70	1,70
9	Trials of annual losses (1-10 000)	A	B	C	D	E	A	B	C	D	E	=SUMPRODUCT(B10:F10;G10:K10)			1,60	2,90	3,80	2,80	1,60
10	1	2	1	0	0	0	1,30	2,85	3,04	2,20	1,49	5,448			1,40	2,90	3,10	2,90	1,10
11	2	0	1	0	0	0	1,24	2,78	2,87	2,14	1,79	2,781			1,70	2,80	2,90	2,80	2,00
12	3	1	0	0	1	0	1,44	2,12	3,21	1,90	1,59	3,339			1,30	2,50	2,70	2,50	1,70
13	4	0	0	0	0	0	1,56	2,58	3,45	2,20	1,79	0,000			Natural log (LN) of observed losses				
14	5	0	1	1	0	0	1,31	2,76	2,90	2,56	2,05	5,658			A	B	C	D	E
15	6	0	0	0	0	0	1,44	2,76	3,26	2,10	1,72	0,000			0,22	0,74	1,10	0,74	0,34
16	7	0	0	2	0	0	1,76	2,75	3,28	1,73	1,19	6,553			0,26	0,92	1,25	0,74	0,34
17	8	1	0	0	0	0	1,26	2,48	3,00	2,19	1,53	1,264			0,59	0,99	1,22	0,69	0,59
18	9	2	0	1	0	1	1,55	2,24	2,95	3,15	1,57	7,621			0,59	1,13	1,10	1,13	0,59
19	10	0	0	0	0	1	1,59	2,30	3,20	3,61	1,90	1,896			0,18	0,69	1,10	0,18	0,41
20	11	0	0	0	0	1	1,15	3,25	3,11	2,72	1,53	1,533			0,53	0,92	1,10	0,99	0,53
21	12	1	0	0	0	1	1,50	2,75	3,19	1,40	1,18	2,688			0,47	1,06	1,34	1,03	0,47
22	13	0	0	0	0	1	1,46	2,97	3,14	2,48	1,92	1,924			0,34	1,06	1,13	1,06	0,10
23	14	1	0	1	0	0	1,35	3,21	3,44	2,28	1,67	4,788			0,53	1,03	1,06	1,03	0,69
24	15	0	0	0	0	1	1,46	3,36	3,11	2,51	1,56	1,564			0,26	0,92	0,99	0,92	0,53

Figure 19. AMA calculation in Excel. (Adapted from Stachanov Holding B.V., 2021).

Figure 20 below shows the trials' distribution of the simulated total annual losses. One can see that majority of the losses are between 0 and 1.95 M€, followed by tail to larger but less probable losses. The model does not consider correlations between risks, but this was not required in requirements (e.g., EBA, 2018; McCormack et. al., 2014). However, the distribution could be quite different, if one included correlation. In this uncorrelated case, the 99,9% percentile, or VaR, is about 15 million e.g., for operational risk capital calculation purposes, but one can see that there are some trials, or years or states of world, in which total losses are larger than that. I.e., reserving capital of about 15 million € should cover operational risk losses in 99,9% cases of the possible futures.

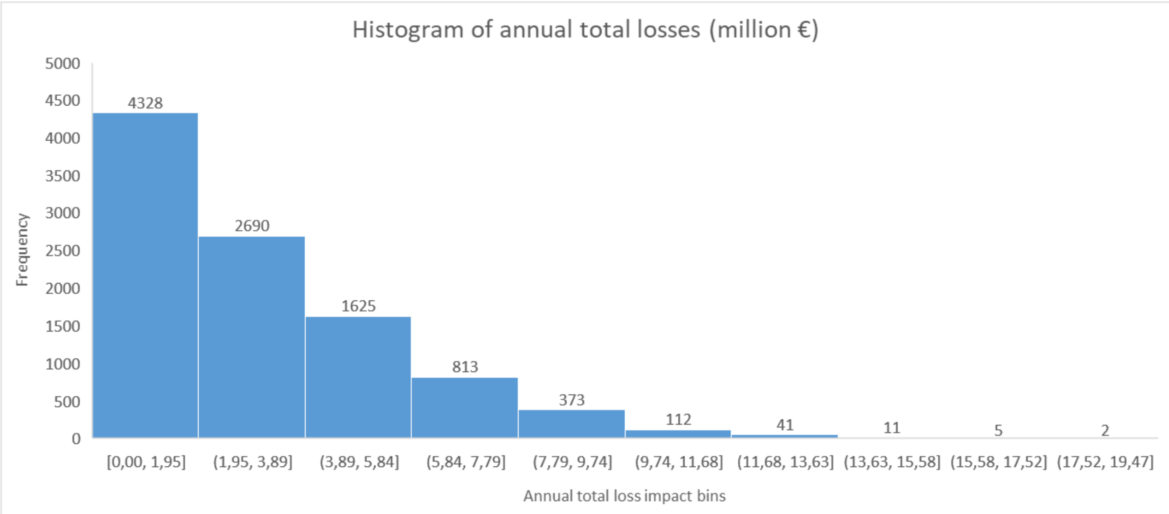


Figure 20. Histogram of AMA calculation losses in Excel.

The simple Excel model above would fulfil most of the requirements presented in chapter 2.1, clearly better what human judgment or risk matrix can do, but admittedly it has its own challenges. For example, Brown (2018) and Vose (2008) describe various limitations in spreadsheet usage leading to operational risks of its own, such as fat finger typing that can lead to input/output errors. As a spreadsheet model grows in complexity, it becomes more and more difficult to manage and maintain the whole, such as formula links and their cell referencing.

As one can see in the figure 19 above, model parts are here and there and without showing the detailed formulas one does not know what refers to what, so it is visually not very clear or transparent. Solutions like ChanceCalc (Probability management, 2023) can include the whole trial range in a single cell, reducing the total area needed for data and more room for e.g., explanations and parameter connections. Nevertheless, keeping the comparative aspect in mind, Excel provides a better modelling environment with proper tools for (operational) risk analysis than most solutions providing only risk matrix, and business most likely uses

Excel anyway, so one can somewhat easily and affordably add uncertainty analysis in business cases.

4.3.2 Base case model in R

With R a more transparent analysis is built e.g., with clearer visual environment and built-in capacity to operate with arrays, and with less opportunities for errors, like making typographical errors. Of course, programming with any solution can lead to errors, but possibility for errors is smaller the less one needs to fill fields or code. For example, considering the Excel analysis above, one can do the same in R more streamlined (see appendix 4).

R code (appendix 4) for the same base case follows the same process as described above with Excel. However, the made-up data is put into arrays into which more data points can be added, and following code will automatically take them into account in future runs, unlike in Excel in which one must change cell references. For each risk the MCS does the loss distribution with one row with R’s own functions rpois for Poisson and rlnorm for Lognormal with the same parameters. Unlike R, Excel needs 10000 rows for each frequency, impact, and their total loss combination. Figure 20 below shows the total loss distribution with similar results as the Excel version of the histogram, but slightly different because of Excel’s randomness’ volatile nature. In R with set seed the model yields the same results in different runs with same initial parameters.

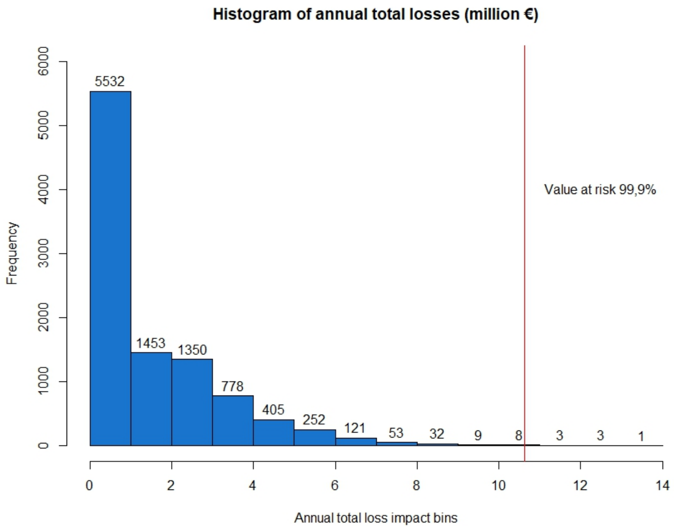


Figure 21. Histogram of AMA calculation losses in R.

Another way to visualize the total losses is a loss exceedance curve (LEC), which is used in various domains, that shows the range of possible losses and probability of the loss impact exceeding certain value, and not just single point value. LEC is a descending version of the cumulative distribution function (CDF), which is usually ascending showing impact value probability being less than certain point. Figure 22 below illustrates the LEC for the base case's total risk loss distribution, via which it is possible to see e.g., how new control placements affect the risk profile.

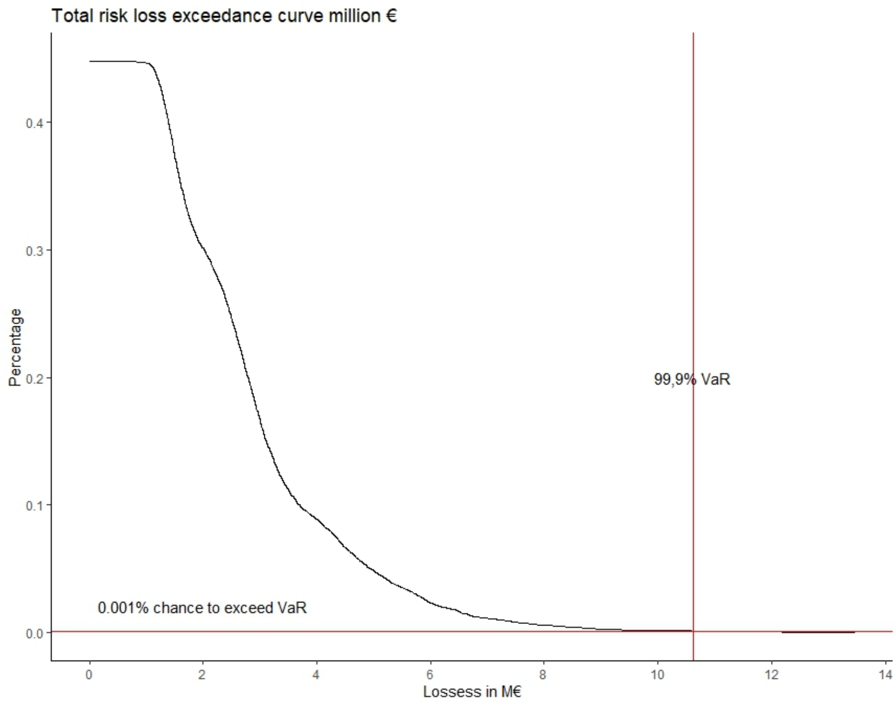
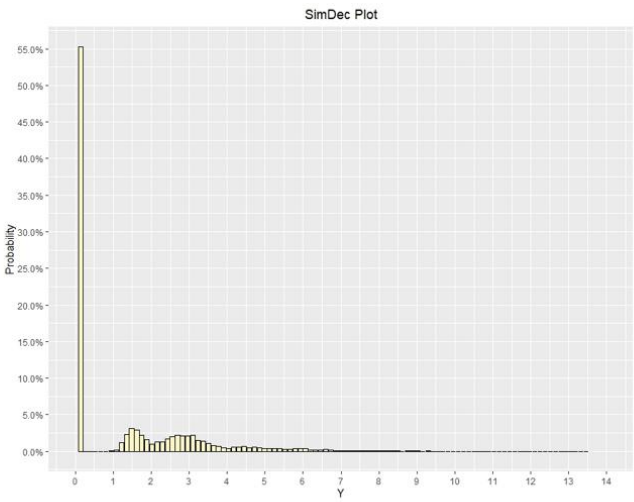


Figure 22. Loss exceedance curve of annual total losses for the R base case.

Next step was further uncertainty analysis and sensitivity analysis with SimDec, which is global, variance-based sensitivity analysis. The purpose was to find possible cause-effect relationships and combinations of risks on total risk distribution. Sensitivity indices of variables are computed, and most influential risks were selected for a decomposition, which are boundary ranges for the selected risks. From the previous different scenario categories are formed and they are applied to MCS data to map total losses to respective scenarios. A percentile-based formation of the automatic thresholds was used with same number of observations in each state.

Lastly, stacked histogram is created to visualize each of the multi-variable scenarios. This is applied to the base case and shown in figure 23 below, but as can be seen this default code's visualization did not work in this base case, because only risk B seems to drive the distribution in all scenarios and risks C and A contribute to the total risk only at high state, but this is clearly not the case as sensitivity indices (SI) show that B, C and A risks are most significant, which is shown correctly in legend. The default code's automatic decomposition did not work most likely because e.g., the defined frequencies and thus also losses in data are mostly zero, and rest are outliers shown in boxplots (see appendix 5). This probably makes the default thresholds misleading as all risks are in high state, but the scenario 8 thresholds are basically from total risk's minimum (0) to mean (1.32) to maximum (13.47).

The results were checked also with median-based thresholds that have equally spaced ranges, but the result is the same but, in this case, almost all results (98%) were in scenario 1, i.e., risks being in low state. So, automatic boundaries by SimDec code seem to be mainly zero, because of the data is mostly zeros. Therefore, the model code is modified with manual settings (Github, 2023) to make the analysis useful for the decision situation.



Color	B	C	A	min(Y)	mean(Y)	max(Y)	probability
1	**low**	low	low	NA	NA	NA	NA%
2		low	high	NA	NA	NA	NA%
3		high	low	NA	NA	NA	NA%
4		high	high	NA	NA	NA	NA%
5	**high**	low	low	NA	NA	NA	NA%
6		low	high	NA	NA	NA	NA%
7		high	low	NA	NA	NA	NA%
8		high	high	0	1	13	100%

Figure 23. Default SimDec sensitivity analysis with base case (histogram and legend).

Based on the first SimDec iteration, further manual modifications were made. In line with the default code decomposition sensitivity indices (SI) risks B, C and A are considered most influential to total risk losses and thus included in a manual improvement to attempt better results. Most influential variables were checked also with linear tornado sensitivity analysis (appendix 5) for the sake of comparison as it is often used in risk management sensitivity analysis. Tornado results are mainly the same, B and C being most influential, but D is above A here as it has wider uncertainty around the total loss mean. As described above, tornado chart is one at a time sensitivity analysis and does not consider variables changing at the same time, unlike in global sensitivity analysis like SimDec that calculates sensitivity indices of input variables changing simultaneously. Thus, in more complex scenarios tornado charts would not perform as well as global sensitivity analysis approaches.

Manual states were put to 2 to have low and high states on included risks B, C and A. Manual thresholds were set in this case and for each risk's profile minimum, mean and maximum were chosen to reflect the impact range but leaning towards unexpected losses (from mean to VaR) to reduce the impact of zeroes. As a result, figure 24 shows that 59% of the cases are in scenario where all risks are low (impact ranging between 0-7). From first scenario upwards as risks' C and A states grow higher the probabilities are 16% for second scenario (first peak/mode with impact around 1-11), 6% for scenario 3 and 2% for 4th (ranging 2-12).

When risk B is high the scenario 5 has probability of 12% and creates another peak/mode for the distribution (ranging 2-10). Again, as C and A states tend towards high states, scenarios 6 and 7 have together probability of 4% (ranging 3-12). Lastly, scenario 8 has zero probability when all risks are in high state. Thus, using manual thresholds as inputs yielded useful results. Since the sensitivity indices seems to be correctly derived in default code, this seems to indicate that something in the decomposition limits or threshold type since other variables are set to empty (NULL). Changing only decomposition limits yields similar results in default code, so threshold type might not work in this kind of scenario and data.

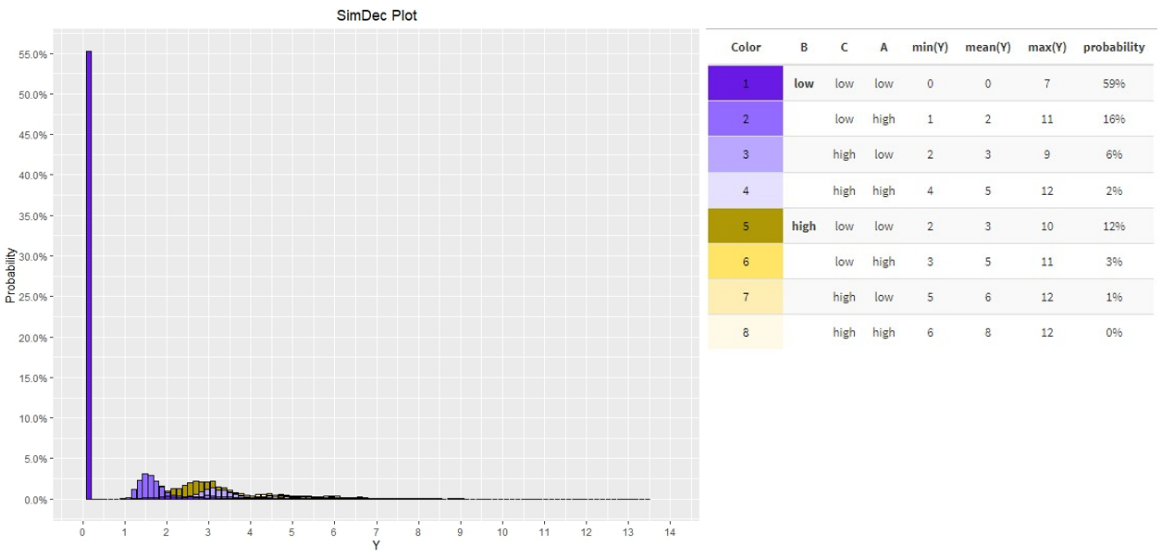


Figure 24. Refined manual SimDec sensitivity analysis with base case (histogram and legend).

Admittedly, the base case R example is also somewhat simple and perhaps functional form could be better in terms of R code notation style. Nevertheless, there are improvements compared to the Excel version, such as clearer connection with used variables and running different statistics at the same time of running the code. Adding risks is easy with copying relevant rows and changing relevant parameters, and adding data points into arrays does not require much if any changes in rest of the code. Unlike in Excel, one must add data to columns with thousands of rows and making sure that the formulas are copied correctly, and cell references changed accordingly.

4.3.3 Refined model in R

The base case data had frequency on all risk very close to zero, so base case is overall somewhat rarer case, but possible. The base case is somewhat typical low frequency and varying impact case, so another case could be that risk are more frequent but similar impact profiles, depending on what sample of risks one has. Changing frequency changes the risks' (A-E) profiles (appendix 7) significantly and total risk loss profile (figure 25 and appendix 7). As is seen below the distribution is more like normal distribution and not that skewed to the right, like in base case where majority of the scenarios are close to zero. VaR is now ten times of the base case, so changes in (total) risk profiles may have significant effects on business objectives.

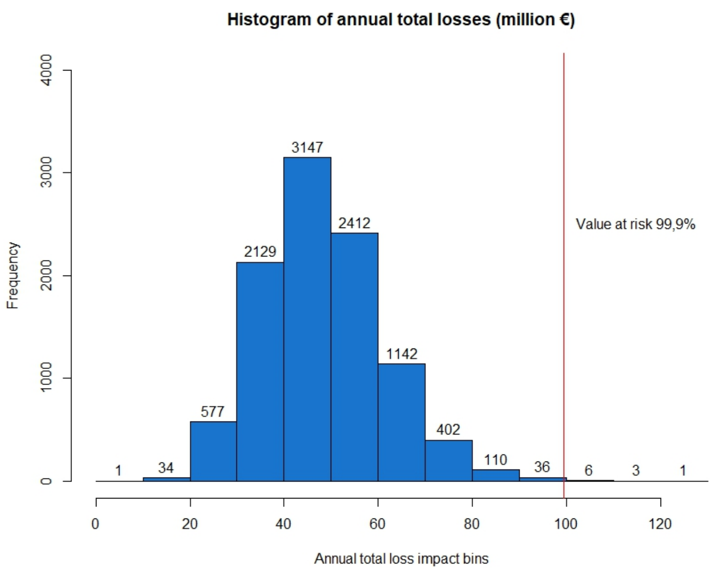


Figure 25. Refined model total risk profile.

The base case simulation described above with Excel and R did not include correlations as it was not required. Figure 26 below shows an added risk F that has its own values, which are positively correlated (coefficient 0.7) with risk E, i.e., as E rise then F rise (see also appendix 7). Another solution to add correlations would be e.g., copula structure (e.g., Vukovic, 2015) to model risk relations in simulation. Depending on how influential the correlated risks are, the effect on total risk profile varies, or not as in this case the VaR only slightly increases with added risk F that is correlated with risk E, which has somewhat minor impact on total risk as can be seen of its profile (appendix 7) and following sensitivity analysis.

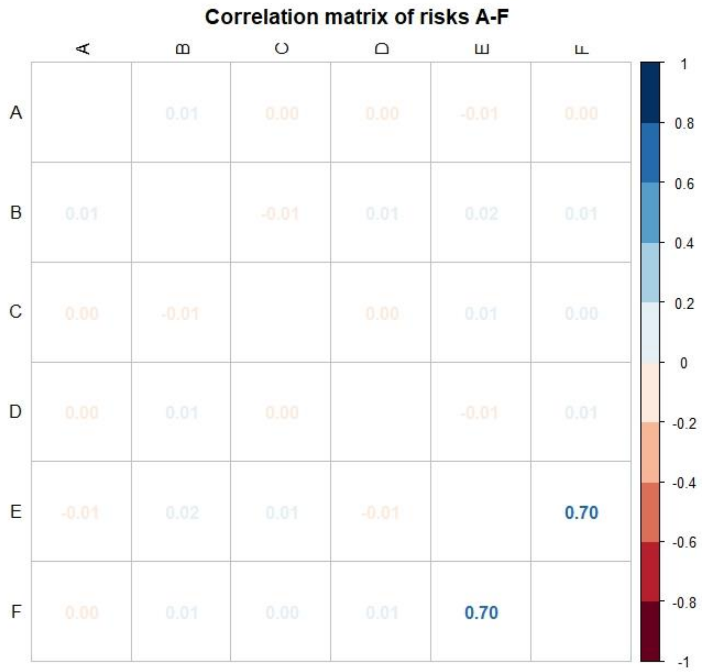
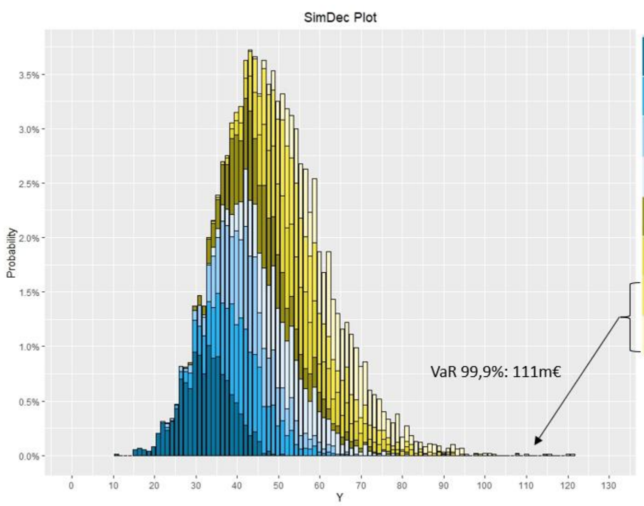


Figure 26. Correlation matrix of the risks A-F with added correlation between E and F.

Regarding risk driving factors and their effect on risk profile, figure 27 below shows how the individual risks behave together and the sensitivity analysis with default SimDec estimates reveal total risk profile's sensitivity to the most influential risks D, B and C. There is quite a lot of uncertainty around the different risks' effects on the total risk profile and each scenario (1-8) has somewhat equal probability of 12-13%. Scenarios while risk D is high and others being in various states have probability about 51%, and towards tail all being in high and around maximum values drive the risk tail close to 99,9%VaR. However, also only risk D being high and others low have maximum values close to VaR (111M€) with 12% probability.

Figure 27 also shows how the different risks drive the risk profile parts, and how the tail is driven by risk D being high with risks B and C increasing the in their values. Risks A, E or F seem not to contribute to the total risk profile in significant way. This kind of analysis shows what risk is/are the main driver(s) on risk profile and how different risks behave.



Color	D	B	C	min(Y)	mean(Y)	max(Y)	probability
1	low	low	low	10	32	50	13%
2		low	high	22	41	65	12%
3		high	low	22	42	68	13%
4		high	high	31	50	90	12%
5	high	low	low	23	46	114	12%
6		low	high	33	54	92	13%
7		high	low	34	56	107	13%
8		high	high	43	64	121	13%

Figure 27. Histogram of risk profile key factors and sensitivity analysis with SimDec.

4.3.4 Evaluation against requirements

This chapter describes the evaluation of the previous models' performance against the set requirement. Internal validation of the previous models is possible against available historical data and the more data one gets the more one can do validation with back testing how the model performs or performed in real situation (R1 & L5). Having some analytics solution, it is possible to automate data flows of realized incident data into the MCS engine to improve the risk profile analysis automatically (R2 & L3). Internal and external data should show improvement in previous risk analysis and with additional data points one can include them in the described MCS to reduce uncertainty in the analysis and do back testing to calibrate both expert judgements and MCS models (R6 & L3).

Also, with data previous models can be tested and modified to see how different risk treatment options affect the risk profiles and choose risk treatment strategies accordingly (P3). Depending on the real data, it is possible to use different kinds of distributions in demonstrated models to describe risks in appropriate manner (L2), and with MCS one can utilize them as shown. However, this cannot be really done with human judgment, and especially not with risk matrix.

The previous models capture risk profiles of the individual risks as well as their combination for total risk profile, including expected losses up to mean, unexpected losses up to VaR, and tails with drivers as well as VaR of 99,9% (R3 & P7). Tail drivers are examined later more closely regarding requirements R7 and R8.

As described, the base case does not include correlation and figure 26 above showed that the simulated risks (A-E) have close to zero correlations, i.e., they have nothing to do with each other. However, aggregating risks to total losses it is assumed that risks are perfectly correlated, i.e., summing all risks together is straightforward, but probably not appropriate. There was no need to include correlations between random variables, in this case individual risks, but if it is needed to include correlations, it is possible as shown with the refined case (R4) (chapter 4.3.3) or with copula structure.

Internal consistency and avoiding multiple counting of risks was avoided with MCS and using ranges that can be added together to avoid multiple assessments of the same risks, unlike risk matrix that requires multiple assessments of same risk in different business lines, and one cannot aggregate their varying impacts. Aggregating risks from business level to institution level should be done appropriately, and as shown in base and refined case models one can do addition of the simulated risks A-E/F (R5, L1 & P1). Having appropriate aggregation method one can also decompose the model and total impacts to individual risks to see where the risks are concentrated (P5).

Using Bayesian or frequentist type of models (L4) is for a financial institution to decide, but with Bayesian approach one can include many sources of information, such as expert opinion and scenario data. Using calibrated experts and thinking about various scenarios widens decision makers' thinking about possible futures and thus e.g., reduces the use of single point, too narrow and overconfident estimates. One should note that these are not strictly or directly required, but from practical, decision-making point of view they useful to consider and possible to apply with MCS.

Having the previous analysis at hand, the few remaining requirement questions (R7, R8) can be answered. One can see e.g., in the refined case SimDec analysis, to some extent, that reducing the uncertainty around most influential risk D (P2) and reducing its impact could yield effective control of total risk profile (P3, R7). However, that depends also on the available budget and available controls to assess where optimally spend risk treatment resources, e.g., to insurance tail losses (P6). With this kind of probabilistic analysis, one has better chances of making informed decisions, unlike with risk matrix. Also, this more thorough analysis reveals more likely whether one is taking too much risk (P4) or is the possible future state of world acceptable. Lastly, regarding the capital reserve calculation one has better way to assess how much capital is the most likely needed in the required VaR level (P7).

4.4 Results

The demonstration (chapter 4.3) attempted to verify and validate MCS usage against the set requirements, as model verification aims to verify that model assumptions are translated correctly into numbers. As can be seen from analysed cases, depending on the nature of the decision problem and its variables, one must iterate within the decision analysis process to find appropriate models and methods for the situation, and not use a single predefined model or method, as the case usually is with risk matrix.

The base case was a simple illustration of the approach development towards better models, but was limited e.g., regarding correlation usage. However, as seen in refined case, adding the correlation between variables, risks in this case, did not affect that much the results as the correlated risks were not that influential on the total result, but change was still visible. Also, as was seen regarding sensitivity analysis, SimDec's default R code did not automatically perform on the low frequency case where many loss scenarios are (closer to) zero (see appendix 5), even as a global sensitivity analysis method is considered more advanced than e.g., tornado (appendix 5), but manual code settings yielded better results. I.e., the SimDec method works, but in this scenario default R code's decomposition did not but was made operational with manual settings. Boxplots, like risks were described (appendix 5 & 7), could have been used to visualize the SimDec scenarios in small probability cases, but boxplots are not implemented in SimDec at the time of writing, so these would have been derived manually from SimDec scenarios.

Regarding the refined case, increasing the frequencies of the risks yielded different results (see appendix 7), especially with SimDec sensitivity analysis that worked with default code. Also, similar visuals like variations of cumulative distributions functions, like LEC, were be used to better communicate the results to wider audiences. The resulting models, or artefacts, indicate that they perform better in this kind of decision situation's uncertainty analysis than e.g., human judgment and especially risk matrix. Also, MCS is useful not only for the decision context described, but also provides good method for other decisions as well, such as investment decisions and uncertainty analysis within.

On one hand the demonstrated cases also show how it is possible to game the models for one's own purposes, i.e., even probabilistic methods provide bad results if misused. If chosen models do not give appropriate results, but they can be "rigorously proven" to e.g., authorities regarding capital reserves to save money or put one's money to better use. One the other hand, it is also about ethics to choose models that are less wrong than others and that actually can provide useful results if used appropriately, rather than resorting to models, such as risk matrix, that are known to be misleading by design.

The demonstration phase showed that MCS, or similar solution, can provide an appropriate risk analysis model to operational risk, and that can be validated against evaluation criteria, namely requirements from regulation, literature, and practice described in chapter 2.1 (appendix 2). Overall, after evaluating the different models, the requirement fulfilment based on literature gave indication of how the results most likely look like. Despite the demonstration being quite simple and with simulated data, one can see that even with simple analysis one can get better information and insight into operational risk analysis and decision making.

Overall, the demonstration gave practical indication that moving towards probabilistic models, such as MCS, in operational risk analysis seems to be beneficial for a financial institution, when looking at the set requirements. As IRM (2015) stated the model should not be just for one purpose, such as capital calculations, but also be useful for other decision situations as well. MCS can be utilized not only for capital calculations, but also for other decision problems, such as investment and project (risk) analysis. Having gone through the DSRP and its phases, the discussion chapter concludes the study.

5 Conclusions and discussion

The purpose of this study was to examine what is needed from an operational risk analysis (internal) model to adequately inform decision-making of relevant uncertainties. Available models were examined and compared against requirements derived from legislation, literature, and practice. Suitable models were utilized for the described decision situation to, qualitatively and quantitatively, analyse the related risks and their individual and overall effect on the business objective. The results show that solutions from decision analysis and analytics can be applied to similar problems, as well as other domains. This chapter goes through the conclusions derived from analysis and discusses its findings, implications, as well as limitations and future research.

5.1 Main findings

The main aim of the study was to answer to the main research question and supporting question, i.e., what is needed from an operational risk analysis model to support both business decision and fulfil a set of requirements, but not limited to those. On general level, applying probabilistic model, MCS, and approaches closely related to it, author demonstrated that they provide a useful way to analyse operational risk to answer the research questions than prevalent model, namely risk matrix, or human judgment. This is in line with the initial comparative analysis done on the different models (appendix 2). This finding is also in line with extant research (e.g., McCormack et. al., 2014; Zhu et. al., 2014; Zhu et. al., 2019), literature (e.g., Vose, 2008; Bedford & Cooke, 2011; Howard & Abbas, 2016) that uses the same models in risk analysis, as well as requirements from banking authorities (EBA, 2017) that describe features for a model to be adequately constructed.

Using unaided human judgment is enough in most cases in everyday (business) decisions, but as decision situations and its requirements grow more complex, better models are needed. Risk matrix does not really meet any of the requirements (appendix 2) and has several problems in risk modelling as described in chapter 2.3. Also, it is not really used outside of operational risk analysis, i.e., it is not considered a useful model for other decision situations to help e.g., business planning, investment decisions or project risk management. Also, as argued in chapter 2.5 risk matrix is not risk analysis, but risk classification as described by Cox (2008). Cox's (2008) findings and more risk matrix flaws are described continuously, also at the time of writing this study (see e.g., Proto et. al., 2023).

Statistical models' one advantage over human judgment is that by specifying how well a prediction is made indicates how badly prediction is made. Knowing the limits of model's predictability and sharing it with audience is an ethical mandate. However, knowing the imperfect accuracy of a statistical model may lead to search for a more perfect model, and this may mean abandoning the good enough statistical model in preference to some unproven method, such as human intuition or risk matrix, which have been found to be worse (e.g., Dawes, 2005; Camarer, 1991). Thus, if a model has error, but the alternative, like risk matrix, has or add even more error, then one better use the better model (e.g., Hubbard & Seiersen, 2016).

MCS or other numerical methods must and can be checked, e.g., via cases where exact methods are possible (Morini, 2011). I.e., when on can calculate the results with simpler mathematics, one can attempt to approximate the results with MCS and then check how the MCS performs. This cannot be really done with risk matrix, because e.g., regarding probabilities one really cannot verify if estimate is correct or not, if a risk is assessed as 3 or possible. One could argue that expert judgment can verify risk matrix performance, but as described in chapter 2.2 the human judgment is also flawed and can e.g., seek confirmation to pre-existing beliefs and not objective data or observations with regards to risks.

Thus, having compared the risk analysis models and considering previous findings, if a financial organization is using risk matrix for operational risk analysis, the organization would benefit from moving to better models, namely unaided human judgment and models supporting it in general areas that do not require further quantification, and use MCS or similar models for more advanced risk analysis where required. This finding is supported by examined research and literature in the domains of decision analysis and probabilistic risk analysis.

5.2 Implications for theory and practice

In general, risk analysis should be about supporting decision situations by answering questions about related risks (Vose, 2008), or more specifically uncertainties, which also include negative risks. Assessing quality of the risk analysis models, in addition to their fitting power, is important to reduce model risk (e.g., Morini, 2011) and to measure the effectiveness of risk analysis one must measure the risk itself with proper models (Hubbard, 2010). Too often used models create false sense of confidence instead of proving understanding, as is the case with risk matrix. Increasing or decreasing complexity of model details hide our ignorance of the examined system and its parts, and is abuse of models (Morini, 2011). Thus, perhaps there is room for improvement in communicating (operational) risk analysis theory to get the useful models into e.g., risk management teaching curriculum and thus as part of the work life where the useful models are needed. Although, operational risk management could utilize existing quantitative experts, if operational risk personnel are not quantitatively inclined.

Decision-makers are good at generating hypotheses and inducing decision rules, but this is not the case with prediction performance, in which experts are just little more accurate than novices, and rarely better than simple statistical models (e.g., Camarer, 1991; Hubbard, 2010). However, a model and its assumptions are always a simplification of reality and by doing simplification, one represents variable values possibly different from reality (e.g., Morini, 2011). Thus, results of risk analysis must be a state of world that could actually occur, which should lead to a model that is both precise and truthful as well as evade issues in modelling (Vose, 2008). Therefore, the useful theoretical approaches that have long history of evident usage should be implemented in practice as well.

Continuing the above, a risk analysis model is not useful if its outcomes are not comprehensible, practical, credible, and customized to the decision situation (Vose, 2008), as the case is with risk matrix (see chapter 2.3.2). Therefore, one should aim to use as good as possible a model and find models providing insight as correct as possible, to provide value to business decisions and other situations. When statistical prediction rules are available to make a relevant prediction, they should be used instead of intuition, i.e., human judgment (e.g., Dawes, 2005; Grove, 2005; Camarer, 1991).

However, also the probabilistic models have their flaws and possibility to be misused. For example, correlation is technically challenging to model, and thus has more model risk involved. Correlations tend to be examined only through past data and as they are unstable parameters; historical estimations tell little about likely future. Whenever one devises a model, one does probably a correlation mistake, e.g., when one reduces a stochastic quantity to a deterministic (flat) value, correlations are implicitly set to zero (Morini, 2011). This is the case especially with risk matrix, which would reduce the stochastic parameters into deterministic single points, in the rare case when e.g., MCS is used to inform risk matrix. Also, risk matrix does not even include correlations in any form, so as Cox (2008) describe in the case of negatively correlated risks risk matrix is worse than useless. However, even correlations can be included in MCS, there is possibility to misapply correlations as was seen with great financial crisis.

Also, if something changes in the business environment, such as market conditions, or if a model is used in a novel situation, one might find out that e.g., some assumptions are not reasonable or actual, making the model unreliable (Morini, 2011). Therefore, one must be careful also when making probabilistic models and this can be controlled with e.g., relevant skills and expertise on the used models and methods. In practice risk matrix is used as a hammer to find nails, i.e., use one thing on all situations, but one must not also use e.g., MCS in similar manner when one can do risk analysis in a simpler manner.

Regarding authorities and their practices, e.g., Finnish Financial Supervisory Authority (FIN-FSA) (Finanssivalvonta, 2023) and their regulations and guidelines document (Finanssivalvonta, 2014) states that a financial institution must prepare for modelling risk. They also collect data of realized operational risk incidents in different financial institutions and thus could do financial institutions' model validation to some extent with the available data. I.e., the FIN-FSA could or should make evaluation of the used models in financial institutions and how they perform against past losses that they get and set criteria, such as described in chapter 2.1. This required also by EBA (2022) guideline on "common procedures and methodologies for the *Supervisory Review and Evaluation Process* (SREP) and supervisory stress testing", for applicable financial organizations.

Regarding work life practice, describing and demonstrating better models seems to still not be enough for many and e.g., risk matrix continues to be a popular model, not because it is useful but because it seemingly improves discourse around risks (e.g., Jordan et. al., 2018).

For example, knowledge resistance (e.g., Klintman, 2019) is one reason why people resist knowledge from others and e.g., need for social belonging is a major obstacle in adopting new or contradicting information. There are several factors that are the reason that more useful models are not adopted, cognitive biases and wrong skills being some of those.

5.1 Limitations and future research

The main limitation of this study was authors personal, limited skills, at least at the time of writing, regarding the handled topic. From theoretical point of view the study is solid and any limitations in authors ability to express the discussed topics are studied in detail in various sources referred to. However, from practical point of view the study was somewhat superficial and reveals authors limitations, such as the production of the technical artefact in the form of qualitative and quantitative analysis, as well as the related coding in R. More detailed examination of quantitative risk analysis can be found e.g., in Vose (2008), Beford & Cooke (2011) and regarding R coding e.g., Brown (2018).

Another limitation is that the examined cases focused on risks, even though they should be analysed more as part of the decision situation and other variables, and how they affect the business objective (function). This might seem like an indication that risks should be analysed in a silo, but that is not the case. However, in practice, it seems to be that (operational) risks are managed outside of business processes with forced approaches, such as risk matrix, that do not help business decisions. This would lead to a future research possibility for a case study that examines why operational risk is so separated and how it could be better integrated into business processes, especially supporting decision-making.

Continuing future research possibilities, e.g., Gigerenzer (2014) argued that banks’ risk models provide false sense of safety and despite the extensive regulation, such as Basels 1-3, e.g., Great financial crisis of 2008 still happened and banking system still (at the time of his writing 2014) is fragile. Now that AMA and BIA are supposedly removed (in Basel 4) and only one standard model will be left to be used for capital calculations, one can ask what the reasoning and usefulness of this change is? Thus, future research possibility is to examine further the demonstrated models here, which are prevalent in current AMA models, whether they should be used instead both for capital reserves and other internal models, as argued by e.g., Peters et. al. (2016).

Another future research topic would be how business management sees how these demonstrated models would aid in decision making (e.g., Estall & Purdy, 2020; Koenig, 2020; Marks, 2015) and whether they provide benefits e.g., through better communication of risks. For example, predictive systems typically present predictions in single points, which are hard for people to account uncertainties when making decisions, i.e., displaying or communicating uncertainty is important for people to make better decisions (Munson, Hullman & Kay, 2018). Munson et. al. (2018) has shown that presenting only single points estimates give people false sense of precision, and people interpret qualitative descriptions of uncertainty very differently, as is the case with risk matrix. However, they show that certain visualization, such as CDF used in demonstration here (see chapter 4.3.3 and appendix 7), lead to more accurate estimates. Thus, further studies could include more practical cases where better visualisations are utilised and examined whether they work, despite being often argued to be not sensible for business audience (see also Padilla, Kay & Hullman, 2021), even though business management often uses far more complex models than risk matrix.

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Appendix 1. Requirements for an operational risk analysis model

“With regards to TSA, EBA (EBA, 2018) sets three criteria to use TSA (author ***emphasis*** *added):*

- *“(a) an institution shall have in place* ***a well-documented assessment and management system for operational risk with clear responsibilities assigned for this system****. It* ***shall identify its exposures to operational risk*** *and* ***track relevant operational risk data, including material loss data****. This system shall be subject to regular independent review carried out by an* ***internal or external party possessing the necessary knowledge*** *to carry out such review;*
- *(b) an institution's operational risk assessment system* ***shall be closely integrated into the risk management processes*** *of the institution. Its output shall be an integral part of the process of monitoring and controlling the institution's* ***operational risk profile****;*
- *(c) an institution shall implement* ***a system of reporting to senior management that provides operational risk reports to relevant functions within the institution****. An institution shall have in place* ***procedures for taking appropriate action according to the information within the reports to management****.”*

AMA (title III, chapter 4, articles 321-324) on the other hand provides considerable increase in requirements, both qualitative and quantitative, of which relevant from modelling perspective are described below (author ***emphasis*** *added):*

Qualitative

- *321 (f) an institution's* ***internal validation processes*** *shall operate in a sound and effective manner;*
- *321 (g)* ***data flows and processes*** *associated with an institution's* ***risk measurement*** *system shall be transparent and accessible.*

Quantitative

- *322 2 Process*

  - *(a) an institution shall calculate its own funds requirement as comprising both* ***expected loss and unexpected loss****, unless expected loss is adequately captured in its internal business practices. The operational risk* ***measure shall capture potentially severe tail events****, achieving a soundness standard comparable to a* ***99,9 % confidence interval*** *over a one-year period;*
  - *(b) an institution's operational risk* ***measurement system shall include the use of internal data, external data, scenario analysis and factors reflecting the business environment and internal control systems*** *as set out in paragraphs 3 to 6. An institution shall have in place a well-documented approach for weighting the use of these four elements in its overall operational risk measurement system;*
  - *(c) an institution's risk measurement system shall capture the* ***major drivers of risk affecting the shape of the tail of the estimated distribution*** *of losses;*
  - *(d) an* ***institution may recognise correlations*** *in operational risk losses across individual operational risk estimates* ***only where its systems for measuring correlations are sound****, implemented with integrity, and take into account the uncertainty surrounding any such correlation estimates, particularly in periods of stress. An institution shall validate its correlation assumptions using appropriate quantitative and qualitative techniques;*
  - *(e) an institution's* ***risk measurement system shall be internally consistent and shall avoid the multiple counting of qualitative assessments or risk mitigation techniques*** *recognised in other areas of this Regulation.*
- *3 Internal data*
  - *(a) an institution shall base its internally generated operational risk measures on a minimum* ***historical observation period of five years****. When an institution first moves to an Advanced Measurement Approach, it* ***may use a three-year historical observation*** *period;*
  - *(f) an institution shall have in place documented procedures for* ***assessing the on-going relevance of historical loss data, including those situations in***

which judgement overrides, scaling, or other adjustments may be used*, to what extent they may be used and who is authorised to make such decisions.*

- *4 External data*
    - *(a) an institution's operational risk measurement system shall use relevant external data,* ***especially when there is reason to believe that the institution is exposed to infrequent, yet potentially severe, losses****. An institution shall have a systematic process for determining the situations for which external data shall be used and the methodologies used to incorporate the data in its measurement system;*
- *5 Scenario analysis*
    - *An institution shall use scenario analysis of* ***expert opinion in conjunction with external data to evaluate its exposure to high severity events****. Over time, the* ***institution shall validate and reassess such assessments through comparison to actual loss experience to ensure their reasonableness****.*
- *6 Business environment and internal control factors*
    - *(a) an institution's firm-wide risk assessment methodology shall capture key business environment and internal control factors that can* ***change the institutions operational risk profile****;*
    - *(b) an institution* ***shall justify the choice of each factor as a meaningful driver of risk****, based on experience and involving the expert judgment of the affected business areas;*
    - *(c) an institution* ***shall be able to justify to competent authorities the sensitivity of risk estimates to changes in the factors and the relative weighting of the various factors****. In addition to capturing changes in risk due to improvements in risk controls, an institution's risk measurement framework shall also capture potential increases in risk due to greater complexity of activities or increased business volume;*
    - *(d) an institution* ***shall document its risk measurement framework and shall subject it to independent review within the institution and by competent***

authorities*. Over time, an institution* ***shall validate and reassess the process and the outcomes through comparison to actual internal loss experience and relevant external data****.”*

Appendix 2. Model comparison against requirements.

Table 1. Comparison of models against model requirements (chapter 2.1). Check: yes/mostly, scale: maybe/to some extent/depends, cross: no.

ID	Unaided human judgment	Risk matrix	MCS	Author's comments
R1	✓	✗	✓	One can back-test human predictions and simulation results but cannot back-test risk matrix results. For example, as percentages are not used for probabilities, one cannot test whether an event was ”possible” or ”unlikely”. Also, risk matrix does not consider event frequency, so one cannot back-test frequency as risk matrix considers only one event and if it happens more than one time the probability is always 5.
R2	⚖	✗	✓	Using data in human judgment is possible, but it is not really automated or directly connected. One can also disregard the data, even provided. With risk matrix one could argue that data can be used in matrix classification, but in practice it seems not to be done. With MCS and analytics one can connect e.g., internal incident data (storage) directly with simulation engine and automate the calculation and correction of risks to some extent. Some human intervention may be needed with e.g., scenario analysis.
R3	⚖	✗	✓	Human mind can imagine a possible range of risk impacts but cannot simulate even a simple system to analyse variable interactions and resulting distribution of outcomes. Risk matrix does not capture the whole risk profile and as described there is no consensus which part of distribution should be used, but usually mode or max is used. I.e., one

				covers only the expected losses or tails with risk matrix, but distributions are not really used with risk matrix. With MCS one can cover all expected, unexpected, and tail losses as well as 99,9% CI.
R4	⚖	✗	✓	Correlations are not required but excluding them may lead to incorrect results. Human judgment can think about correlations and understand them to some extent, but humans tend/want to see correlations/causality where it does not exist. Risk matrix cannot include correlations and in practice they are not used. MCS can include correlations, if/when needed.
R5	⚖	✗	✓	All models can include multiple counting of risks and controls. However, assuming it is controlled, one can assess this through aggregation. Human mind can aggregate to some extent and qualitatively model different risk, but really cannot calculate a whole risk distribution or risk profile from multiple risks. Risk matrix cannot aggregate as e.g., ordinal scales or colours cannot be added together. MCS can aggregate different risks with different distributions, to create a whole risk profile (see R3).
R6	⚖	✗	✓	Human judgment can utilize given data to some extent and can improve expert judgment when data are given. Risk matrix's incoherent classification does not really benefit from data, because e.g., a risk classification may stay the same even new data indicates movement in input variables. I.e., one does not see uncertainty reduction, and in practice this kind of improvement seems not to be done. MCS can utilize given data points and improve the assessments, i.e., more data reduces the uncertainty of the examined phenomena.

R7	⚖	✗	✓	Human judgment can to some extent identify and examine driving factors to risk profile, but cannot really do e.g., sensitivity analysis that shows which variables are the most influential to risk profile. Risk matrix does not utilize factor analysis and does not cover a whole risk profile. MCS can include sensitivity analysis to see which factors are the most influential and which drive the parts of distributions, such as tails (see R3).
R8	⚖	✗	✓	Human judgment can utilize e.g., min-best guess-max scenarios in analysis, but cannot really simulate the whole range of factor sensitivities. Risk matrix cannot do and does not do sensitivity analysis in practice. MCS can utilize sensitivity analysis to assess sensitivity of risk estimates and factors (see R3 and R7).
L1	✗	✗	✓	See R5. Human judgment can do aggregation to some extent, but most likely is not accurate enough, especially in larger organizations like financial institution. As in R5, risk matrix cannot do aggregation in practice. MCS can aggregate different risks and their distributions from business lines to create an institution level risk profile.
L2	⚖	✗	✓	Human judgment can think in different distributions or scenarios for different risks but is limited and tend to think in Uniform distribution, i.e., all outcomes are equally probable (Fox & Clemens, 2005). Risk matrix does not use distributions, but in a way assumes only single event to occur, i.e., Bernoulli distribution, 0 or 1. However, risk matrix assumes that even in the "very unlikely" case the risk still occurs as it multiplies the impact with 1 and does not consider states of world when risk does not happen, i.e., 0. Also, risk matrix does not consider an event happening more than once, i.e., frequency: Poisson distribution. MCS can utilize the distributions mentioned above and many others.

L3	⚖	✗	✓	Model can be fitted to risk (data). See R6.
L4	✓	✗	✓	Choosing between frequentist and Bayesian models is more administrative task and for a financial institution to decide. Bayesian formulation can adequately incorporate multiple sources of information, such as expert judgment and scenario data. Thus, human judgment can utilize Bayesian thinking and MCS can be used to derive e.g., prior, and posterior risk distributions. These cannot be and are not used in practice with risk matrix.
L5	✓	✗	✓	Model can be calibrated to loss experience. See R1.
P1	⚖	✗	✓	What is overall risk profile? See R5 and L1.
P2	⚖	✗	✓	Which are top risks? See R8.
P3	⚖	✗	✓	Human judgment can utilize e.g., information security frameworks to identify to what areas one should invest to reduce operational risk. This might be enough to cover the mandatory basics, but after that one needs more efficient analysis to compare control effectiveness. With risk matrix one does not know whether money was well spent or not, even one could argue that a risk went from yellow to green based on new control acquisition. In practice available budget, or other factors for that matter, are not used as restriction in risk matrix analysis. With MCS and similar models one can test one's assumptions on control effectiveness against risk profile to see how the risk profile changes

				based on the assumed investments. One can also do optimization against available budget to choose risk treatment strategies.
P4	⚖	✗	✓	See R3 and L1. Risk limits tend to be personal or stated in business policies. Thus, human judgment can be used to some extent to assess whether one takes too much operational risk. With risk matrix one does not have a clear understanding what the limits are as they tend to refer to colours or ordinal numbers. Also, one does not know the whole risk profile with risk matrix. MCS can be used to analyse a more whole risk profile and use sensitivity analysis and other features to check whether one seems to be taking too much risk, and act accordingly.
P5	⚖	⚖	✓	See R3 and L1. Human judgment can examine to some extent where business areas risks are concentrated but cannot really aggregate and do accurate analysis of data without analytical solutions, such as even some spreadsheet. One could argue that risk matrix can do this by showing how many risks are in different business lines, but matrix cannot do show e.g., expected losses in each business unit. MCS can calculate the risk profiles in business units and use different statistics to show aggregate data and use data visualization to e.g., filter by business units where risks (impacts) are concentrated.
P6	✗	✗	✓	How much insurance to buy? See P1, P3 and R3.
P7	⚖	✗	✓	See all R and L points. In near future (writing in 2023) internal models cannot be used for capital calculation as there will be a new SMA. Even internal models could be used for comparative analysis, capital calculation should not be the only purpose of risk

				analysis model but should also be used for business decisions. Human judgment is not a capital calculation model but can be used as an input into the capital calculation. Risk matrix cannot do capital calculation, or if used the results would be misleading. MCS can be used for capital calculations.

Appendix 3. Risk parameters and profiles

Created/imaginary data table.

Table 1. Created data.

"Actual" observed losses for each risk in millions

A	B	C	D	E
1,25	2,10	3,00	2,10	1,40
1,30	2,50	3,50	2,10	1,40
1,80	2,70	3,40	2,00	1,80
1,80	3,10	3,00	3,10	1,80
1,20	2,00	3,00	1,20	1,50
1,70	2,50	3,00	2,70	1,70
1,60	2,90	3,80	2,80	1,60
1,40	2,90	3,10	2,90	1,10
1,70	2,80	2,90	2,80	2,00
1,30	2,50	2,70	2,50	1,70

Natural log (LN) of observed losses in millions

A	B	C	D	E
0,22	0,74	1,10	0,74	0,34
0,26	0,92	1,25	0,74	0,34
0,59	0,99	1,22	0,69	0,59
0,59	1,13	1,10	1,13	0,59
0,18	0,69	1,10	0,18	0,41
0,53	0,92	1,10	0,99	0,53
0,47	1,06	1,34	1,03	0,47
0,34	1,06	1,13	1,06	0,10
0,53	1,03	1,06	1,03	0,69
0,26	0,92	0,99	0,92	0,53

Risk	A	B	C	D	E
Frequency per year	0,25	0,2	0,1	0,05	0,01
Trials binomial	10000	10000	10000	10000	10000
p value binomial	0,000025	0,00002	0,00001	0,000005	0,000001
Input lognormal mean	0,40	0,95	1,14	0,85	0,46
Input lognormal standard deviation	0,16	0,14	0,10	0,28	0,17

Figure 1. Risk parameters.

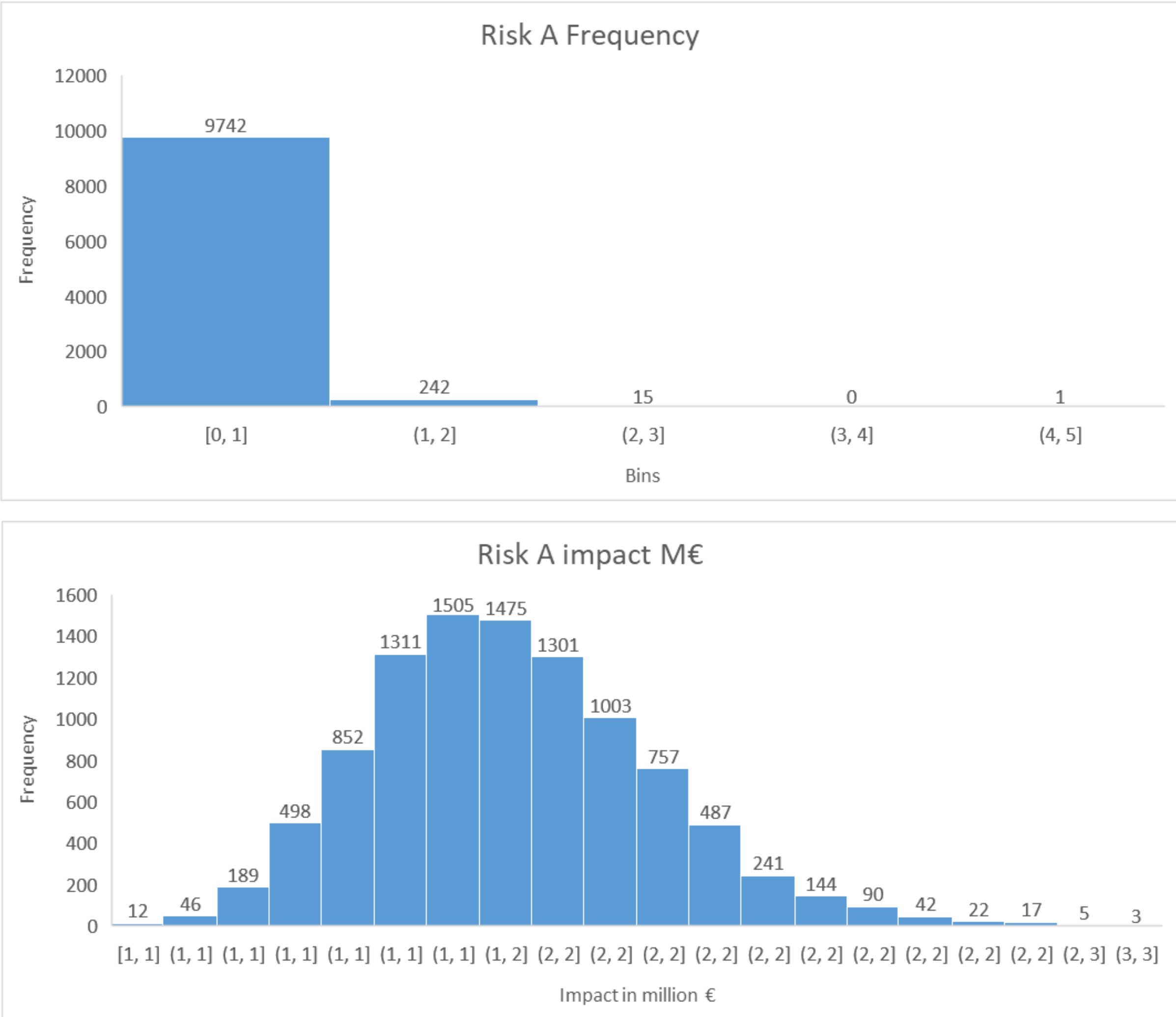
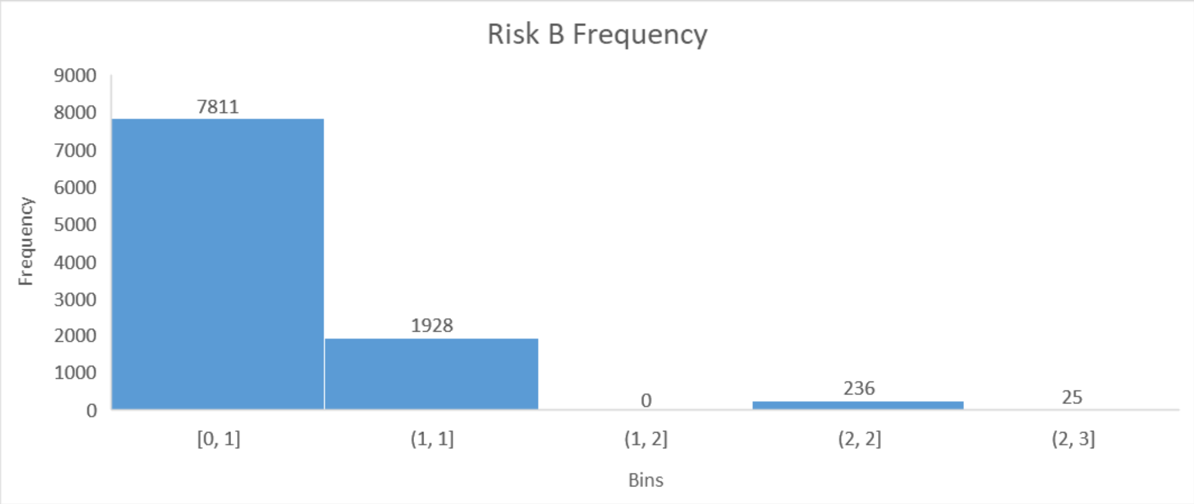


Figure 2. Risk A profile: frequency and impact



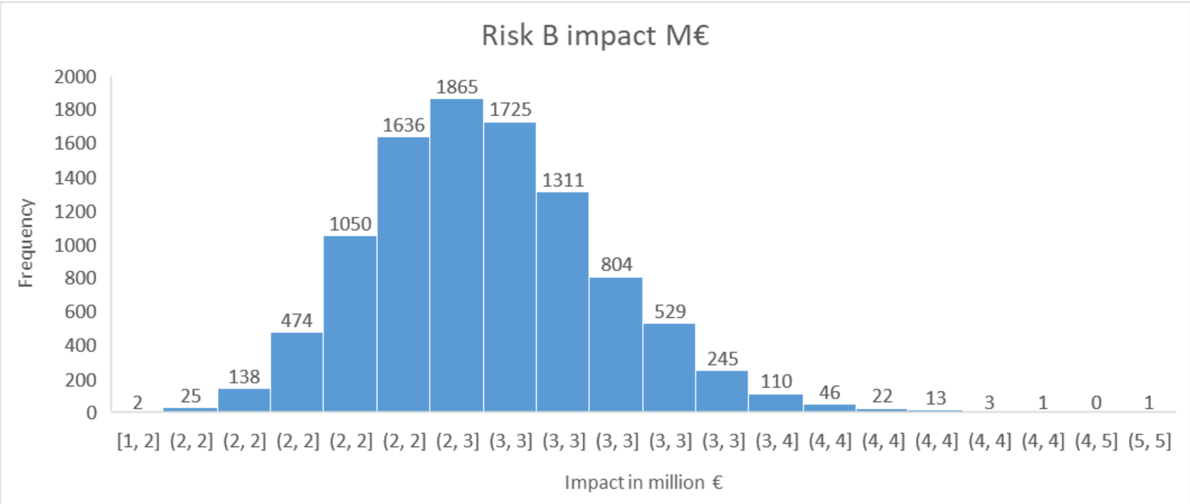
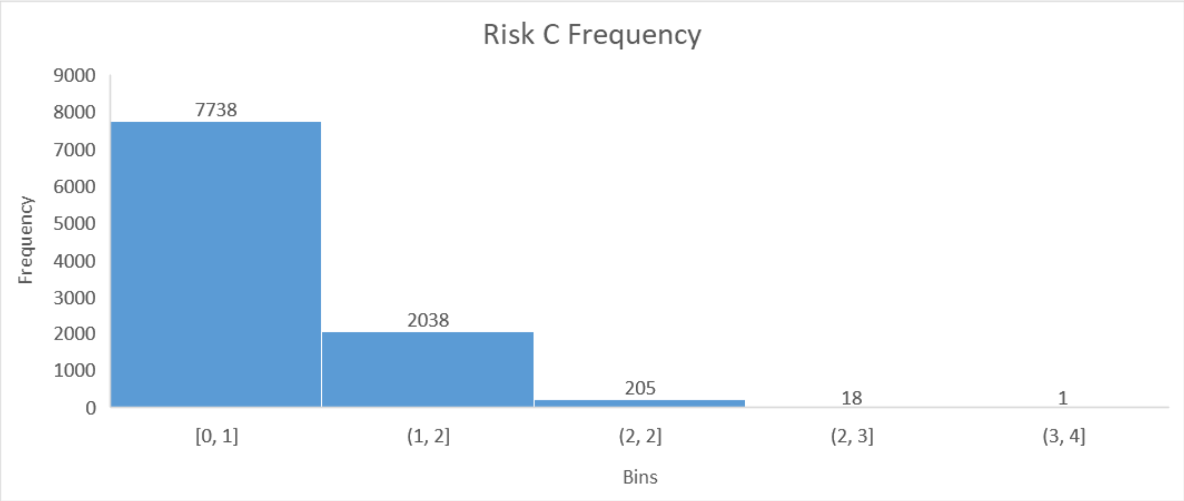


Figure 3. Risk B profile: frequency and impact



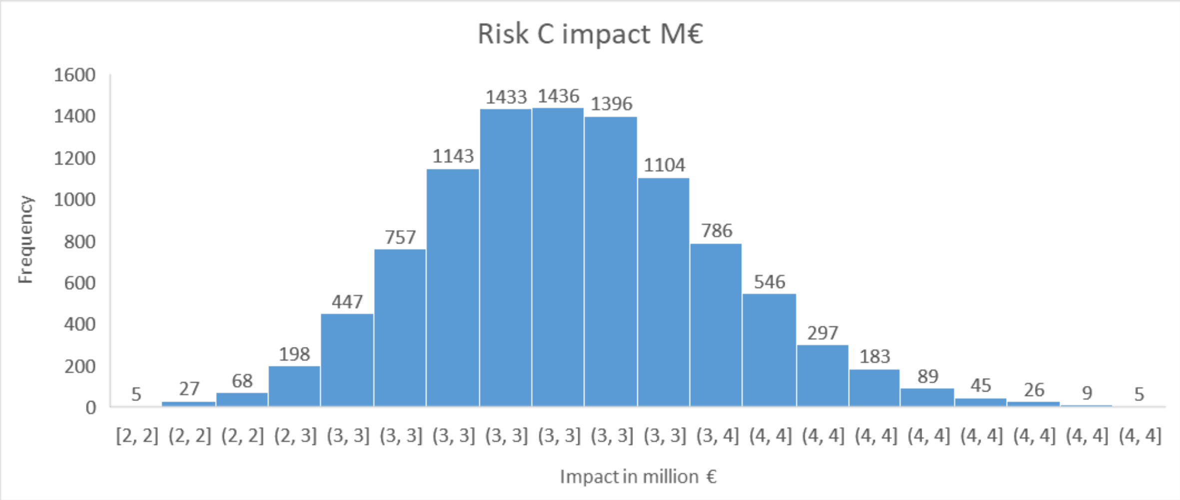
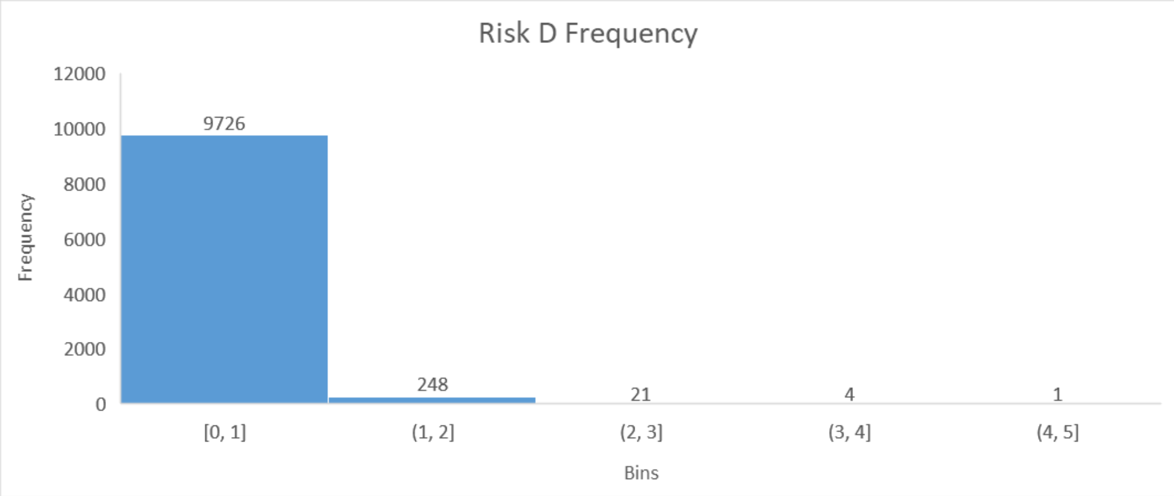


Figure 4. Risk C profile: frequency and impact



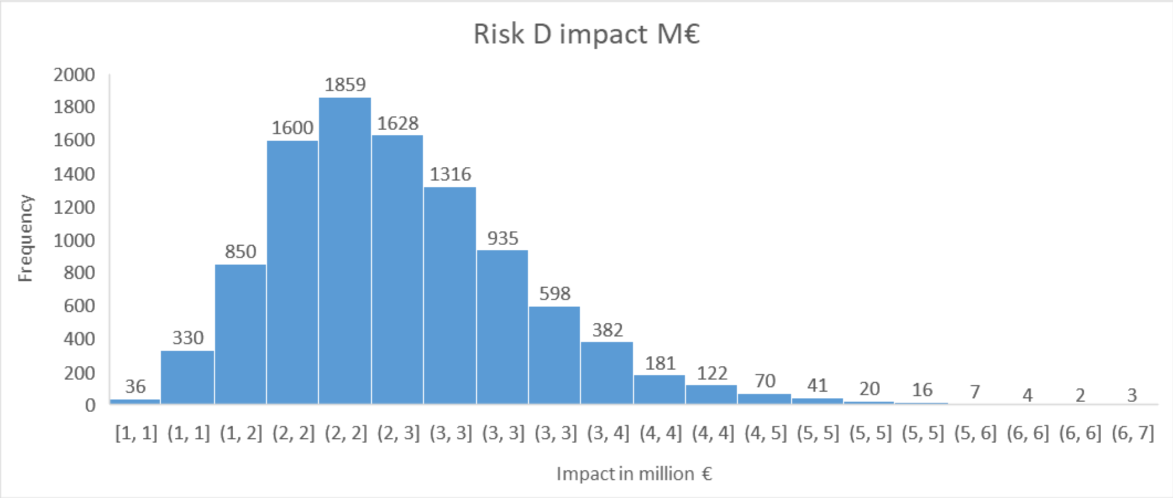
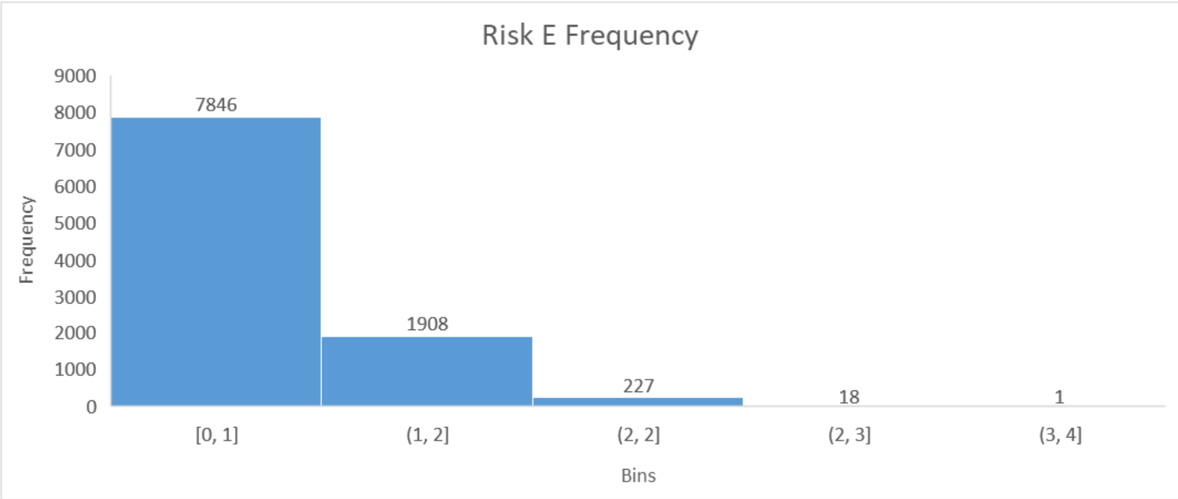


Figure 5. Risk D profile: frequency and impact



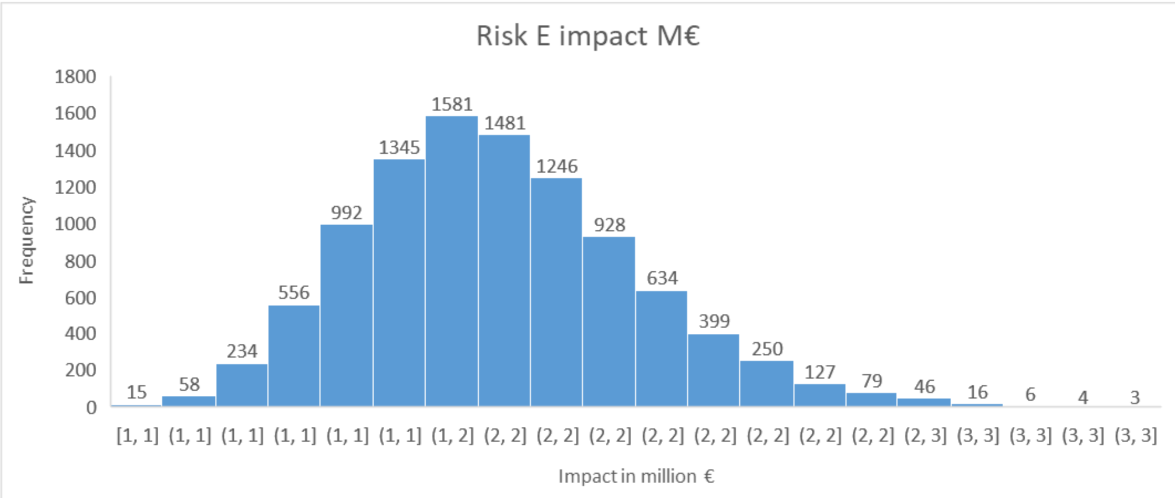


Figure 6. Risk E profile: frequency and impact

Appendix 4. R code for base case

```
#R code for thesis: Base case model

#Empty environment
rm(list = ls())
dev.off()

#Packages
install.packages("tidyverse")
library("tidyverse")
install.packages("ppcor")
library("ppcor")
install.packages("corrplot")
library("corrplot")

# AMA Base Case with R -----------------------------------------------------

#Setting a seed yields same results for validation purposes
set.seed(123)
#AMA model in R: Poisson-log-normal process with same Excel inputs
#Observation data from excel model in arrays
RA_data = c(1.25, 1.30, 1.80, 1.80, 1.20, 1.70, 1.60, 1.40, 1.70, 1.30)
RB_data = c(2.10, 2.50, 2.70, 3.10, 2.00, 2.50, 2.90, 2.90, 2.80, 2.50)
RC_data = c(3.00, 3.50, 3.40, 3.00, 3.00, 3.00, 3.80, 3.10, 2.90, 2.70)
RD_data = c(2.10, 2.10, 2.00, 3.10, 1.20, 2.70, 2.80, 2.90, 2.80, 2.50)
RE_data = c(1.40, 1.40, 1.80, 1.80, 1.50, 1.70, 1.60, 1.10, 2.00, 1.70)
#Natural log of the observations
RA_log = log(RA_data)
RB_log = log(RB_data)
RC_log = log(RC_data)
RD_log = log(RD_data)
```

```
RE_log = log(RE_data)

#Mean and standard deviation of the natural logs for the log normal distribution
#Means
RA_mean = mean(RA_log)
RB_mean = mean(RB_log)
RC_mean = mean(RC_log)
RD_mean = mean(RD_log)
RE_mean = mean(RE_log)
#Standard deviations
RA_std = sd(RA_log)
RB_std = sd(RB_log)
RC_std = sd(RC_log)
RD_std = sd(RD_log)
RE_std = sd(RE_log)

#Probability density function for a risk A
A = rpois (10000, 0.25) * rlnorm (10000,RA_mean,RA_std)
summary(A)
quantile (A, c(0.99))
hist(A)

#Probability density function for a risk B
B = rpois (10000, 0.2) * rlnorm (10000,RB_mean,RB_std)
summary(B)
quantile (B, c(0.999))
hist(B)

#Probability density function for a risk C
C = rpois (10000, 0.1) * rlnorm (10000,RC_mean,RC_std)
summary(C)
quantile (C, c(0.999))
```

```
hist(C)

#Probability density function for a risk D
D = rpois (10000, 0.05) * rlnorm (10000,RD_mean,RD_std)
summary(D)
quantile (D, c(0.999))
hist(D)

#Probability density function for a risk E
E = rpois (10000, 0.01) * rlnorm (10000,RE_mean,RE_std)
summary(E)
quantile (E, c(0.999))
hist(E)

#All risk histograms for refined case
par(mfrow = c(3, 2))
hist(A, main = "Risk A profile", xlab = "Impact M€")
hist(B, main = "Risk B profile", xlab = "Impact M€")
hist(C, main = "Risk C profile", xlab = "Impact M€")
hist(D, main = "Risk D profile", xlab = "Impact M€")
hist(E, main = "Risk E profile", xlab = "Impact M€")

#Return plot area to 1:1
par(mfrow = c(1, 1))

#Total annual losses Million €
total_risk = A+B+C+D+E
summary(total_risk)
VaR = quantile(total_risk, c(0.999))
hist(total_risk, main = "Histogram of annual total losses (million €)", breaks = 10,
   xlab = "Annual total loss impact bins", labels = TRUE, col="dodgerblue3", ylim = c(0,6000))
abline(v=VaR,col="red") #Value at risk 99,9% in histogram
```

```
text(x=12.5, y=4000, 'Value at risk 99,9%')

# Cumulative distribution function (CDF) ---------------------------------

#Total risk Cumulative distribution function: Ascending
risk_data = data.frame(A, B, C, D, E)
ggplot(risk_data, aes(total_risk)) +
  labs(title="Total risk CDF", x="Lossess in M€", y="Percentage")+
  geom_vline(xintercept = VaR, color = "red")+
  annotate("text", x=VaR, y=0.5, label= "99,9% VaR")+
  stat_ecdf(geom = "step") +
  theme_classic()

#Total risk Cumulative distribution function: descending (loss exceedance curve)
CDF = ecdf(total_risk)
DF <- data.frame(x = sort(total_risk),
                 y = 1-CDF(sort(total_risk)))
# plot
ggplot(data=DF, aes(x, y) )+
  geom_line(lty = "solid")+
  labs(title="Total risk loss exceedance curve million €", x="Lossess in M€", y="Percentage")+
  geom_vline(xintercept = VaR, color = "red")+
  geom_hline(yintercept = 0.001, color = "red")+
  annotate("text", x=VaR, y=0.2, label= "99,9% VaR")+
  annotate("text", x=2, y=0.02, label= "0.001% chance to exceed VaR")+
  scale_x_continuous(breaks=seq(0,20,2))+
  scale_y_continuous(breaks=seq(0,1,0.1))+
  theme_classic()

##
#Risk boxplots
par(mfrow = c(5, 1))
```

```
boxplot(A, horizontal=TRUE, main = "Risk A")
boxplot(B, horizontal=TRUE, main = "Risk B")
boxplot(C, horizontal=TRUE, main = "Risk C")
boxplot(D, horizontal=TRUE, main = "Risk D")
boxplot(E, horizontal=TRUE, main = "Risk E")
#Return plot area to 1:1
par(mfrow = c(1, 1))


#Sensitivity analysis: Tornado chart one at a time analysis
#One variable (risk) is moved from its mean value at a time and how it affect total risk profile
#Chart displays sensitivity of the total risk mean to individual risks
risks = data.frame(A, B, C, D, E)
risk_data = data.frame(total_risk,risks)
#Tornado plot
lm <- lm(total_risk ~ A*B*C*D*E, data = risk_data)
tornados <- tornado::tornado(lm, type = "percentiles", alpha = 0.01)
plot(tornados, xlabel = "Total risk losses (mean 1.3171)", geom_bar_control = list(width =
0.4),main="title")


# Simulation Decomposition (SimDec) ---------------------------------------
install.packages("devtools")
library(devtools)
install_github("Simulation-Decomposition/simdec-R")
library(Simdec)
install.packages("gridExtra")
library(gridExtra)
install.packages("kableExtra")
library(kableExtra)

#Data into SimDec
```

```
output = total_risk

inputs = data.frame(A, B, C, D, E)


#Significance indices

sig <- significance(output, inputs)

SI  <- sig[[2]] #Saving SI as a separate for later use

FOE <- sig[[3]] #First order effects

SOE <- sig[[4]] #Second order effects

print(SI)

print(FOE)

print(SOE)


#Run decomposition

# Initialize decomposition

dec_limit      =  0.8 # cumulative significance threshold; % (used to decide how many variables to take for decomposition)

threshold_type  =  1   # 1 for 'percentile-based' (same amount of observations in each state), 2 for 'median-based' (equally-spaced ranges)

output_name     =  "Total_risk"

var_names       =  colnames(inputs)

dec             =  decomposition(output, inputs, SI, dec_limit = 0.8,

                             manual_vars = NULL, manual_thresholds = NULL,

                             manual_states = NULL, threshold_type = 1,

                             var_names = colnames(inputs))

scenario       = dec[[1]]

scenario_legend = dec[[2]]

var_names_dec   = dec[[4]]

print(SI)

print(scenario_legend)

print(var_names_dec)


#SimDec visualization

# Initializing plot for automatic aesthetics
```

```
axistitle   = c()

main_colors = c()

visuals     = build_simdec_chart(output, scenario, scenario_legend,

                             main_colors, axistitle, var_names_dec)

SimDec_Plot   = visuals[[1]]

Legend_Table = visuals[[2]]

print(SimDec_Plot)

print(Legend_Table)



###########################



#SimDec manual modifications

output = total_risk #Sum of A-E

inputs = data.frame(A, B, C, D, E) #Individual risks


#Manual parameters

manual_vars       <- c(3, 1, 2, 0, 0)  # Specify the order of variables for decomposition, use 0 to ex-
clude

manual_states     <- c(2, 2, 2, 2, 2)  # Specify the number of states for each variable


manual_thresholds <- matrix(c(min(inputs[,1]), min(inputs[,2]), min(inputs[,3]), min(in-
puts[,4],min(inputs[,5])),

                          0.36, 0.53, 0.31, 0.13, 0.015,

                          max(inputs[,1]), max(inputs[,2]), max(inputs[,3]), max(inputs[,4]), max(in-
puts[,5])),

                          nrow = max(manual_states)+1,

                          ncol = length(manual_vars),

                          byrow = TRUE)  # Specify numeric thresholds for every state # Size: (max(man-
ual_states)+1, N_inputs)

main_colors       <- c('#8c5eff', '#ffe252', '#0dd189')

sig               <- significance(output, inputs)
```

```
SI             <- sig[[2]]
dec             <-  decomposition(output, inputs, SI, dec_limit = 0.8,
                        manual_vars = manual_vars,
                        manual_thresholds = manual_thresholds,
                        manual_states = manual_states,
                        threshold_type = 1,
                        var_names = colnames(inputs))
scenario        <- dec[[1]]
scenario_legend   <- dec[[2]]
var_names_dec     <- dec[[4]]
visuals          <- build_simdec_chart(output, scenario, scenario_legend,
                          main_colors, axistitle, var_names_dec)
SimDec_Plot   <- visuals[[1]]
Legend_Table <- visuals[[2]]
print(SimDec_Plot)
print(Legend_Table)
```

Appendix 5. Base case model R visualizations

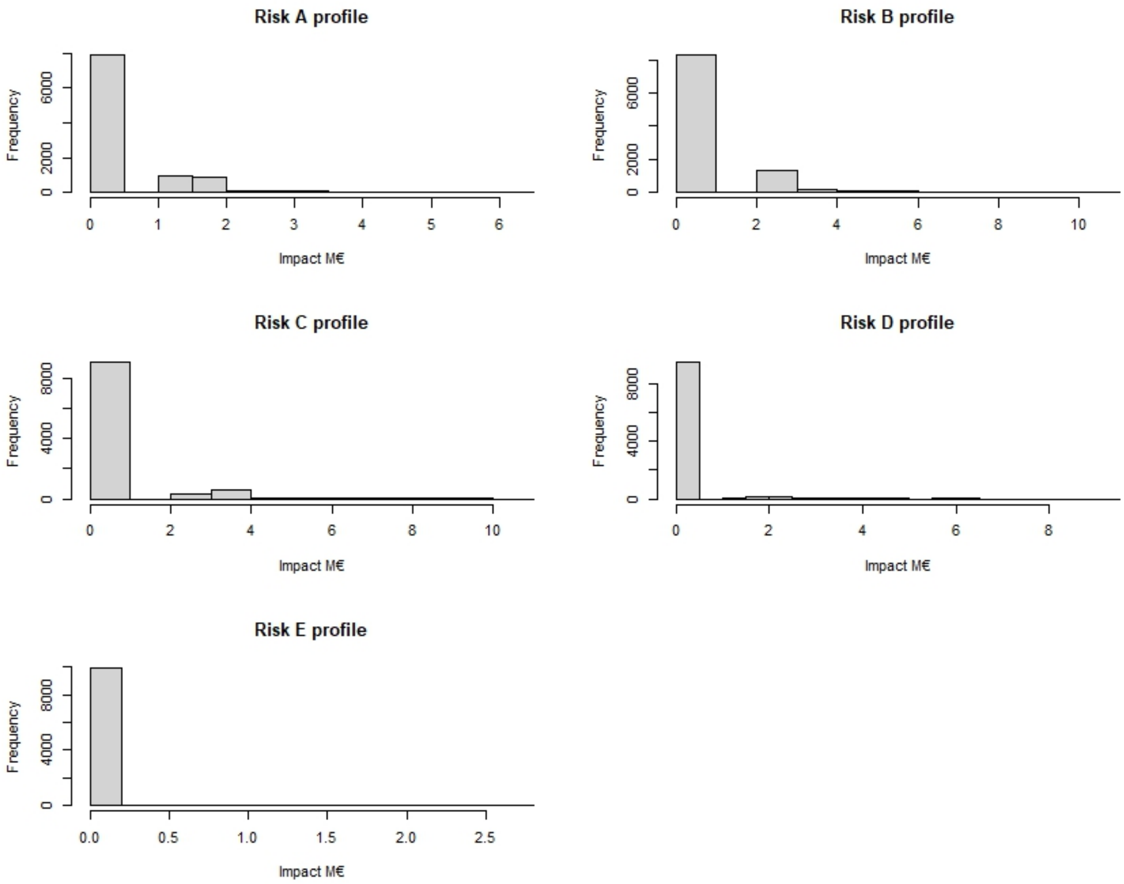


Figure 1. Histograms of the risks A-E.

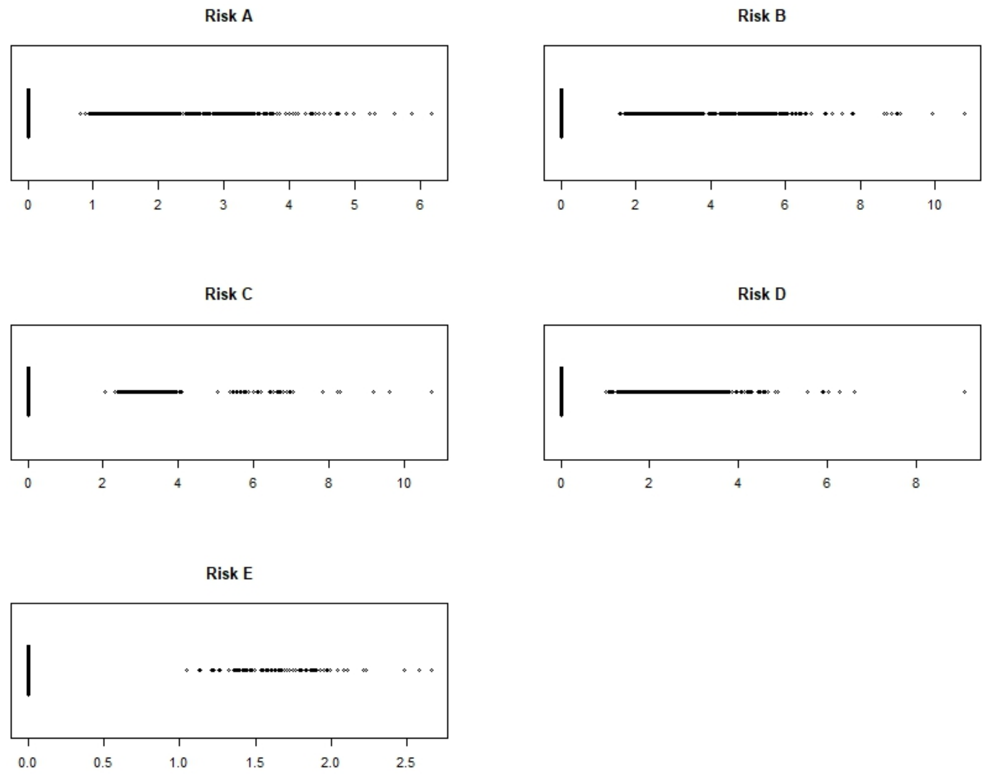


Figure 2. Boxplots of the risks A-E.

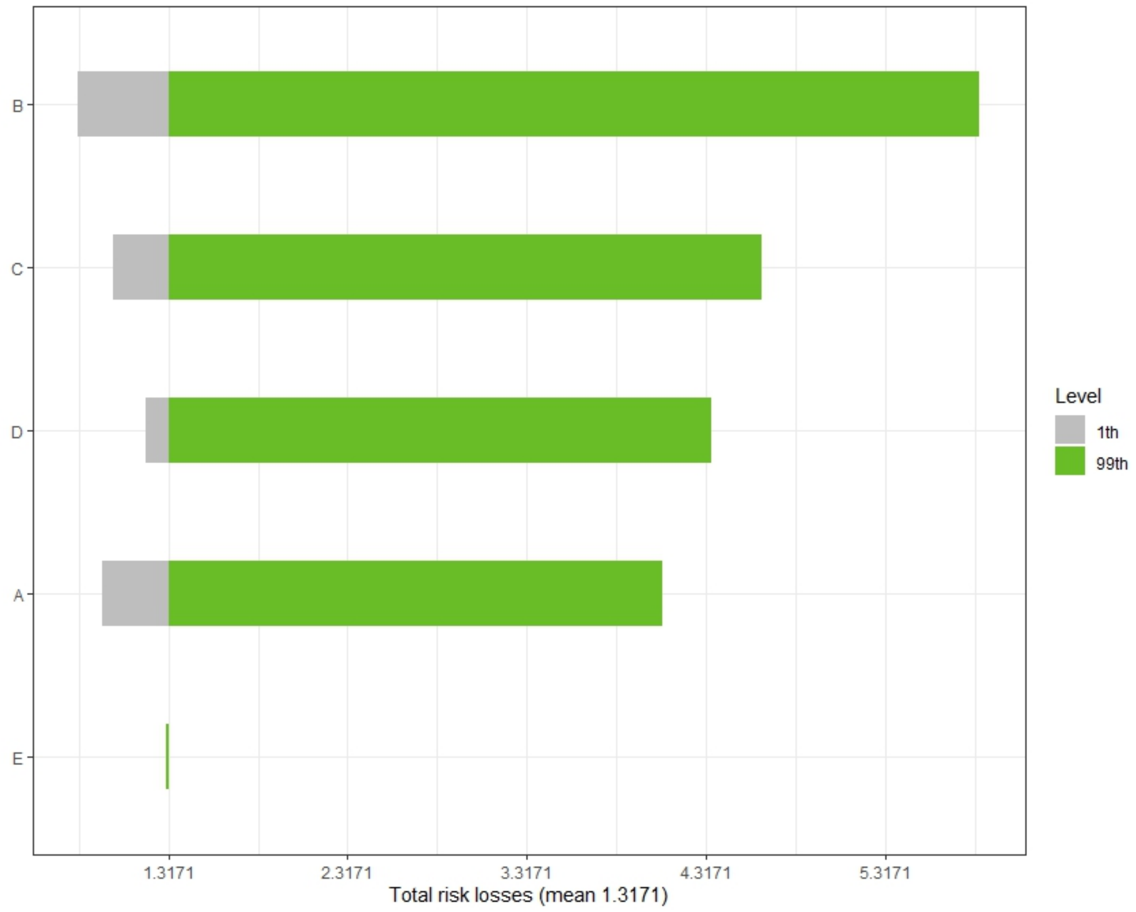


Figure 3. Tornado sensitivity analysis of risks A-E against total risk loss and 1st and 99th percentile variance around its mean.

Appendix 6. R code for refined model

```
#R code for thesis: Refined model

#Empty environment and plots
rm(list = ls())
dev.off()

#Packages
install.packages("tidyverse")
library("tidyverse")
install.packages("ppcor")
library("ppcor")
install.packages("corrplot")
library("corrplot")

# AMA refined case with R -------------------------------------------------------------

#Setting a seed yields same results for validation purposes
set.seed(123)
#AMA model in R: Poisson-log-normal process with same Excel inputs
#Observation data from excel model in arrays
RA_data = c(1.25, 1.30, 1.80, 1.80, 1.20, 1.70, 1.60, 1.40, 1.70, 1.30)
RB_data = c(2.10, 2.50, 2.70, 3.10, 2.00, 2.50, 2.90, 2.90, 2.80, 2.50)
RC_data = c(3.00, 3.50, 3.40, 3.00, 3.00, 3.00, 3.80, 3.10, 2.90, 2.70)
RD_data = c(2.10, 2.10, 2.00, 3.10, 1.20, 2.70, 2.80, 2.90, 2.80, 2.50)
RE_data = c(1.40, 1.40, 1.80, 1.80, 1.50, 1.70, 1.60, 1.10, 2.00, 1.70)
#Natural log of the observations
RA_log = log(RA_data)
RB_log = log(RB_data)
RC_log = log(RC_data)
RD_log = log(RD_data)
```

```
RE_log = log(RE_data)

#Mean and standard deviation of the natural logs for the log normal distribution
#Means
RA_mean = mean(RA_log)
RB_mean = mean(RB_log)
RC_mean = mean(RC_log)
RD_mean = mean(RD_log)
RE_mean = mean(RE_log)
#Standard deviations
RA_std = sd(RA_log)
RB_std = sd(RB_log)
RC_std = sd(RC_log)
RD_std = sd(RD_log)
RE_std = sd(RE_log)

#Probability density function for a risk A
#In this version of the code notice the increased frequencies for refined model
A = rpois (10000, 2) * rlnorm (10000,RA_mean,RA_std)
summary(A)
quantile (A, c(0.999))
hist(A)

#Probability density function for a risk B
B = rpois (10000, 5) * rlnorm (10000,RB_mean,RB_std)
summary(B)
quantile (B, c(0.999))
hist(B)

#Probability density function for a risk C
C = rpois (10000, 3) * rlnorm (10000,RC_mean,RC_std)
summary(C)
```

```
quantile (C, c(0.999))
hist(C)

#Probability density function for a risk D
D = rpois (10000, 8) * rlnorm (10000,RD_mean,RD_std)
summary(D)
quantile (D, c(0.999))
hist(D)

#Probability density function for a risk E
E = rpois (10000, 2) * rlnorm (10000,RE_mean,RE_std)
summary(E)
quantile (E, c(0.999))
hist(E)

#All risk histograms for refined case
par(mfrow = c(3, 2))
hist(A, main = "Risk A profile", xlab = "Impact M€")
hist(B, main = "Risk B profile", xlab = "Impact M€")
hist(C, main = "Risk C profile", xlab = "Impact M€")
hist(D, main = "Risk D profile", xlab = "Impact M€")
hist(E, main = "Risk E profile", xlab = "Impact M€")

#Return plot area to 1:1
par(mfrow = c(1, 1))

#All risk boxplots for refined case
par(mfrow = c(3, 2))
boxplot(A, main = "Risk A profile", xlab = "Impact M€",horizontal=TRUE)
boxplot(B, main = "Risk B profile", xlab = "Impact M€",horizontal=TRUE)
boxplot(C, main = "Risk C profile", xlab = "Impact M€",horizontal=TRUE)
boxplot(D, main = "Risk D profile", xlab = "Impact M€",horizontal=TRUE)
```

```
boxplot(E, main = "Risk E profile", xlab = "Impact M€",horizontal=TRUE)

#Return plot area to 1:1
par(mfrow = c(1, 1))

#Total annual losses Million €
total_risk = A+B+C+D+E
summary(total_risk)
VaR = quantile (total_risk, c(0.999))
hist(total_risk, main = "Histogram of annual total losses (million €)", breaks = 10,
    xlab = "Annual total loss impact bins", labels = TRUE, col="dodgerblue3", ylim = c(0,4000))
abline(v=VaR,col="red") #Value at risk 99,9% in histogram
text(x=115, y=2500, 'Value at risk 99,9%')

# Cumulative distribution function (CDF) ----------------------------------

#Cumulative distribution function: Ascending
risk_data = data.frame(A, B, C, D, E)
ggplot(risk_data, aes(total_risk)) +
  labs(title="Total risk CDF", x="Lossess in M€", y="Percentage")+
  geom_vline(xintercept = VaR, color = "red")+
  annotate("text", x=VaR, y=0.5, label= "99,9% VaR")+
  stat_ecdf(geom = "step") +
  theme_classic()

#Cumulative distribution function: descending (loss exceedance curve)
CDF = ecdf(total_risk)
DF <- data.frame(x = sort(total_risk),
                 y = 1-CDF(sort(total_risk)))
# plot
ggplot(data=DF, aes(x, y) )+
  geom_line(lty = "solid")+
```

```
 labs(title="Total risk loss exceedance curve", x="Lossess in M€", y="Percentage")+
 geom_vline(xintercept = VaR, color = "red")+
 annotate("text", x=VaR, y=0.2, label= "99,9% VaR")+
 theme_classic()



# Correlations -----------------------------------------------------------
install.packages("faux")
library(faux)
#Checking current correlations with risks A-E
output = total_risk
inputs = data.frame(A, B, C, D, E)
corrs = cor(inputs)
corrmat = corrplot(corrs, method = "number",
         col = COL2('RdBu', 10),
         tl.col = "black",
         title ="Correlation matrix of risks A-E",
         mar=c(0,0,2,0),
         diag=FALSE)
#Add a risk F that is correlated with risk E
inputs$F = rnorm_pre(inputs$E, mu = 10, sd = 2, r = 0.7, empirical = TRUE)

#Check correlations with the new risk F
corrs_F = cor(inputs)
corrmat_F = corrplot(corrs_F, method = "number",
         col = COL2('RdBu', 10),
         tl.col = "black",
         title ="Correlation matrix of risks A-F",
         mar=c(0,0,2,0),
         diag=FALSE)

#Scatterplot of the risks E and F to see their relation
```

```
plot(inputs$E,inputs$F,
     main = "Scatterplot of Risks E and F (coefficient 0.7)",
     xlab = "Risk E", ylab = "Risk F",
     pch = 19, frame = FALSE)
# plot a regression line
abline(lm(inputs$F~inputs$E,data=inputs),col='red')

#Histogram of total risks including risk F
total_risk_F = A+B+C+D+E+inputs$F
VaR_F = quantile (total_risk_F, c(0.999))
hist(total_risk_F, main = "Total losses with Risk F", xlab = "Impact M€")
abline(v=VaR_F,col="red") #Value at risk 99,9% in histogram
text(x=VaR_F, y=2500, 'Value at risk 99,9%')



# Simulation Decomposition (SimDec) ---------------------------------------
install.packages("devtools")
library(devtools)
install_github("Simulation-Decomposition/simdec-R")
library(Simdec)
install.packages("gridExtra")
library(gridExtra)
install.packages("kableExtra")
library(kableExtra)

#Data into SimDec
output = total_risk
inputs = inputs

#Significance indices
sig <- significance(output, inputs)
SI  <- sig[[2]] # Saving SI as a separate for later use
```

```
FOE <- sig[[3]] #First order effects
SOE <- sig[[4]] #Second order effects
print(SI)
print(FOE)
print(SOE)

#Run decomposition
# Initialize decomposition
dec_limit      =  0.8 # cumulative significance threshold; % (used to decide how many variables to take for decomposition)
threshold_type  =  1   # 1 for 'percentile-based' (same amount of observations in each state), 2 for 'median-based' (equally-spaced ranges)
output_name    =  "Total_risk"
var_names      =  colnames(inputs)
dec            =  decomposition(output, inputs, SI, dec_limit = 0.8,
                         manual_vars = NULL, manual_thresholds = NULL,
                         manual_states = NULL, threshold_type = 1,
                         var_names = colnames(inputs))
scenario       = dec[[1]]
scenario_legend = dec[[2]]
var_names_dec   = dec[[4]]
print(SI)
print(scenario_legend)
print(var_names_dec)

#SimDec visualization
# Initializing plot for automatic aesthetics
axistitle   = c()
main_colors = c()
visuals     = build_simdec_chart(output, scenario, scenario_legend,
                         main_colors, axistitle, var_names_dec)
SimDec_Plot   = visuals[[1]]
Legend_Table = visuals[[2]]
```

```
print(SimDec_Plot)

print(Legend_Table)
```

Appendix 7. Refined case model R visualizations

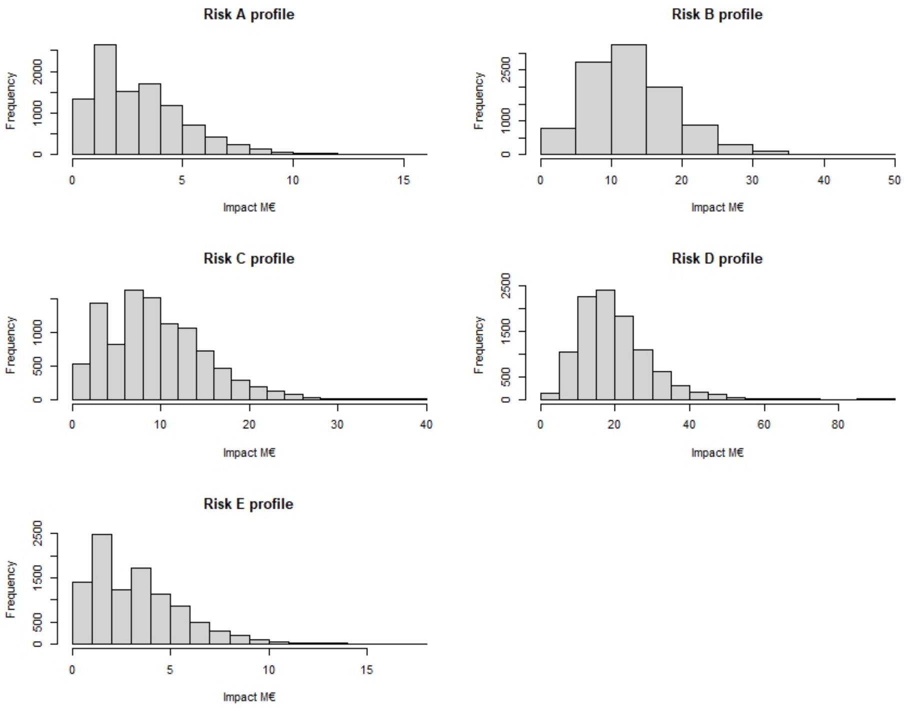


Figure 1. Refined model risks’ A-E risk profile histograms.

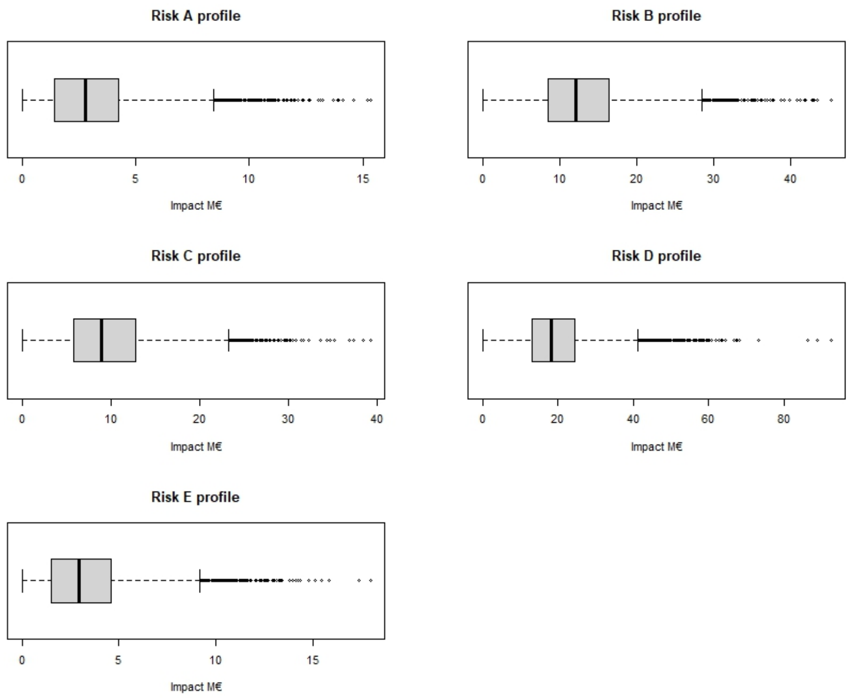


Figure 2. Refined model risks’ A-E risk profile boxplots.

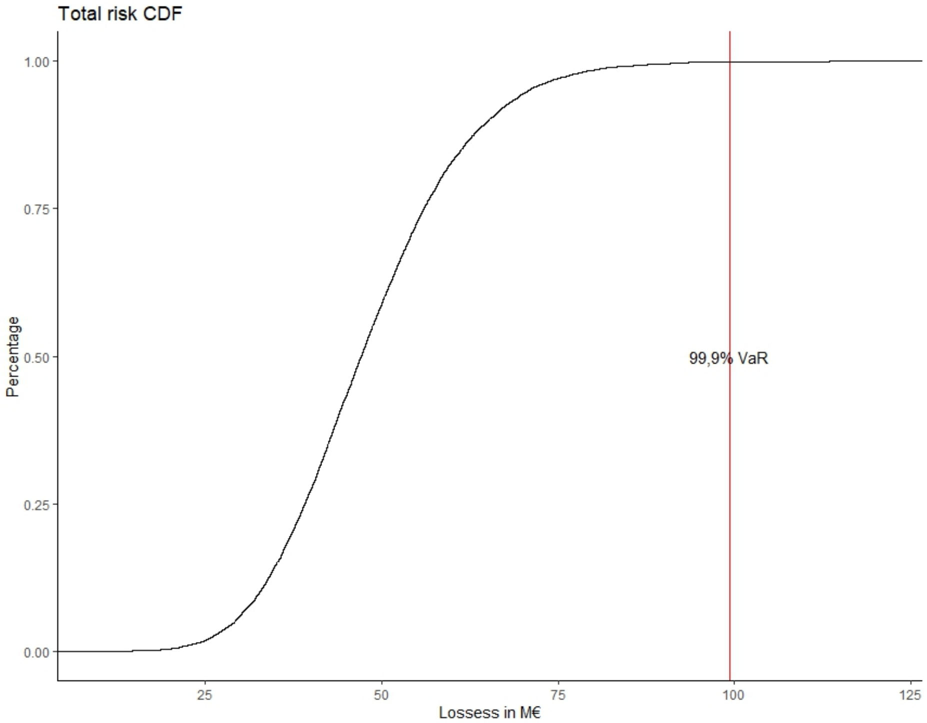


Figure 3. Refined model cumulative distribution of total losses.

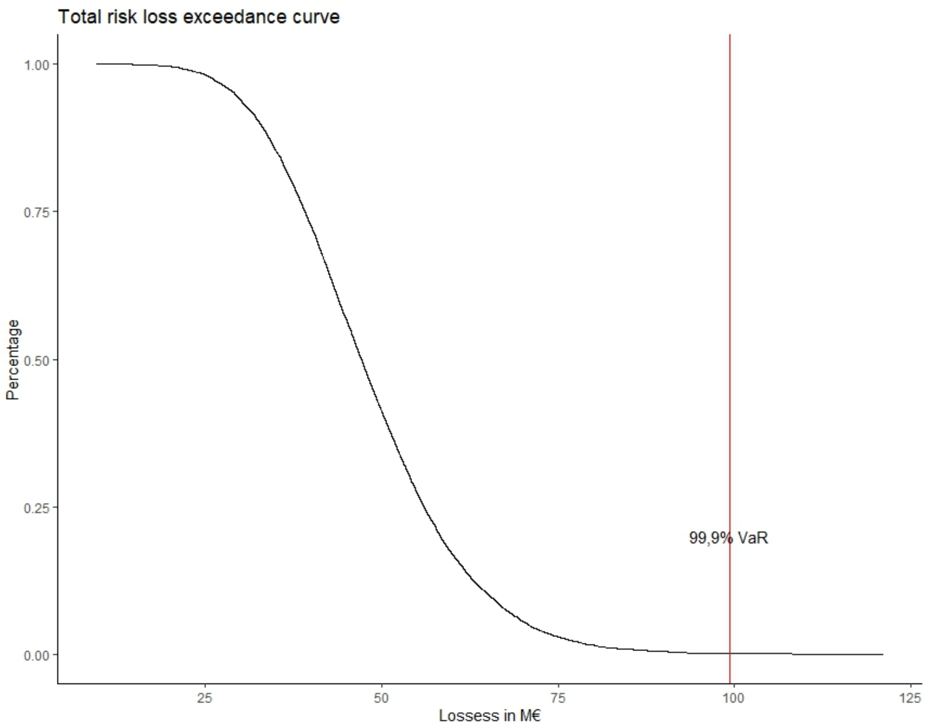


Figure 4. Refined model loss exceedance curve (LEC) (complementary cumulative distribution function, CCDF).

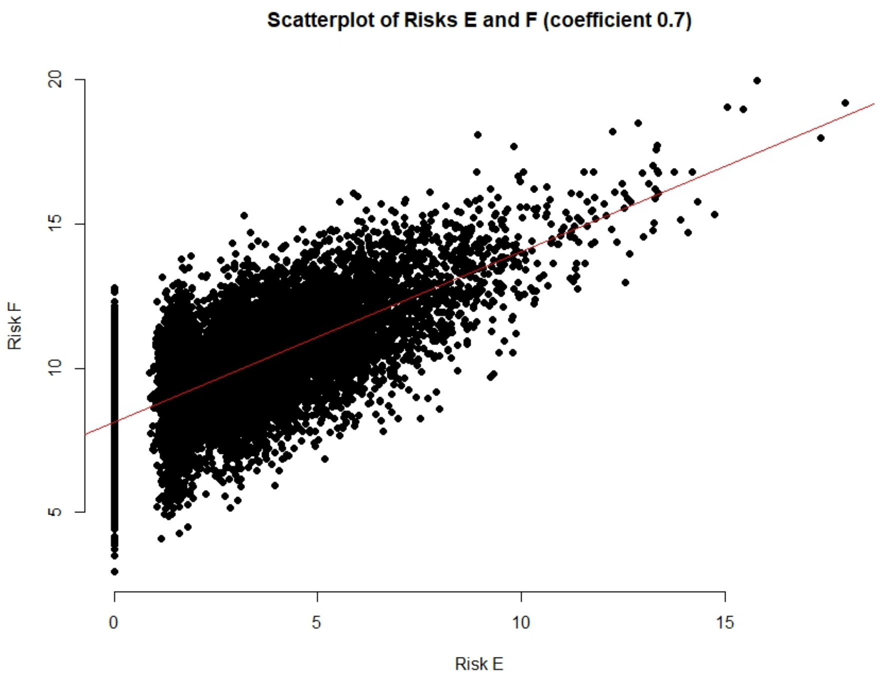


Figure 5. Correlation matrix of the risks A-E excluding correlation.

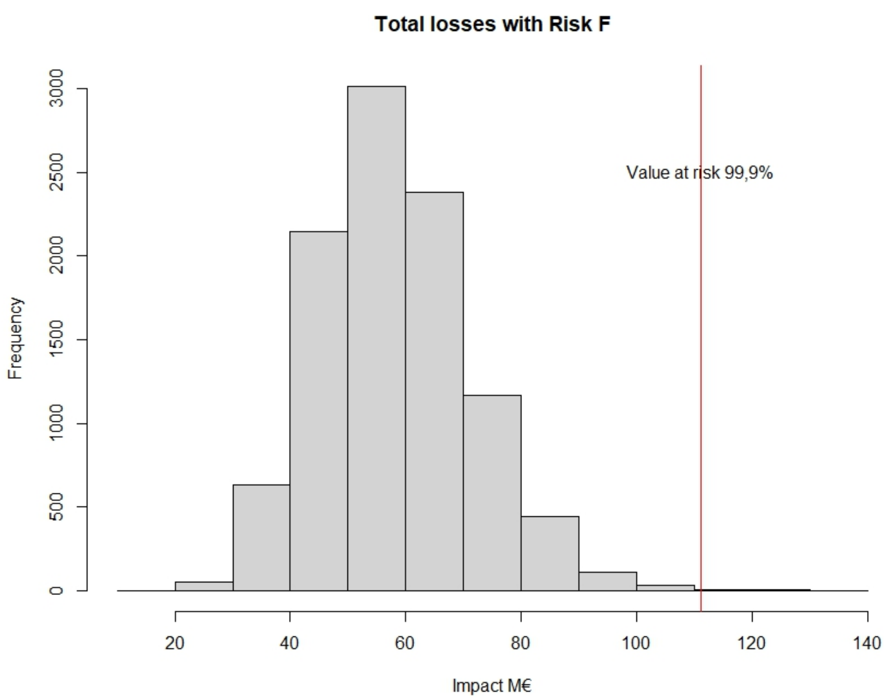


Figure 6. Histogram of total risk losses with risk F. VaR rose about 10M€.