MS-E2177 - Seminar on Case Studies in Operations Research

Final report - Inclus

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1 Introduction

1.1 Background

This is the final report of a project in collaboration with Inclus on understanding and developing tools and methodologies for risk management in construction projects, specifically, the use of Monte Carlo simulation for quantifying and ranking the risks.

Inclus is a company founded in 2016 with roots in peace mediation at CMI and methodology developed in collaboration with Aalto University's Systems Analysis Laboratory. It specializes in developing technological tools for building common understanding. Inclus' software and technology have been in use in negotiations between direct conflict parties and has been utilised in decision-making situations and in risk management, both within and between companies.

Monte Carlo simulation is used for estimating mathematical functions and the outcomes of complex systems by using random sampling and predefined probability distributions Atanassov and Dimov [1]. The method simulates a given system by repeatedly sampling the distributions of the underlying random variables. The outcome of the simulation depends on the distributions of these random variables and these must be properly defined. Common distributions for the random variables include for example uniform, exponential, normal, and Poisson distributions.

During our study, we frequently encountered the PERT (Program Evaluation and Review Technique) framework as a common tool utilized for risk management in the construction industry. In short, the PERT framework utilizes a variation of the beta-distribution defined by three parameters: a (minimum), m (most likely), and b (maximum). The activities/stages/events of a construction project can be assessed with the PERT framework to form a distribution for the duration/cost of each, which can then be utilized for example in a Monte Carlo simulation process. The PERT framework would have required some changes to Inclus' current data collection methods, which is why we only briefly outline this process as more of a prospective solution for future development.

In industry, Monte Carlo simulation is often used as a tool of risk management. It is commonly used in finance and project management among other use cases. In construction projects, there is a convention of using Monte Carlo based tools to quantify the scheduling and monetary risk, which is often done based on the PERT method outlined above. Another approach to using Monte Carlo is to first qualitatively assess the likelihood and severity of different scenarios often based on questionnaires to the project managers. The answers are then modelled with the help of some probability distributions and Monte Carlo simulation is performed yielding a probability distribution of the risk of different decisions that can in turn be used to rank or compare the risks.

Methods relying on human judgement are vulnerable to biases of the project managers or other people filling out the questionnaires. These methods also often assume the events to be uncorrelated and thus are incapable of modelling cross-dependencies between the different risks.

Inclus has developed a tool for risk management based on collecting the risk estimates from a variety of people independently leading to less bias. This data could be used in Monte Carlo simulation to get more reliable estimates of the risk in construction projects.

By utilizing state of the art literature and working closely with Inclus, we present, in this report, a risk matrix -based framework to utilize Monte Carlo simulation in risk management along with a scheduling and budget planning scheme based on the PERT method. We also discuss their relevancy and applicability for Inclus.

In section 2, titled Literature Review, we explore the literature on risk management in construction projects and provide the necessary background to the methods discussed in the following section. After the section outlining the methods proposed, called Data and Methods, we go on to present the results for the Inclus use case in section Results. Finally, we discuss the findings and draw conclusions based on the needs of Inclus on each of the methods presented.

1.2 Objectives

To investigate how Monte Carlo simulation can best be used for risk management in construction projects by Inclus, there are multiple factors to consider. First the prior art needs to be understood and then these findings can be compared the current capabilities of Inclus. The usefulness of the models can then be evaluated for Inclus based on which suggestions can be made. To accomplish all this, we divide the objectives of this project into four categories, literature review, presentation of simulation results and understanding how cross-dependencies between risks are taken into accont in current methods.

We perform a literature review on project risk modelling and explore risk management related simulation tools with an emphasis on construction. The aim of simulation is to quantify the likelihood/expectation of realizing certain project related risks such as cost, time or quality. Our goal is to take stock of how risk management simulations have been done before, which includes identifying construction events contributing to project risk, gathering expert/stakeholder insights, modelling the distribution of possible events, and performing a simulation of the project risk. We also aim to understand the main challenges in the area, and how to tackle some of the problems in the field. We present existing risk management related simulation tools. Finally, we assess how the literature can help Inclus to simulate the total risk of a construction project, and how they might identify events that have a large impact on the realized risk.

For presenting the simulation results, our objective is to understand what information in addition to the information that Inclus presents in their product is helpful for risk analysis. The aim of the project is to focus on Monte Carlo simulation tools for risk management and we aim to find efficient ways of communicating the results of the simulations. The results should be helpful and easy to understand to the customers of Inclus. We get information on what information could and should be presented through exploring literature and existing tools. We give recommendations and ideas on what information should be presented and how in a few concrete use cases.

Our objective for understanding how modeling and simulating risk cross-dependencies has been done before will be centered around what challenges there are in implementing it in practise, and how to resolve some of them. Our goal is to give recommendations on how to implement modelling and simulation of cross-dependencies in practise.

Beneficial project outputs for Inclus

We briefly summarize what Inclus expects our project to provide:

1. Recommendations on how to implement Monte Carlo –style simulations on top of data collected with Inclus. Focus on construction projects, but would likely be used in other situations too.
2. Recommendations on how to translate multiple differing risk assessments to a Monte Carlo –compatible probability distribution; and what distributions should be supported.
    - Likely to be implemented with a design where the service suggests the

distribution and its parameters, but the user can still change the decisions before running the simulation.

3. Recommendations on how to present simulation results.

    - Best case: end user easily understands the results, but still feels they are advanced and can showcase their own professionalism by presenting the results forward.

4. Suggestions/ideas on how to combine risk cross-dependency data with the simulation.

2 Literature Review

Early forms of risk management have been practiced at least since the Roman empire but modern forms of academic risk management started after the second world war in the 1950s and corporate financial risk management started developing in the 1970s (Dionne [2]). During this relatively short time, the risk management has given rise to a new industry, the insurance industry and risk management has become a obligatory part of organizations, governments and corporations alike (Dionne [2]). With the expansion of the EU in 1990s and early 2000s there was a growing need for more organized and efficient construction projects in Europe. This lead to a more rigorous integration of risk management practices in the construction industry (Schieg [3]).

General concepts and a framework for risk management in construction projects is outlined by Schieg [3]. He discusses risk management process in construction and defines it as a continuous cyclic process starting with risk identification, followed by risk analysis and then risk assessment. These make up the risk valuation part of the risk management process. It includes everything related to gathering data and understanding of the project along with the consequent analysis and assessment of the identified risks based on their estimated probability and impact. After the risk valuation part, the risk governing part of risk management follows. This includes risk control, risk surveillance and goal control which together make up the active part of risk management where the results of the valuation are used in strategic way to take action into the identified risks and mitigating the possible effects along with ensuring no new risks emerge. They also outline the importance of risk management over the lifetime of the construction project. While organisations may use different terminology, the general ideas outlined here are followed by most risk management processes in construction. A similar process is discussed in detail in Zou and Zhang [4].

Risks can be difficult to identify and analyse quantitatively as they are inherently stochastic and they have, by definition, not yet happened or the consequences of the actions that include the risks have not yet come into fruition. To tackle this uncertainty, Goodpasture [5] discusses several different methods, such as expert evaluations, probabilistic methods, analysis of historical data, machine learning methods, simulation models. Each of them have its strengths and downsides. The main issue these methods try to tackle is the lack of certainty about the identified possible risks and a method that has within the last few decades started gaining traction, not only from academia but also from industry, are Monte Carlo based simulation methods. In general, Monte Carlo simulation is based on first identifying the variables to simulate and then fit them to some distributions based on their properties. Then, the model consists of randomly sampling the distributions to yield some kind of resulting distribution that has been averaged over multiple samples (Rezaie et al. [6]). This step may include combining the sampled values from the variable distributions using some equation to obtain the measure of interest, e.g. total risk. The idea is that the averaging over randomly sampled estimates can uncover the underlying distribution of the measure of interest in the system. An introduction to Monte Carlo simulation methods and considerations thereof is presented in Bonate [7].

In risk management of construction projects the goal of the risk assessment is usually to find the risk factors that might affect either the budget, schedule or quality of the project along with safety and environmental factors (Zou and Zhang [4]). Budget and schedule overrun risks can be investigated using the PERT method. Here respondents give optimistic, likely and pessimistic cost or duration valuations of different sections of the project at hand. In the traditional PERT method, the estimates are naively used as given but in the Monte Carlo-based PERT, as discussed in Tysiak [8], these answers are fitted to a variant of the beta distribution that can be fed to a Monte Carlo simulation that randomly samples the distribution to quantify the uncertainty in the collected answers. The results for each section can then be interpreted to as revealing how likely the costs or time will run out and critical paths or bottlenecks may be identified. Examples of the usage of such frameworks in both cost and time related risks can be found in Bouayed [9] Naderpour, Kheyroddin, and Mortazavi [10] Senova, Tobisova, and Rozenberg [11].

Monte Carlo simulation has been used in understanding the occupational health risks of dust in construction projects (Tong et al. [12]). Here, Monte Carlo simulation is used to quantify the uncertainty in health risks for workers in a construction mega-project based on what zone they were working in. Another approach to utilise Monte Carlo in construction projects is proposed by Qazi et al. [13], where risk matrix data is used to simulate, with Monte Carlo, the risk exposure for all identified risks later to be used for prioritization. This study focuses specifically on prioritizing sustainability risks in construction projects. This was to the best of the authors knowledge, the first time the combination of risk matrix-based techniques have been used together with Monte Carlo simulation in risk management.

Risk matrices have been identified as one of the most common techniques for quantifying risks in project management, both in practice and in literature (Qazi and Dikmen [14]). Risk matrices are a two dimensional grid of probability and impact as illustrated by Qazi and Dikmen [14] in figure 1 below. The different risks that have been identified are evaluated, often using a Likert-scale as in the picture from 1 to 5 for both probability of occurrence and the impact if it did occur. These values are then usually averaged over answers and then multiplied together to yield a risk exposure that can be put into one of the squares in the risk matrix (Duijm [15]). The risk zones are derived, often based on the decision makers risk profile simply as arbitrary thresholds above which a risk exposure is considered to be high, medium or low. This is a common practice not only in the construction industry but in project risk management in general. The downside of this method is mainly that it does not account for uncertainty in the answers and is unable to distinguish heavy tailed risks due to the use of average statistics (Qazi and Dikmen [14] Duijm [15]).

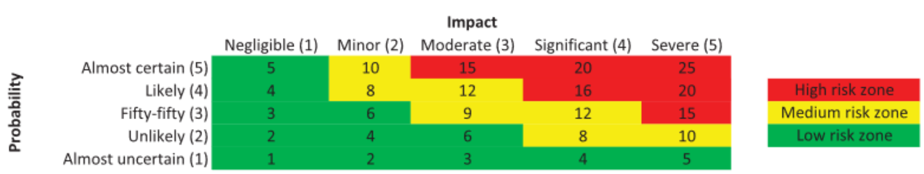

Figure 1: Illustrative risk matrix showing how estimated probabilities and impact are arranged into the 2D-grid structure and how partitioning can be done into different risk zones represented by color (Qazi and Dikmen [14]).

To combat the downsides of traditional risk matrix-based methods, Qazi et al. [13] modified the traditional approach to include a Monte Carlo simulation step before partitioning the risks into the risk matrix. They collected the Likert questionnaire data from multiple respondents for each of the sustainability risks and used the discretised distribution of the answers as the input to the Monte Carlo simulation that then was able to quantify the uncertainty in the answers and take into account heavy tailed risks by producing a distribution for the risk exposures. Then, a traditional risk matrix was developed and based on the boundaries of the risk zones the risks were prioritized with a novel prioritization metric they proposed. While this was done specifically for sustainability risks, this framework could be generalized to work in other risk management situations as well. In this report we will demonstrate how this framework can be applied in the Inclus case.

With all the aforementioned methods and techniques there is fundamental problem. No cross-dependencies between the risks are taken into consideration. Kwan and Leung [16] presents a framework for including the assessment of risk dependencies into project risk management. They first discuss different ways to model cross-dependencies in data in general. The discussed methodologies were: tree-based analyses, Markov Analysis, Bayesian networks and goal-risk models. The method they propose, treats the dependencies as directed edges in a graph and they discuss in detail with case examples how to measure and analyse the risks when taking the cross-dependencies into account. However, the risks in the cases had only few dependencies and as the authors pointed out, the same framework might be difficult to use in cases with more risks and more dependencies. Also, the problem of how to identify the risk cross-dependencies in a questionnaire still remains. If one wanted to utilize Monte Carlo simulation approaches for the benefits discussed earlier, this framework does not provide a straightforward way to do so. These are issues that would require further investigation.

3 Data and Methods

In this section, two frameworks for simulation in risk management are presented.

3.1 Program Evaluation and Review Technique (PERT) in project management

The PERT framework requires eliciting the minimum (a), most likely (m), and maximum (b) duration/cost for events within a larger project. The original method was presented by Malcolm et al. [17] in 1959 as a method for approximating project durations within an R&D context. Malcolm et al. present the mean and variance for the duration of a single event defined by the three parameters as:

$$\mu_x = \frac{a + 4m + b}{6}$$
$$\sigma_x^2 = \frac{(b-a)^2}{36}.$$

The authors simply state that the underlying distribution is a Beta-distribution defined by the shape-parameters α and β and the domain-parameters a and b:

$$f(x) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) + \Gamma(\beta)} \frac{(x-a)^{\alpha-1}(b-x)^{\beta-1}}{(b-a)^{\alpha+\beta-1}},$$

where $\Gamma(.)$ is the Gamma-function. Since the parametrization of α and β as well as the inclusion of m were not evident from the original article, the method caused considerable confusion and came under scrutiny even by one of the original authors, see Clark [18] and Miklós and Orsolya [19]. There are reverse-engineered parametrizations for α and β which depend on a, m, b such that the mean and variance will be approximated as above, see Davis [20]. Various modifications of the PERT method also exist, but the underlying principal is the same: begin by eliciting from experts/stakeholders the minimum, most likely, and maximum parameters and utilize those in computing the expected duration/cost of events and/or of the total project.

The PERT approach can be utilized either as the original authors intended – using the parametrized mean and variance approximations directly – or by forming the underlying beta distribution (or PERT/PERT-Beta distribution as in much of the literature) and sampling from it in a Monte Carlo simulation as done by Hovhannisyan et al. [21]. Furthermore, even though the PERT method was originally intended for consideration of project duration, it also seems applicable to cost consideration simulations as per Hosein, Ali, and Seyedmehdi [22].

The PERT method was discussed and presented to Inclus, which found it as interesting but too far out of the companies current offering and focus; the method would have required a new survey/question format (for which we would not have had data) and the focus on time/duration simulation for different stages of a construction project was seen more-so as a project management tool as opposed to pure risk management and/or risk assessment. If Inclus was to consider the PERT method in future development, our summarized recommendations would be to:

- Create a new survey template that requests for participants assessments on the minimum, most likely, and maximum values of the measure in question

- Aggregate survey participant answers (e.g. by mean)
- Form event-specific PERT-Beta distributions
- Use these distributions for sampling in a Monte Carlo simulation

However, prior to a full-scale solution there remains some key questions to consider, such as:

1. Choosing the most relevant form of various PERT-Beta distributions
2. The applicability of the method (and Beta distributions in general) in cost related settings as opposed to duration settings
3. Benchmarking of the method; how successful (in terms of accuracy) have applications been when compared to realized project durations and/or costs
4. Cross-dependencies; if some phases of a project are chronologically ordered, delays in an earlier will of course affect the later

3.2 Risk prioritization with risk matrix based Monte Carlo simulation

We modified the process proposed by Qazi et al. [13] to fit the objectives of this project and to work for asymetric risk matrix partitions. Figure 2 shows the modified outline of the process. The focus of the outline was changed from sustainability risks in construction projects to risks in construction projects, since the project is focused on construction projects and not only on sustainability risks in construction projects. Next, we present each step of the process separately.

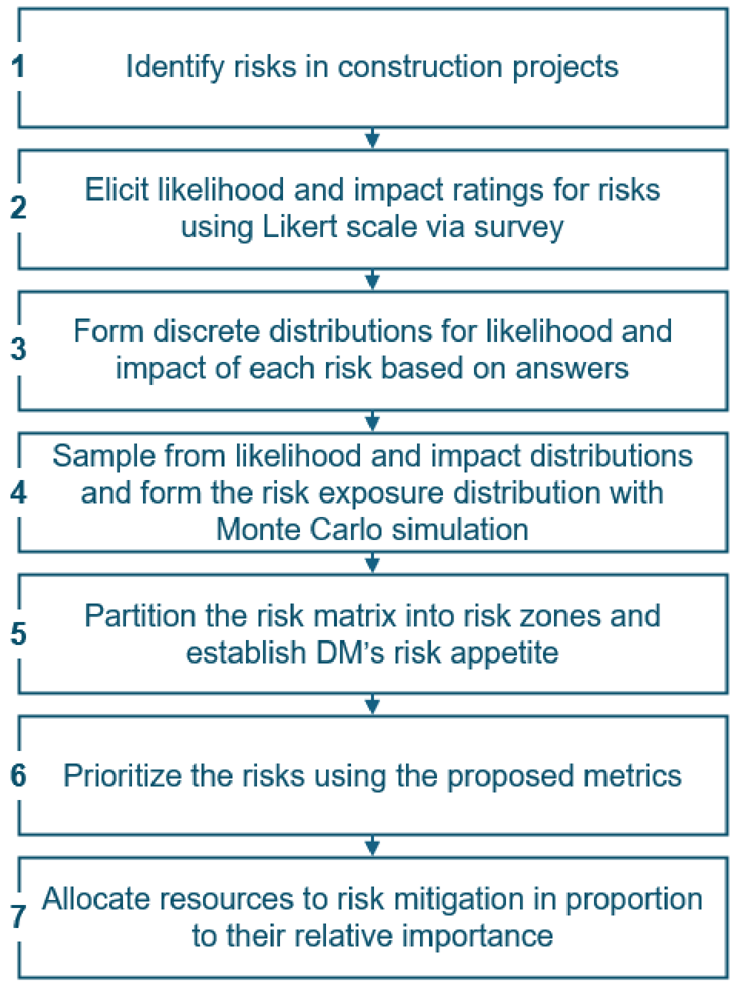

Figure 2: The outline of the proposed process

1. Identify risks in construction projects - The risks of the construction projects are identified. Inclus' platform can be used to identify risks. No new features are needed on Inclus' platform to perform this step in the process.

2. Elicit likelihood and impact ratings for risks using Likert scale via survey - The likelihoods and impacts are assessed for each risk on a Likert scale. Inclus' platform can be used to assess the likelihoods and impacts of risks. No new features are needed on Inclus' platform to perform this step in the process.

3. Form discrete distributions for likelihood and impact of each risk based on answers - The distributions are formed based on the assessments. For each risk, the distribution of the impact is formed by the frequencies of the results of the assessments. For instance, if 30% of the participants assess that the impact of the risk is 3, then in the distribution of the impact of the risk, there is a 30% probability that the impact of the risk is 3. The distribution of the likelihood is obtained in the same way. For instance, if 65% of the participants have assessed that the likelihood of a risk is 3 and the rest assessed that the likelihood is 4, the distribution of the likelihood is 65% probability for likelihood 3 and 35% probability for likelihood 3. Forming the probability distributions for likelihood and impact would be a new feature on Inclus platform, but it would not be difficult to implement, since Inclus already collects the assessments of likelihoods and impacts from multiple participants on their platform.

4. Sample from likelihood and impact distributions and form the risk exposure distribution with Monte Carlo simulation - The Monte Carlo simulation is done by sampling likelihoods and impacts for each risk from their respective likelihood and impact distributions. The sampled likelihood-impact pairs are stored. For each likelihood-impact pair, the risk exposure is calculated and stored. Risk exposure (RE) is given by

$$RE = L \times I,$$

where L is the likelihood and I is the impact. Monte Carlo simulation would be a new feature on Inclus' platform.

5. Partition the risk matrix into risk zones and establish the decision makers risk appetite - The risk matrix has to be partitioned into risk zones. The risk matrix can be partitioned into any number of risk zones. The risk matrix can be symmetric or asymmetric. Partitioning risk matrices would be a new feature on Inclus' platform. The risk appetite of a risk zone is the maximum probability of a risk being in a risk zone, such that no risk mitigation strategies are needed. For instance, if a risk zone has the risk appetite 15 %, a risk that has a smaller probability than 15 % of being that risk exposure zone is not considered significant. The risk appetite for a risk zone is $(1 - RA_{Z_j})$, where Z_j is risk zone j. Establishing the decision makers risk appetite would require a new feature on Inclus' platform.

6. Prioritize the risks using the proposed metrics - We suggest two metrics for risk prioritization, the normalized criticality index and high risk exposure zone probability. The normalised criticality index is proposed by Qazi et al. [13]. Qazi et al. [13] assumes a risk matrix partition of three risk zones - low risk zone (Z_L), medium risk zone (Z_M),

high risk zone (Z_H)- and that the risk appetite of the decision maker of the zones Z_M and Z_H is less than 1. Then the normalized criticality index is calculated for risk R_i by

$$NCI_{R_i} = \frac{\max\{0, P(R_i \in Z_M) - (1 - RA_{Z_M})\} + \max\{0, P(R_i \in Z_H) - (1 - RA_{Z_H})\}}{\sum_i \max\{0, P(R_i \in Z_M) - (1 - RA_{Z_M})\} + \sum_i \max\{0, P(R_i \in Z_H) - (1 - RA_{Z_H})\}},$$

where NCI_{R_i} is the normalized criticality index for risk R_i, Z_M is the medium risk zone, Z_H is the high risk zone, $1 - RA_{Z_M}$ is the risk appetite of the medium risk zone, and $1 - RA_{Z_H}$ is the risk appetite of the high risk zone. The normalized criticality is in the range $[0, 1]$.

In general, $P(R_i \in Z_j)$ can be estimated by calculating the frequency of the probability-impact pair of being in the cells in zone Z_j. When the risk matrix partition is symmetric, $P(R_i \in Z_j)$ can be determined by estimating the probability of the risk exposure of R_i being in zone Z_j. Figure 3 shows a symmetrically partitioned risk matrix. The probability $P(R_i \in Z_H)$ is the probability that the risk corresponds to one of the cells with red color. Since matrix is symmetric, all the cells with red color correspond to a risk exposure that is greater or equal to 15. Calculating $P(R_i \in Z_j)$ is different in the case of an asymmetric matrix. Figure 4 shows an asymmetric matrix. Similarly to the symmetric risk matrix partition, the probability $P(R_i \in Z_H)$ is the probability that the risk corresponds to a red cell. However, when the risk matrix partition is asymmetric, we consider the probability-impact pair instead of the risk exposure. The distribution of the risk exposure can not be used, since there is both a cell corresponding to the risk exposure 10 in both in the yellow medium risk zone Z_m and the red high risk zone Z_H. Therefore, the probability of each likelihood-impact pair has to be calculated and the probability $P(Z_j)$ is the sum of the probabilities of the likelihood-impact pairs that are in zone Z_j. In case of the asymmetric risk matrix partition in figure 4 and the high risk zone in red, $P(R_i \in Z_H)$ is the sum of the probabilities of the likelihood impact pairs that are red.

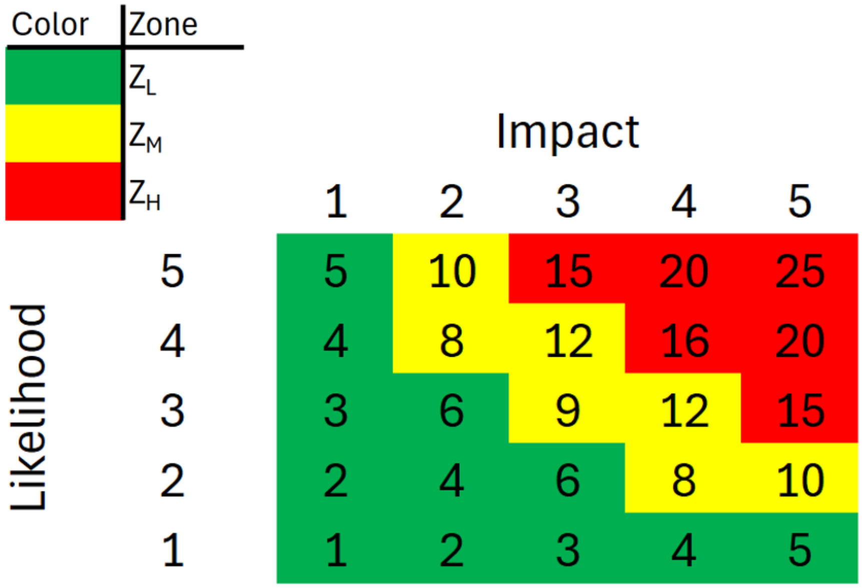

Figure 3: An example of a symmetric risk matrix partition.

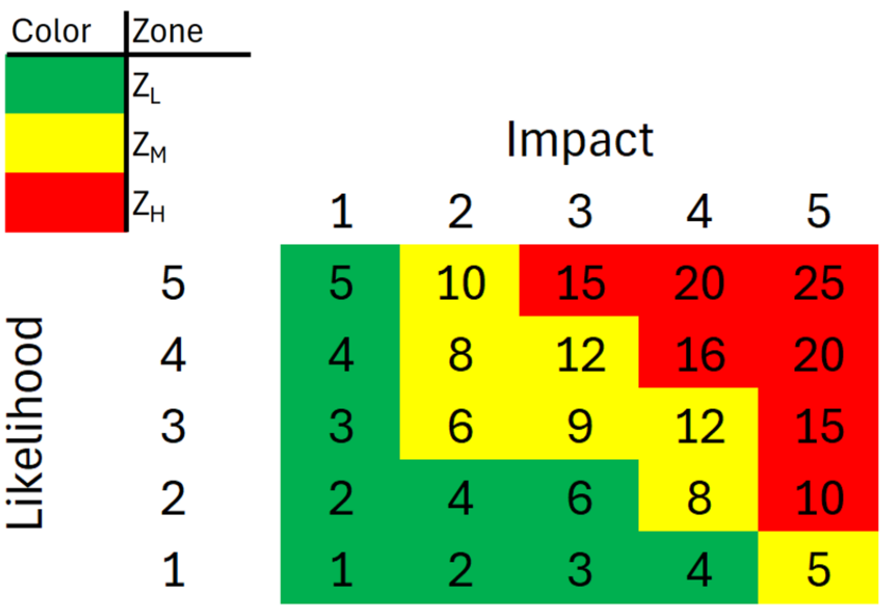

Figure 4: An example of an asymmetric risk matrix partition.

It may take some effort to understand the normalized criticality index. Therefore, we propose a simpler metric for risk prioritization. We propose ranking the risks according to their high risk zone probability

$$P(R_i \in Z_H).$$

The metric helps identifying the risks that, when combining the views of all the participants, are most likely to be in the high risk zone. Similarly, the risks can be ranked according to their probability of being in a general risk zone Z_j, or in multiple risk zones. If multiple risk zones are considered, the metric could for instance be a weighted average.

7. Allocate resources to risk mitigation in proportion to their relative importance - Allocate resources to risk mitigation of risks depending on their relative importance. The relative importance of each risk is the normalized criticality index of each risk.

4 Results

This section contains a demonstration of the process of risk prioritization with risk matrix based Monte Carlo simulation.

Simulated data from Inclus' platform is used. The data is artificially created, but the format of the data is real. The first step in the process is identifying risks. Figure 5 shows the identified risks in the example dataset.

- **Construction planning and solutions related risks**
  - #45 - Inadequate site investigation
  - #46 - Inadequate design
  - #47 - Construction delays
  - #48 - Regulatory compliance
  - #49 - Technology failure
  - #60 - Workforce availability and skills
  - #61 - Safety incidents
  - #62 - Cost overruns
  - #63 - Contractual disputes
- **Procurement and production risks**
  - #50 - Supplier insolvency
  - #51 - Component production delays
  - #52 - Material and component quality issues
  - #53 - Transportation issues
  - #54 - Price fluctuations
- **Local government and environment related risks**
  - #38 - Regulatory changes
  - #39 - Public opposition
  - #40 - Land acquisition issues
  - #41 - Cultural or archaeological issues
  - #42 - Local economic conditions
  - #66 - Weather and climate risks
  - #67 - Environmental impact
- **Life cycle, functionality and maintenance related risks**
  - #55 - Equipment failure
  - #56 - Inadequate maintenance
  - #57 - Technological obsolescence
  - #58 - Extreme weather conditions
  - #59 - Lifespan shortfall

Figure 5: The list of the identified risks in the example data.

The second step in the process is to assess the probabilities and impacts of the risks. On Inclus' platform, multiple people participate in the assessments of the likelihoods and impacts by giving their own estimates of the likelihoods and impacts. Figure 6 shows how the risks are assessed on Inclus' platform. In this example, the likelihoods of the risks are assessed on the scale: 1: Very unlikely 2: Unlikely 3: Uncertain 4: Likely 5: Almost certain. The impacts are assessed on the scale 1: Very small 2: Small 3: Moderate 4: Large 5: Very large.

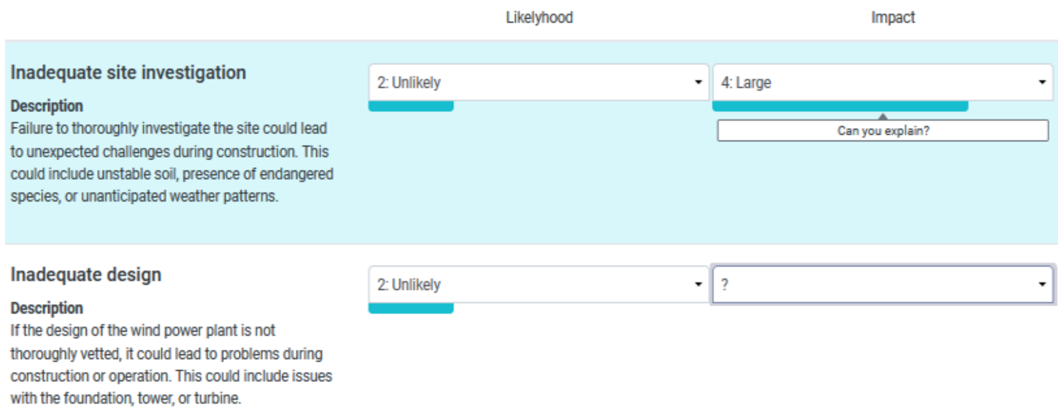

Figure 6: Assessing risks on Inclus' platform.

The third step of the process is to form discrete distributions for likelihood and impact based on the answers. The formed probability distribution represents the frequencies of the answers. Figure 7 shows the distributions for likelihood and impact for the risk "Component Production Delay". For instance, we can see that the probability of a likelihood of 3 is 45%, which means that 45% of the participants assessed that the likelihood is 3. Similar distributions are made to every risk.

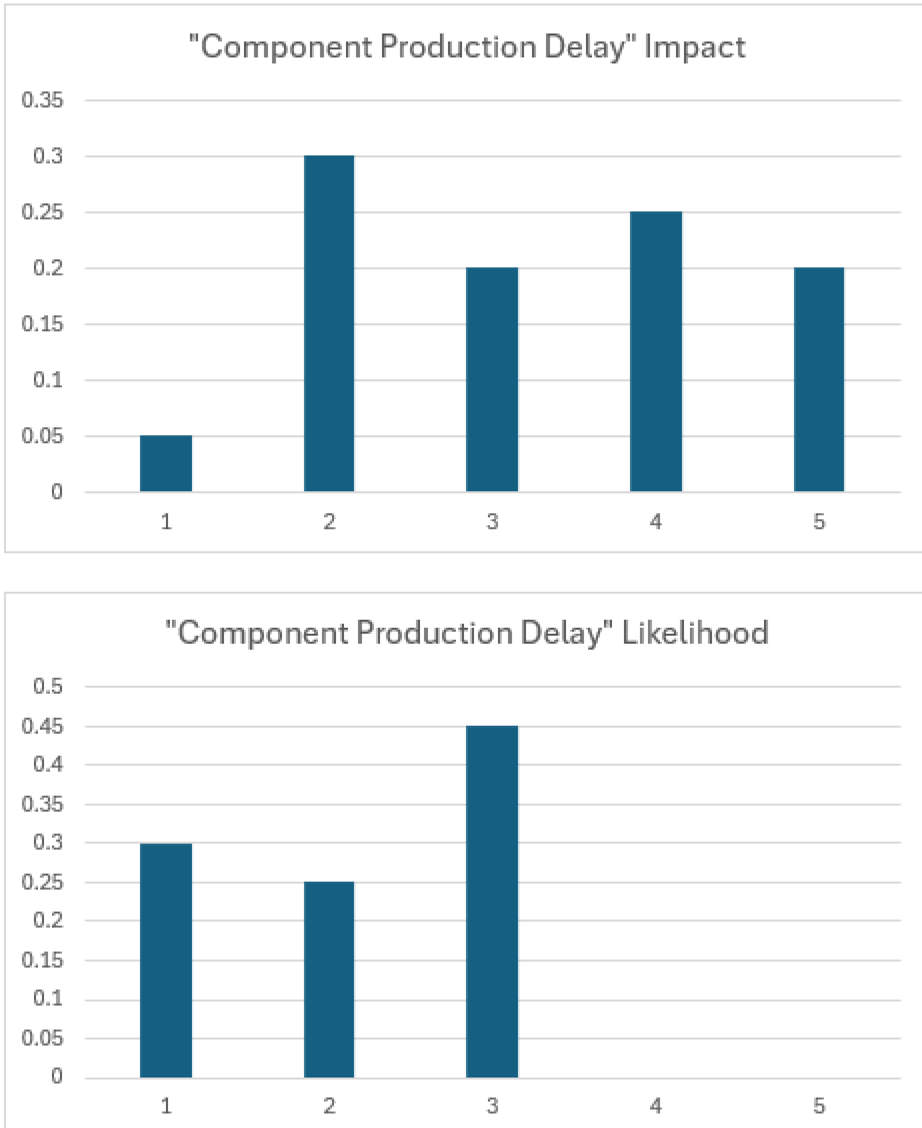

Figure 7: The likelihood and impact distribution of ”Component Production Delay”.

The fourth step in the process is to for each risk sample likelihood and impact pairs and calculate the risk exposure for each likelihood-impact pair to form the probability distribution of the risk exposure. Likelihood and impact pairs are sampled from the likelihood and impact distributions. The likelihood and impact pairs are stored. The risk exposure distribution is the probability distribution of the risk exposure for a risk. Figure 8 shows the risk exposure distribution for the risk "Component production delays". A risk exposure distribution is formed for each risk.

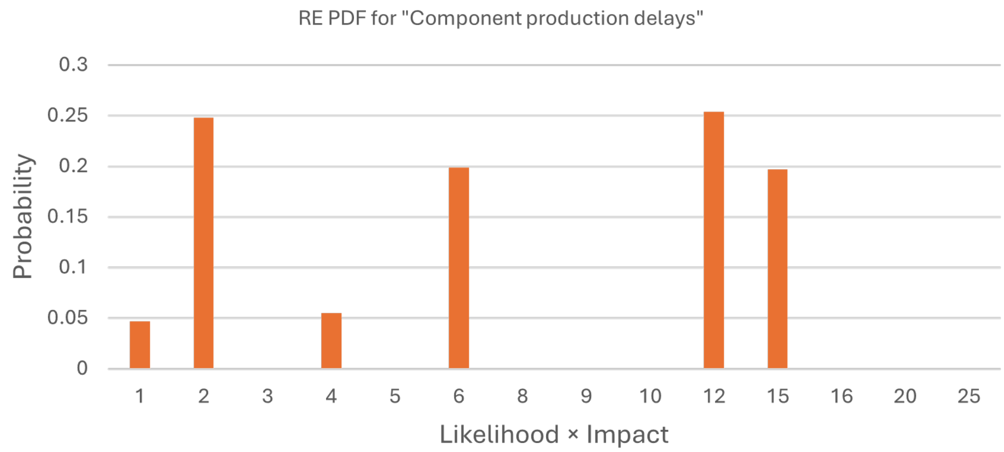

Figure 8: The risk exposure distribution for "Component Production Delay"

The fifth step in the process is to partition the risk matrix into risk zones and establish the decision makers risk appetite. This demonstration is for a symmetric risk matrix. See the methods section for how the method is applied to asymmetric matrices. Figure 3 shows the symmetric risk matrix partition used in this example.

The sixth step in the process is to prioritize the risks according the proposed metrics. Figure 9 shows the risks ranked based on the normalized criticality index with the medium and high risk zones. Figure 10 shows the risks ranked based on the high risk zone probability. The rankings of the risks generally vary 0-4 placements between the normalized criticality index and the high risk zone probability. One exception is the risk "Extreme weather conditions", which is ranked 8 placements higher with the normalized criticality index than with the high risk zone probability. The difference of the rankings is explained by that the normalized criticality index takes into account the probability of the risk being in the medium risk zone and the risk appetite, which high risk zone probability does not take into account. To compare the results to the metric used on Inclus platform, Figure 11 shows the risks ranked with the total risk. Total risk is likelihood times impact. There are differences between the rankings when using total risk, the normalized criticality index and the high risk zone probability, but the variation in the placements of the risks is generally less than or equal to 4. It can be seen that the ranking of the risk ”Extreme weather conditions” with total risk is close to the ranking of the risk with high risk zone probability.

	Risk Factor	Normalized Criticality Index
1	Construction delays	0.0487
2	Price fluctuations	0.0487
3	Local economic conditions	0.0457
4	Inadequate site investigation	0.0457
5	Weather and climate risks	0.0361
6	Equipment failure	0.0327
7	Extreme weather conditions	0.0327
8	Material and component quality issues	0.0327
9	Inadequate design	0.0326
10	Public opposition	0.0296
11	Contractual disputes	0.0288
12	Regulatory compliance	0.0260
13	Inadequate maintenance	0.0260
14	Transportation issues	0.0228
15	Supplier insolvency	0.0218
16	Cost overruns	0.0198
17	Lifespan shortfall	0.0196
18	Environmental impact	0.0162
19	Regulatory changes	0.0159
20	Component production delays	0.0131
21	Land acquisition issues	0.0105
22	Workforce availability and skills	0.0105
23	Technology failure	0.0035
24	Cultural or archaeological issues	0
25	Safety incidents	0
26	Technological obsolescence	0

Figure 9: The risks ranked according to the normalized criticality index.

	Risk Factor	High Risk Zone Probability
1	Construction delays	0.7530
2	Price fluctuations	0.7530
3	Local economic conditions	0.7050
4	Inadequate site investigation	0.6240
5	Inadequate design	0.5520
6	Contractual disputes	0.4940
7	Weather and climate risks	0.4940
8	Material and component quality issues	0.4510
9	Regulatory compliance	0.4510
10	Equipment failure	0.4110
11	Public opposition	0.4110
12	Supplier insolvency	0.3850
13	Cost overruns	0.3550
14	Inadequate maintenance	0.2980
15	Extreme weather conditions	0.2980
16	Lifespan shortfall	0.2430
17	Regulatory changes	0.2430
18	Transportation issues	0.2430
19	Component production delays	0.1970
20	Land acquisition issues	0.1970
21	Workforce availability and skills	0.0910
22	Environmental impact	0.0440
23	Technological obsolescence	0.0440
24	Technology failure	0.0440
25	Cultural or archaeological issues	0.0000
26	Safety incidents	0.0000

Figure 10: The risks ranked by the high risk exposure zone probability

	Risk Factor	Total Risk
1	Price fluctuations	18.3
2	Local economic conditions	17.2
3	Construction delays	16.6
4	Inadequate site investigation	16
5	Weather and climate risks	15.6
6	Inadequate design	12.8
7	Material and component quality issues	12
8	Public opposition	11.5
9	Contractual disputes	11.2
10	Equipment failure	10.9
11	Inadequate maintenance	10.3
12	Regulatory compliance	10.1
13	Lifespan shortfall	9
14	Extreme weather conditions	8.9
15	Supplier insolvency	8.5
16	Transportation issues	8
17	Regulatory changes	7.6
18	Cost overruns	7.6
19	Component production delays	6.9
20	Workforce availability and skills	6.3
21	Environmental impact	6.1
22	Land acquisition issues	5.9
23	Technology failure	5.5
24	Safety incidents	5.2
25	Technological obsolescence	4.9
26	Cultural or archaeological issues	4.3

Figure 11: The risks ranked with the average risk exposure

The seventh and last step in the process is to allocate resources to risk mitigation in proportion to the relative importance of the risks. The relative importance of each risk is the normalized criticality index of each risk. The normalized criticality index of each risk are shown in figure 9. For instance, 4.87% of the risk mitigation resources should be allocated to the risk "Construction delays".

5 Discussion

The proposed process for risk prioritization utilizes what Inclus already does and implementing the process does not require many new features. It utilizes the assessments of multiple people from different groups, which is a core feature of Inclus' platform.

The normalized criticality index and the high risk exposure probability-metric can be modified by using different risk exposure zones. Any number of risk exposure zones can be used and which risk exposure zones are used in the risk prioritization metrics can be adjusted to the users preferences. When an organization wants use the normalized criticality index, they should have the opportunity to choose which risk zones that should be used when calculating the normalized criticality index.

The high risk exposure zone probability metric and the normalized criticality index emphasizes risks that have been assessed to have high likelihoods and high impacts by some of the participants. Thus, they would be good metrics for the users of Inclus' platform to consider. It is up to the user of Inclus' platform to decide which metrics they consider important.

The high risk exposure zone probability metric and the normalized criticality index assume that every assessment is equally likely to be correct. This assumption may not hold in practise. Thus, it would be a good idea to give the user of Inclus' platform the opportunity to remove unreliable assessments of the risks. However, removing assessments from the risk analysis should be done with care, since it may remove important perspectives and it may be difficult to objectively determine which assessments are not reliable.

We suggest as a topic for future work how cross-dependencies could be taken into account in risk prioritization. The proposed metrics in this project do not take into account cross-dependencies of the risks. A metric taking into account cross-dependencies would be an interesting addition to Inclus' platform.

6 Conclusions

This report contains the results of a project on simulation methods in risk management for Inclus as a part of the course MS-E2177 - Seminar on Case Studies in Operations Research. The project was introduced and the objectives of the project were defined. A literature review was conducted on simulation in risk management. PERT for scheduling and cost overruns was presented. A method for risk prioritization was presented. The risk prioritization method was applied to an example dataset.

In the literature review we condensed the information we had gathered through reading the current art literature on the topic Monte Carlo simulation risk management of construction projects. This might serve as a good starting point when Inclus decides to start implementing a Monte Carlo simulation feature into their portfolio of tools. Here they can find references to relevant literature that can be a good place to start further investigations.

We demonstrated how the risk prioritisation of risk matrix based Monte Carlo simulation framework could be generalized from what was proposed in Qazi et al. [13] for sustainability risks to the general construction project risks obtained with the existing Inclus risk management tool. This framework could be utilized by Inclus to integrate a tool based on the principles outlined here.

The PERT model was also discussed briefly but as it would require significant changes to how Inclus gathers their data from the customers we decided to focus more on the aforementioned risk prioritization model. Commercial tools utilizing the PERT model for project scheduling and budgeting are also readily available in the market and it might not be the goal of Inclus to compete with current products.

In general, the report provides multiple suggestions to Inclus on current art of Monte Carlo simulation for risk management along with suggestions on directions on what to investigate and what developments might be useful for the Inclus use case.

Self Assessment

How closely did the actual implementation of the project follow the initial project plan?

For the most parts the actual implantation followed the project plan reasonably well. There were some departures from the original project plan. Cross-dependencies did not receive as much attention as planned. Adding cross-dependencies to the plan was perhaps a bit too ambitious, however, we did not exactly know how we would complete the project at the start.

In the beginning, we planned to compare multiple different methods for Monte Carlo simulation to the Inclus use case based on the literature. However, we soon realized that many of the methods discussed in the articles did not solve the problems Inclus had set out to solve or did not easily fit their current infrastructure. As a result of discussing this with Inclus, we ended up focusing most our efforts on the one method that fits Inclus the best.

In what regard was the project successful? In what regard was it less so?

The project was successful in finding simple, practical and implementable recommendations. Furthermore, the presented method fit well into Inclus' already existing pipeline. Our literature review was comprehensive and we were able to find and present literature relevant for most of the task that we planned to cover. The review gave a good overview on risk management. Our project team was successful in meeting regularly and on communication along the way. This also applied to communication with Inclus.

In our previous report we listed beneficial outputs for Inclus. These were:

1. Recommendations on how to implement Monte Carlo –style simulations on top of data collected with Inclus.
2. Recommendations on how to translate multiple differing risk assessments to a Monte Carlo –compatible probability distribution; and what distributions should be supported.
3. Recommendations on how to present simulation results.
4. Suggestions/ideas on how to combine risk cross-dependency data with the simulation.

As mentioned we were successful in the first output. We were also successful in the second output by choosing discrete distributions to sample from for the simulation rather than considering continuous distributions. This enabled us to circumvent the the issue of translating the distributions. We were also successful in the third output. We discussed two main models in this report, PERT and risk matrix-based Monte Carlo simulation. In the latter, risk prioritisation is in a major role. We presented ranking of risks done with normalized criticality index and further a ranking made with simplified version of that. We did not focus on PERT and therefore do not have recommendations on how to present simulation results. That would be something to consider if Inclus wishes to include it in their platform. We were not as successful in the last output presented in the previous section. We focused on a method that is closer to Inclus' current method because it was higher in their priorities. If we were to focus on cross-dependencies the project would have gotten out of hand and we would not have been able to properly focus on anything.

What could have been done better, in hindsight?

In hindsight, we could have set internal deadlines of the deliverables a few days ahead of the real deadline. It would have given us more time to polish our reports and presentations.

We could have arranged more meetings with Inclus. Our philosophy was to arrange meetings only when we had something to show or some critical questions. This philosophy resulted in a few meetings, however as a result all the meetings were useful. If we could start the project again, we would have tried to have scheduled meetings every 2 weeks at the same time every 2 weeks.

If necessary we could have arranged meeting with Inclus' client. We did not see the added value of such a meeting and thus did not request one. In retrospect it would have been interesting to hear their input on the topic.

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