Navigating Through Uncertainty

A Decision Support Model to Identify Key Risks and Uncertainties

OE54035: Master Thesis Offshore and Dredging Engineering

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A Decision Support Model to Identify Key Risks and Uncertainties

by

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to obtain the degree of Master of Science
at the Delft University of Technology

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Project Duration:	February, 2025 - September, 2025
Faculty:	Faculty of Mechanical Engineering, Delft

Cover:	Maintenance Dredging Project in Harbor of Southhampton UK, Backhoe Dredger Magnor and Hopper Barge Terraferre 501 (photograhp by Boskalis)
Style:	TU Delft Report Style

Preface

This thesis was conducted in collaboration with Boskalis to fulfill the requirements for the Master of Science degree in Offshore & Dredging Engineering at the Faculty of Mechanical Engineering.

I would like to express my sincere gratitude to my supervisors, in particular, I would like to thank Mark van Koningsveld for his intensive involvement and for helping to shape my ideas into a coherent whole. My thanks also go to José Antolinez for the crucial support that enhanced the quality of this research.

Furthermore, I would like to thank my supervisors from Boskalis, Raoul Rutten and Jeanine Vonkeman. Their practical insights and guidance from the industry were essential in anchoring the theoretical aspects of this research in the reality of the business.

Finally, I want to express my gratitude to my brother who supported me immensely during the course of my thesis. The resilience needed to see this work through was also provided by the continuous encouragement, patience, and belief from my girlfriend and parents. Their unwavering support helped me making this a successful journey.

Beyond the academic knowledge I have gained, completing this thesis has been an important lesson in decisiveness, effective time management, and self-advocacy. For all these lessons, I am truly grateful.

J.A.A Meursing
Rotterdam, September 2025

Summary

Dredging projects are capital-intensive, logistically complex, and exposed to multiple sources of uncertainty. To stay competitive during early tender bidding, contractors must estimate project duration, costs, and emissions under severe constraints of time, budget, and engineering capacity. At this stage, detailed engineering studies are rarely feasible, yet contractors still need to anticipate which uncertainties are likely to drive project outcomes. Besides, projects take place in highly uncertain environments; weather, soil conditions, technical reliability, and logistical interactions can disrupt operations in ways that are difficult to anticipate. This makes early tendering particularly challenging: contractors must decide where to allocate scarce engineering resources without knowing which risks and uncertainties will matter most for project success.

Existing approaches provide partial answers. Current methods can analyze individual aspects of a project in great detail—for example, estimating workability downtime, costs, or environmental impacts. However, these approaches depend on extensive data and engineering resources that are rarely available in early tendering. What is missing is a structured way to systematically identify and prioritize the most critical risks when information is still limited. This thesis addresses that gap by developing a rapid risk-assessment methodology that combines expert judgment with simulation, enabling contractors to focus their limited engineering capacity on the uncertainties that most affect project success.

The experimental methodology is based on Discrete Event Simulation (DES), which was chosen as the most suitable simulation approach for this research. OpenCLSim was selected as the simulation platform due to its open-source accessibility, its ability to represent projects through hierarchical layers (activity, sequence, asset, and multi-site), and its flexibility to integrate custom extensions tailored to dredging logistics. This makes it suitable for modeling the complex interactions between multiple assets and for embedding probabilistic risk events directly into the simulation framework.

The inputs to the model are expert judgments, expressed as probabilistic estimates of both the likelihood and impact of characteristic risks and uncertainties. These inputs are organized into four categories—workability, technical, logistical, and environmental/social—and are mapped to the appropriate project layer. A dedicated Risk & Uncertainty custom extension then encodes these estimates in the simulation, using occurrence models and impact distributions. This ensures that risks are represented at the correct level of detail: as activity-level variability, sequence-specific delays, or project-wide interruptions.

The simulation output consists of probabilistic Key Performance Indicators (KPIs) for project duration, costs, and emissions. Monte Carlo experiments are used to calculate a set of project outcomes to propagate the uncertainty, and results are reported at the 80th percentile (P80). This reflects a conservative but industry-accepted confidence level, providing contractors with risk-aware estimates of project outcomes.

Finally, the methodology includes a mitigation evaluation, in which experts provide updated risk parameters for scenarios with countermeasures in place. By comparing the cost of each measure with the reduction in project cost, time, and emissions achieved in the simulations, the analysis identifies which measures are financially viable and where scarce engineering capacity should be allocated during the tender phase.

The methodology demonstrates how risks and uncertainties are applied to specific layers of a dredging project—activity, sequence, and project-wide. This allows their effects to be isolated and compared, revealing how risks interact with each other and how they influence project KPIs differently based on their location within the project structure. Using a DES tool, the method captures system interactions that other approaches miss. It shows that delays that do not fall on the critical path are often absorbed, partially buffering the total project duration. However, even if activities are not on the critical path, they still cause costs and emissions to accumulate, as idle assets continue to accrue costs and consume fuel in parallel. This distinction between the buffering of time and the cascading of financial and en-

vironmental impacts provides a clearer picture of the relative importance of different uncertainties for each KPI.

Applied to the Malmporten case, expert elicitation identified three representative risks: mooring-time uncertainty, a sequence-level backhoe breakdown, and project-wide turbidity exceedance, each estimation is parameterized with probabilistic occurrence and impact distributions. The simulations revealed that, in this specific case, the backhoe breakdown had the largest impact, as it delayed multiple dependent assets. Turbidity exceedance, while less influential on project duration, strongly contributed to cost and emissions through system-wide idling. Mooring-time uncertainty had a modest but measurable effect, mainly by increasing operational (rather than idle) emissions. The mitigation analysis showed that sequence-critical risks offer the greatest leverage: on-site spare parts sharply reduced repair durations and delivered the highest benefit–cost ratio, while silt screens and experienced captains provided smaller, complementary improvements. These case-specific findings illustrate how the method can identify which risks most strongly affect KPIs and which mitigation strategies justify scarce engineering capacity in the tender phase.

In conclusion, the approach developed here can support contractors in the early tender phase by providing insights into where scarce engineering capacity should be allocated. This is achieved by combining structured expert judgment with probabilistic estimates, implementing them in a discrete event simulation through a dedicated custom extension, and analyzing their impacts on project duration, costs, and emissions. Importantly, the elicitation of inputs and the execution of simulations can be done within the short time frames typical of early tendering, ensuring that timely insights are available when they matter most. While demonstrated on a single case, the methodology can be generalized to common dredging project topologies and extended with more advanced failure models, calibration of expert inputs, and broader KPI frameworks. It thereby equips contractors with a practical decision-support tool for early tendering, where reliable insights must be gained quickly under uncertainty.

Contents

Preface i

Summary ii

Nomenclature vi

1 Introduction 1
- 1.1 Industry Context & Relevance 1
  - 1.1.1 Work Method Design 2
  - 1.1.2 Dredging complexities 2
- 1.2 Problem Statement 3
- 1.3 Research Gap 4
- 1.4 Objectives 4
- 1.5 Reader Guide 5

2 Literature Review: Simulation Methods 7
- 2.1 Queueing Theory 8
  - 2.1.1 Applications 8
  - 2.1.2 Limitations 8
  - 2.1.3 Evaluation 8
- 2.2 System Dynamics 9
  - 2.2.1 Applications 9
  - 2.2.2 Limitations 9
  - 2.2.3 Evaluation 10
- 2.3 Discrete Event Simulation 11
  - 2.3.1 Applications 12
  - 2.3.2 Limitations 12
  - 2.3.3 Evaluation 12
- 2.4 Comparison of Modeling Methods 13
- 2.5 Existing DES Software 14
- 2.6 OpenCLSim 16
  - 2.6.1 Building Blocks 16
  - 2.6.2 Project Schematization 18
- 2.7 Summary 20

3 Risk Assessment Methodology 21
- 3.1 Characteristic Risks & Uncertainties 23
  - 3.1.1 Risk Identification 23
  - 3.1.2 Risk Categorization 24
  - 3.1.3 Project Layers 24
  - 3.1.4 Level of Impact 25
  - 3.1.5 Quantifying 26
  - 3.1.6 Expert Elicitation 27
- 3.2 Integration into Simulation Software 29
  - 3.2.1 Implementation 29
  - 3.2.2 Converting Data 30
- 3.3 Assessing Risks & Uncertainties 32
  - 3.3.1 Operational Tracking & KPIs 32
  - 3.3.2 Impact Assessment 33
- 3.4 Mitigation Evaluation 36
  - 3.4.1 Response Plan 36

3.4.2 Integration and Evaluation . . . 36
3.5 Summary . . . 38

4 Case Studies for Model Applications 39
4.1 Tender Review: Hypothetical Example . . . 40
4.1.1 Project Layer Schematization . . . 40
4.1.2 Scenario Setup of Impact Levels . . . 41
4.2 Tender Review: Case Study (Malmporten) . . . 43
4.2.1 Project outline . . . 43
4.2.2 Dredging scope . . . 43
4.2.3 Work method . . . 44
4.2.4 Project parameters . . . 45
4.2.5 Project Schematization . . . 46
4.3 Summary . . . 48

5 Results 49
5.1 Hypothetical Example: Isolated Impact Levels . . . 50
5.2 Case Study: Expert Elicitation . . . 51
5.3 Case Study: Integration Expert Judgment into the Simulation . . . 52
5.4 Case Study: Assessing Risks & Uncertainties . . . 54
5.4.1 Operational Tracking & KPI Basis . . . 54
5.4.2 Scenario Impacts on KPIs . . . 55
5.4.3 Dependencies Between Risks and Uncertainties . . . 58
5.4.4 Propagation of a Sequence Delay (Backhoe Breakdown) . . . 59
5.5 Case Study: Mitigation Evaluation . . . 60
5.5.1 Mitigated KPI impact (all-risks scenario) . . . 61
5.5.2 Financial feasibility . . . 62
5.5.3 Benefit–Cost Ratios . . . 63

6 Discussion 64
6.1 Estimating Software for Early-Phase Tendering . . . 65
6.2 Characteristic Risks & Uncertainties . . . 66
6.3 Translating Expert Judgment to Simulation Parameters . . . 67
6.4 Impact of Risks & Uncertainties on KPIs . . . 68
6.5 Synthesis and Contribution . . . 70

7 Conclusions & Recommendations 72
7.1 Conclusions . . . 72
7.2 Recommendations . . . 74

References 76

A Illustrative Example of OBS–ABS Structures 81

B Expert Elicitation: Protocol, Notes, and Transcript 83
B.1 Purpose and Context . . . 83
B.2 Participants and Logistics . . . 83
B.3 Elicitation Protocol (overview) . . . 83
B.4 Transcript (edited for clarity) . . . 83
B.5 Follow-up Validation . . . 84
B.6 From Elicitation to Model Inputs (traceability) . . . 85
B.7 Notes on Uncertainty and Limitations (as raised in the sessions) . . . 85
B.8 Link to Main Tables . . . 85

C Analysis on Statistical Stability 86

Nomenclature

Abbreviations

Abbreviation	Definition
ABS	Activity Breakdown Structure
DES	Discrete Event Simulation
ETS	Emission Trading System
IMO	International Maritime Organization
KPI	Key Performance Indicator
MCS	Monte Carlo Simulation
MDO	Marine Diesel Oil
MGO	Marine Gas Oil
NOH	Number of Operating Hours
OBS	Object Breakdown Structure
P20/P50/P80	Percentiles of distribution (20th, 50th, 80th)
QT	Queuing Theory
SD	System Dynamics
TSHD	Trailing Suction Hopper Dredger
WBS	Work Breakdown Structure

Symbols

Symbol	Definition	Unit
t	Simulation time variable	[h] or [s]
V	Velocity	[m/s]
K	System capacity (queueing)	[-]
k	Model frequency	[-]
N	Population size (queueing)	[-]
D	Queueing discipline (FIFO, LIFO, SIRO)	[-]
λ	Failure/event rate (Poisson parameter)	[1/time]
μ	Mean or average value	[-]
ρ	Density	[kg/m^3]
σ	Standard deviation	[-]
Δ	Difference in KPI (all-present – all-minus-i)	[various]

1
Introduction

1.1. Industry Context & Relevance

Dredging operations are key activities across various industries, including harbor maintenance, coastal protection, and underwater construction projects. Beyond their industrial significance, these operations hold broader societal relevance, directly supporting global trade by maintaining navigable waterways, protecting coastal communities from erosion and rising sea levels, and facilitating the development of essential infrastructure. These projects are inherently complex and dynamic, frequently carried out in ever-changing environments where factors such as weather conditions, tides, water depth, and soil composition can significantly impact their progress and efficiency. This variability presents a considerable challenge for contractors striving to accurately predict project performance. To address this, simulation models have become usefull, allowing contractors to estimate project outcomes like time, costs, and emissions.

A dredging project inherently involves a diverse array of stakeholders, each possessing unique objectives and responsibilities. Of course the contractors, tasked with the execution of the dredging operations themselves. Other important stakeholders are the clients, such as port authorities or private entities, whose primary concern is the timely and cost-effective completion of the dredging work. Local authorities play a vital role in overseeing the project's impact on local infrastructure and communities, often with specific concerns regarding operational noise levels and local disruptions. Finally, environmental agencies, groups like the coastal protection community, are crucial for ensuring strict adherence to environmental regulations. Their scope also extends particularly to mitigating impacts on marine life and controlling factors such as emissions and water turbidity. While each of these stakeholders approaches a project from a distinct perspective, they all share a common interest in minimizing risks and optimizing project efficiency. Given these varied interests and the versatile nature of dredging operations, understanding and quantifying project performance becomes highly important. This necessitates the use of Key Performance Indicators (KPIs), which provide the metrics for assessing project success from all relevant viewpoints.

In dredging projects, KPIs serve as core metrics, providing contractors and stakeholders with quantifiable measures of success. The main KPIs are time, costs, and emissions, where time represents the project's duration vital for meeting deadlines and optimizing resource utilization. Another major KPI is costs, encompassing the financial investment in equipment, labor, and fuel. Beyond economic factors, emissions have emerged as a increasingly important KPI as well, reflecting the environmental impact of dredging activities. The Emissions Trading System (ETS) [Buitendijk, 2025], for example, ensures that emissions play a role in awarding projects to more sustainable contractors. With a growing global focus on sustainability and increasingly stricter environmental regulations, particularly driven by bodies such as the International Maritime Organization [IMO, 2022], minimizing the ecological footprint of these operations has become a top priority. Understanding and effectively managing these KPIs is crucial as they directly influence a dredging operation's profitability, completion window, and adherence to environmental compliance. The ability to accurately predict and optimize these interconnected factors is therefore vital for contractors to manage risks, ensuring projects remain within budget and on schedule.

1.1.1. Work Method Design

Dredging operations involve a dynamic interaction among several core components that collectively form the foundation of the entire process. These essential elements typically include Sites, referring to the geographical locations where dredging and disposal occur. Processors are equipment assets that are capable of processing material, such as BackHoes (BH), Cutter Suction Dredgers (CSD). Transporters, which encompass various types of vessels or equipment responsible for transportation of material, like barges or discharge pipelines. Trailing Suction Hopper Dredgers (TSHD) are responsible for the extraction, transportation, and discharge of materials, so they are considered as Processor-Transporting units (Figure 1.1).

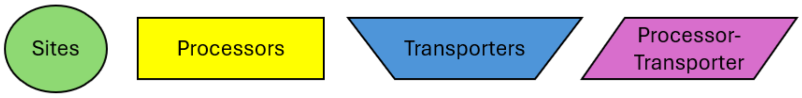


Figure 1.1: Dynamic Components of Typical Dredging Work Method that each have different characteristics. Green circle; sites can contain materials, yellow rectangle; processors can shift/process materials (BH/CSD), blue trapezium; transporters can move materials (barges/pipelines), purple parallelogram; processor-transporter can process and move materials (TSDH).

For a dredging operation to succeed, its various components must work together seamlessly, following a defined strategy. The formulation of a precise work method is particular important for contractors, as it directly impacts the efficiency and cost-effectiveness of the dredging project. A well-defined work method involves careful determination the sequence of activities, the efficient allocation of resources, recognizing asset availability, and keeping all stakeholders satisfied. All these elements must align with the project's specific goals, such as completing the work on time, within budget, and in an environmentally responsible manner. Ultimately, optimizing the work method ensures that a project can maximize its output, minimize potential delays, and maintain peak resource efficiency.

Ultimately, the design of a work method is not only about coordinating assets efficiently but also about achieving the project's Key Performance Indicators. Choices made in the work method—such as the number of barges assigned to a dredger, the sailing distances to disposal sites, or the unloading configuration—directly influence project duration, total costs, and emissions. A method that minimizes idle time may shorten the schedule but increase emissions through more frequent sailing, while a more conservative design may reduce environmental impact at the expense of higher costs or longer duration. This intrinsic link between work method design and KPI outcomes underscores why simulation is a valuable tool: it enables contractors to evaluate alternative strategies quantitatively and select the work method most likely to meet client and regulatory objectives.

1.1.2. Dredging complexities

Once a work method has been formulated by the contractor, the next step is to gain a sound understanding of the project's KPIs. For simpler operations, back-of-the-envelope calculations or engineering intuition may suffice. However, when there are complex interactions between project components—such as interdependencies among assets or uncertain site conditions—these shortcuts become inadequate. In such scenarios, simulation becomes increasingly valuable [Kaizer et al., 2021]. Larger dredging firms are applying these advanced approaches more frequently. For instance, Van Oord has developed proprietary mixins for detailed dredging simulations and contributes to open-source extensions—highlighting how simulation capabilities are becoming more integral in modern engineering workflows [de Boer et al., 2022]. However, real-world dredging operations are always subject to unforeseen events and unexpected occurrences that can significantly affect project execution. This includes not only operational uncertainties but also, especially during the tender phase for new projects sites, inherent uncertainties within the environmental scope. So what are these uncertainties and complexities that a simulation must account for?

Dredging projects are inherently complex due to the confluence of careful planning requirements, diverse site conditions, critical environmental considerations, and the varied approaches to material handling and disposal. These factors collectively necessitate specialized equipment, highly skilled personnel, and diligent management to mitigate potential environmental impacts.

The details of dredging primarily arise from several key areas, often coming with significant uncertainty. Firstly, site-specific conditions introduce considerable unpredictability. While factors like equipment accessibility, the dynamic nature of tides, currents, and water depths can be reasonably well-estimated with available data and established methods, a significant unknown lies in the variability of soil quality between measured points. Moreover, highly variable climate and weather patterns pose constant threats by directly impacting the workability of all assets, leading to operational halts, delays, and safety risks. Finally, the location of suitable disposal sites also directly impacts project logistics and costs, and these locations can shift based on unforeseen circumstances, such as sudden marine life activity.

Secondly, the environmental impact of dredging is filled with uncertainties. While specific environmental restrictions tied to protected habitats or water quality are clearly defined, an inherent uncertainty exists regarding the extent of turbidity generated during operations, creating a risk of exceeding these regulatory limits, making safe handling and disposal planning challenging. Similarly, predicting the exact degree of turbidity is complex and highly dependent on real-time conditions, which can unpredictably affect water quality and marine habitats.

Thirdly, technical aspects introduce operational uncertainties. Beyond selecting the right equipment for sediment removal, the core challenges lie in ensuring consistent performance and managing unexpected events. Equipment, such as dredgers or pumps, is inevitably affected by unforeseen breakdowns, and the rate of wear and tear can be highly unpredictable. For instance, encountering unexpected presence of boulders, or harder than expected soil conditions can lead to sudden damage or complete equipment failure, directly impacting project timelines and costs.

Finally, the project success is heavily influenced by stakeholder involvement and regulatory compliance. Navigating complex permitting, environmental regulations, and impact assessments is crucial. This requires clear communication and flexible management with all parties, from regulators to local communities, to account for inherent uncertainties.

Effectively incorporating all these dynamic and uncertain factors into a simulation and estimate their impact on KPIs presents a substantial challenge. While such comprehensive modeling is indeed possible, it necessitates the large amount of data and the execution of sophisticated computational models to produce reliable engineering estimates. This effort, however, demands considerable investments in time, financial resources, and specialized engineering capacity.

1.2. Problem Statement

Dredging operations are often simulated at the beginning of a tender phase to define the optimal work methods and estimating KPIs such as project duration, associated costs, and environmental emissions. However, this early stage is inherently characterized by numerous uncertainties, significantly complicating the accurate estimation of these key indicators and the generation of reliable engineering estimates. To truly comprehend potential project outcomes and identify the most effective work method, extensive engineering capacity is typically required for detailed data analysis and the development of sophisticated simulation models. This demanding process, consequently, requires substantial investments in time, financial resources, and specialized engineering capacity, all of which are often scarce during the competitive and time-sensitive initial tender phase. This mismatch between the need for comprehensive analysis and the availability of resources creates a significant challenge. Consequently, contractors frequently encounter difficulties in precisely identifying during early tendering which specific uncertainties will exert the most significant impact on the project outcome, leading to inefficiencies in allocating their already limited engineering capacity.

> **Problem Statement:** Dredging contractors face the challenge of efficiently identifying the most critical uncertainties on project KPIs during the resource-constrained early tender phase to optimize the allocation of limited engineering capacity.

1.3. Research Gap

Existing research has made progress in providing methods for conducting specific analyses to address project uncertainties and accurately calculate key performance indicators. For instance, simulation models leveraging historical weather data have been developed to predict the workability of a project under varying weather conditions [Muskulus, 2013; Kikuchi et al., 2016; Bruijn et al., 2019]. These common methods are used by contractors already and there even exists full project teams that calculate the workability of future projects. Similarly, analytical frameworks and computational tools exist to estimate the multifaceted costs of a complete project, encompassing various operational and logistical expenditures [Deng et al., 2022; Curto et al., 2022]. Furthermore, calculation models have been established to provide engineering assumptions regarding environmental impacts such as turbidity [Mahgoub et al., 2025], and emissions during dredging operations [Van der Bilt, 2019; Janssen, 2023; Lamers, 2022; de Boer et al., 2023]. All these sophisticated methods, which collectively strive to encompass the inherent complexities of a dredging project, have been extensively explored in previous studies, though their application demands considerable time and substantial engineering resources.

However, a clear gap remains: while there are numerous engineering studies focused on specific themes—such as weather-based workability, turbidity impacts, cost models, or emissions—there is scarce literature examining how to quantitatively compare the relative influence of these factors during the early stages of a project, especially when only limited data are available. For example, Laboyrie et al., [2018] offers guidance on adapting environmental measures in dredging, but it does not provide a framework for systematically prioritizing uncertainties during the early tender phase. Similarly, PIANC WG 100 report [Netzband et al., 2009] offer valuable best-practice insights for environmental management, yet do not provide a probabilistic decision model for ranking uncertainties under time pressure.

What is missing, therefore, is a method that allows contractors to systematically prioritize uncertainties during the tender phase—quickly indicating which factors are most likely to affect project KPIs, based on both their likelihood and magnitude. Despite extensive literature on individual aspects such as workability, turbidity, and emissions, no studies were found that propose a probabilistic framework to compare their relative importance early in a project when detailed data are scarce. A streamlined approach that leverages expert judgment to generate probabilistic inputs, and then translates these into simulation-ready parameters, remains undeveloped. Such a method would enable contractors to obtain rapid, structured insight into the most influential uncertainties, improving the allocation of limited engineering capacity. From a societal perspective, this contributes to more predictable and sustainable infrastructure delivery; scientifically, it offers a novel framework for early-stage risk prioritization in complex, resource-constrained environments, with potential applicability beyond dredging.

1.4. Objectives

Aim: The aim of this research is to develop a method that integrates expert-judgment estimates for key risks and uncertainties into existing simulation software to clarify their impact on project outcomes during the early tender phase of a project, enabling contractors to utilize scarce engineering capacity effectively. To achieve this aim, the following research questions are formulated.

Research Questions

Main:

- How can key risks and uncertainties be identified in the tender phase of a dredging project by combining expert judgment with simulation software to optimize engineering resource allocation?

Sub-questions:

1. What are the most common estimation tools currently available and how can they encompass complexity in dredging operations?
2. What are the most characteristic risks for dredging projects that create uncertainties early in the tender phase, and what potential mitigation measures exist?
3. How can rough expert judgment of key risks and uncertainties be integrated into existing simulation software?

4. How can simulations assess the impact of risks and uncertainties on KPIs, evaluate the effect of mitigation measures, and translate these insights into guidance for allocating engineering resources?

Scope

This thesis targets early-tender decision support where uncertainty is high and resources are limited. The scope is operational KPIs—project time, costs, and emissions—derived from discrete-event simulation. Expert judgment is used where historical data are absent or insufficient; methods for expert calibration/validation are acknowledged but not implemented here (discussed later). The risk space is framed for dredging via categories (workability, technical, logistical, environmental/social) and mapped into impact levels (activity uncertainty, delay in sequence, delay across project). Detailed workability, cost, turbidity, and emissions *physics-based* sub-models are out of scope in the tender workflow; instead, their effects are represented through probabilities/distributions at the appropriate simulation layer. Cost KPIs exclude overheads/penalties and use per-asset fixed/variable costs; emissions use operating/idle rates per asset. The approach targets common multi-site↔single-site topologies typical in dredging tenders; generalization beyond this is discussed later. Validation with realized project data is outside scope and addressed in recommendations.

1.5. Reader Guide

To clarify how the thesis addresses the research objective step by step, Figure 1.2 presents the overall methodology as a reader guide. Each Chapter corresponds to a stage in the research pipeline, beginning with the choice of modeling paradigm and software (Ch. 2) and continuing through the development of the Risk Assessment Methodology (Ch. 3), its application in case studies (Ch. 4), and the simulation results (Ch. 5). The final chapters (Ch. 6–7) interpret these findings, discuss their implications, and conclude with recommendations.

The figure highlights how the sub-research questions are distributed across the Chapters and shows the logical flow from tender review inputs to simulation outputs and decision-relevant indicators. This structure ensures that readers can trace how each methodological step contributes to answering the research questions and, ultimately, to the main objective.

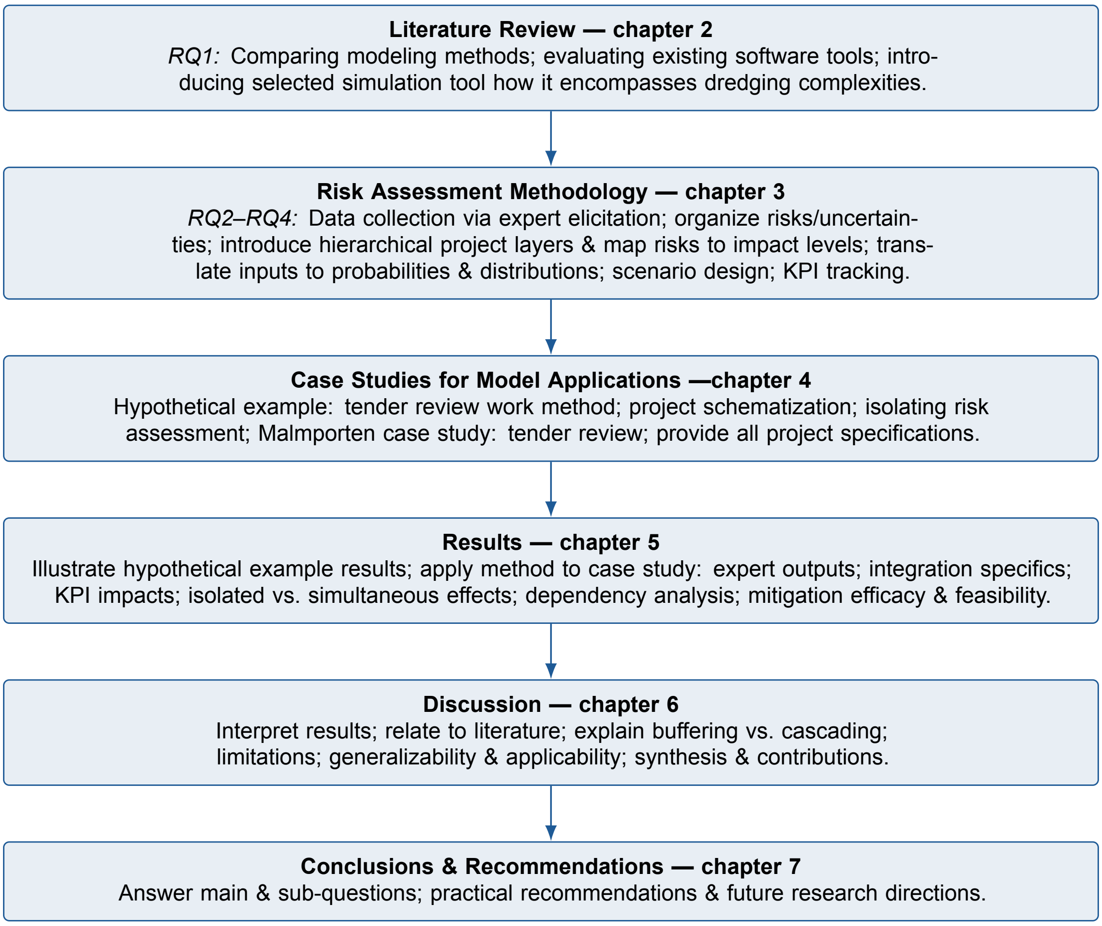


Figure 1.2: Reader Guide: Thesis Flow and Chapter Roles

2 Literature Review: Simulation Methods

The execution of dredging projects involves complex interactions between multiple assets, activities, and environmental conditions. To represent and analyze these dynamics effectively, different modeling methodologies have been applied within maritime engineering and operational research. Here we review these approaches to determine which methodology is most appropriate for this research and to position the later choice of simulation framework within an established academic and industrial context.

This Chapter examines three modeling methodologies particularly relevant for logistical estimation and operational planning in dredging projects: Queueing Theory (Section 2.1), System Dynamics (Section 2.2), and Discrete Event Simulation (Section 2.3). Each method is reviewed in terms of its principles, applications, and limitations when applied to dredging contexts. Their relative strengths are then compared in Section 2.4, where their suitability for this research is evaluated.

Building on this comparison, Section 2.5 and Section 2.6 indicate which method best suits the research objectives of this thesis and describes some key concepts needed further in our analysis. Finally, Section 2.7 summarizes the review and explicitly answers the first research question on which simulation methodology and software are most appropriate for this thesis.

It is important to note that other modeling approaches, such as Agent-Based Modeling (ABM), also offer powerful ways to represent complex systems. In ABM, the focus is on decentralized decision-making: individual agents are modeled with their own rules of behavior and interactions with the environment. System outcomes then emerge from these local interactions, rather than from explicitly modeled processes or sequences. While this microscopic perspective is valuable in domains where autonomous behavior is dominant, it is less suited for the objectives of this thesis.

In contrast, the three approaches reviewed in this Chapter—Queueing Theory (QT), System Dynamics (SD), and Discrete-Event Simulation (DES)—share a centralized perspective: they model service systems where activities, resources, and process flows are explicitly organized and coordinated. This makes them directly applicable to dredging projects, where work methods are planned in advance and asset interactions follow predefined sequences. For this reason, these centralized, service-oriented methodologies are the focus of this thesis, while ABM is left outside the scope.

Together, the methods and tools reviewed in this Chapter highlight the trade-offs between different modeling paradigms. By systematically evaluating their capabilities and constraints, this Chapter establishes the rationale for selecting a methodology that balances micro-level operational detail with system-wide insight, setting the foundation for the risk assessment methodology developed in the following Chapter.

2.1. Queueing Theory

Queueing Theory (QT) studies how entities (e.g., tasks, customers, or vessels) move through systems with limited capacity [Adan et al., 2001]. A generic queueing system can be described using the Kendall notation [Kendall, 1953]: $A/S/c/K/N/D$; where A denotes the inter-arrival distribution of entities, S the service-time distribution, c the number of servers, K the system capacity, N the population size, and D the service discipline (e.g., FIFO, LIFO, or SIRO). Arrival and service times are often represented by exponential (M), deterministic (D), or general (G) distributions. This framework provides analytical solutions for steady-state performance, enabling insights into waiting times, throughput, utilization, and system bottlenecks.

2.1.1. Applications

QT has been applied across diverse logistical and industrial contexts. Koenigsberg et al., [1976] developed a cyclic queueing model for LNG carrier operations, estimating vessel states (sailing, loading, waiting) and port delays. They showed that increasing fleet size raised delays, while adding berths reduced them significantly. Sailing-to-port time ratios had stronger effects on waiting times than fleet size itself.

In manufacturing, Saini et al., [2024] applied QT (M/M/1 models) to evaluate performance metrics such as utilization, throughput, and cycle times. Using Little's Law [Little et al., 2008], they demonstrated how QT helps identify bottlenecks and optimize system design.

Closer to dredging, Kaizer et al., [2021] developed a decision-support application using M/G/1 models to coordinate vessel traffic and dredging activities in a port. The system optimized dredging schedules while minimizing disruption to commercial vessel traffic. Results highlighted reduced waiting times, improved dredger efficiency, and better alignment of dredging with port operations.

Although such applications show the analytical power of QT, studies explicitly applying it to dredging logistics remain scarce. Most works focus on narrow subsystems (e.g., loading stations, vessel queues) rather than the multi-agent, multi-activity structure of full dredging projects.

2.1.2. Limitations

Several limitations restrict the applicability of QT in dredging. First, QT primarily analyzes performance at the service point (e.g., a loading crane or berth), while other operational phases such as sailing or disposal are influenced by external factors (weather, currents, breakdowns) that QT cannot represent directly. This makes it difficult to capture multi-agent interactions in dredging projects.

Second, QT models often rely on steady-state assumptions and long-term averages, which are not representative of dredging works. Unlike container terminals or manufacturing systems with millions of repetitions, dredging projects involve a finite number of cycles, where variability between cycles strongly influences outcomes.

Third, QT requires precise data on arrival rates, service times, and buffer capacities. In the early tender phase, such data are typically uncertain or unavailable (e.g., dredging production rates, breakdown frequencies, weather downtime), limiting the feasibility of implementing QT at this stage.

Finally, and most importantly for this thesis, there is very limited literature applying QT directly to dredging projects. Existing works (e.g., Kaizer et al., 2021) consider simplified single-service models, but comprehensive applications that cover multiple agents and operational uncertainties are absent.

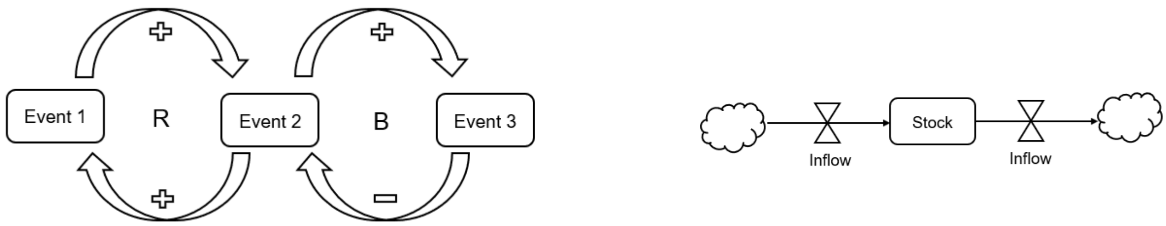
2.1.3. Evaluation

QT provides valuable tools for examining service systems, offering insights into waiting times, utilization, and resource allocation. However, dredging projects involve complex interactions and uncertainties that QT cannot fully represent.

> While QT offers powerful insights into single-service systems, its applicability to entire dredging operations with multiple interacting agents is limited. Dredging's complexities and uncertainties are not well-captured, as long-term averages and steady-state behavior are rarely reached.

2.2. System Dynamics

System Dynamics (SD) is a methodology for understanding how complex systems evolve over time, particularly where feedback loops and delays drive behavior [Lukmanulhakim Almamalik, 2020]. Reinforcing (positive) loops amplify changes, while balancing (negative) loops counteract them and push systems toward equilibrium. To represent these dynamics, SD uses Causal Loop Diagrams (CLDs) for qualitative mapping and Stock-and-Flow Diagrams (SFDs) for quantitative simulation, where stocks capture accumulations and flows define rates of change (Figure 2.1). Together, these tools allow SD to model macro-level dynamics and analyze system performance under different assumptions.



(a) Causal Loop Diagram (CLD)

(b) Stock and Flow Diagram (SFD)

Figure 2.1: Principles of SD modeling: CLDs capture causal relations qualitatively, while SFDs quantify accumulations and flows.

2.2.1. Applications

SD has been widely used in transportation and maritime studies. Shepherd, [2014] reviewed more than 50 applications across logistics and supply chains, emphasizing SD's strength in capturing dynamic interdependencies. Similarly, Oztanriseven et al., [2014] showed that SD has been applied to maritime disruptions, port management, and shipping reliability.

In port operations, several studies [Dvornik et al., 2006; Munitic et al., 2003; Dundović et al., 2009] applied SD models to cargo-handling processes, demonstrating how scenario testing and feedback analysis can improve berth allocation and cargo flow. Dundović et al., [2009] validated these approaches in the Port of Šibenik, confirming SD's potential to test operational strategies without disrupting real systems.

Cheng et al., [2010] analyzed interdependencies between berth and yard operations in container terminals, showing how bottlenecks in one subsystem propagate through the whole terminal. Their model, later cited by Kurniawan et al., [2024], illustrated SD's usefulness for strategic port planning.

Although these applications demonstrate SD's value for macro-level analysis, its use in dredging-specific contexts is nearly absent. The few conceptual overlaps (e.g., sediment flows resembling stock–flow systems) have not been translated into detailed operational models of dredging projects.

2.2.2. Limitations

Despite its strengths for policy and planning, SD is limited when applied to dredging. First, SD lacks spatial and micro-level resolution: it models system-level trends but not the detailed activities of individual assets such as dredgers, barges, or pontoons. This is problematic for dredging projects, where cycle times, breakdowns, and workability constraints strongly affect outcomes.

Second, SD models often exclude detailed financial indicators. As noted by Oztanriseven et al., [2014] and seen in studies by Kurniawan et al., [2024] and Dundović et al., [2009], costs are rarely treated as explicit variables. For dredging, where daily asset rates dominate tender decisions, this omission reduces practical relevance.

Third, many SD applications rely on simplified system representations (e.g., a single berth or fixed equipment numbers), making them ill-suited for projects with multiple dredging sites, heterogeneous equipment, and variable logistics.

Finally, and most importantly, there is almost no literature that applies SD directly to dredging operations. While port studies offer analogies, they do not capture dredging-specific uncertainties such as soil heterogeneity, breakdowns, or weather-induced downtime.

2.2.3. Evaluation

SD provides a useful top-down perspective for understanding feedback loops, long-term trends, and overall causal relations in maritime and transport systems. However, its level of abstraction means it cannot capture the fine-grained operational detail that is central to dredging projects. In this context, it is important to distinguish between *macro-level* modeling, which focuses on aggregated system behavior and long-term interactions, and *micro-level* modeling, which represents the detailed activities and interactions of individual agents such as dredgers, barges, and pontoons [Van Koningsveld et al., 2023b]. SD firmly belongs to the macro-level end of this spectrum, while dredging projects require micro-level tracking of asset activities and uncertainties.

While SD is suitable for modeling dredging operations in macro-level focus, detailed micro-level analysis is not covered by such models. Its inability to track individual agents and their specific activities, combined with limited capacity to encompass dredging-specific operational complexities, makes SD unsuited for simulating such projects.

2.3. Discrete Event Simulation

Discrete Event Simulation (DES) is a modeling methodology in which the state of a system evolves over time through discrete events that instantly change its condition [Law et al., 2014]. Each event (e.g., (un)loading, sailing) updates the system state and triggers future scheduled events. By maintaining an event list and iteratively updating the system, DES enables the detailed tracking of all activities until termination conditions are met. This approach is often applied to systems with many interacting components, since it allows their activities and state changes to be represented explicitly over time.

The functioning of a DES model can be explained through a few essential components. Ross, [2013] distinguishes three core variables (Table 2.1): the simulation time variable t, which keeps track of the simulated clock; counter variables, which register the number of times events have occurred; and system state variables (SS), which describe the current configuration of the system at time t (e.g., vessel location or soil quantity remaining at a site).

Variable	Description
Time (t)	Tracks the progress of simulated time
Counter	Counts the number of times an event has occurred
System State (SS)	Describes the status of the system at time t (e.g., asset position, load level)

Table 2.1: Key variables in DES [Ross, 2013]

The simulation is driven by an event list, which schedules future events and determines when the next update occurs. Figure 2.2 shows a typical DES cycle: the system is initialized, the next scheduled event is executed, system variables are updated, output statistics are collected, and future events are scheduled. This loop continues until the termination condition is met (e.g., a project is completed). Through multiple runs, probability distributions of outcomes such as duration, costs, and emissions can be obtained.

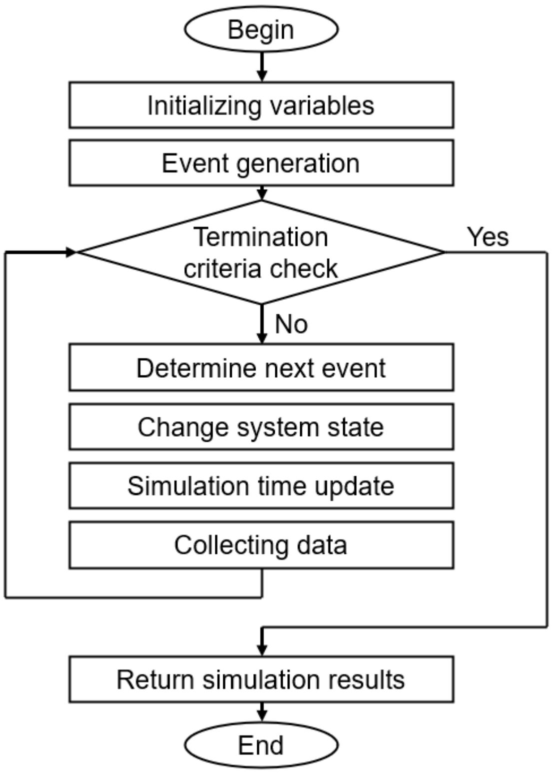


Figure 2.2: Typical flow of a DES model, where the system state is updated by sequential discrete events until termination criteria are met [Ross, 2013].

2.3.1. Applications

DES has been increasingly applied across the maritime and offshore sectors. Christiansen et al., [2004] and later Christiansen et al., [2013] reviewed over 200 papers on ship routing and scheduling, noting a growing shift from deterministic models to stochastic DES approaches that better capture real-world uncertainty.

In offshore logistics, Shyshou et al., [2010] applied DES to optimize fleet sizing of Anchor Handling Tug Supply (AHTS) vessels, explicitly modeling price volatility and uncertain operation times caused by weather. Their findings showed that stochastic simulation supports more robust chartering strategies compared to deterministic planning.

In offshore wind deployment, Lütjen et al., [2012] and Morandeau et al., [2013] integrated weather limits and time-series hindcast data into DES, enabling more realistic estimates of downtime and critical-path delays. Similarly, Stempinski et al., [2014] combined DES with Monte Carlo simulation to quantify duration and cost risk profiles for heavy-lift operations in the North Sea, underscoring the role of DES in uncertainty analysis.

Additionally, Troncoso-Palacio, [2021] applied DES in a Colombian port case, where expert judgment was used to decompose cargo handling into 17 activities. This showed that DES can flexibly incorporate operational knowledge from practitioners, producing models that reveal bottlenecks and delays in cargo unloading and vehicle loading.

For dredging specifically, published DES applications are scarce, even though the methodology aligns well with its operational characteristics: multiple interacting assets, uncertain cycle times, and environmental dependencies. As Bottani et al., [2024] note, DES use in logistics is becoming increasingly established, which underscores the opportunity to extend it more systematically to dredging projects where similar stochastic and resource-coupled processes are present.

2.3.2. Limitations

While DES offers a strong basis for simulating operations, important challenges remain for its application to dredging projects, which are characterized by multiple interacting assets (e.g., dredgers, barges), multi-site logistics chains, and strong dependencies on external environmental conditions such as weather, tides, and soil variability. A first issue is granularity: while DES can model detailed processes, many existing studies simplify asset behavior or omit human factors, limiting realism. For dredging projects, where breakdowns, soil variability, and operator decisions are critical, such simplifications risk underestimating uncertainty.

Second, data demands remain high. Accurate distributions for activity durations (e.g., dredging production, sailing times) and probabilities of disruptions are often difficult to obtain in early tendering, where little project-specific data is available. This is particularly problematic in dredging, where soil conditions, weather, and equipment performance can vary widely.

Finally, validation is limited: while DES can generate detailed risk profiles, empirical validation against real project data is often missing, as seen in Stempinski et al., [2014]. This challenge also applies to dredging tenders, where access to reliable validation datasets is constrained.

2.3.3. Evaluation

DES provides a bottom-up, event-driven approach that tracks both individual agents and overall project outcomes. Its ability to model stochastic events, integrate expert judgment, and scale across sites makes it particularly suitable for dredging operations. Unlike QT, which focuses narrowly on single service points, and SD, which abstracts to macro-level dynamics, DES offers the necessary detail to represent multiple agents, sequences, and uncertainties in parallel.

> Given its ability to model individual agents, track discrete activities, integrate stochastic risks, and scale across multiple sites, DES is the most suitable methodology for simulating dredging projects. It provides the necessary balance of micro-level detail and system-wide insight that QT and SD cannot offer.

2.4. Comparison of Modeling Methods

This section compares the three simulation approaches reviewed in the previous sections—Queueing Theory (QT), System Dynamics (SD), and Discrete Event Simulation (DES)—and assesses their suitability for dredging projects. These methods were selected because they represent the main *centralized modeling paradigms* used to study service systems, where the sequence of activities and resource use is defined in advance. In contrast, approaches such as Agent-Based Modeling (ABM) emphasize decentralized decision-making by individual agents interacting with their environment. While powerful for studying emergent behavior, ABM is less suited to modeling the structured service systems that characterize dredging operations. For this reason, QT, SD, and DES form the relevant scope of this review.

Each of the three methods brings a perspective that is relevant to dredging projects and to this research objective. QT is attractive because dredging operations often include single-service points, such as coupling stations or unloading points, where waiting times and utilization are critical. SD is relevant because dredging projects involve dynamic interactions, dependencies, and long-term feedbacks across environmental, logistical, and technical dimensions. DES, finally, directly represents projects as ordered activities linked to resources, enabling the integration of uncertainty at the level of activities, sequences, or across the whole project.

The literature shows, however, that these strengths come with important limitations. QT provides valuable mathematical insight into waiting times and throughput but remains too narrow for multi-agent, multi-activity operations. SD offers a powerful top-down view of causal relations and long-term system behavior, but its aggregated nature makes it too broad to capture the detailed activity-level processes central to dredging. DES balances these perspectives by combining micro-level precision (tracking assets and activities) with system-wide perspective (project KPIs), while also accommodating stochastic variability. This makes DES the most appropriate methodological basis for modeling dredging operations.

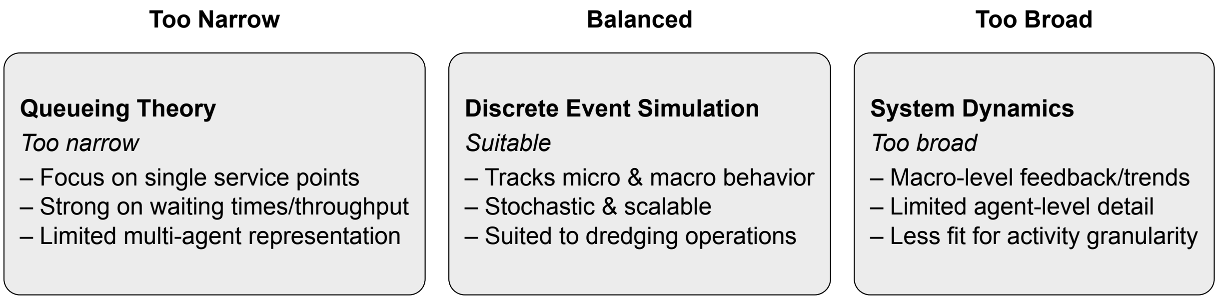


Figure 2.3: Comparison of Queueing Theory, Discrete Event Simulation, and System Dynamics

Having established DES as the most suitable methodology, the next section reviews existing DES software packages, comparing their capabilities against dredging requirements, and introduces the selected tool for this research.

2.5. Existing DES Software

Having identified DES as a suitable modeling methodology, the next step involves selecting an appropriate software tool for its implementation. A comprehensive evaluation of commercial DES software packages was provided by Dias et al., [2016] up to 2016, listing tools such as Arena, FlexSim, SIMUL8, Simio, AnyLogic, and GM Opsim. While these commercial solutions offer robust functionalities, their property rights nature, often high licensing costs, and inherent limitations in customizability for specific research needs can present challenges.

Exploring open-source alternatives, Salabim was reviewed as a potential option; however, its suitability for this research was limited by a less accessible development community. Furthermore, OpenQTSim was evaluated as a potential tool. Developed by Van Koningsveld and Den Uijl [2023] for the numerical approximation of Kendall type queueing systems, OpenQTSim leverages SimPy for DES and queue handling, and SciPy for statistical functionalities. This enables the simulation of queueing system behavior, drawing inter-arrival and service times from predefined statistical distributions. The tool includes a multi-thread engine for parallel calculations and allows for the integration of additional restrictions (such as quay lengths, tidal windows, and fairway restrictions) not typically part of standard queueing simulators [Van Koningsveld et al., 2023b]. However, while OpenQTSim provides valuable insights for specific service points, its output remains insufficient to encompass the entire, interconnected logistical process of a complex dredging operation, reflecting the broader limitation of QT models in capturing dynamic interactions beyond a single service point.

Another Python package, OpenTNSim, was also assessed. OpenTNSim, which focuses on researching meso-scopic traffic behavior across networks, was created by Van Koningsveld and Den Uijl [2024] to offer a versatile framework for examining canal systems. This meso-scopic approach is particularly useful at modeling numerous agents and large study areas, allowing for the integration of detailed engineering models. These models quantify specific network aspects or agent interactions, with their impacts on durations efficiently tracked by the underlying discrete event simulation, such as the effects of network restrictions or environmental costs of policy measures [van Koningsveld et al., 2023b]. The package utilizes SimPy for discrete event simulation and to investigate traffic flows and queueing patterns. However, despite its advanced capabilities for network analysis and traffic flow, OpenTNSim's primary focus on waterway traffic behavior rather than the detailed, cargo-specific activities central to dredging, like sediment loading and unloading, means it is not an applicable choice for modeling complex dredging operations in this research.

Considering these various options and the specific requirements of this research, OpenCLSim emerged as the most appropriate tool. OpenCLSim, which notably appeared on the market after the 2016 review by Dias et al., [2016], quickly gained traction within the maritime industry [Van Koningsveld et al., 2019]. While OpenTNSim primarily focuses on quantifying traffic flows and network performance for a given traffic load on waterway corridors, OpenCLSim is specifically designed to assess the performance of complex waterborne supply chains. It aims to quantify behavior stemming from rule-based planning of interdependent cyclic activities, a common characteristic of marine construction processes where tasks are sensitive to environmental conditions and depend on each other's completion [van Koningsveld et al., 2023b]. OpenCLSim's ability to simulate the intricate dynamics of such interdependent supply chains, subject to logical rules, aligns perfectly with the needs of this study. Its open-source framework, Python compatibility, and high degree of customizability, coupled with its explicit design for schematizing material handling processes and dynamic interactions between individual dredging assets, make it a uniquely specialized and comprehensive choice for this research.

One of the major reasons OpenCLSim was chosen over other tools is its unique application for water infrastructure projects. Developed through collaboration between TU Delft, Deltares, and Van Oord, OpenCLSim integrates specialist knowledge in logistics, water movement, and dredging and offshore projects. This collaboration resulted in a robust, open-source simulation tool that is capable of modeling the behavior of complex maritime logistics, considering factors such as weather and risks. The open-source nature of OpenCLSim also allows for integration with in-house data, making it a highly adaptable and customizable tool for real-world applications. As a result, it can simulate the impact of different equipment choices, production rates, sailing distances, and weather-related downtime, providing a comprehensive comparison of various execution strategies under different conditions.

Software Tools	Open/Closed Source	Maritime Specific	Development Community	Application Ability
Arena	Closed	No	No	No
FlexSim	Closed	No	No	No
Simul8	Closed	No	No	No
Simio	Closed	No	No	No
AnyLogic	Closed	Yes	No	No
GM Opsim	Closed	Yes	No	No
Salabim	Open	Yes	No	No
OpenQTSim	Open	Yes	Yes	No
OpenTNSim	Open	Yes	Yes	No
OpenCLSim	Open	Yes	Yes	Yes

Table 2.2: Comparison of Simulation Software Tools

Additionally, OpenCLSim has an active and accessible developer community. Beyond the core package, users routinely share add-on modules that extend its capability—for example, a critical-path analysis (CPM) overlay implemented on OpenCLSim that derives path criticality directly from DES logs [De Niet et al., 2023], and practitioner-contributed utilities for fleet sizing and eco-sailing policy experiments [De Boer et al., 2023] that couple DES outputs to simple optimizers. This community momentum means the tool evolves with the needs of the maritime sector and remains both scalable and adaptable for future use. Finally, OpenCLSim is also the basis of Boskalis' in-house simulation tooling, further validating its selection as the platform for this research.

OpenCLSim stands out as the most suitable software for this research because it is open-source, maritime-specific, and active development community, while also being explicitly designed for interdependent, cyclic processes in dredging projects. Its flexibility, community support, and proven industry adoption ensure that it can accurately capture the complex logistics and uncertainties central to this thesis.

2.6. OpenCLSim

2.6.1. Building Blocks

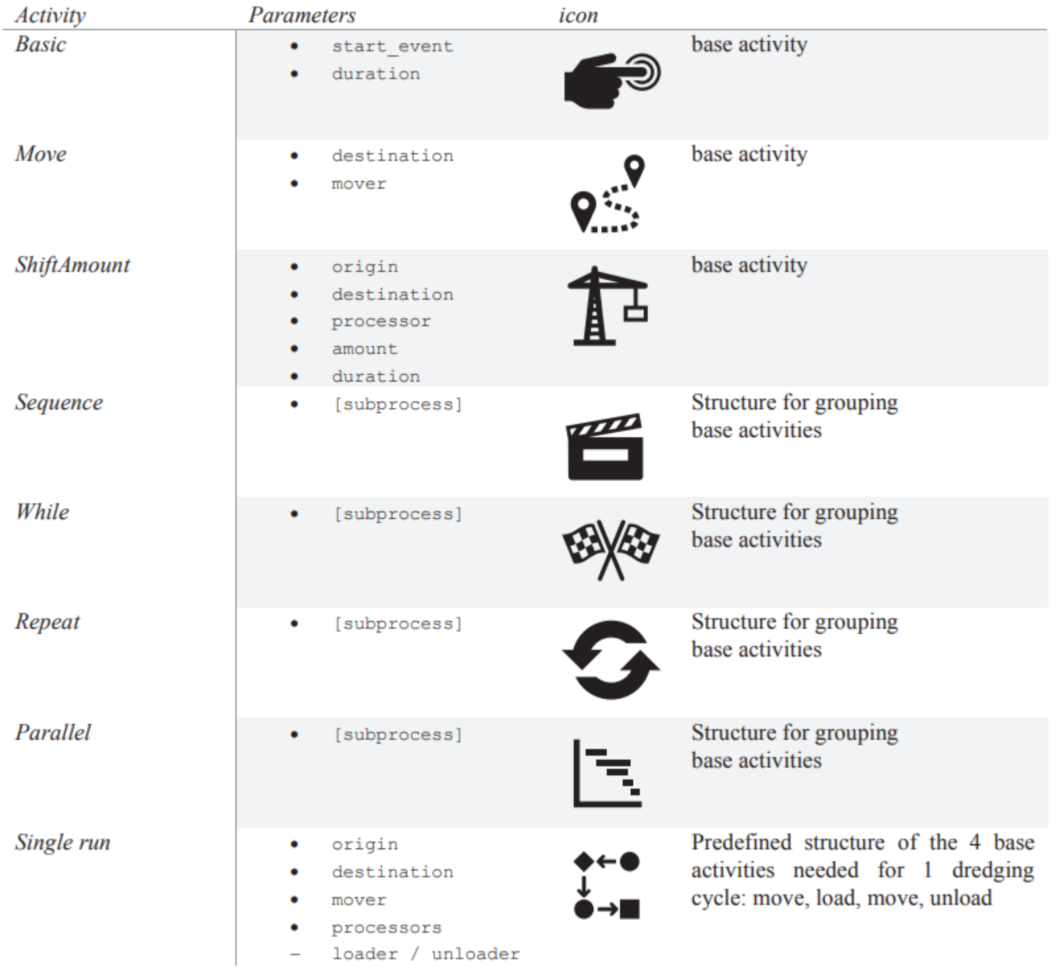
OpenCLSim, introduced by Van Koningsveld et al., [2019], serves as an advanced DES platform specifically designed for maritime projects. This software package is built upon an open-source Simpy library. SimPy is fundamentally structured around processes, which represent the progression of a defined period of time [De Boer et al., 2022]. These processes can generate events, either triggered or untriggered, and can establish dependencies on one another; the start or completion of one process can thus initiate others, with multiple processes capable of awaiting the same event. SimPy also provides a mechanism for modeling resources, which allow multiple processes to access shared elements. All processes, events, and resources coexist within a single simulation environment.

Built upon the this library, it extends core DES functionalities with a modular architecture. This architecture utilizes 'Mixins' to define asset properties, 'Plugins' for process characteristics like weather and delays, and custom 'Activities' that model the unique elements of maritime logistics such as moving vessels or shifting cargo. In OpenCLSim, Mixins, illustrated in Figure 2.4, are reusable software objects, each representing a limited set of system aspects like "Movable" or "HasContainer". By grouping these mixins, complex assets such as vessels or terminals can be constructed with the necessary properties to accurately model a logistical chain. This approach significantly promotes modularity and allowing users the flexibility to either maintain specific mixins for internal use or contribute them to the broader open-source community.

Mixin	*Parameters*	*icon*	*Remark*
Processor	• `LoadingFunction` • `UnLoadingFunction`		e.g. crane
HasResource	• `number`		Manage access if only a limited number of Processors can operate simultaneously. Has Resource allows an object to be a Processor.
Locatable	• `geometry`		(lat, lon) position
HasContainer	• `capacity` • `level`		Storage space. HasContainer allows an object to be an origin or destination.
Movable	• `origin` • `destination` • `v = f(level)`		Any Movable is implicitly also a Locatable

Figure 2.4: Mixins in OpenCLSim [De Boer et al., 2022]

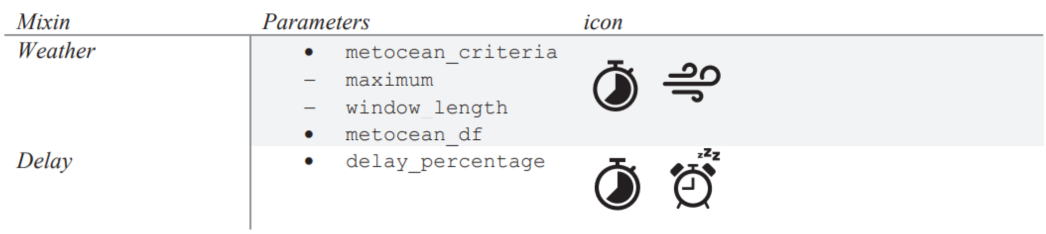
SimPy's basic processes are like simple timers that just let time pass. OpenCLSim builds on this by adding its own specialized 'Activities' to these processes, giving them more specific functions (Figure 2.5). The simplest of these activities, the "Basic Activity", just marks time passing, with no other effects on the system variables, like capacity or location. For marine logistics and offshore construction, two additional core activities are crucial: "ShiftAmount", which handles the loading and unloading of items or materials, and "Move", dedicated to sailing operations, whether without a load or with a partial or full load. To organize these three main activities into complete workflows, OpenCLSim provides four structuring activities. "Sequence" arranges sub-processes in a specific order, with a specialized "Single run" activity specifically tailored for the essential dredging cycle (sailing empty, loading, sailing loaded, and unloading). "While" and "Repeat" activities enable the continuation of a group of main activities (also packed in a sub-process) until a certain condition or goal is met. Finally, the "Parallel" activity lets you group several tasks, in sub-processes, that run at the same time. These tasks don't have to follow a strict order. So it is possible to set them to wait for a bit if certain conditions are met before moving on.



Activity	Parameters	icon	
Basic	• start_event • duration		base activity
Move	• destination • mover		base activity
ShiftAmount	• origin • destination • processor • amount • duration		base activity
Sequence	• [subprocess]		Structure for grouping base activities
While	• [subprocess]		Structure for grouping base activities
Repeat	• [subprocess]		Structure for grouping base activities
Parallel	• [subprocess]		Structure for grouping base activities
Single run	• origin • destination • mover • processors – loader / unloader		Predefined structure of the 4 base activities needed for 1 dredging cycle: move, load, move, unload

Figure 2.5: Activities in OpenCLSim [De Boer et al., 2022]

Beyond Mixins, OpenCLSim employs the concept of Plugins to offer a comparable modular approach for modeling processes (Figure 2.6). Each Plugin represents a single, isolated property of a process, allowing a process to integrate multiple Plugins. For example, the "Weather Plugin" calculates an object's workability by utilizing metocean data, maximum accepted conditions, and window length as parameters. The "Delay Plugin" allows for the simulation of delays in a fixed manner by applying a specified delay percentage, which proportionally extends the duration of an activity. Similar to mixins, OpenCLSim plugins can be maintained for internal use, held under embargo, or released as open source for community sharing.



Mixin	Parameters	icon
Weather	• metocean_criteria – maximum – window_length • metocean_df	
Delay	• delay_percentage	

Figure 2.6: Plugins in OpenCLSim [De Boer et al., 2022]

After the introduction of Mixins, Activities, and Plugins, understanding how a project is structured in OpenCLSim necessitates defining the various agents, or "objects", present within the system. Typically, the programming language distinguishes between three core object types: Activities (as previously discussed), Sites, and Vessels (Figure 2.7). Both Sites and Vessels are characterized by their own specific sets of Mixins. For instance, a Site is inherently static and does not move, yet it might possess a "HasContainer" Mixin, allowing it to have storage capacity for materials or cargo. Vessels, conversely, are always "Movable" and can include a "Processor" Mixin if they are equipped with machinery like a crane capable of transferring cargo from the vessel to a site.

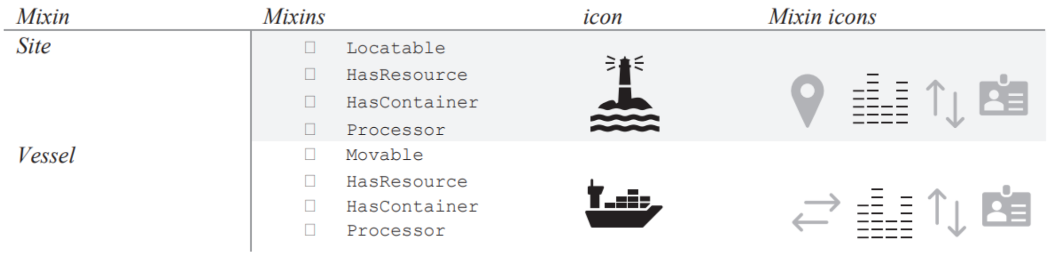


Figure 2.7: Objects in OpenCLSim [De Boer et al., 2022]

Furthermore, OpenCLSim significantly enhances SimPy's capabilities by incorporating extensive logging features that use universally unique identifiers (UUIDs) to all objects, enabling automatic comparison across different simulation scenarios. This addition to the SimPy library enables detailed data export for analysis in various business intelligence and project planning software. Finally, OpenCLSim provides built-in charts, such as Gantt diagrams and step chart overviews, for visual inspection and analysis of simulation results to aid project planning.

2.6.2. Project Schematization

In marine construction project planning and production estimating, three foundational concepts serve as indispensable elements: Sites, Vessels, and Activities [De Boer et al., 2022]. The structural composition of both Sites and Vessels relies on the previously introduced Mixins and Plugins. These fundamental concepts also underpin the development of Work Breakdown Structures (WBS) for projects, a critical methodology for work estimation, progress tracking, and risk assessment [USDOE, 1981; Hudoyo et al., 2019]. Within this organizational framework, Sites are specifically linked to the Object Breakdown Structure (OBS). Another key concept for this research is the Activity Breakdown Structure (ABS), which directly relates to the defined Activities. These Activities represent all processes executed by an asset that consume time. The comprehensive WBS of a project is then understood as the application of an ABS activity to an OBS site by an asset.

Leveraging the comprehensive WBS, including its OBS and ABS components, OpenCLSim employs a highly structured workflow for project implementation (Figure 2.8).

0. Before every project the OpenCLSim package libraries has to be imported before the initial phase begins.
1. Step 1: Initialize environment, where a simulation environment is initiated, allowing for the specification of the project's start date.
2. Define object classes and mixin assignment follows in Step 2, focusing on implementing the OBS. Here, locations are assigned appropriate mixins to define their characteristics; for example, the sites have to contain mixins that grants the locations to have a capacity level. If the site has a resource that is capable of handling a 'ShiftAmount' activity, then the corresponding mixin has to be assigned to the site class as well. Similarly, vessels (such as the hoppers) are given their relevant mixins, denoting their 'Movable' nature, defining their volume capacity, and enabling loading and unloading functionalities. These mixins are crucial as they give the object classes with their specific operational properties.
3. In Step 3: Create objects, specific instances of these objects are then generated. Locations are instantiated with details such as geometric points, capacity, and initial levels, while vessels receive parameters like loading and sailing speeds. Subsequently, the Activities, forming the

ABS, are defined. Referencing the previous dredging example, the activities are structured to reflect parallel operations: two hoppers operate simultaneously within the simulation environment. Each hopper executes its tasks within a 'While' loop, conditioned to continue its sequence until the specified quantity of sediment has been removed from the harbor. Each such sequence encapsulates a complete dredging cycle, consisting of loading, sailing loaded, unloading, and sailing empty.

4. Once all activity objects are fully defined, Step 4: Register processes and run SimPy commences. In this stage, all processes are registered, and the SimPy-based simulation is executed.
5. Finally, Step 5: Inspect Result allows for a thorough examination of the simulation outcomes using OpenCLSim's integrated plot package to inspect all activities of all objects in a log data-frame, visualize these activities in the environment in a Gantt chart or inspect the volume evolution of different object in the Step charts.

Figure 2.8: OpenCLSim Work Flow

2.7. Summary

This Chapter has reviewed the main simulation methodologies and tools relevant to modeling dredging operations. Three theoretical approaches were considered: Queueing Theory (QT), System Dynamics (SD), and Discrete Event Simulation (DES). QT provides valuable insights into waiting lines and service performance but is too narrow to represent the multi-agent, multi-activity nature of dredging projects. SD offers a system-level view of feedbacks and long-term dynamics but lacks the operational detail needed to model individual assets and their stochastic interactions. DES, by contrast, captures both micro-level events and system-wide effects, while accommodating randomness and scalability. As shown in the comparison, DES is therefore the most appropriate methodological basis for this thesis.

Having established DES as the preferred approach, this research adopts OpenCLSim as the simulation environment. OpenCLSim stands out because it is open source, has an active development community, and has already proven its applicability in dredging and offshore projects. The software is build on the SimPy engine and is structured around clear building blocks such as activities, objects, and plugins, which can be combined to represent the operations of complex maritime projects. Its modularity and extensibility allow users to adapt and expand the framework for specific project needs. Through an Object Breakdown Structure (OBS) linked to an Activity Breakdown Structure (ABS), OpenCLSim schematizes projects by allowing assets to execute sequences of activities, with behaviors encapsulated in reusable mixins and extended through plugins. This object-oriented design ensures that real-world work methods can be explicitly encoded and systematically compared across scenarios. Beyond project schematization, OpenCLSim also provides strong monitoring and analysis capabilities. All entities are uniquely logged, which enables precise comparison of scenarios and downstream processing. These features make OpenCLSim particularly suitable for this research, as it balances accessibility with the ability to realistically capture the dynamics of dredging operations.

In summary, this Chapter reviewed the main modeling approaches and available software to determine which tools are most appropriate for dredging projects. The most suitable estimation tool is OpenCLSim, a Discrete Event Simulation (DES) environment that is open source, widely applicable in maritime contexts, and supported by an active development community. It can encompass the complexity of dredging operations through its modular building blocks—activities, objects, and plugins—that together construct project simulations. Moreover, its customizable plugin structure enables the inclusion of project-specific complexities, such as workability limits linked to weather conditions or delay factors modeled as percentage extensions.

3 Risk Assessment Methodology

This Chapter presents the methodology used to capture, encode, and analyze risks and uncertainties in dredging projects within a discrete-event simulation environment. The approach emerged iteratively from multiple tender reviews: through consultations with industry experts, review of archival projects and tender dossiers, schematization of representative work methods to identify the "red thread" across projects, and hands-on prototyping with the simulation framework introduced earlier. These activities were consolidated into a reproducible pipeline that links expert judgment to model parameters and model outputs to decision-relevant indicators.

At a high level, the methodology proceeds in four stages, summarized in the flowchart in Figure 3.1. First, the Characteristic Risks & Uncertainties (Section 3.1) section serves as the data collection, that establishes a structured inventory of project-specific risks and uncertainties (Section 3.1.1) and organizes them into coherent categories relevant to dredging (Section 3.1.2). Then, the hierarchal project layers (Section 3.1.3) are introduced and how the risks and uncertainties maps to each of its appropriate level of impact within the simulation architecture (Section 3.1.4). Second, Integration into Simulation Software (Section 3.2) serves as the translation of the gathered data and converts elicited judgments into model-ready inputs for the custom Risk & Uncertainty Mixin by defining implementation levels (Section 3.2.1) and converting qualitative expert estimations into probabilities and impact distributions consistent with the event logic (Section 3.2.2). Third, Assessing Risks & Uncertainties (Section 3.3) analyses the translated data and uses the instrumented model to track operations (Section 3.3.1), compute Key Performance Indicators (time, cost, emissions), attribute impacts to individual risks in the presence of concurrent risks, examine interaction effects (buffering or cascading) (Section 3.3.2). Lastly, the Mitigation Evaluation (Section 3.4) assesses the effectiveness of each mitigation measure and compares the financial feasibility of which measure combination is most favorable.

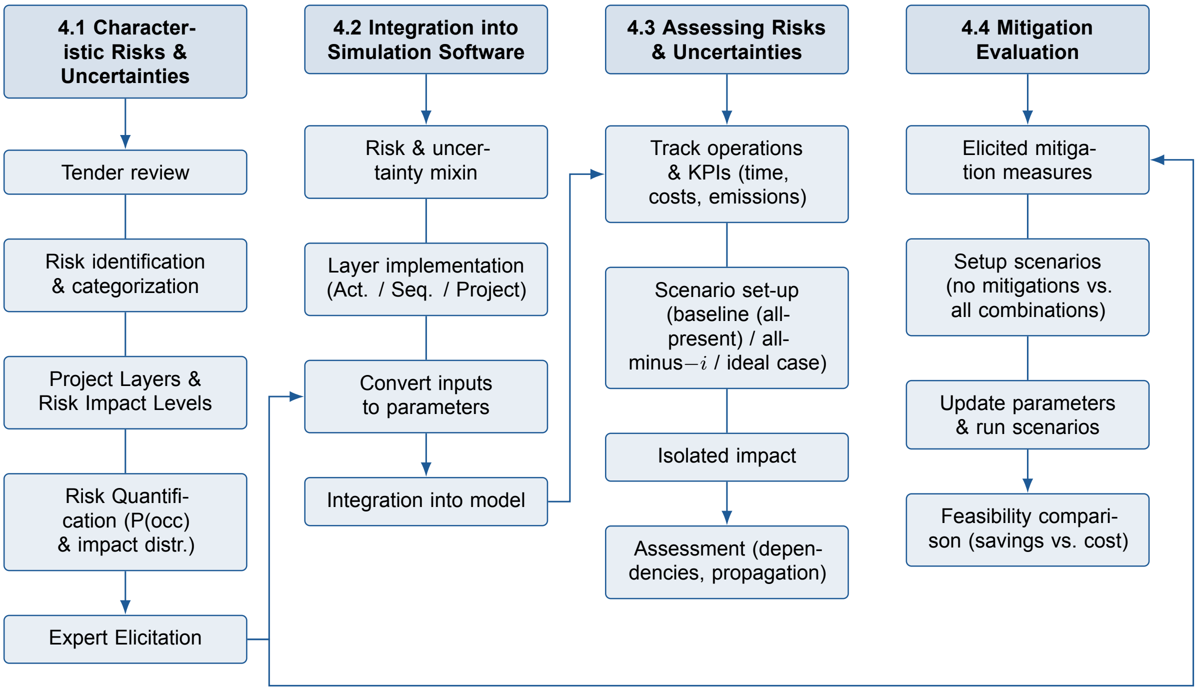


Figure 3.1: Flowchart: Risk Assessment Methodology

3.1. Characteristic Risks & Uncertainties

Early in the tender phase, dredging projects are shaped by characteristic risks and uncertainties while detailed data are limited. To capture these factors in a way that is consistent and usable for simulation, this section develops a structured procedure that first establishes the analytical framework and then gathers expert input to parameterize it.

The procedure proceeds in five steps. First, risk identification compiles a preliminary list of relevant risks and uncertainties from prior work methods, project documentation, and domain literature. Second, risk categorization organizes these items into coherent groups tailored to dredging (e.g., workability, technical, logistical, environmental/social), ensuring comparability across projects. Third, each item is mapped to a level of impact within the simulation architecture (activity-level variability, delay within a sequence/asset, or project-wide delays), so effects can be modeled at the appropriate layer. Fourth, a quantification framework is defined (probability of occurrence and impact distributions) to enable later translation into simulation parameters. Finally, expert elicitation is conducted to provide project-specific estimates for the defined probabilities and impacts, and to refine the earlier steps where needed. Mitigation strategies are treated separately and will be addressed later in this chapter.

The subsections that follow adopt this order: identification (Section 3.1.1), categorization (Section 3.1.2), hierarchical project layers (Section 3.1.3), level of impact (Section 3.1.4), quantifying (Section 3.1.5), and expert elicitation (Section 3.1.6).

3.1.1. Risk Identification

Effective risk identification is a crucial initial step in managing project complexities, as highlighted by Siraj et al., [2019], who extensively reviews various methods emphasizing its high importance. In project management, understanding the distinction between risk and uncertainty is crucial for effective planning [Samson et al., 2009]. Therefore, to ensure clarity and consistency within this thesis, the following definitions are adopted.(Table 3.1):

Risk	A discrete event that, if it occurs, could have a negative consequence on project objectives. A risk is generally characterized by its probability of occurrence (how likely it is to happen) and the impact it would have.
Uncertainty	This refers to a range of possible outcomes around a prediction, it reflects the inherent variability when anticipating future events. Crucially, uncertainty always occurs when the event takes place, meaning its probability of occurrence is effectively 1.

Table 3.1: Risk and Uncertainty Definition

Beyond the general definitions, various methods exist for identifying and analyzing risks, which is of high importance in project management, as extensively reviewed by Siraj et al., [2019]. Regarding qualitative risk analysis, Gupta et al., [2018] identifies commonly used methods such as risk probability and impact assessment, risk categorization, and expert judgment. These qualitative approaches provide a structured way to evaluate and prioritize risks, often serving as an initial step before more detailed quantitative analyses.

When considering the complexities of dredging projects, it is crucial to distinguish between uncertainties and risks that exist at the beginning of the project and those related to the final project outcome. On one hand, the project's ultimate results can have restrictions like the time window for completion, adherence to a strict budget, or compliance with environmental emission limits. If these restrictions are exceeded or not can be uncertain at the beginning of the tender phase. This represent uncertainties about the project's success relative to client or regulatory targets. These are often project and client-specific, for example a project can have a strict time window due to seasonal weather condition that only allow a few months of work in a specific region. Another reason can be that for some clients cost efficiency may prioritize over emission reduction, while others emphasize environmental adherence. On the other hand, a distinct set of uncertainties exists early in the tender phase that directly influence how the KPIs will ultimately result. Understanding these initial uncertainties is paramount, as they directly impact the ability to make solid estimations on the final KPIs. Therefore, this section will primarily zoom in on identifying and characterizing these fundamental risks and uncertainties that arise in the early stages of a dredging project, setting the stage for their integration into simulation models.

3.1.2. Risk Categorization

Risk categorization is a crucial preparatory step for a comprehensive risk analysis, a process that [Stackpole, 2013] highlights for its importance in effectively understanding potential impacts. For this research, specific risk categories were defined that relate to dredging projects, focusing on those that could influence the KPIs and can be taken into account by the logistical simulation. These categories, detailed below, encapsulate the primary areas of uncertainty relevant to project planning.

- **Workability**
  This category encompasses risks directly arising from unfavorable environmental conditions that impact the physical execution of dredging operations. This may involve uncertainties related to waves, currents, and other weather related conditions (such as high winds, storms, or fog), all of which can limit operational efficiency, safety, and the deployment of equipment.
- **Technical**
  This category consists of risks associated with the functioning, performance, and reliability of the dredging equipment, vessels, systems, or other auxiliary equipment used. This includes uncertainties regarding equipment breakdowns, unexpected wear and tear, performance degradation of machinery, malfunctions in specialized systems, challenges in equipment selection, and incidents occurring due to technical faults.
- **Logistical**
  This category covers risks related to the planning, coordination, and management of the supply chain and transport processes within a dredging project. Uncertainties can arise from the availability and movement of vessels (such as transit times, waiting times), the efficiency of loading and unloading activities, the supply of fuel or spare parts, and the optimization of transport routes. Risks associated with traffic in the operational area, planned maintenance, crew changes, and bunkering (refueling) also fall under this category.
- **Environmental/Social**
  This category concerns risks from the interaction of the dredging project with the natural environment and local communities, as well as regulatory compliance. This includes uncertainties about soil characteristics (e.g., unexpected contaminations, sediment quality or rare obstacles), the generation and dispersion of turbidity in the water column, disturbance of ecosystems and marine flora and fauna, noise pollution for local residents, and the complexity or strictness of permitting and compliance requirements.

3.1.3. Project Layers

To integrate risks consistently into the simulation, it is essential to understand how dredging projects are represented within OpenCLSim. With its fundamental building blocks and project schematization with OBS and ABS (Section 2.6) it can systematically construct work methods into a simulation model. With these building blocks, OpenCLSim is able to structure a project into four distinct hierarchical project layers, each representing an increasing scale of operational complexity.

1. At the most granular level is the Activity layer. An activity represents the smallest unit of work performed within the simulation, such as a 'loading' action or a 'sailing' movement. These discrete activities form the basis for all project operations.
2. Next, activities are combined into an Sequence. The sequence layer defines a specific series of interdependent activities that are performed in a defined order. For a typical dredging operation, a common sequence might include 'loading', 'sailing loaded', 'unloading', and 'sailing empty'. This entire sequence is often encapsulated within a while loop (Figure 2.5), ensuring that the cycle repeats until a specific condition, such as all sediment being dredged, is met.
3. The subsequent layer is called the Asset layer. At this level, multiple assets, such as several transporters, work concurrently and in parallel to achieve a common objective. Each asset executes its own activity sequence independently, but interactions between these resources can

influence waiting times and resource utilization. This highlights the interdependencies within the fleet as they contribute to the overall project progress.

4. Above this is the Multi-Site layer. This layer accounts for projects involving multiple distinct geographical locations where one or more assets or even entire fleets perform their respective sequences in parallel. This represents a higher level of complexity, coordinating operations across various physical sites.

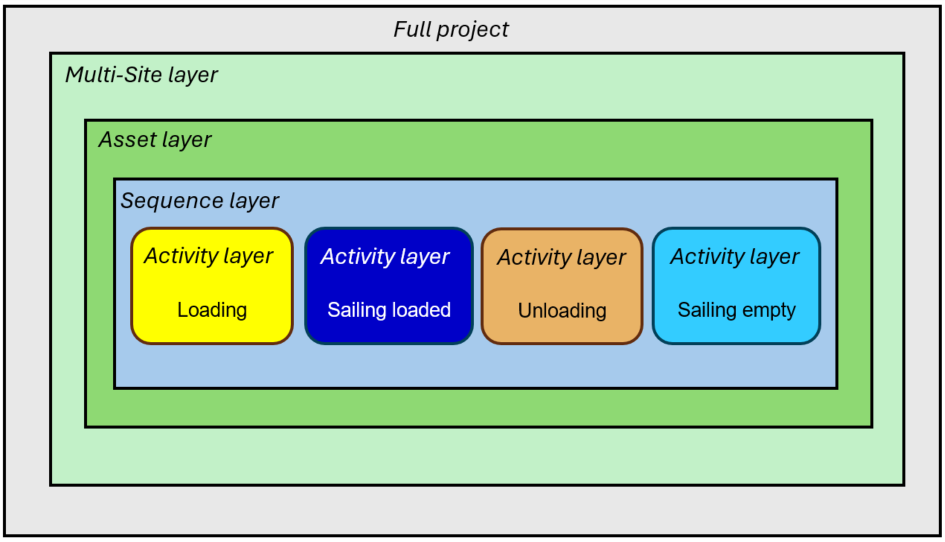


Figure 3.2: Hierarchal structure within OpenCLSim: Project Layers (Activity, Sequence, Asset, Multi-Site).

Collectively, these layers, from individual activities to sequences, fleet operations (with multiple assets), and multi-site execution (multiple dredge/discharge locations), form the complete project structure within OpenCLSim (Figure 3.2). The coordination and interaction between these layers ultimately define the comprehensive overall hierarchal project structure, allowing for the detailed simulation of complex dredging projects. An illustrative example of how such a structure can be schematized for a dredging project is provided in Appendix A.

By defining risks within this layered framework, it becomes possible to assign their occurrence and impact at the appropriate level of the project. The following section builds on this by mapping identified risks and uncertainties to their corresponding levels of impact.

3.1.4. Level of Impact

Once risks and uncertainties are categorized, it is essential to understand the specific layers at which they can exert their influence within a project simulation. Any identified risk, regardless of its category, can be situated within one of three distinct levels of impact, which will be elaborated below. This hierarchical understanding is crucial for precisely modeling their effects on project progression.

1. **Activity Uncertainty**
   The first level of impact is in the most granular layer: the Activity layer. Here activities are prone to uncertainties primarily influencing the precise duration of a specific activity. The activity itself is performed, but its exact completion time is variable. For example, during a dredging loading operation, even without prior risks, the duration can be uncertain due to factors like varying sediment quality (e.g., harder or softer than anticipated, affecting efficiency). Similarly, the sailing activity's duration can fluctuate based on changing current conditions, or the time required for a vessel to moor at a quay or processor might vary depending on the captain's experience. Crucially, these uncertainties always occurs whenever the activity is executed, as they represent the inherent variability of the activity itself (Table 3.1).

2. **Delay in Sequence**
   The second level of impact is a delay in the Sequence layer. Risks at this level specifically affect

only the particular asset(s) involved in that sequence, rather than the entire project. These risks typically manifest before another activity can commence, causing a delay. If delays occur in a particular sequence it does not have to mean that other parallel sequences are also delayed. A risk in the Sequence layer can mean that a new activity can occur with an uncertain duration, like an activity waiting on weather or waiting on repair services. Instances include technical breakdowns of a particular asset, which sidelines only that unit. Or if a specific asset's operational workability limitation is exceeded, causing an inability to work in certain wave heights while other assets remain operational. Another example could be if one of multiple dredging locations in a project generates excessive turbidity, leading to work suspension only for the processor operating in that specific area, while operations continue elsewhere.

3. **Delay across Project**
   The highest level of impact is in the Multi-Site layer of the OpenCLSim structure (Section 3.1.3), encompassing risks that causes delays across the full project. When such a risk occurs, all project activities may come to a halt. The delay is then noticeable in the entire project evolution. Examples include severe storm conditions causing that all operations become impossible to execute, region-wide exceedances of turbidity limits so that all assets must stop dredging or dumping, or significant governmental or permitting issues that enforce a project-wide stop or postponement.

These three distinct levels provide a framework for classifying how each risk or uncertainty in a dredging project can impact the simulation, thus preparing the ground for the subsequent step of quantifying these uncertainties and risks.

3.1.5. Quantifying

To effectively quantify risks, it is essential to understand two primary characteristics of each identified uncertainty: its probability of occurrence and its impact distribution [Stackpole, 2013].

Probability of Occurrence

When determining the probability of occurrence for risks, the focus is on their frequency, whether that's daily, monthly, or based on a certain number of operating hours. For risks tied to specific equipment or resources, like machinery breakdowns, experts can often estimate a Mean Time To Failure (MTTF) [Odeyar et al., 2022]. The failure rate (λ), defined as the inverse of the MTTF, serves as a crucial parameter for quantifying this frequency.

$$Failure\ Rate : \lambda = \frac{1}{MTTF} \tag{3.1}$$

It's important to clarify that this concept of a failure rate, inherently linked to the likelihood of an asset or component malfunctioning, directly applies to risks at the sequence layer. This is because failure rates describe a discrete event (a breakdown for example) that may or may not occur, distinct from the inherent variability in duration that characterizes uncertainties at the activity layer. While uncertainties at the activity level always occurs, a failure only occurs probabilistically. Therefore, the failure rate is a direct measure of a risk's probability of occurrence for a specific asset, influencing operations from the sequence layer upwards.

In addition to probabilities derived from failure rates, certain risks—particularly at the project-wide level—are better described in terms of an expected frequency of occurrence (e.g., "once per month"). These frequency-based estimates can be incorporated into the simulation as discrete counts of how many times a disruption is likely to occur during the project duration, providing an alternative way to parameterize occurrence alongside failure rates.

Probability of Impact

When assessing impact, the focus is on the direct duration or extent of the risk or uncertainty's immediate effect. The simulation then calculates how this initial effect ultimately influences the KPIs. Therefore, the critical question becomes: how long does this specific disruption or deviation last? This duration, being an inherent uncertainty itself, is typically estimated using a statistical distribution [Stackpole, 2013]. Commonly employed distributions for this purpose include the Uniform, Triangular, or

PERT distributions, each allowing for the representation of different levels of uncertainty in the impact's duration.

The simple uniform distribution is one of the most basic probability distributions and is often used to model situations where every outcome within a specified interval is equally likely [Kerzner, 2025].

$$Mean_{Uniform} = \frac{Min + Max}{2} \tag{3.2}$$

The triangular distribution is a widely used probability distribution in project management and risk analysis, often applied to model task durations when detailed statistical data is unavailable. This distribution can be easily estimated using a minimum, maximum, and most likely (ML or mode) value [Kerzner, 2025].

$$Mean_{Triangular} = \frac{Min + ML + Max}{3} \tag{3.3}$$

The PERT distribution is a constrained form of the beta distribution, which is commonly used to model the duration of activities. It is also defined by minimum, most likely, and maximum values. A key distinction from the triangular distribution is that the PERT mean is weighted more heavily towards the ML value (4/6), unlike the equal weighting (1/3) of L, ML, and H in a triangular distribution [Sailing et al., 2007].

$$Mean_{PERT} = \frac{Min + 4 * ML + Max}{6} \tag{3.4}$$

For assessing the temporal impact of a risk, understanding the distribution of its duration, specifically its minimum, maximum, and most likely values, is essential. This is especially pertinent for uncertainties in the activity layer, where the inherent variability of an activity's duration needs to be captured. While a broader array of probability distributions exists, the Uniform, Triangular, and PERT distributions are among the most prevalent and commonly applied in construction management due to their ease of use and suitability for various scenarios [Stackpole, 2013].

3.1.6. Expert Elicitation

Obtaining the necessary minimum, maximum, and most likely values for the defined risk distributions, along with their respective types, relies heavily on the systematic application of expert judgment. Various methodologies exist for expert elicitation and the structured acquisition of such insights [Cooke, 1991; Cooke et al., 2000; Colson et al., 2018; Hemming et al., 2018; Hanea et al., 2021].

Expert elicitation involves systematically gathering probabilistic assessments from knowledgeable individuals regarding uncertain variables, particularly when empirical data is scarce [Colson et al., 2018]. While expert judgment is invaluable, it is crucial to acknowledge that such techniques can inherently introduce biases into risk identification, analysis, and the selection of response strategies. These biases are context-dependent and may affect estimates of both probability and impact. Therefore, selecting experts with relevant experience in comparable projects is very important to ensuring the reliability and validity of the assessments. Furthermore, employing structured elicitation protocols is vital for enhancing the overall quality of expert judgments, especially when these insights are intended to inform critical project decisions [Hemming et al., 2018].

To effectively obtain expert judgment on the various uncertain categories at the project's start, a structured approach is imperative. Given the inherent uniqueness of each dredging project, it is impractical to ask experts generic questions about the likelihood and impact of the duration of specific risks. Therefore, a systematic process is required to enable experts to make more realistic and project-specific assumptions. The following steps outline this elicitation structure:

1. **Thorough Tender Analysis:**
   The initial step involves a comprehensive analysis of the project tender. This includes identifying the dredge work location, the volume of material to be displaced, the available assets for project

execution, and the estimated start date. By addressing these foundational questions, experts can formulate a basic working method for project delivery.

2. **Understanding Client KPIs:**
   A crucial subsequent step is to align with the client's most important KPIs. This requires understanding all stakeholders involved and their primary values. These priorities vary significantly per project, influenced by factors such as the location of the sites, the client's financial status, or the environmental vulnerability of the dredge site. Identifying whether cost, time window, or environmental impact is most critical allows the expert to make more accurate engineering estimates based on a clearer understanding of project goals.

3. **Determining Project-Specific Key Risks:**
   Given the dynamic nature of dredging operations, the key risks and uncertainties are project-specific. Expert judgment is therefore essential to inform the identification of these critical risks for each unique tender. For instance, regions rich in marine life might present turbidity as a significant risk causing potential delays, while stern permitting processes by clients or regulatory bodies could introduce substantial social risks. These issues underscore the necessity of eliciting insights from the most appropriate and experienced experts.

4. **Identifying Risk Impact Layers:**
   Once experts have provided their insights on the key risks for a specific project, it is vital to determine the layer at which each risk or uncertainty will exert its impact within the simulation model. This involves assessing whether, for example, turbidity risks affect only a specific resource, or if a potential turbidity limit exceedance necessitates a complete project halt. Clearly defining each risk's impact layer is fundamental for the subsequent steps in the elicitation structure.

5. **Estimating Risk Distribution and Impact Duration:**
   Finally, the expert provides rough estimates regarding the probability distribution that each identified risk or uncertainty follows. Concurrently, they offer engineering estimates for the duration of its impact, specifying minimum, maximum, and most likely values. This range of estimates enables the construction of a probability distribution that can then be integrated into the simulation model, as detailed in Section 3.2.

3.2. Integration into Simulation Software

Having established the risk framework and elicited project-specific judgments in Section 3.1, the next step is to translate these inputs into parameters that the simulation can execute consistently. This section defines how qualitative and quantitative expert inputs are converted into model-ready values and bound to the appropriate layers of the simulation architecture.

The translation proceeds in two parts. First, we specify the implementation framework: a dedicated mixin structure that attaches probabilities and impact distributions to the correct level of impact, ensuring effects are applied at the intended point in the event logic (Section 3.2.1). Secondly, it details the data conversion from expert statements to usable probability and duration parameters, e.g., mapping frequencies or MTTF to occurrence probabilities, and encoding minimum/most-likely/maximum impact durations via selected distributions (Section 3.2.2). A concise demonstration of effects using a controlled example is presented later in the Results (chapter 5), where the outcomes of this integration are visualized and interpreted.

3.2.1. Implementation

This section outlines the methodological approach for integrating expert judgment into the simulation model, detailing how the software handles uncertain event occurrences and their impacts. The primary goal of the code is to track all activities within an initialized simulation environment, as established in Section 2.3. Consistent with the principles of discrete event simulation, any delays or uncertain deviations in activity duration are systematically logged.

The core of this integration consists within the simulation's activity calling mechanism, conceptually represented as ”step 3” in the project's schematization (Figure 2.8). As previously discussed in the section on levels of impact (Section 3.1.4), risks and uncertainties can exert their influence either on individual activities (activity uncertainty and sequence delay) or on the entire project (delay across full project). It is at this ”step 3” where the expert judgment, in the form of engineering estimates for these uncertainties, is implemented.

This implementation needs a dedicated mixin, as conceptually outlined in Figure 2.6. This mixin is parameterized by: a ‘probability‘ (expressed as a percentage) for the risk's occurrence; a ‘distribution‘ type (which can be Uniform, Triangular, or PERT); and the corresponding ‘minimum‘, ‘most likely‘, and ‘maximum‘ values for that chosen distribution (Table 3.2).

Mixin	*Parameters*	*Value*
Risk & Uncertainty	Probability	Percentage
	Distribution	Uniform/Triangular/PERT
	Minimum	Value in seconds
	Most likely	Value in seconds
	Maximum	Value in seconds

Table 3.2: Details of Risk and Uncertainty Parameters

When activated by the simulation, this plugin probabilistically determines whether a specific risk event occurs. If the risk is triggered, the simulation employs a random sampling method to draw a time value from the specified distribution. This sampled time is then added to the discrete event simulator's logbook, effectively changing the activity's duration or imposing a delay. This mechanism allows the simulation to accurately track both the frequency and the duration of any induced delays. The subsequent sections will detail how this plugin is implemented for each identified impact layer.

Activity Layer

At the Activity Layer, the risk and uncertainty mixin is specifically focused on modeling the inherent uncertainty in the duration of an activity. Implementation at this level involves integrating the mixin directly within the definition of the activity itself. For uncertainties that are intrinsic to an activity's execution, the probability of occurrence for the mixin is typically set to 1, signifying that this variability is always present whenever the activity is performed.

When an activity with this mixin is called during the simulation, its precise duration is determined by sampling a value from the activity's associated impact distribution. This distribution is defined by its minimum, maximum, and most likely, which could have a positive or negative sign. An example is the docking actions a transporter performs after each sailing event, either at a quay or another destination. This docking is an integral part of a sailing activity and has an uncertain duration that can sometimes extend longer or shorter than the expected sailing time. The mixin, which is implemented in this sailing activity, ensures that each instance of sailing activity reflects this variable docking time. Risks and uncertainties at this layer therefore relate to the uncertain duration of activities that are called upon and apply consistently across all objects performing that specific activity.

Delay in Sequence

At the Delay in Sequence impact level, the risk and uncertainty mixin is designed to simulate events that specifically impact individual assets, such as a particular processor or transporter, without necessarily halting the entire project. Implementation at this level involves associating the mixin directly with the respective asset object within the simulation. This mixin is typically activated and evaluated before an activity assigned to that specific asset is set to commence. It effectively acts as a probabilistic gate, determining whether the activity can proceed as planned or if it will incur a delay.

When a risk at this level is triggered, based on its defined probability of occurrence, the affected asset becomes temporarily unavailable or delayed for a duration sampled from the risk's associated impact distribution (characterized by its minimum, maximum, and most likely values). For instance, if a breakdown risk is activated for a specific processor, only that processor's subsequent activities are prevented from executing, and it must wait for the duration of the sampled repair time. During this period, other assets and their independent activities within the project can continue to operate, highlighting the localized impact of risks at this level. Once the assets delay or downtime has ended, it becomes available to resume its scheduled activities.

Delay across Project

At the Delay across Project level, the risk and uncertainty mixin is designed to simulate events that bring the entire project to a halt, affecting all ongoing and scheduled activities. While in reality, such an event, like a severe storm or a project-wide permitting issue, would cause an immediate operational stop for all assets, the simulation implements this effect differently to achieve the same outcome.

The implementation at this level requires the mixin to be applied to the highest project layer in the simulation structure, the Multi-Site layer. Instead of pausing the simulation in real-time, the probability of the risk is evaluated at each simulation run. If the risk is activated, a delay duration is randomly drawn from the impact distribution. This delay is then integrated into the total waiting time of each asset, which increases the total project time accordingly. This approach ensures that the delay across the project is accurately reflected in the final simulation results. By adding all the aggregated delays to the total waiting time per asset and thus total project time, all subsequent KPI calculations are based on values that correctly account for the impact of these high-level risks. This effectively mirrors the consequences of a real-world project interruption.

For risks at this level, the simulation not only samples the impact duration but can also incorporate expert estimates of frequency. By translating inputs such as “once per month” into the expected number of occurrences over the project duration, the model introduces these delays the appropriate number of times in a run. This ensures that both the likelihood and repetition of project-wide disruptions are realistically represented.

3.2.2. Converting Data

Having explained where the risk and uncertainty mixins are to be inserted based on their impact layer, the next step involves filling in their parameters with data derived from expert judgment. The mixin requires the probability of occurrence as a percentage, and the minimum, most likely (mode), and maximum values for impact duration in seconds, along with a specified distribution type. The latter and their associated values can be given as specifically as the expert has them ready. However, experts may not always provide the probability of occurrence directly as a percentage. Therefore, a clear methodology is needed to convert these expert estimates into usable and accurate percentage values for the mixin.

First, it's crucial to consider where the mixin is invoked. As described in the previous section, this can be at a Multi-Site layer for a Delay across Project, before an activity (for a Delay in Sequence), or within an activity (Uncertainty in Activity level). The latter, the activity layer, is often the simplest to implement, as its inherent uncertainty typically means the probability of occurrence is 1. The values for the distribution do not need any conversion and can be implemented straight out of the expert judgments estimates.

Moving up to the Sequence layer, where risks can introduce delays into asset activities, common scenarios involve various disruptive events. A key assumption made in this study is that these risk events follow a Poisson distribution, a principle confirmed by O'Connor, [2011]. The exponential distribution, which has a constant failure rate (λ), is used to model cases where no wear or cumulative damage occurs, and it can approximate the failure rate over a component's useful life. This "memoryless property" allows for a more accurate estimation of the failure rate over a component's useful life.

Experts might describe the frequency of such risks in terms of a specific interval, for example, occurring once a week or monthly, or per a certain number of operating hours. For equipment related risks, experts can often provide a Mean Time To Failure (MTTF) [Odeyar et al., 2022]. From MTTF, the failure rate (λ) can be calculated using the formula $\lambda = 1/\text{MTTF}$. To then determine the probability of occurrence ($P(occ)$) for an asset breakdown, the following formula derived from exponential distributions is used [Verma et al., 2010]:

$$P(occ) = 1 - e^{-\lambda t} \tag{3.5}$$

Here, λ represents the failure rate obtained from the expert's MTTF estimate, and t is the operational time of that specific asset. The operational time (t) of the asset is continuously logged by the discrete event simulator. This approach allows for the conversion of an expert's MTTF estimate, or even general expert input describing frequencies, into a consistent percentage.

Moving on to the Multi-Site layer, where the delay across the project impact level risks are handled, a different method is required to determine the frequency of implementation. Assuming that these risk events follow a Poisson distribution [O'Connor, 2011], the probability of a given number of events occurring in a specified time period can be calculated. This "given number of events" represents the frequency (k) with which the risk will be triggered in the simulation.

The Poisson distribution formula is given by:

$$P(k) = \frac{\lambda^k \cdot e^{-\lambda}}{k!} \tag{3.6}$$

Here, $P(k)$ is the probability of the event occurring exactly k times, and λ represents the expected frequency of the event over the project duration, as provided by expert input (e.g., "once per month"). It is important to note that here, λ is an expected frequency value, not a failure rate as in the exponential distribution.

To determine the most probable frequency for the simulation, an assumption is made that the k value with the highest $P(k)$ is the most representative and should be implemented. To find this value, the Poisson probability is calculated for multiple k values. The frequency of failure used in the simulation is therefore statistically substantiated and representative of the expected project conditions.

3.3. Assessing Risks & Uncertainties

With expert inputs encoded into the model, the simulation becomes an analysis model for understanding how risks and uncertainties shape project performance. This section sets out the procedure for extracting decision-relevant insights from the simulated operations.

The assessment proceeds in two stages. First, operational tracking and KPI computation: all activity executions and waiting times are logged per asset and aggregated into the Key Performance Indicators (KPIs), time, cost, and emissions (Section 3.3.1). And second, impact attribution and interactions are assessed: the contribution of individual risks is quantified against a baseline scenario, and dependencies are examined to reveal buffering or cascading effects across layers and assets (Section 3.3.2).

Together, these steps provide a consistent basis to identify the most critical risks, explain their pathways of impact in the operational chain, and prioritize where engineering capacity should be devoted to.

3.3.1. Operational Tracking & KPIs

This section details how the simulation tracks each individual activity per asset, along with any associated uncertainties and risks. Drawing upon DES principles , the simulation logs the operational and waiting times for every activity executed by each asset (Section 2.3). Crucially, this tracking also extends to the specific durations of triggered risks, such as ”Delay in Sequence” and ”Delay across Project” activities, which are logged as distinct events when activated by the simulation. While uncertainties inherent to individual activity durations are directly captured as part of that activity's recorded time, these delay activities can contribute to additional waiting times when they occur. Next up, the methodology for calculating the project's KPIs from this comprehensive tracked data will be explained.

Time

Within the simulation, time is tracked for each individual asset. This involves logging both the actual operational times spent on executing activities and any associated waiting times encountered during its sequence. For each asset, these discrete time components are aggregated to provide a comprehensive timeline of its complete operational engagement throughout the project duration.

The primary KPI related to time, the total project time, is determined by the completion of the entire project scope. This is specifically defined as the moment the very last asset finishes its final scheduled sequence and activity. In projects encompassing multiple sites, such as those within the Multi-Site layer, the project is considered complete only when all operations across every site have concluded, and the final asset has finished its work. The simulation's clock effectively stops at this point, providing the definitive total project time.

Costs

Total project costs are calculated as a KPI by aggregating the financial expenditure associated with each operational asset throughout the project's duration. For every asset category, including transporters, processors, and other auxiliary equipment costs are categorized into a fixed component and a variable component. The variable cost is directly tied to the asset's active duration. Which is calculated based on its total operational and waiting time, rounded up to full days, and including any project-wide delays. The specific cost parameters used in these calculations, such as fixed costs and daily rates for each asset type, are derived from expert estimations, which are notably based on publicly available CIRIA (Construction Industry Research and Information Association) asset cost assessments.

Emissions

The last KPI is the total project emissions, are calculated by summing the individual CO_2 equivalent emissions generated by each asset throughout the simulation. The method used divided the fuel consumption into two primary categories: fuel consumed during active operation and fuel consumed while waiting, both values are liters per hour.

For each asset (transporters and processors) the fuel consumption in liters (V_{Fuel}) is determined by multiplying its operational hours (O_h) by an operational consumption rate (C_o), and adding this to its waiting hours (W_h) multiplied by a waiting consumption rate (C_w). This can be expressed by the formula:

$$V_{Fuel} = (O_h \times C_o) + (W_h \times C_w) \tag{3.7}$$

It is assumed that specific consumption rates for both operational and waiting states are applied based on the asset type. Given that typical marine operations primarily utilize fuels such as marine diesel oil (MDO) or marine gas oil (MGO), the calculated fuel volume (V_{Fuel}) is then converted into mass (M_{Fuel}) using a fuel density (ρ), typically expressed in kg/m^3:

$$M_{Fuel} = V_{Fuel} \times \frac{\rho}{1000} \tag{3.8}$$

Finally, the CO_2 equivalent emissions in kilograms are calculated by multiplying the fuel mass by a conversion factor (CF) of the specific fuel used [Miyake, 2023], which represents the amount of $CO_2\ eq$ emitted per kilogram of fuel:

$$CO_2\ eq = M_{Fuel} \times CF \tag{3.9}$$

These calculations are performed for every asset over the simulation period. The total project CO_2 emissions are then obtained by summing the individual emissions from all assets, providing a rough estimate on the environmental impact for the simulated project. The specific values for consumption rates, fuel density, and conversion factors are derived from expert input, based on industry standards and equipment specifications.

3.3.2. Impact Assessment

Baseline and Comparator Design

Assessing the impact of identified risks and uncertainties on a project's KPIs is a critical analytical step. This assessment necessitates a comparison against a baseline scenario where all risks or uncertainties are incorporated. To determine the impact of individual risks, particularly in the context of interconnected events, a specific methodological approach is adopted to drill down and identify which risk impacts the KPIs the most. So, in the Baseline scenario all risks are enabled and in the comparator scenario all risks except the target one are enabled.

Isolating Individual Risk Contributions

The methodology for isolating the effect of a specific risk involves running two distinct simulation scenarios. First, a comprehensive scenario is executed where all identified risks and uncertainties are simultaneously active. Subsequently, to determine the isolated impact of a particular risk (e.g., Risk A), a second scenario is run where all risks are present except for Risk A. The difference in the resulting KPIs between these two scenarios then quantifies the impact attributed by Risk A.

> *Example: What is the impact on the cost KPI of Risk A in a project where risks A, B, and C are present?*
>
> - *Run a simulation with all risks (A, B, and C) present to determine the total costs, which we call S.*
> - *Run a simulation with risks B and C present, but excluding Risk A, to determine the total costs, which we call X.*
> - *The impact of Risk A on the cost KPI is then calculated as the difference between these two scenarios:*
>
> $$\textit{Impact of Risk A} = S - X$$

This approach is preferred over assessing individual risks in isolation (i.e., by running a scenario with only one risk active) for several compelling reasons [Bañuls et al., 2017]. Primarily, it accounts for the inherent interdependencies between risks within a complex project environment. Risks rarely occur independently, their presence can influence the likelihood or impact of other risks, leading to cascading or knock on effects, or, conversely, buffering effects where one risk mitigates the impact of another. By comparing scenarios with and without a specific risk while other risks remain active, a more realistic and nuanced understanding of its contribution to total project impact is achieved. This method thus provides insights into how a risk interacts within the system, which is crucial for practical project management where risks do not manifest in isolation.

Detecting Interactions: Buffering vs. Cascading

To analyze the dependencies between risks, a comparison is made between the sum of the impacts of analyzed risks and the total impact when all risks are present simultaneously in the simulation. This approach also allows for the investigation of cascading/knock on or buffering/mitigating effects between risks across different project layers.

The procedure is as follows:

1. Calculate the total impact. The overall impact on a given KPI (e.g., total project time) is determined when all risks and uncertainties are included simultaneously in the model.
2. Calculate the individual impacts. The impact of each individual risk or uncertainty is determined by eliminating only that risk or uncertainty and comparing that simulating outcome to the outcome of the scenario where all risks are present simultaneously.
3. Sum the individual impacts. The impacts of all analyzed risks are added together.
4. Compare the sums. The sum of all the individual risk impacts is then compared to the total impact of the all-risks scenario.
   - If the sum of the individual impacts is greater than the total impact of the all-risks scenario, a buffering effect has occurred. This suggests that some delays may have been absorbed by other events or parallel processes.
   - If the sum of the individual impacts is less than the total impact of the all-risks scenario, a knock-on or cascading effect has occurred. This indicates a cumulative or amplifying effect where risks negatively influence each other.
   - If both values are approximately equal, it is concluded that the risks are independent of each other and do not significantly influence one another.

   Example: How to analyze the dependencies of the three risks A, B and C on time KPI?

   1. *Impact on time when all risks are present (A, B, C) is simulated and simulation outcome value is called:* S
   2. *Calculate each individual impact of A, B, and C:*
      - *Impact A on time: run simulation with B and C, impact value is called:* X
      - *Impact B on time: run simulation with A and C, impact value is called:* Y
      - *Impact C on time: run simulation with A and B, impact value is called:* Z
   3. *Sum individual impacts of A, B, and C :* $X + Y + Z$
   4. *Compare sum of A, B, and C with simultaneous impact* S*:*
      - *If* $X + Y + Z > S$*: Buffering / mitigating effect between risks has occurred*
      - *If* $X + Y + Z < S$*: Knock-on / cascading effect between risks has occurred*
      - *If* $X + Y + Z \approx S$*: Risks are independent on each other*

Propagation to Other Assets

To investigate the effects a specific risk has on other project activities, a method is applied that compares two simulation scenarios. This methodology is specifically designed to quantify the impact of a delay in a sequence on the waiting times, costs, and emissions of other assets. The steps are as follows:

1. Ideal scenario without any risk: A simulation is first executed with the specific delay in sequence risk disabled. For all assets in the project, the operational, waiting, and total times are tracked.
2. Scenario with specific risk: The simulation is then repeated with the delay in sequence risk enabled. The new operational, waiting, and total times for all assets are recorded. It is important to note that a delay in a sequence, by definition, does not affect the operational times of the assets but solely increases their waiting and total times.

3. Quantifying effects: By comparing the waiting times of the assets from the ideal scenario to those of the risk included scenario, the extra waiting time caused specifically by the delay in sequence risk is calculated. This extra time is then used to quantify the resulting additional costs.

This comparison allows for the measurement of interdependencies between the assets. If a delay in one activity (e.g., in a sequence) leads to a significant increase in the waiting times, and consequently the costs of other assets, it can be concluded that a significant cascading effect is present. This approach provides down drilling of the detailed understanding of the chain reactions that risks can trigger within the project. Given the complexities characteristic of dredging projects, including interactions between factors from each risk and uncertainty category, this comparative scenario based method provides a more accurate and realistic estimation of risk impact on project KPIs.

Probabilistic Reporting

All KPI outcomes are evaluated probabilistically using Monte Carlo simulation. For each model configuration (e.g., baseline with all risks; comparator with a specific risk removed), multiple replications are executed to sample from the specified occurrence and impact distributions. This yields an empirical distribution for each KPI rather than a single deterministic value.

Consistent with industry practice for conservative planning, KPI results are reported at the P80 confidence level, i.e., the value at or below which 80% of simulated outcomes fall [Eldosouky et al., 2014; Acebes et al., 2024]. Where informative, additional percentiles (e.g., P50, P95) may be provided. To ensure comparability across scenarios, all configurations use the same number of replications and identical sampling settings.

When attributing the impact of a given risk on a KPI, differences are computed at the same percentile level. For example, the contribution of Risk A to total cost is calculated as:

$$\Delta\text{Cost}_{\text{Risk A}} = \text{Cost}_{\text{P80}}(\text{all risks}) - \text{Cost}_{\text{P80}}(\text{all except A}).$$

This convention avoids mixing percentile levels and ensures that reported deltas reflect differences in the underlying risk configuration rather than differences in summary statistics.

3.4. Mitigation Evaluation

Once risks and uncertainties have been encoded and their impacts assessed, the final step is to determine which countermeasures merit implementation. This section sets out (Section 3.4.1) how mitigation options are defined and structured within a standard response-planning framework, and (Section 3.4.2) how their effectiveness is quantified in the simulation relative to implementation cost. The goal is to provide a consistent, simulation-driven basis for prioritizing what the best actions are to reduce adverse effects on project KPIs.

3.4.1. Response Plan

When facing threats or risks with potential negative impacts on project objectives, four primary response strategies are typically considered [Stackpole, 2013]: avoid, transfer, mitigate, and accept. Avoidance involves eliminating the threat entirely by changing the project work strategy or using other assets. Transference shifts the impact and ownership of a threat to a third party, often through contractual means. Mitigation focuses on reducing the probability or impact of a risk to more acceptable levels. Lastly, acceptance acknowledges the impact of the risk where no response strategy will change its effect.

Among these, mitigation is a critical strategy where the project team proactively acts to reduce either the likelihood of a risk occurring or the severity of its impact. This strategy aims to bring the probability and/or impact of an unfavorable risk within a more acceptable range. Taking early action to minimize a risk's potential harm is often more effective than attempting to rectify damage after a risk has materialized [Stackpole, 2013].

Building on the insights gained from expert elicitation (Section 3.1.6), the interview process also serves to identify potential mitigation measures. Crucially, experts are then asked to provide updated estimates for the probability of occurrence and the range of impact estimates for risks after these mitigation measures have been implemented. In practice, mitigation strategies generally fall into two categories: those designed to reduce a risk's probability of occurrence and those aimed at decreasing its impact if it occurs [Stackpole, 2013]. While certain risks can have their likelihood significantly reduced, or their potential consequences limited, it is important to recognize that complete elimination of risks is often impractical or impossible due to inherent project complexities and unforeseen circumstances.

3.4.2. Integration and Evaluation

Implementing mitigation measures frequently requires an initial investment, which can manifest as financial expenditure and the allocation of additional resources, such as increased engineering capacity. To assess the effectiveness and financial viability of such measures, a structured evaluation methodology is employed. This involves considering the cost of the mitigation measure itself. Subsequently, experts provide revised probability and/or impact values for the mitigated risks. The simulation is then re-run with these updated risk parameters. The return on investment for a mitigation measure is quantified by how much it reduces the project's total cost KPI. An investment is deemed efficient if the reduction in total KPI impact outweighs the cost of implementing the mitigation measure. Conversely, if the cost of the measure exceeds the realized benefit, it is considered an inefficient investment.

The cost structure of mitigation measures can vary. Some measures entail a fixed, one-time investment, such as preparing emergency reserve materials. Other measures may be time-dependent; for instance, investing in additional assets to accelerate project completion could lead to higher initial expenditures but potentially result in lower overall project costs due to the reduced total project duration. Therefore, when calculating the cost-effectiveness of mitigation strategies, it is imperative to accurately account for whether the measure's cost is a fixed sum or varies with project time. Such detailed insights are ultimately only feasible through robust and granular simulation.

Making informed decisions about the optimal allocation of resources for risk mitigation is crucial. The procedure for determining the financial feasibility of a mitigation measure is as follows:

1. **Calculate the baseline cost.** The total project cost is determined from the simulation scenario where all risks and uncertainties are included simultaneously in the model (the unmitigated scenario).

2. **Determine the mitigation cost and updated risk values.** The cost of implementing the specific mitigation measure is identified. Experts provide new, mitigated probability and/or impact values for the relevant risks and uncertainties.
3. **Calculate the mitigated cost.** A new simulation is run with the updated, mitigated parameters to determine the new total project cost.
4. **Compare costs.** The cost of the mitigation measure is then compared to the reduction in the total project cost.
5. **Compare different combinations of mitigation measures.** Run separate simulations and perform the same steps with all plausible combinations of mitigation measures to determine the best set.

   Example: Is it financially feasible to implement a mitigation measure for Risk A?

   1. *Run a simulation with all risks (A, B, and C) present to determine the baseline total cost, which we call S.*
   2. *The cost of implementing the mitigation measure is M. Experts estimate that this measure reduces the impact of Risk A.*
   3. *Run a simulation with all risks (A, B, and C) and the updated, mitigated impact of Risk A to determine the new total cost, which we call Y.*
   4. *Compare the costs:*
      - *If $(S - Y) > M$, the mitigation measure is financially feasible.*
      - *If $(S - Y) < M$, the mitigation measure is not financially feasible.*

Benefit–Cost Ratio (BCR): In addition to comparing net benefits, this study employs the *Benefit–Cost Ratio* (BCR) [Shively, 2012] as a relative efficiency metric for mitigation measures. The BCR is defined as the reduction in total project costs achieved by the measure, divided by its investment cost:

$$\mathrm{BCR} = \frac{\Delta \text{ (cost reduction vs. unmitigated baseline)}}{\text{Measure investment}}.$$

A ratio greater than one indicates that the measure delivers more cost savings than it requires in investment, while values below one suggest inefficiency. By computing BCR values for individual measures and their combinations, the analysis not only highlights absolute financial feasibility but also provides a comparative ranking of which strategies deliver the highest return per euro invested.

3.5. Summary

This Chapter set out a reproducible pipeline for bringing expert judgment into a discrete-event simulation of dredging projects. First, risks and uncertainties were identified and organized into four working categories (workability, technical, logistical, and environmental/social). Then, the hierarchical project layers were introduced and risks and uncertainties are mapped to the impact levels consistent with the modeling architecture: (i) activity-level uncertainty, (ii) sequence-level delays affecting individual assets, and (iii) interruptions across the full project. A structured expert elicitation then provided occurrence information and impact ranges (minimum, most likely, maximum) for project-specific items.

Second, these expert inputs were translated into model parameters and implemented at the correct layer via a dedicated mixin: probabilities (or frequencies) and impact distributions were specified per risk, with conversion procedures for common forms of practitioner input (e.g., MTTF → failure rate → probability over operating time; expected event frequencies → Poisson counts). This ensured a coherent linkage between qualitative expert statements and the event logic of the simulation.

Third, the instrumented model was used to assess impacts on KPIs (time, cost, emissions). Operations and delay events were logged per asset; KPI summaries were reported probabilistically from Monte Carlo replications at a consistent confidence level (P80 by default). To attribute effects, a with–without comparator isolated each risk's contribution while other risks remained active, and an interaction check contrasted the sum of individual impacts with the combined impact to detect buffering or cascading behavior. Finally, mitigation options (identified during elicitation) were evaluated by re-running the model with updated, mitigated parameters and comparing the reduction in KPI impact against implementation cost, both for single measures and for practical combinations.

4 Case Studies for Model Applications

This Chapter demonstrates how selected steps of the Risk Assessment Methodology are applied in two modeling contexts. The goal is to make the methodological flowchart more tangible by showing how it translates into practical model applications before the simulated results are presented. First, a simplified hypothetical example is introduced to illustrate the early steps of the methodology on a minimal system. Second, a real-world case study, the Malmporten project at the Port of Luleå, anchors the same procedure in an operational setting with realistic scope, assets, and constraints.

The hypothetical example begins with a tender review of a simple work method, describing how a processor and transporters interact in a compact dredging cycle. It then proceeds to the project layer schematization, where the Object and Activity Breakdown Structures (OBS/ABS) are defined, corresponding to the project layers step of the methodology (Section 3.1.3). Finally, the scenario setup of impact levels previews how the "Risk & Uncertainty Mixin" is used to embed risks at different levels of impact in the simulation. This illustrates how the model can be used to assess the isolated impact of individual risks (methodology step Section 3.3.2). The quantitative outcomes for this example are reported later in the Results (chapter 5), where they are shown alongside the case study outputs.

In the following section a tender review is done on the real case study (Section 4.2). The Malmporten project is a real dredging project segment, covering contaminated-sediment removal and controlled offshore disposal. All project specifics—including the project outline, dredging scope, work method, parameters and simplified schematizations-are compiled from project documentation and refined through expert consultation. The given inputs are organized using the OBS/ABS structures to directly link the tender review to the model. This allows the subsequent steps of the Risk Assessment Methodology to be carried out in the next Chapter, where the scenarios are executed in simulation, risks are assessed, and mitigation measures are evaluated.

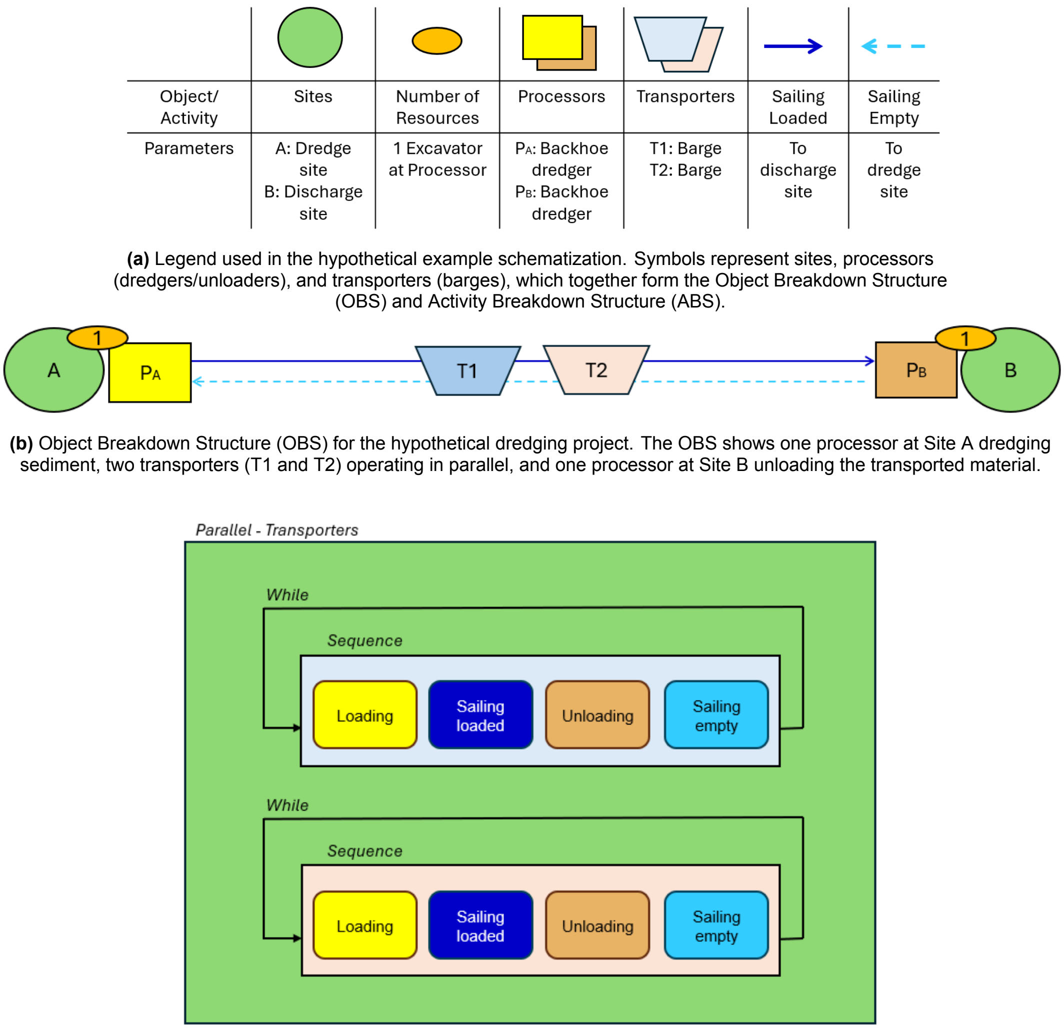
4.1. Tender Review: Hypothetical Example

To effectively illustrate the principles of the methodology, a straightforward, hypothetical example is introduced here as a model set-up. It provides a compact environment to show how objects, activities, and risk layers are mapped into the simulation architecture; quantitative outcomes and visualizations are presented later in the Results Chapter (chapter 5).

This example considers a simplified dredging operation where sediment is excavated from Site A by a designated processor (P_A). This processor transfers the sediment onto one of two transporters ($T1$ or $T2$), which operate in parallel within the Asset layer (Section 3.1.3). Loaded transporters sail to Site B, where another processor (P_B) unloads the sediment. After discharge, each transporter returns empty to Site A. An operational constraint is that each processor (at Site A and Site B) can handle only one transporter at a time, highlighting the potential for interaction and queuing. In this simplified scenario, the cycle is executed once per transporter, and the sediment at Site A is considered fully dredged after both transporters complete a single loading–sailing–unloading–return loop.

4.1.1. Project Layer Schematization

This hypothetical case is characterized by an Object Breakdown Structure (OBS) with defined sites, processors, and transporters, which directly translates into an Activity Breakdown Structure (ABS) within the OpenCLSim programming language (Section 2.6.2). As depicted in Figure 4.1, each transporter executes a sequence of fundamental activities: loading, sailing loaded, unloading, and sailing empty. While such sequences typically run within a while loop, for this example the loop executes only a single cycle per transporter, since the scope is completed after the initial cycles. This structured approach schematizes the entire example within the ABS used by the simulation framework.



(a) Legend used in the hypothetical example schematization. Symbols represent sites, processors (dredgers/unloaders), and transporters (barges), which together form the Object Breakdown Structure (OBS) and Activity Breakdown Structure (ABS).

(b) Object Breakdown Structure (OBS) for the hypothetical dredging project. The OBS shows one processor at Site A dredging sediment, two transporters (T1 and T2) operating in parallel, and one processor at Site B unloading the transported material.

(c) Activity Breakdown Structure (ABS) corresponding to the OBS. Each transporter executes a sequence of activities: loading at Site A, sailing loaded, unloading at Site B, and sailing empty back. The processors perform dredging at Site A and unloading at Site B.

Figure 4.1: Hypothetical example of dredging logistics represented in OpenCLSim. (a) Legend of symbols, (b) Object Breakdown Structure (OBS) with processors and transporters linking Site A to Site B, and (c) Activity Breakdown Structure (ABS) showing the detailed sequence of activities for each asset. Together, the OBS and ABS illustrate how a simple dredging project is schematized in the simulation framework.

4.1.2. Scenario Setup of Impact Levels

In the Results Chapter (Section 5.1), the operational cycle of this example will be visualized and analyzed using Gantt charts to demonstrate how risks and uncertainties are applied at different impact layers (introduced in Section 3.1.3):

- **Ideal (risk-free) configuration:** The sequence executes once per transporter without added uncertainty or delay.
- **Uncertainty in Activity:** Variability is introduced in activity durations (e.g., sailing), applied via the activity's impact distribution.
- **Delay in Sequence:** A discrete risk (e.g., a breakdown) affects a single asset's sequence, generating a repair/wait period without halting other assets.
- **Delay across Project:** A high-level event (e.g., severe storm) introduces a delay across the full project scope.

These scenarios are presented in isolation in the Results Chapter to clearly show how the implementation points in the model (activity, sequence, and multi-site layers) translate expert-judgment parameters into simulated effects on the timeline. The corresponding figures and quantitative outcomes are deferred to that Chapter to maintain a clean separation between model set-up and results.

4.2. Tender Review: Case Study (Malmporten)

This section introduces the real-world project that is used to implement the methodology: the Malmporten works at the Port of Luleå. The case was selected because it concerns a live tender pursued by a Boskalis–Van Oord consortium, providing both practical relevance and access to realistic inputs. The description below covers the overall work method and scope, followed by all project specifics, operational parameters, and contextual information required to parameterize the simulation. These inputs function as model data; quantitative outcomes are presented in the subsequent Results chapter.

4.2.1. Project outline

The Malmporten project addresses the critical need to enhance shipping capacity for iron ore exports from northern Sweden and Finland. The existing railway infrastructure is overutilized, and the port of Luleå's current capacity limits vessel size, hindering competitive shipping for the industry. Driven by increased production from existing mines and the establishment of new ones, an urgent upgrade to shipping lanes is required. This project, strategically prioritized and financially supported by the EU, aims to enable the port of Luleå to accommodate significantly larger vessels. This expansion is expected to benefit the environment by lowering fuel use and emissions for each ton of goods shipped. This makes the shipping process more sustainable and competitive.

Figure 4.2: Malmporten project location

The Malmporten project is situated in the Port of Luleå, located in the northern Gulf of Bothnia, Sweden, a region characterized by being ice-bound for five to six months annually. Its location is visually represented in Figure 4.2. The undertaking is a collaborative effort between the Swedish Maritime Administration (SMA) and Luleå Hamn AB, with Luleå Hamn responsible for the area within the port limits, and SMA overseeing operations outside the port limits.

4.2.2. Dredging scope

The comprehensive Malmporten project itself encompasses multiple components extending across several seasons. However, for the purpose of this case study, the focus is narrowed to a specific segment of the overall undertaking. This particular scope centers on the task of removing contaminated soil present at various locations within the harbor. The scope of the contaminated areas are simplified and categorized into three distinct dredging locations: A1, A2, and A3. All material dredged from these locations must then be transported and deposited at a designated dump site, location B. The spatial distribution of these dredge and dump locations is illustrated in Figure 4.3.

Figure 4.3: Luleå dredging scope

4.2.3. Work method

The project's work method is designed for the scope, utilizing three backhoe dredgers (Figure 4.4). Each dredger is stationed at a specific dredge location (A1, A2, and A3). These backhoe dredgers excavate the sediment from the seabed and load it into transporter vessels, commonly known as barges. Each backhoe operates in conjunction with three barges.

Figure 4.4: Manu Pekka and transporter barge - Environmental dredging (Boskalis)

Once loaded, the barges navigate to dump location B, where they moor at a floating pontoon. This pontoon is equipped with two cranes capable of simultaneously unloading two barges. The pontoon cranes extract the sediment from the barges and deposit it through a fall pipe beneath the pontoon to the seafloor. The purpose of this fall pipe is twofold: to discharge the material close to the seabed and thus reduce its spread, and to accurately deposit the sediment within the existing pits of an old dredge site. The contaminated soil is ultimately contained by covering it with a layer of clean sand in a separate activity. After a barge is emptied, it returns to its designated backhoe at the dredge location to be refilled. This continuous process forms the "dredge cycle," which repeats until all sediment at a specific location has been excavated. The dredging work is considered complete once all three locations are cleared and all the sediment has been successfully deposited via the pontoon.

4.2.4. Project parameters

All parameter values presented in the following tables were obtained from project specifications and subsequently refined through consultation with project experts. These values collectively form the foundational data used to drive the simulation and apply the methodologies described in this chapter.

Table Table 4.1 outlines the site parameters. For the sake of simplicity, the location of each site is represented by the coordinates of its midpoint. The specified quantities of material to be dredged are given in net cubic meters, which excludes water content. It should be noted that Site B is assumed to have a non-applicable or effectively infinite capacity for the dredged sediment.

Sites	Location	Quantity
A1	65.548, 22.226	57500 $[m^3]$
A2	65.543, 22.270	170778 $[m^3]$
A3	65.532, 22.321	161600 $[m^3]$
B	65.4868, 22.4082	N/A

Table 4.1: Site Parameters

The assets used in the work method are detailed in Table 4.2, including their quantity and location. The project utilizes one backhoe dredger at each of the dredge locations (A1, A2, and A3), while a single pontoon is stationed at the dump location, Site B. The transporters, or barges, are dedicated to specific dredge sites; three barges operate exclusively between Site A1 and B, three between A2 and B, and three between A3 and B.

Assets	Type	Amount	Location
Processor	Backhoe dredger	3	A1/A2/A3
Transporter	Barge	9	N/A
Processor	Pontoon	1	B

Table 4.2: Asset Parameters

The parameters for the processors are shown in Table 4.3. As illustrated in Figure 4.4, each backhoe dredger is equipped with one crane, whereas the pontoon at Site B has two cranes, allowing it to unload two barges simultaneously. The production rate of the pontoon's cranes is significantly higher than that of the backhoe dredgers, as the task of transferring sediment from a moored barge is less complex than dredging from the seabed. These production rates are specified in net volume per hour.

Processor	No. of Excavators	Production rate per Excavator
Backhoe dredger	1	100 $[m^3/hr]$
Pontoon	2	250 $[m^3/hr]$

Table 4.3: Processor Parameters

Regarding the transporter parameters, Table 4.4 details the characteristics of the barges. All barges have the same effective load capacity, which represents the net volume they transport to location B. The speed of the barges varies based on their load; they travel slower when loaded and faster on their return journey when empty.

Transporters	Capacity	Sailing speed loaded	Sailing speed empty
Barge	350 $[m^3]$	5.5 [knts]	6 [knts]

Table 4.4: Transporter Parameters

The subsequent tables provide the parameters necessary for calculating the KPIs. The cost parameters specified in Table 4.5 distinguish between fixed and variable costs. Fixed costs per unit primarily encompass asset mobilization and other associated one-time investments. Variable costs, on the other hand, are mainly tied to asset rental and personnel wages, which are directly dependent on the project's duration.

Asset	Fixed costs (per unit)	Variable costs (per unit)
Backhoe dredger	1.000.000 [€]	15.000 [€/day]
Barge	500.000 [€]	7.500 [€/day]
Pontoon	2.000.000 [€]	20.000 [€/day]

Table 4.5: Asset Costs

Finally, Table 4.6 provides the parameters to support the emissions KPI. Each asset is assigned distinct fuel consumption rates for its operating and waiting states. For processors, operating hours refer to the net time the excavators are actively working. For transporters, this refers to the net sailing hours, both loaded and empty. The waiting consumption rate specifies the fuel consumed per hour while the asset is idle, awaiting its next primary task. All assets use the same fuel type, namely marine diesel oil (MDO) or marine gas oil (MGO). They have a conversion factor of 3.255 and a fuel density of $890kg/m^3$ [Miyake, 2023].

Asset	Operating Consumption rate	Waiting Consumption rate
Backhoe dredger	100 [ltr/noh]	15 [ltr/hr]
Barge	110 [ltr/noh]	12 [ltr/hr]
Pontoon	120 [ltr/noh]	15 [ltr/hr]

Table 4.6: Fuel Consumption Parameters

These parameters, in their entirety, define the project and its operational environment. With this comprehensive set of values, the project can be accurately simulated according to the methodologies detailed throughout this chapter.

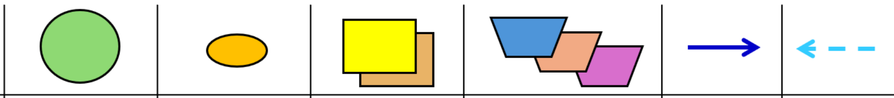
4.2.5. Project Schematization

Following the parameterization of the project, this section details the schematization of the defined work method and scope, which is essential for simulation. This process follows to the Work Breakdown Structures discussed by Hudoyo et al., [2019] in Section 2.6.2.

As shown in Figure 4.5b, the Object Breakdown Structure (OBS) for this project includes three dredge sites (A1, A2, A3) on the left, with a single backhoe dredger (processor/P_An) assigned to each. The orange ellipse with the number "1" indicates that each backhoe has one excavator. Each site has its own dedicated set of transporters (barges/T_An_n) that travel between their respective dredge site and dump site B. At site B, a processor (the pontoon/P_B) is stationed, which can unload two transporters simultaneously, as indicated by the orange ellipse with the number "2".

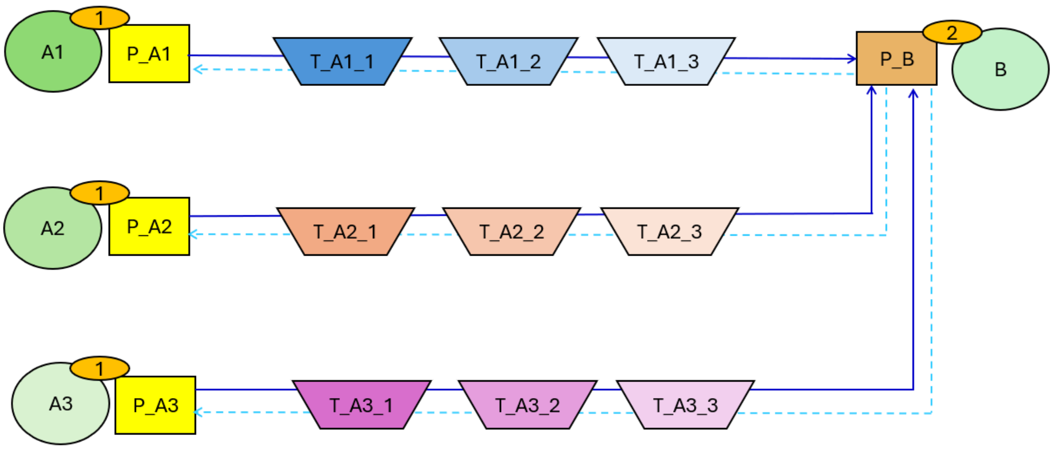
The Activity Breakdown Structure (ABS), depicted in Figure 4.5c, shows that multiple parallel transporters perform their individual sequences within a while activity. These transporters operate in parallel with the operations at the other locations. In terms of the project layers discussed in Section 3.1.3, the project is modeled with three multi-site layers, each containing three assets in the asset layer. Each asset (transporter/barge) consists of a sequence of four activities: loading, sailing loaded, unloading, and sailing empty.

With the project fully schematized and all parameters defined, it is now ready to be simulated using the existing simulation software.

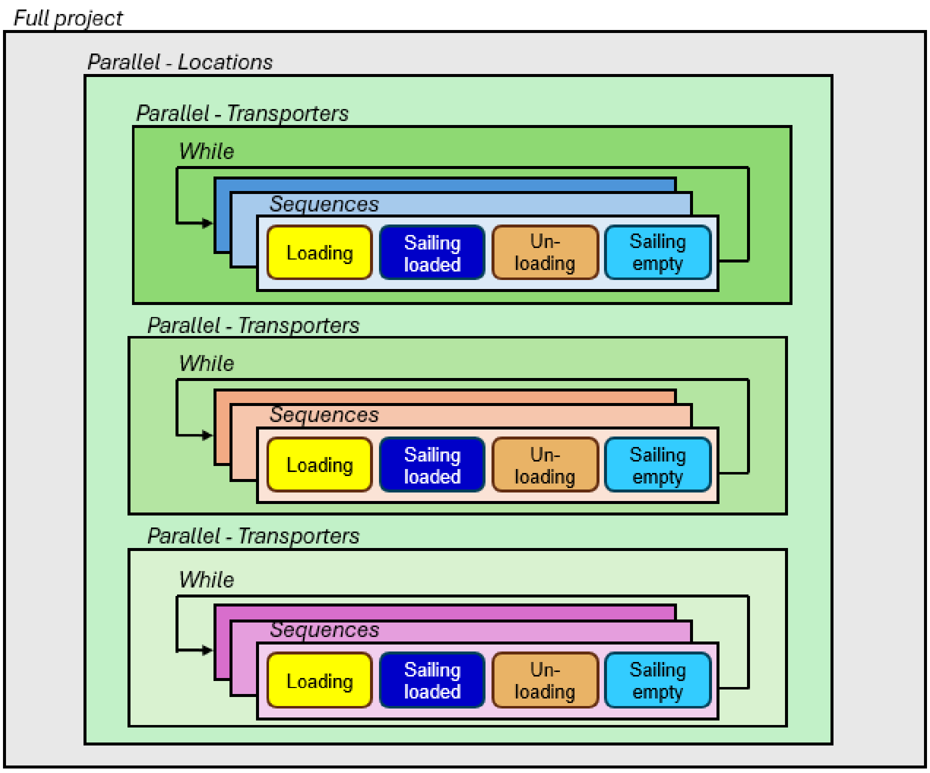


Object/ Activity	Sites	Number of Resources	Processors	Transporters	Sailing Loaded	Sailing Empty
Parameters	A1: Port A2: Port A3: Port B: Discharge site	1 Excavator at BHs 2 Excavators at Pontoon	P_{A1}: BH P_{A2}: BH P_{A3}: BH P_{B}: Pontoon	$T_{A1,1\text{-}3}$: Barges (A1-B) $T_{A2,1\text{-}3}$: Barges (A2-B) $T_{A3,1\text{-}3}$: Barges (A3-B)	To discharge site	To dredge site

(a) Legend used in the case study schematization. Symbols represent dredge sites, processors (backhoes or pontoon), and transporters (barges), as well as the number of parallel resources assigned to each processor.



(b) Object Breakdown Structure (OBS) of the Luleå project. Three dredge sites (A1, A2, A3) are each equipped with one backhoe dredger (processor), supported by dedicated barges (transporters) that sail to dump site B. At dump site B, a pontoon processor can unload two barges simultaneously.



(c) Activity Breakdown Structure (ABS) corresponding to the OBS. Each barge executes a cyclic sequence of four activities: loading, sailing loaded, unloading at the pontoon, and sailing empty back. Multiple barges operate in parallel across the three dredge sites, while the pontoon coordinates unloading.

Figure 4.5: Schematization of the Luleå case study in OpenCLSim. (a) Legend of symbols, (b) Object Breakdown Structure (OBS) showing the assets and their allocation across dredge and dump sites, and (c) Activity Breakdown Structure (ABS) showing the activity cycles of transporters and their coordination with processors. Together, the OBS and ABS provide the full Work Breakdown Structure (WBS) used as input for the simulation model.

4.3. Summary

This Chapter has demonstrated how the Risk Assessment Methodology is instantiated in two modeling contexts. A simplified hypothetical example illustrated the early steps of the flowchart, including a tender review, project layer schematization through OBS/ABS, and the scenario setup of impact levels using the Risk & Uncertainty mixin. This example served to show how risks can be embedded at different levels of impact within the simulation.

The Malmporten case study provided a tender review of a real dredging project segment, where project scope, assets, parameters, and schematization were compiled and translated into model-ready inputs. Together, these applications established the input data and structures required to run the simulation model.

The subsequent Results Chapter (chapter 5) builds on this foundation by executing the remaining steps of the methodology: running scenario analyses, assessing the impact of risks on project KPIs, evaluating their interactions, and evaluating the mitigation measures.

5
Results

This Chapter reports the outcomes of the *Risk Assessment Methodology* applied on the Case Study Malmporten: (i) Expert Elicitation results (Section 5.2), (ii) Integration into Simulation Software (Section 5.3), (iii) Impact Assessment (Section 5.4), and (iv) Mitigation Evaluation (Section 5.5). First, the *hypothetical example* (Section 5.1) that is introduced in Section 4.1 illustrates how the three impact levels (activity, sequence, project) manifest in outputs. Then, the full workflow to the Malmporten case is applied in the remaining sections.

Unless stated otherwise, results are based on Monte Carlo runs and reported at the 80th percentile (industry-standard conservative view). Figures and tables reference only analysis outputs; details of procedures and model constructs are given in the preceding Chapters.

5.1. Hypothetical Example: Isolated Impact Levels

This section reports the operational outcomes for the hypothetical example introduced in Figure 4.1. The scenarios are shown and interpreted in isolation to make the effect of each impact layer explicit. Implementation details for activity-, sequence-, and project-level integration follow the methodology in Section 3.2.1.

Ideal vs. Uncertainty in Activity (Activity Layer)

Figure 5.1 compares the ideal (risk-free) execution to a configuration with *activity-level uncertainty* applied to sailing durations (loaded and empty). The ideal illustrates a single-cycle execution per transporter without added variability. In the uncertainty case, stochastic extensions to the sailing activities lengthen the corresponding tasks. The processor constraint at Site A (single resource) introduces a visible queue: the loading of the second transporter begins only after the first completes. At Site B, the unloading processor is available when required in this example, so no additional queue forms there.

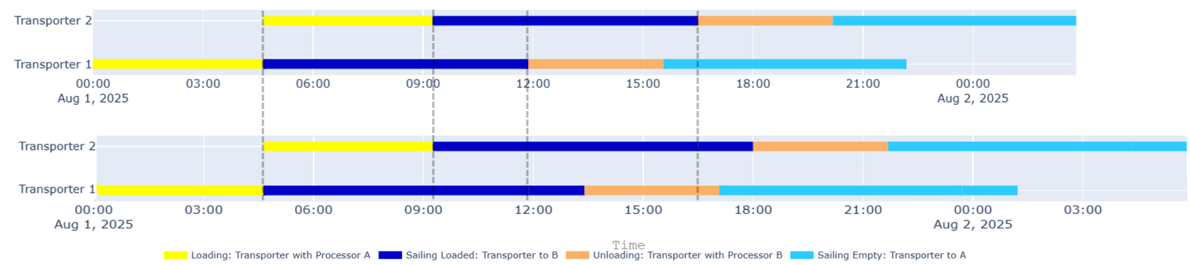


Figure 5.1: Hypothetical example: ideal (upper) versus sailing-duration uncertainty at the *activity* layer (lower). See Figure 4.1 for the setup (OBS/ABS).

Delay in Sequence (Asset-Specific Risk)

Figure 5.2 shows a discrete delay in the sequence layer affecting one transporter (e.g., breakdown prior to sailing empty). When triggered, a repair/wait period is inserted into that asset's sequence, temporarily disabling it. The other transporter proceeds unaffected, reflecting that sequence-level risks are localized to the impacted asset. In line with Section 3.2.1, operational times are unchanged for unaffected activities; only waiting/idle periods are increased.

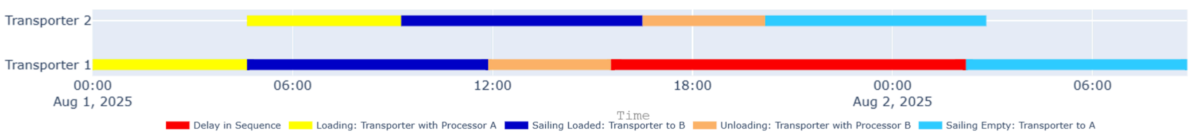


Figure 5.2: Hypothetical example: *sequence*-level delay on a single transporter (e.g., breakdown) generates a repair/wait interval without halting the other transporter.

Delay across Project (Multi-Site Layer)

Figure 5.3 illustrates a project-wide delay (e.g., severe storm) implemented at the multi-site layer. All activities are shifted by the sampled interruption duration, after which the planned cycle proceeds. As described in Section 3.2.1, this high-level effect is integrated into assets' waiting time and thus into downstream KPI calculations.

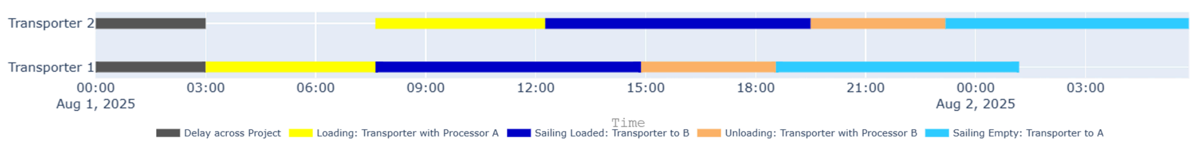


Figure 5.3: Hypothetical example: delay across project (e.g., storm) defers the start of all activities by the interruption duration.

5.2. Case Study: Expert Elicitation

This section reports the outputs from the expert elicitation for the Malmporten case, aligned with the structure used in the methodology. For the interview protocol, participant roles, conversion steps, and an edited transcript of the sessions, see Appendix B.

Project KPIs and Primary Constraint

Experts confirmed that the client's dominant constraint is a strict **20-week time window**, driven by seasonal ice conditions that render the area inaccessible outside the summer period.

Identified Risks and Categories

The elicitation produced a focused set of project-specific risks/uncertainties, mapped to the four working categories and assigned to an impact level within the modeling architecture. These items are summarized in Table 5.1.

ID	Risk / Uncertainty	Category	Level of Impact
1	Backhoe crane breakdown	Technical	Delay in sequence
2	Barge mooring duration	Logistical	Activity uncertainty
3	Exceeds critical turbidity limit	Environmental/Social	Delay across project

Table 5.1: Risk and uncertainty analysis from expert elicitation.

Elicited Occurrence and Impact Distributions

For each item, experts provided occurrence information and impact ranges, to be implemented as **triangular** distributions in the model. Table 5.2 lists the elicited values. Units reflect the natural scale given by experts (e.g., per cycle, per NOH, per calendar window) and are converted to model probabilities in the integration step.

ID	Occurrence	Min	Mode	Max	Unit
1	120 NOH	2	3	168	hrs
2	cycle	-3	0	10	min
3	30 days	24	24	168	hrs

Table 5.2: Elicited parameters (occurrence and triangular impact ranges). "NOH" denotes net operating hours.

5.3. Case Study: Integration Expert Judgment into the Simulation

This section reports how the elicited inputs were translated into simulation parameters at the correct impact levels (compared with Section 3.2). The custom *Risk and Uncertainty Mixin* was parameterized per item with an activation metric (probability or event count), a distribution type (triangular), and the corresponding minimum, mode, and maximum values in seconds.

Implementation per Risk/Uncertainty

1. **Backhoe crane breakdown (Sequence-level).** The expert specified a Mean Time To Failure (MTTF) of 120 Net Operating Hours (NOH):

$$\text{MTTF} = 120 \text{ hr} \times 3600 \text{ s/hr} = 432{,}000 \text{ s}, \qquad \lambda = \frac{1}{432{,}000} = 2.315 \times 10^{-6} \text{ s}^{-1}.$$

   The duration of a single loading event is estimated from capacity and rate:

$$t = \frac{C_{\text{transporter}}}{P_{\text{processor}}} = \frac{350 \text{ m}^3}{100 \text{ m}^3/\text{hr}} = 3.5 \text{ hr} = 12{,}600 \text{ s}.$$

   Using $P(\text{occ}) = 1 - e^{-\lambda t}$ [Verma et al., 2010] gives

$$P(\text{occ}) = 1 - e^{-(2.315\times10^{-6})\cdot 12{,}600} \approx 0.0287 \ (2.87\%).$$

   Impact durations (triangular) were implemented directly from the elicited min/mode/max (converted to seconds).

2. **Barge mooring duration (Activity-level).** Mooring is an inherent part of *sailing loaded* and *sailing empty*; therefore the activation is set to 1.0 (always applied when the activity is called). The elicited triangular parameters (min, mode, max) were implemented in seconds, allowing for negative deviations (shorter-than-expected mooring).

3. **Exceeds critical turbidity limit (Delay across Project).** Experts indicated a frequency of "once per month." Using the most realistic project duration of 13.3 weeks (~ 3.1 months, see Table 5.6), the expected count for a Poisson process is $\lambda = 3.1$. The modal count k is obtained by maximizing $P(k) = \frac{\lambda^k e^{-\lambda}}{k!}$, which yields $k = 3$ (Figure 5.4). Hence, the simulation schedules **three** project-wide activations; for each activation the delay is sampled from the elicited triangular distribution (in seconds).

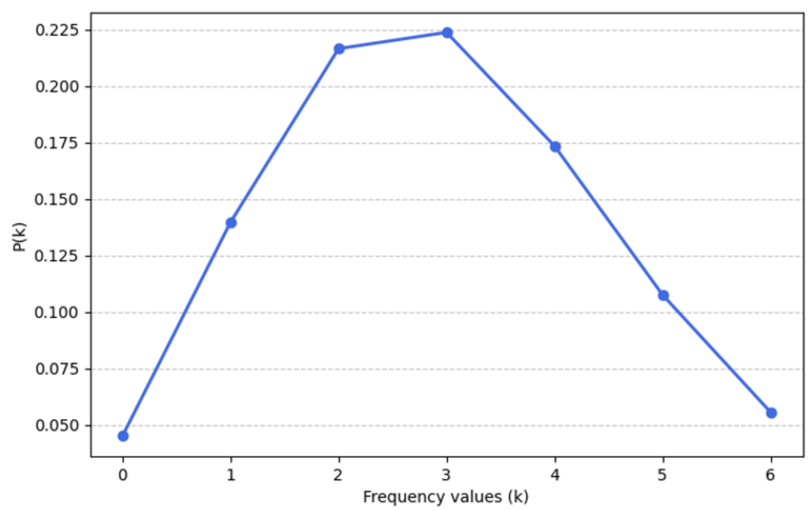


Figure 5.4: Poisson analysis for turbidity exceedance with $\lambda = 3.1$: modal frequency $k = 3$.

Converted Mixin Parameters

ID	Risk / Uncertainty	Activation †	Min	Mode	Max
1	Backhoe crane breakdown	$P(\text{occ}) = 2.87\%$	7,200 s	10,800 s	604,800 s
2	Barge mooring duration	Always $(= 1.0)$	-180 s	0 s	600 s
3	Exceeds critical turbidity limit	$\mathbf{k} = \mathbf{3}$ activations	86,400 s	86,400 s	604,800 s

Table 5.3: Converted mixin parameters used in the simulation. †Activation is expressed as a probability per call (ID 1), an always-on activity deviation (ID 2), or a fixed project-wide event count (ID 3) derived from a Poisson mode at $\lambda = 3.1$.

5.4. Case Study: Assessing Risks & Uncertainties

This section reports the simulation results for risk and uncertainty assessment, following the structure of Section 3.3. All results are based on 200 Monte Carlo runs; statistical stability checks (Appendix C) show the project time KPI with a standard deviation below 1.5%. Unless stated otherwise, KPIs are reported at P80.

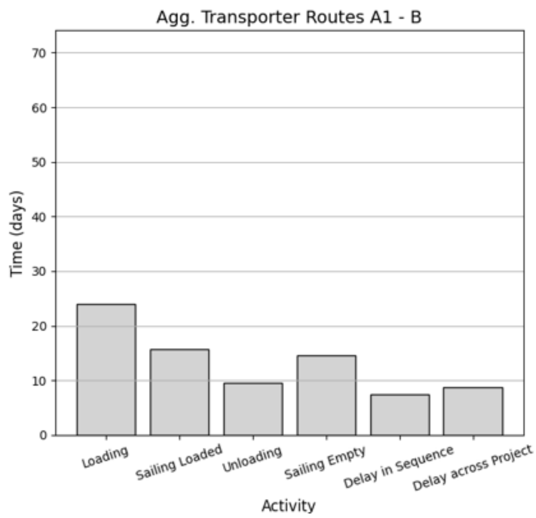
5.4.1. Operational Tracking & KPI Basis

The DES logs operating, waiting, and total times per asset. In the "all risks present" scenario, P80 values are listed in Table 5.4. As per the logging design, risks and uncertainties do not change *operating* time; their effect appears as additional *waiting* time. For the pontoon, "operating" is recorded as long as at least one of its two cranes is active (i.e., no intra-asset split between one vs two cranes).

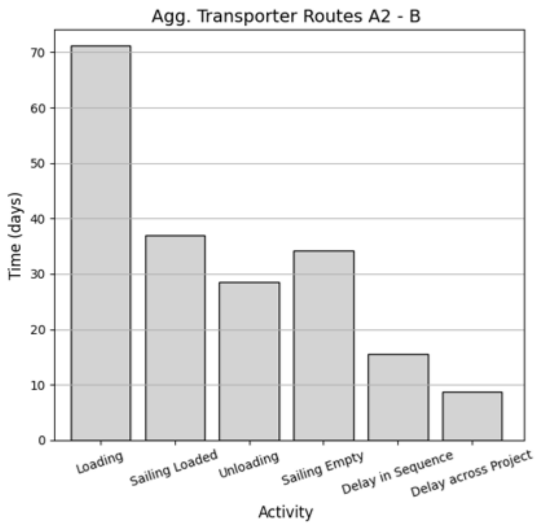
Asset	Operating Time (hrs)	Waiting Time (hrs)	Total Time (hrs)
Backhoe dredger (Site A1)	575	214	789
Backhoe dredger (Site A2)	1708	472	2180
Backhoe dredger (Site A3)	1616	455	2071
Transporter (Site A1-1)	488	295	783
Transporter (Site A1-2)	488	293	781
Transporter (Site A1-3)	485	293	778
Transporter (Site A2-1)	1301	881	2181
Transporter (Site A2-2)	1300	881	2181
Transporter (Site A2-3)	1293	874	2167
Transporter (Site A3-1)	1065	1003	2068
Transporter (Site A3-2)	1065	1003	2068
Transporter (Site A3-3)	1064	1003	2066
Pontoon	1319	954	2273

Table 5.4: Operating and waiting times (P80) in the all-risks-present scenario.

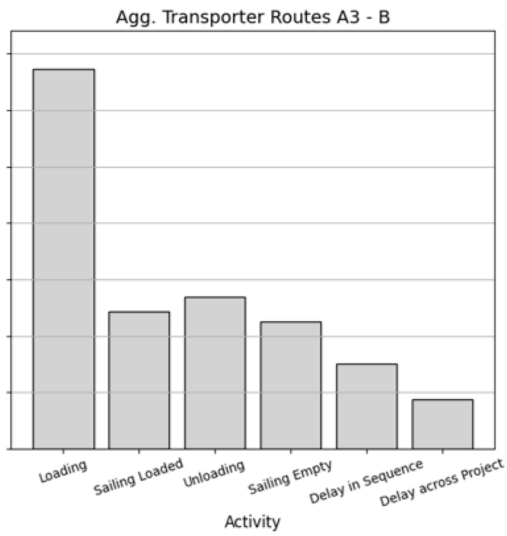
Ideal (risk-free) cycle times are driven by route length (loading/unloading rates are constant): A1–B: 9h11m; A2–B: 8h13m; A3–B: 7h04m. With risks and uncertainties included, the activity-time composition per route is shown in Figure 5.5 and Table 5.5.



(a) Aggregated time spent of all transporters on route A1–B.



(b) Aggregated time spent of all transporters on route A2–B.



(c) Aggregated time spent of all transporters on route A3–B.

Figure 5.5: Comparison of aggregated activity durations for three transporter routes (A1–B, A2–B, and A3–B). Results are reported as P80 values.

Event	Route A1–B	Route A2–B	Route A3–B
Simulation Ending Time	40 d 01:53	99 d 21:23	93 d 19:31
Loading	23 d 22:57	71 d 03:38	67 d 07:52
Sailing Loaded	15 d 16:42	36 d 21:11	24 d 05:57
Unloading	9 d 14:00	28 d 11:09	26 d 22:26
Sailing Empty	14 d 12:06	34 d 03:31	22 d 13:18
Delay in Sequence	7 d 12:24	15 d 12:07	15 d 00:18
Delay across Project	8 d 16:28	8 d 16:28	8 d 16:28

Table 5.5: Activity-time distribution per route (P80).

5.4.2. Scenario Impacts on KPIs

Scenario design follows the “all risks present” baseline and three “all-but-one” runs to isolate each risk/uncertainty, plus an ideal (none present) reference. Figure 5.6–Figure 5.8 and Table 5.6–Table 5.8 summarize P80 outcomes and deltas Δ relative to the all-risks baseline (negative Δ indicates a reduction when excluding that item). Absolute impacts (magnitudes) are also listed.

Time KPI

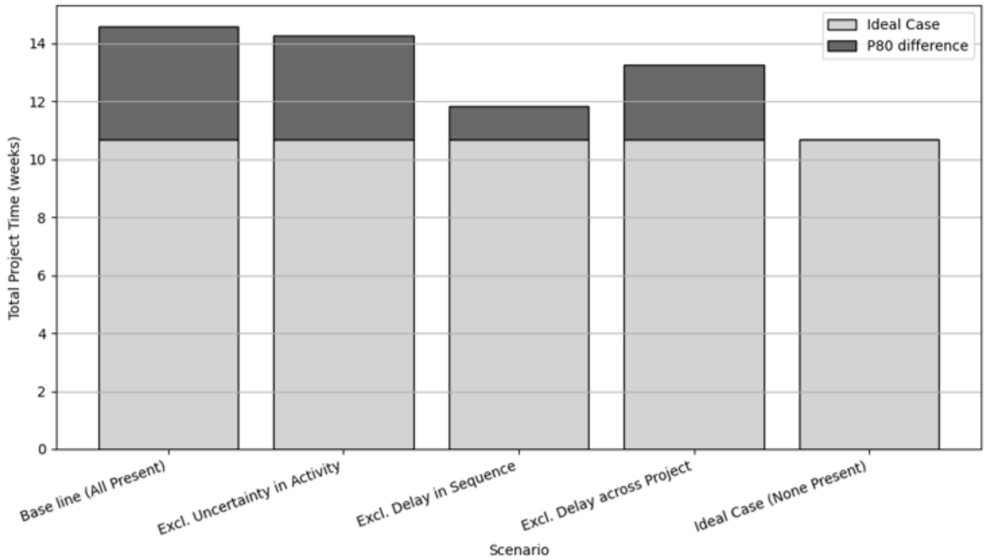


Figure 5.6: Project duration in weeks per scenario. The light gray bars represent the *ideal case* with no risk factors present, while the dark gray stacked portions indicate the additional project time (P80 difference).

ID	Scenario	Weeks	Total Time [hrs]	Δ [hrs]	Δ [%]
1	Base line (All Present)	14.58	2449.06	0	0
2	Excl. Uncertainty in Activity	14.29	2400.96	-48.1	-1.96
3	Excl. Delay in Sequence	11.85	1990.65	-458.4	-18.72
4	Excl. Delay across Project	13.28	2231.56	-217.5	-8.88
5	Ideal Case (None Present)	10.68	1793.53	-655.5	-26.77

Table 5.6: Project duration and deltas (P80).

Isolated impacts (P80, absolute):

- Mooring uncertainty (activity): 48.1 hours.
- Backhoe breakdown (sequence): 458.4 hours.
- Turbidity exceedance (project-wide): 217.5 hours.
- Combined (all present) vs. ideal: 655.5 hours.

Cost KPI

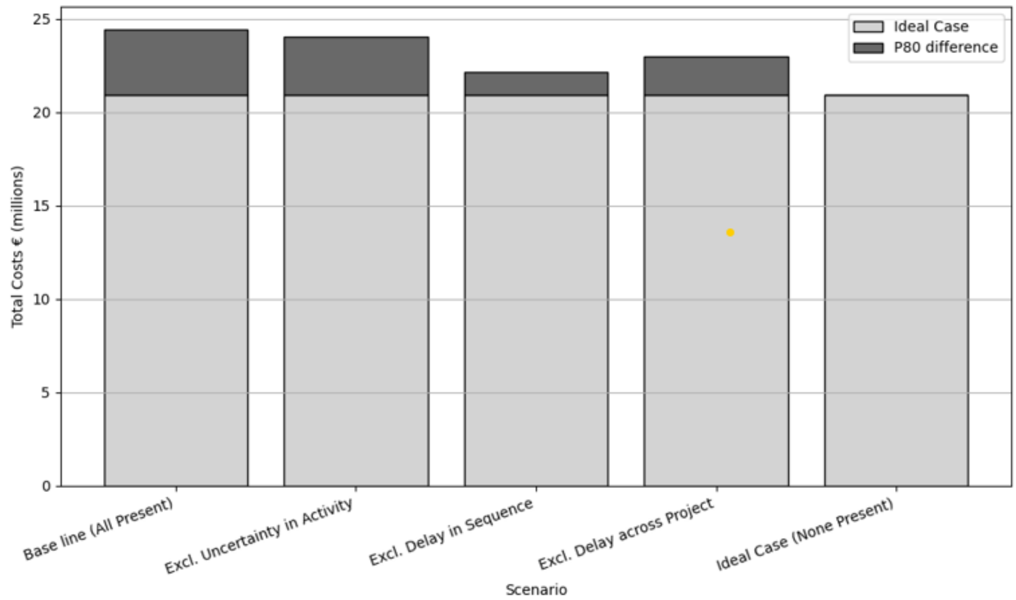


Figure 5.7: Total project costs in € per scenario. The light gray bars represent the *ideal case* with no risk factors present, while the dark gray stacked portions indicate the additional project costs (P80 difference).

ID	Scenario	Total Cost [€]	$\triangle$ [€]	$\triangle$ [%]
1	Base line (All Present)	24,418,000	0	0
2	Excl. Uncertainty in Activity	24,086,500	-331,500	-1.36
3	Excl. Delay in Sequence	22,132,500	-2,285,500	-9.36
4	Excl. Delay across Project	22,985,000	-1,433,000	-5.87
5	Ideal Case (None Present)	20,942,500	-3,475,500	-14.23

Table 5.7: Total cost and deltas (P80).

Isolated impacts (P80, absolute, in €):

- Mooring uncertainty: $\mathbf{331{,}500}$.
- Backhoe breakdown: $\mathbf{2{,}285{,}500}$.
- Turbidity exceedance: $\mathbf{1{,}433{,}000}$.
- Combined (all present) vs. ideal: $\mathbf{3{,}475{,}500}$.

Emissions KPI

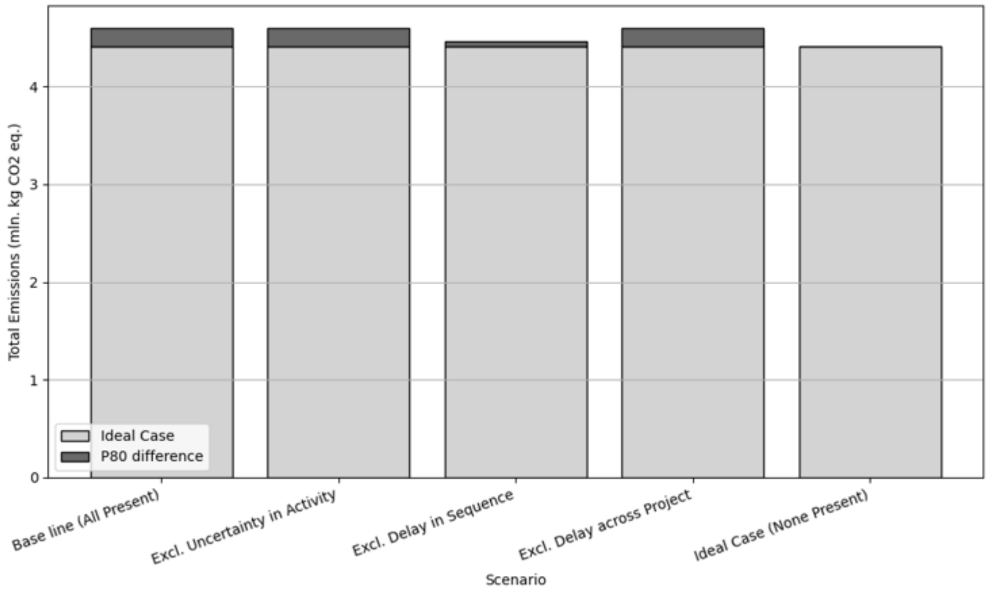


Figure 5.8: Total project emissions in tons CO_2 eq. per scenario. The light gray bars represent the *ideal case* with no risk factors present, while the dark gray stacked portions indicate the additional project emissions (P80 difference).

ID	Scenario	Total CO_2 [tons]	Δ [tons]	Δ [%]
1	Base line (All Present)	4597	0	0
2	Excl. Uncertainty in Activity	4593	-4.4	-0.10
3	Excl. Delay in Sequence	4464	-133.0	-2.89
4	Excl. Delay across Project	4596	-1.5	-0.03
5	Ideal Case (None Present)	4404	-193.2	-4.20

Table 5.8: Total emissions and deltas (P80).

Isolated impacts (P80, absolute):

- Mooring uncertainty: $\mathbf{4.4}$ tons CO_2 eq.
- Backhoe breakdown: $\mathbf{133.0}$ tons CO_2 eq.
- Turbidity exceedance: $\mathbf{1.5}$ tons CO_2 eq.
- Combined (all present) vs. ideal: $\mathbf{193.2}$ tons CO_2 eq.

5.4.3. Dependencies Between Risks and Uncertainties

We compare the sum of isolated impacts to the simultaneous-all-risks impact (Table Table 5.9) to diagnose buffering vs cascading effects:

KPI	Aggregated individual impacts	Simultaneous scenario impact
Time [hrs]	724.0	655.6
Costs [€]	2,760,300	3,475,500
Emissions [tons]	138.9	193.2

Table 5.9: Comparison of aggregated individual impacts vs. simultaneous P80 impact.

5.4.4. Propagation of a Sequence Delay (Backhoe Breakdown)

To quantify knock-on effects from a single sequence-level risk, we compare a “no risks” scenario against a scenario with only the backhoe breakdown enabled. Table 5.10 reports waiting and total times per asset and the percentage increase in total time.

Assets	Waiting (No Risks)	Total (No Risks)	Waiting (BH Risk)	Total (BH Risk)	Δ Total (hrs)	Δ Total (%)
BH.1	28	602	178	753	151	25%
BH.2	81	1789	464	2172	383	21%
BH.3	77	1693	430	2046	353	21%
T.11	115	604	266	754	150	25%
T.12	115	604	265	754	150	25%
T.13	115	600	266	750	150	25%
T.21	490	1790	864	2164	374	21%
T.22	490	1790	872	2173	383	21%
T.23	487	1779	861	2153	374	21%
T.31	625	1690	978	2043	353	21%
T.32	625	1690	978	2043	353	21%
T.33	625	1689	978	2042	353	21%
Pontoon	682	1787	955	2201	414	23%

Table 5.10: Waiting and total times by asset (no risks vs backhoe breakdown only).

Using the time deltas and asset day rates, Table 5.11 separates *direct* extra cost (the backhoes themselves) from *dependency* costs (all other assets impacted by the breakdown). The breakdown’s direct cost is €79,200; the induced dependency cost across the fleet is €167,200.

Assets	Direct Extra Costs	Dependency Additional Costs
BH.1	€ 13,500	
BH.2	€ 34,200	
BH.3	€ 31,500	
T.11		€ 6,700
T.12		€ 6,700
T.13		€ 6,700
T.21		€ 16,700
T.22		€ 17,100
T.23		€ 16,700
T.31		€ 15,800
T.32		€ 15,800
T.33		€ 15,800
Pontoon		€ 49,300

Table 5.11: Direct vs dependency additional costs due to backhoe breakdown (P80).

5.5. Case Study: Mitigation Evaluation

This section reports the impact of the proposed mitigation measures on the project KPIs and their financial feasibility. The measures (with associated investments) originate from the expert elicitation and are summarized in Table 5.12. The corresponding mitigated parameters (changed occurrence and/or impact distributions) are shown in Table 5.13, where green cells indicate updates relative to the unmitigated case. We then present the mitigated asset time profiles (Table 5.14, Figure 5.9, Table 5.15), the KPI deltas versus the unmitigated scenario (Table Table 5.16, Figure 5.11), and finally the financial feasibility for individual and combined measures (Table 5.17, Figure 5.12). *Total Project Costs exclude the mitigation investment; Net Benefit = cost reduction (Δ) − investment.*

ID	Mitigation measure	Measure investment
1	Critical spare parts mobilized and stored on-site	50,000 EUR
2	Experienced captain on board	1,000 EUR/wk/barge
3	Silt screen installation around discharge location	500,000 EUR

Table 5.12: Mitigation Measures and Investments

ID	Occurrence	Min	Mode	Max	Unit
1	120 NOH	2	3	48	hrs
2	cycle	-4	0	5	min
3	60 days	24	24	168	hrs

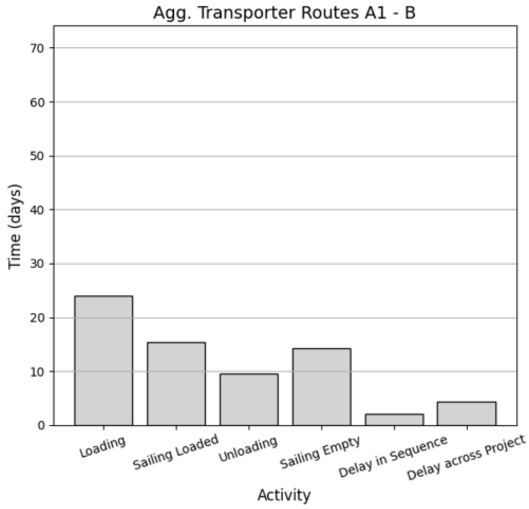
Table 5.13: Mitigated Risk and Uncertainty Parameters (green = updated)

In the mitigated all-risks scenario, asset operating, waiting, and total times (P80) are reported in Table 5.14. These time profiles underpin the KPI calculations.

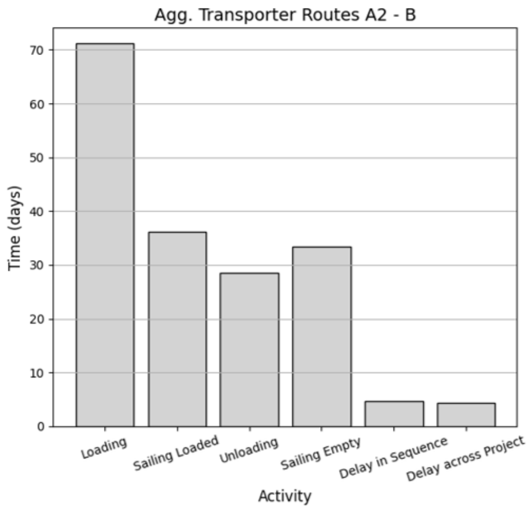
Asset	Operating Time (hrs)	Waiting Time (hrs)	Total Time (hrs)
Backhoe dredger (Site A1)	575	79	654
Backhoe dredger (Site A2)	1708	197	1905
Backhoe dredger (Site A3)	1616	187	1803
Transporter (Site A1-1)	488	167	655
Transporter (Site A1-2)	488	166	655
Transporter (Site A1-3)	485	167	652
Transporter (Site A2-1)	1301	605	1905
Transporter (Site A2-2)	1300	605	1905
Transporter (Site A2-3)	1293	601	1894
Transporter (Site A3-1)	1065	735	1800
Transporter (Site A3-2)	1065	735	1800
Transporter (Site A3-3)	1064	734	1798
Pontoon	1296	715	2011

Table 5.14: Mitigated Operating and Waiting Times (all risks present, P80)

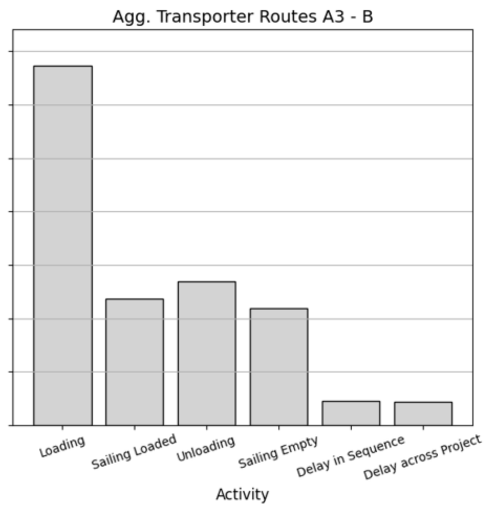
Following implementation, aggregated time per activity and route (P80) is shown in Figure 5.9 and Table 5.15.



(a) *Mitigated* aggregated time spent of all transporters on route A1–B.



(b) *Mitigated* aggregated time spent of all transporters on route A2–B.



(c) *Mitigated* aggregated time spent of all transporters on route A3–B.

Figure 5.9: Comparison of *mitigated* aggregated activity durations for three transporter routes (A1–B, A2–B, and A3–B). Results are reported as P80 values.

Event	Route A1–B	Route A2–B	Route A3–B
Simulation Ending Time	31 d 08:15	83 d 03:52	78 d 13:02
Loading	23 d 22:57	71 d 03:38	67 d 07:52
Sailing Loaded	15 d 11:04	36 d 04:34	23 d 14:20
Unloading	9 d 14:00	28 d 11:09	26 d 22:26
Sailing Empty	14 d 06:35	33 d 11:06	21 d 21:41
Delay in Sequence	2 d 02:53	4 d 17:35	4 d 11:29
Delay across Project	4 d 09:45	4 d 09:45	4 d 09:45

Table 5.15: Mitigated time distribution per route (P80)

5.5.1. Mitigated KPI impact (all-risks scenario)

Figure 5.10 and Table 5.16 summarize the mitigated vs. unmitigated KPIs (P80). Normalized improvements are shown in Figure 5.11.

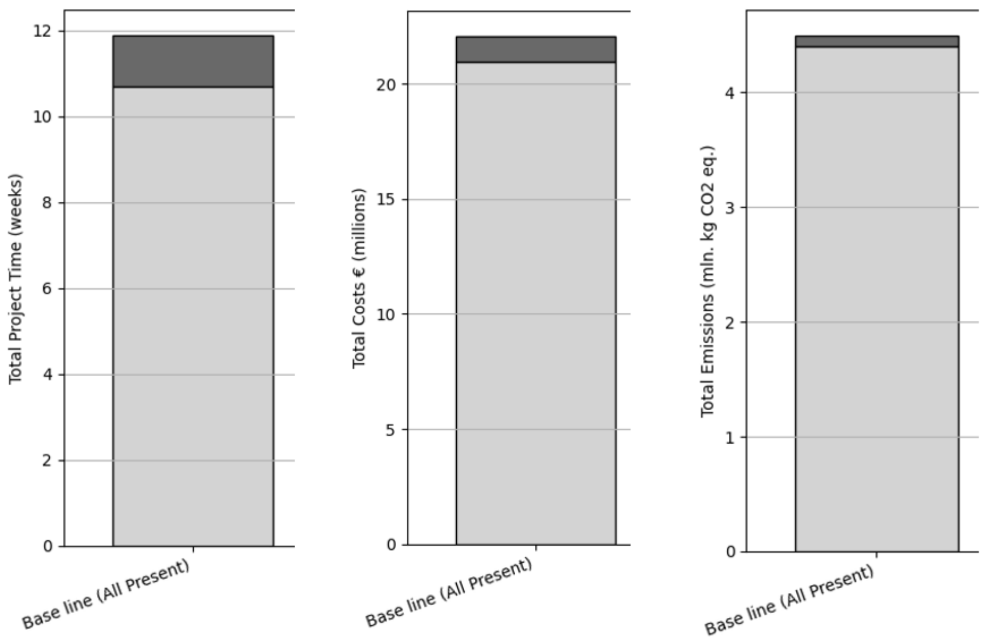


Figure 5.10: KPI Impact of mitigated scenario (all risks present, P80)

KPIs	Unmitigated	Mitigated	Impact	Δ [%]
Time (weeks)	14.58	11.88	-2.70	-18.5
Costs (mln. €)	24.42	22.06	-2.36	-9.6
Emissions (tons CO_2 eq.)	4597	4493	-104	-2.3

Table 5.16: KPI comparison: unmitigated vs. mitigated (all risks present, P80)

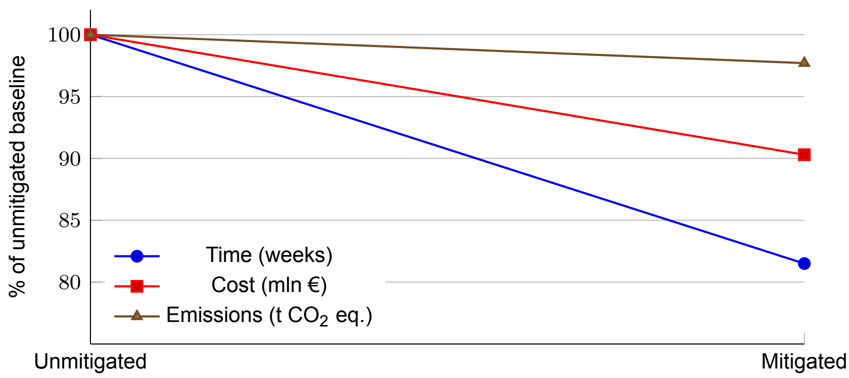


Figure 5.11: Normalized KPI improvements from unmitigated (100%) to mitigated scenario (P80).

5.5.2. Financial feasibility

We compared *Total Project Costs* (excluding investments) for each mitigation setting to the unmitigated all-risks baseline and derived *Net Benefit* as $\Delta-$ investment (Table 5.17). **Top net benefits** were achieved by *Spare parts* + *Silt screen* (€1.740 M), *Experienced captain* + *Spare parts* (€1.735 M), and *All three* (€1.729 M). Individually, *Spare parts* yielded €1.628 M, *Silt screen* €0.519 M, and *Experienced captains* €0.018 M.

Benefit–Cost Ratios (BCR = Δ/investment) underline these findings: *Spare parts* had the highest BCR (33.6), *Experienced captain* + *Spare parts* was also very efficient (13.6), followed by *Spare parts* + *Silt* *screen* (4.16) and *All three* (3.73). *Experienced captains* alone were near break-even (BCR $\approx$ 1.18) at P80. Rankings were unchanged at P50 and P90.

#	Added mitigation measures	Total Project Costs	$\triangle$	Tot. Measures Costs	Profit/Loss
0	None	€ 24,418,000	€ –	€ –	—
1	Silt screen + Spare parts + Experienced captain	€ 22,056,000	€ 2,362,000	€ 633,500	€ 1,728,500
2	Silt screen	€ 23,399,000	€ 1,019,000	€ 500,000	€ 519,000
3	Spare parts	€ 22,740,500	€ 1,677,500	€ 50,000	€ 1,627,500
4	Experienced captain	€ 24,300,500	€ 117,500	€ 99,800	€ 17,700
5	Experienced captain + Spare parts	€ 22,545,500	€ 1,872,500	€ 137,400	€ 1,735,100
6	Experienced captain + Silt screen	€ 23,417,500	€ 1,000,500	€ 594,700	€ 405,800
7	Spare parts + Silt screen	€ 22,128,000	€ 2,290,000	€ 550,000	€ 1,740,000

Table 5.17: Financial Feasibility of Mitigation Measures (Net Benefit shading, P80)

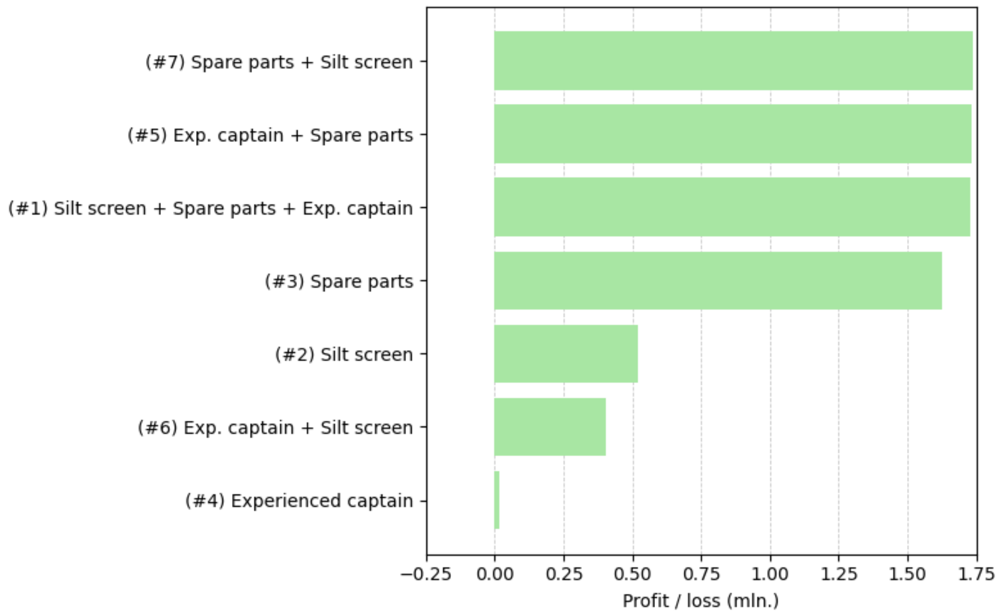


Figure 5.12: Profit/Loss by mitigation combination (ranked, P80)

5.5.3. Benefit–Cost Ratios

The calculated BCR values confirm the ranking of mitigation measures observed in the net benefit analysis (Table 5.17). *Spare parts* alone delivered the highest efficiency, with a BCR of approximately 33.6. The combination of *Experienced captain* + *Spare parts* also performed well (BCR ≈ 13.6), followed by *Spare parts* + *Silt screen* (BCR ≈ 4.16) and *All three measures* (BCR ≈ 3.73). Individually, the *Silt screen* had a moderate BCR (≈ 2.0), while *Experienced captains* were close to break-even (≈ 1.18). Rankings were consistent across P50, P80, and P90 percentiles.

6 Discussion

This Chapter interprets the findings presented in the Results Chapter, relating them to the thesis objectives and the prior literature. No new analyses or data are introduced; the focus is on explaining what the results mean, why they matter, and where their validity is bounded. The discussion is organized to mirror the methodological flow: (i) suitability of estimating software for early-phase tendering, (ii) characteristic risks and uncertainties in typical dredging projects, (iii) translation of expert judgment into the simulation model, and (iv) the impact of risks together with the effectiveness of mitigation measures. A final synthesis integrates these strands into a risk-aware tendering workflow and describes the limits of generalization from this study.

6.1. Estimating Software for Early-Phase Tendering

Summary of key findings

This study compared candidate approaches for early phase estimation and selected discrete-event simulation (DES) as the most suitable paradigm for time, cost, and emissions forecasting under uncertainty. OpenCLSim was chosen as the implementation platform because its layered project abstraction (Activity, Sequence, Asset, Multi-Site) aligns with how dredging work is organized and because it supports modular “mixins” to inject risk/uncertainty logic at the appropriate level of impact. In practice, OpenCLSim allowed us to: (i) schematize tender work methods transparently (OBS/ABS), (ii) capture resource conflicts and queues explicitly, and (iii) run Monte Carlo experiments while logging operating and waiting times per asset, from which KPIs are computed.

Interpretation

In the tender phase, data is scarce and decisions are time-critical. Methods that rely on deterministic durations or coarse system-level averages tend to miss the effects of queues, shared resources, and stochastic stoppages. DES, by contrast, is built to model event sequencing, contention for processors (e.g., backhoes, pontoons), and transporter cycles. This makes it possible to represent three distinct impact levels consistently: activity-level uncertainty (duration variability), sequence-level risks (asset-specific downtime), and project-wide stops (multi-site halts).

OpenCLSim’s object/activity breakdown maps cleanly onto the “red thread” of dredging cycles (loading–sailing loaded–unloading–sailing empty). The framework’s extensibility enabled an additional plugin (“Risk & Uncertainty mixin”) that accepts expert-elicited probabilities and impact distributions without modifying core simulation logic. The resulting traces (per-asset operating and waiting time) are exactly the granularity needed to derive the three KPIs used in tendering (time, cost via daily rates, and emissions via operating/idle consumption).

Implications for practice and research

For practitioners, the implication is that a light-weight DES model can serve as an “decision support model” in tenders: proposed work methods can be encoded once, expert judgments can be translated into parameters, and scenarios can be compared consistently (including mitigation variants). Because the model yields per-asset time states, it also supports downstream analyses such as knock-on effects, critical-route identification, and cost/emissions attribution—outputs that are difficult to obtain from deterministic spreadsheets alone.

For research, the combination of a layered DES with parameterized risk mixins provides a reproducible bridge between expert elicitation and quantitative assessment. It also creates a platform to test methodological choices (e.g., distributional assumptions for failures, alternative routing or queuing policies) without re-architecting the model.

Limitations

Adopting DES (and OpenCLSim specifically) comes with trade-offs. First, there is modeling effort: building an OBS/ABS and validating activity logic requires domain familiarity and coding fluency; this is not a “black-box estimator.” Second, runtime and sampling: Monte Carlo stability demands multiple replications; while acceptable for this study, very large scenario sets or heavier models may strain tender timelines unless parallelization is used. Third, OpenCLSim’s current abstractions privilege discrete events over continuous processes; highly detailed hydrodynamic workability models or mid-activity failures require additional implementation. Ultimately, DES outputs can reflect precision; nevertheless, inputs such as expert opinions and simplified costs/emissions continue to represent the primary uncertainty in initial tenders. So, results should be communicated with their probabilistic context (e.g., P50/P90) rather than as point estimates.

6.2. Characteristic Risks & Uncertainties

Summary of key findings

This section discusses the characteristic risks and uncertainties for early tendering in dredging and their plausible mitigation measures. Through structured expert elicitation, risks were organized into four categories (workability, technical, logistical, environmental/social) and mapped to three levels of impact (activity uncertainty, delay in sequence, delay across project). For the case application, the experts converged on three representative items spanning categories and impact levels: (i) **barge mooring duration** (logistical; activity uncertainty), (ii) **backhoe crane breakdown** (technical; delay in sequence), and (iii) **turbidity exceedance at the pontoon** (environmental/social; delay across project). They also proposed targeted mitigations: *critical spare parts* (reducing breakdown impact), *experienced captains* (tightening mooring variability), and a *silt screen* (lowering the frequency of turbidity stops).

Interpretation

The three chosen issues illustrate the primary early-phase challenges contractors face under time and information limitations:

- **Logistical duration variability (mooring):** Mooring is inherent to each cycle; its variability accumulates across many cycles and can be positive/negative around a mode of zero. Modeling it as activity-level uncertainty preserves its high-frequency, low-magnitude nature.
- **Asset reliability (breakdown):** A single processor on the loading side governs throughput on its route; even a modest probability of breakdown, evaluated at every loading attempt, can dominate total delay because the impact distribution (repair time) is heavy relative to cycle times.
- **Environmental compliance halts (turbidity):** Environmental exceedances are episodic and project-wide; representing them at the Multi-Site layer captures their systemic effect on all assets and aligns with how operations are actually suspended.

Instead of just creating a simple list of all possible risks, this approach created a structured map. This map shows not only what the risks are, but also where they will have an impact in the model and how their details (like probability and impact) will be determined from expert judgment. This is a more systematic and strategic way of selecting risks for a simulation study.

Implications

For practice, the results suggest a concise early-tender screening template:

1. Classify candidate risks by *category* and *impact level*;
2. Prioritize items that (a) are cycle-wide (always-on duration variability), (b) identify critical assets (low-frequency/high-impact downtime), or (c) can halt the project (compliance stops);
3. Pair each prioritized item with a concrete *mitigation measure* (probability-reducing vs impact-reducing) and record elicited pre/post parameters.

This aligns the identification step with downstream integration: once a risk has an impact level, its injection point in the simulation software is clear, and its mitigation can be tested quantitatively. More broadly, the trio (mooring, breakdown, turbidity) are typical across many dredging tenders, so the same template can be reused project-to-project with project-specific parameterization.

Limitations

The identified set is illustrative, not extensive. Experts were drawn from a single consortium with recent experience on the same port, which may bias selection and parameter ranges. Workability was deprioritized here because mature estimation methods often exist outside expert judgment; in other projects, workability may need to be reintroduced explicitly. Finally, early-tender elicitation typically favors triangular distributions and coarse frequencies; while appropriate for speed, this constrains fidelity. As data accumulate (internally or via analogues), the classification should be revisited and expanded, and parameters recalibrated to improve transferability beyond the present case.

6.3. Translating Expert Judgment to Simulation Parameters

Summary of key findings

This section reflects on how rough engineering estimates provided by experts were converted into inputs that the simulation could execute. In line with the methodological flow, expert statements about *likelihood* and *impact* were mapped to (i) injection points in the model (activity, sequence, multi-site) and (ii) parametric forms (Uniform/Triangular/PERT). Occurrence frequencies expressed as “once per X hours” or MTTF were translated to probabilities per decision point via an exponential assumption; occasional, project-wide events expressed as “k per month” were mapped with a Poisson formulation. Inherently variable activities (e.g., mooring in sailing activity) were treated as always-on uncertainties with $P(\text{occ}) = 1$ and signed duration deltas.

Interpretation

The translation step serves two purposes. First, it preserves the *place* where a risk acts: activity-level risks alters the activity’s duration; sequence-level risks gate the start of an asset’s next activity; risks in the multi-site layer inject project-wide delays. Second, it renders expert inputs computable without over-engineering: (a) triangular distributions capture rough min–mode–max; the use of an (b) exponential failure model is a good fit for components that have a consistent chance of failing over many short periods; (c) the Poisson distribution is used for capturing random, single events, such as a compliance-driven halt.

Two simplifying choices deserve emphasis. Selecting the Poisson *mode* ($k^{\star}$) as the implemented frequency yields a clear, reproducible parameter for the DES, but it compresses inter-run variability in how often a project-wide halt might occur. Likewise, computing $P(\text{occ})$ from MTTF at each decision point assumes a memoryless hazard; this is pragmatic in tender timelines but not universally true (e.g., wear-out).

Implications

Practically, the translation scheme makes expert knowledge immediately actionable: once a risk is positioned on an impact layer and parameterized, it can be turned on and off, stress-tested, and combined with others in Monte Carlo runs. It also creates a clear data pathway: *where historical data exist*, they should *replace* or *calibrate* expert inputs at the same parametric interface (e.g., empirical repair-time samples in place of a triangular, survival-model estimates instead of exponential). Expert elicitation should therefore be *concentrated where data are sparse* (novel geographies, novel work method strategies, or new equipment configurations), reducing reliance on judgment where reliable records already exist.

Limitations

The present implementation is **heavily dependent on expert judgment** for both occurrence and impact in the absence of datasets. Elicited ranges were not externally validated; this affects absolute accuracy (addressed in the Recommendations via calibration/validation routes). The exponential/Poisson assumptions may under-represent aging or burstiness; more suitable distributions (e.g., Weibull for wear-out, negative binomial or Hawkes-type processes for clustered events) could increase fidelity. Finally, implementing only the most likely Poisson frequency per run underestimates cross-run dispersion; sampling the frequency from the distribution each run would better reflect tail risk (unlikely, but high-impact) at some computational cost.

6.4. Impact of Risks & Uncertainties on KPIs

Summary of key findings

Addressing the question of how simulations can reveal the most critical risks and quantify their effects on time, cost, and emissions, the results show three consistent patterns. First, the backhoe breakdown (sequence-level risk) dominates KPI impact: removing it reduces project duration by ~ 458 hours (P80) relative to the all-risks scenario, far more than removing the mooring-time uncertainty (~ 48 hours) or the project-wide turbidity exceedance (~ 218 hours) (Table 5.6). Second, when comparing the sum of isolated impacts with the simultaneous all-risks impact, *time* exhibits a buffering effect (724 h aggregated vs. 656 h simultaneous), while *costs* and *emissions* exhibit cascading (aggregated €2.76M vs. simultaneous €3.48M; 138.9 t CO_2 vs. 193.2 t) (Table 5.9). Third, all mitigations improve the KPIs at P80: time -18.5%, costs -9.6%, emissions -2.3% (Table 5.16); financially, spare parts alone and spare parts+silt screen deliver the largest net savings (Table 5.17).

Interpretation

Why time buffers while cost & emissions cascade: Project duration is governed by the critical path across parallel assets and activities. When multiple delays occur simultaneously (or on non-critical routes), their *calendar* effects overlap and are partially absorbed: one delay "covers" another, or a non-critical delay does not move the overall completion at all. Hence the sum of isolated time impacts can exceed the single simultaneous impact.

By contrast, costs and emissions *accumulate across assets in parallel*. Even if schedule growth is buffered, several assets can be idling and accruing variable-day costs and fuel use at the same time. Two modeling features amplify this: (i) variable costs are rounded to full days *per asset*, so overlapping waits can push multiple assets over daily boundaries simultaneously; (ii) emissions include idle consumption rates, so parallel idling raises total CO_2 even when the calendar does not stretch as much. This produces the observed super-additive (cascading) simultaneous impact for costs and emissions.

Why the backhoe breakdown dominates: The backhoes sit on route-critical chains (A2 in particular) and gate the start of each barge cycle. A sequence-level halt directly induces waiting for three dependent barges plus the pontoon's berth allocation. Even with a relatively low per-decision-point probability, the gate is evaluated frequently (every loading start), and sampled repairs can be long; together these mechanisms generate the largest P80 deltas in time and, consequently, in cost and emissions.

Why turbidity exceedance matters less for time but more for total project costs: A delay across the project affects all assets uniformly, but in the simultaneous scenario it often partially overlaps other waiting times, limiting its marginal contribution to *completion time*. However, because all assets idle in parallel, the same event drives *broad* cost/emission accumulation, contributing to the cascading effect noted above.

Uncertainty in mooring time: small but structurally different: Mooring uncertainty is an *activity-level* fluctuation with $P(\mathrm{occ}) = 1$ on every call; its signed triangular distribution slightly disturbs cycle times. Because the median effect is near zero and the tails are short, its isolated impact on duration is modest. It does, however, marginally increase *operational* time (not just idle), which is why its relative influence on emissions can be proportionally larger than on costs.

Mitigation outcomes and BCR logic: Among the mitigation strategies, the spare-parts measure is by far the most effective: by sharply reducing repair durations, it removes the single most damaging tail in the system, yielding both large net savings and the highest Benefit–Cost Ratio (BCR). The silt screen also performs positively by halving the frequency of project-wide halts; although its calendar benefit is partly buffered, it still reduces system-wide idle costs. In contrast, the experienced-captain measure targets small, frequent activity-level variations and therefore delivers only modest benefits relative to its time-indexed cost. Combinations of measures can be attractive, but their efficiency declines once the dominant gain from spare parts is already captured. Overall, the BCR results highlight that sequence-critical technical mitigations provide the best return per euro invested, offering contractors a rational basis for prioritizing scarce resources in the tender phase.

Implications

For early tender phase decision-making, three operational implications follow. (i) Target sequence-critical risks first: small reductions in repair-time tails on critical routes buy disproportionate gains in both schedule and cost. (ii) Expect divergence between *schedule* and *cost/emissions*: calendar buffers do not imply financial neutrality—parallel idling still accumulates expense and CO_2. (iii) Use BCR (or cost-of-delay avoided per euro invested) to prioritize a basket of mitigations; measures that remove long-tail sequence delays tend to outperform frequent small-variance improvements when budget is constrained.

Limitations

These interpretations depend on modelling choices that bias toward the observed patterns: per-asset daily cost rounding, inclusion of idle fuel rates, and choice of P80 for reporting. Different client cost structures (e.g., true hourly charging, explicit overheads/penalties) or percentile targets (P50/P90) would shift the magnitudes and, in edge cases, the rank of mitigations. Moreover, the buffering/cascading diagnosis is based on a limited risk set on a single case; projects with different network topologies, resource pools, or compliance regimes may display different overlap properties. Finally, BCRs here are computed on modelled deltas without external validation of elicited parameters; their relative ordering is informative for tenders, but absolute values should be revisited as better data become available.

6.5. Synthesis and Contribution

Positioning against prior work

These results build on existing evidence that DES is well suited to maritime and construction operations with queues, resources, and precedence constraints, and that Work/Activity Breakdown Structures help formalize such systems [Hudoyo et al., 2019]. The translation of rough reliability inputs into simulation-ready probabilities follows standard practice in reliability engineering—using exponential/Poisson processes for time-to-failure in the useful-life region [Verma et al., 2010; Odeyar et al., 2022]. The mitigation strategy (avoid/transfer/mitigate/accept) aligns with project risk management guidance [Stackpole, 2013]. Reporting at P80 mirrors common industry convention for conservative planning (e.g.,[Eldosouky et al., 2014; Acebes et al., 2024]).

Where this work extends the literature is in the *end-to-end* operationalization for early tendering: (i) a structured elicitation focused on project-specific risks; (ii) a clear mapping of each risk to one of three impact layers (activity, sequence, project-wide) inside a multi-layer DES; (iii) a generic "risk & uncertainty mixin" that parameterizes occurrence and impact consistently; and (iv) analytic outputs that connect schedule effects to cost and emissions and then to mitigation economics (benefit–cost). The experiment provides a new insight into the relationship between *overlap on the critical path* and *parallel accumulation of costs/emissions*: time exhibits buffering under simultaneity, while costs and emissions can cascade due to parallel idling and per-asset daily cost rounding.

What is novel here

While previous research has focused on either schedule-risk quantification or cost/emissions separately, these results demonstrate that a single simulation pipeline can: (a) rank risks by KPI impact at P80; (b) diagnose interaction patterns (buffering vs. knock-on); and (c) evaluate mitigation sets by net savings and simple BCR, all with inputs that are feasible to obtain during tendering. The explicit three-level implementation (activity, sequence, project-wide) provides a clearer understanding of *where* to place each risk in the model so that its operational footprint (who waits, who idles) is steadily reproduced.

Implications for practitioners

These results should be taken into account when considering how to prioritize engineering capacity and resource allocation in early tender phase. A practical rule emerges: sequence-critical technical failures (e.g., backhoe breakdowns) typically dominate P80 outcomes—mitigations that truncate repair tails (spare parts, maintenance readiness) offer outsized returns. Conversely, small, frequent activity-level variances (e.g., mooring time) improve cycle smoothness but rarely drive major P80 savings unless they sit on the critical route. Cost/emission planning should not infer "low financial risk" from buffered schedule growth: overlapping waiting times still generate expense and CO_2. Use benefit–cost ratios alongside KPI deltas to assemble mitigation portfolios under budget constraints.

Generalizability and scope

The data contribute a clearer understanding of risk propagation in the project configuration studied, but generalizability is conditioned by the single case, the selected risk set, and reliance on expert judgments. That said, the topology modeled here, multiple dredge locations feeding a shared discharge location (many-to-one), or conversely one source serving multiple discharge sites (one-to-many), is not unusual. Based on expert consultation and the portfolio of projects reviewed during this thesis, *approximately 80% of dredging tenders exhibit a multi-site $\leftrightarrow$ single-site structure*. This prevalence increases the practical value of the methodology (Figure 6.1) which is directly portable across most layouts, with only work method and parameterization changing.

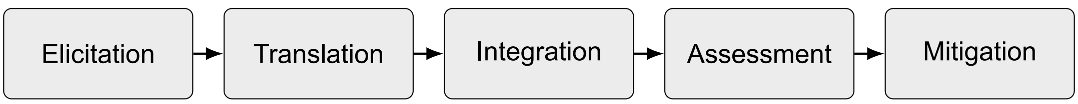


Figure 6.1: Practical value of the methodology pipeline.

Transfer to other projects remains promising because the approach is method-centric rather than case-centric; nevertheless, several elements should be adapted: charging rules (hourly vs. daily), inclusion of overheads and penalties, idle-fuel policies, and the choice of occurrence models (exponential/Poisson vs. Weibull or Bayesian updating when wear-out or learning effects apply [Odeyar et al., 2022; Cooke, 1991]). For cross-project comparability, we recommend normalizing KPIs (e.g., m^3/week, €/m^3, tCO_2/m^3) and re-establishing critical routes per site before extrapolating conclusions. Projects with different operational archetypes (e.g., continuous hopper dredging without shared processors, or purely linear channels) may require minor adjustments to how sequence or project-wide delays are injected, but the three-level mapping (activity, sequence, project-wide) and the mixin mechanism remain applicable.

Reflections along the methodological flow

When reflecting on the high-level flowchart of the risk assessment method (Figure 3.1), each stage can be evaluated in terms of what worked well, what limitations remain, and what logical next steps could strengthen the methodology.

Table 6.1 summarizes these reflections in a compact format. Each row corresponds to one stage of the methodological flow, and the three columns highlight (i) the aspects that proved effective in practice, (ii) the main constraints observed during application, and (iii) potential directions for improvement or extension.

Stage	**Worked**	**Limits**	**Next**
Risk identification & quantification	Fast convergence on a few material risks across the four categories.	Dependence on a small expert pool.	Structured Expert Judgment calibration [Cooke, 1991].
Converting to parameters	Uniform mixin schema (probability + distribution).	Memoryless occurrence for all risks.	Add Weibull/Bayesian updates where wear out or learning applies [Odeyar et al., 2022].
Integration in DES	Clean separation by impact level (activity/sequence/project).	Sequence delays realized only at activity starts; across project delays applied as aggregated waiting times.	Mid activity failures and time synchronized project wide halts.
Assessment (KPIs)	P80 summary with interaction diagnosis.	Daily cost rounding and simplified emission model.	Overheads, penalties, loaded/empty sailing rates.
Mitigation evaluation	Rankable portfolios with net savings and BCR.	Cost inputs simplified; emissions not monetized.	Include social/environmental costs and contractual incentives.

Table 6.1: Reflections along the methodological flow: worked aspects, limitations, and next steps.

7

Conclusions & Recommendations

7.1. Conclusions

This Chapter synthesizes the work undertaken to design and apply a rapid, early–tender risk assessment for dredging projects. The study combined structured expert elicitation with a Discrete Event Simulation (DES) implementation in OpenCLSim, translating qualitative judgements into probabilistic parameters, and assessing their impact on time, cost, and emissions through Monte Carlo analysis (reported at P80).

Estimation software for complex dredging operations (RQ1)

Discrete Event Simulation is the most suitable paradigm to represent the event–driven, resource–constrained, and queue–dominated nature of dredging logistics. Among available tools, OpenCLSim (on SimPy) provided the most appropriate foundation: it mirrors project hierarchy (activity–sequence–asset–multi-site), allows explicit queuing and resource contention, and is extensible via custom mixins for risk/uncertainty. This enabled a faithful mapping from field operations to executable models within the scope and timelines of an early tender study.

Characteristic risks and uncertainties in tenders (RQ2)

Because dredging projects are context–specific, a universal risk set is neither practical nor desirable. A repeatable *process* proved effective: (i) structure a risk catalogue by category (workability, technical, logistical, environmental/social), (ii) localize project–specific candidates via expert elicitation, and (iii) assign each to an impact level (activity uncertainty, delay in sequence, delay across project). Applied to the case, experts prioritized uncertainty in mooring duration (activity), backhoe crane breakdown (sequence), and turbidity limit exceedance (project–wide), together with candidate mitigations.

Translating expert judgment into simulation parameters (RQ3)

Elicited probabilities and impacts were systematically converted into simulation–ready inputs by (i) choosing occurrence models (e.g., exponential/Poisson for time-based events or frequencies), (ii) encoding impacts as triangular distributions (min–mode–max) consistent with expert ranges, and (iii) injecting a *Risk & Uncertainty* mixin at the correct impact level. This "translation" preserved intent (what the expert means operationally) while enforcing consistency (what the simulator needs numerically).

Risk impacts, mitigations, and resource allocation (RQ4)

The model quantified impacts by comparing an all-risks baseline with variants excluding one element at a time. Results showed that project duration tends to *buffer* overlapping delays, while costs and emissions *cascade* due to parallel idling and daily cost rounding. In the case study, sequence-level failures on critical routes had the largest effect on KPIs. Mitigations were assessed by updating risk parameters and adding measure costs; measures that reduced KPIs more than their investment were considered attractive. The analysis revealed that targeting sequence-critical risks delivered the highest benefit–cost ratios, providing direct guidance on where scarce engineering resources should be allocated during early tendering.

Answer to the main research question

How can key risks and uncertainties be identified in the tender phase of a dredging project by combining expert judgment with simulation software to optimize engineering resource allocation?

By running a structured pipeline: elicit and categorize project-specific risks with experts; translate their qualitative judgments into quantitative occurrence and impact inputs aligned to activity, sequence, and project-wide layers; integrate these into an OpenCLSim DES via a mixin; and use Monte Carlo comparisons (all-risks vs. single-risk-removed) at P80 to rank critical drivers and test mitigations.

This approach directly addresses the gap in existing practice by providing a systematic way to quantify the relative importance of early-stage uncertainties when detailed data are not yet available. It is most valuable in the early tendering phase of dredging projects with multiple assets—particularly multi-site $\leftrightarrow$ single-site layouts with limited data and significant engineering uncertainty—where a quick risk assessment and prioritization of scarce resource allocation is needed.

The outcome is a defensible short-list of “high-leverage” risks and cost-effective mitigations, providing project managers with clear guidance on where scarce engineering capacity should be allocated. Importantly, the methodology is lightweight: expert elicitation, parameter translation, and simulation can realistically be completed within one or two days, fitting the tight time constraints of early tendering.

7.2. Recommendations

For practice

These recommendations are directed at *project managers and tender teams*, focusing on how the elicitation–translation–simulation loop can be embedded into day-to-day project management routines to improve risk awareness and KPI reporting.

- Use the presented elicitation $\rightarrow$ translation $\rightarrow$ simulation loop as a standard tender routine; report KPI impacts at P80 by default, with P50/P90 bands for context.
- Prioritize sequence-level risks on critical routes; where breakdown impacts dominate, pre-position spares and streamline repair logistics before mobilization.
- Normalize KPI reporting to enable cross-project comparison (e.g., €/m^3, m^3/week, tCO_2/m^3).
- Apply the method selectively in the *early tendering phase*, especially for projects with multiple dredging sites feeding into a single disposal site (or vice versa). Such projects typically involve higher uncertainty or limited data, making quick expert-based risk assessment particularly valuable. Managers should allocate one to two days within the tender process to run the elicitation–translation–simulation loop, ensuring that scarce engineering capacity is focused on the most critical uncertainties.

For data and modeling

These recommendations target *future research and model developers*, aiming to enhance the robustness and versatility of the decision-support model by strengthening inputs and extending its analytical capabilities.

- Strengthen expert inputs via calibration/weighting (e.g., Structured Expert Judgment [Cooke, 1991]) and progressive validation against logged project data.
- Overlay CPM on DES to expose critical routes/activities. Implement the OpenCLSim CPM overlay [De Niet et al., 2023] to compute stochastic criticality indices from simulated traces. Use these indices to target sequence-level risk reduction where it most shortens the P80 schedule.
- Where wear-out or learning is expected, replace constant-rate occurrence models with time-dependent (e.g., Weibull) or Bayesian-updated models.
- Increase Monte Carlo runs when computationally feasible and parallelize scenario batches to better sample tail behavior.

For scenario design and KPIs

These recommendations are mainly for *future research with direct relevance to project management*, helping contractors use the model to compare alternative work methods and assess KPI trade-offs in the early tender phase.

- Extend scenarios to alternative work methods (different asset types or amount), and assess their risk–KPI trade-offs.
- Fleet sustainability optimization scenarios. Build scenario families that vary fleet mix (number/-type of barges, dredgers), sailing policies (eco-speed vs. max speed), and routing rules. Use DES outputs (cost and CO_2 per asset/state) to generate cost–emissions Pareto fronts, optionally monetize CO_2 via ETS factors to compare different scenarios. This identifies fleet configurations that minimize cost for a given emissions target (and vice versa).
- Refine KPIs: include overheads, fuel costs, and penalties in cost; distinguish loaded/empty and speed regimes in emissions; allow client-specific thresholds and associated consequences.

For transferability

This recommendation addresses *both researchers and practitioners*, highlighting how the approach can be adapted when project topologies differ, ensuring broader applicability beyond the case studies tested here.

- The approach generalizes well to common multi-site $\leftrightarrow$ single-site topologies; re-wire sites and re-parameterize risks, then re-identify critical routes before extrapolating conclusions.

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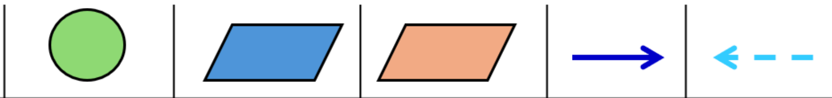
A

Illustrative Example of OBS–ABS Structures

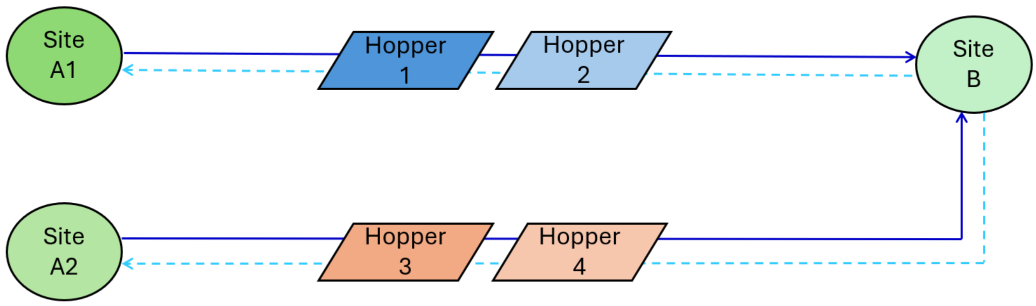
This Appendix provides a worked example of how dredging projects can be represented within OpenCLSim using the hierarchical project structure. The aim is to illustrate how the Object Breakdown Structure (OBS) and Activity Breakdown Structure (ABS) interact to capture project logic, and how assets, activities, and sites are organized into parallel processes. The example is deliberately simplified but reflects a realistic maintenance dredging scenario, making it easier to understand how the abstract concepts introduced in Chapter 2 translate into an operational model.

To illustrate the application of these concepts and the hierarchical project layers, consider a dredging project focused on maintaining passage within a harbor area. This project involves sediment removal from two distinct locations within the harbor, with all dredged material subsequently dumped at one specific offshore site. The operation utilizes a total of four hoppers. Two hoppers are assigned to excavate sediment from the first harbor location, while simultaneously, the other two hoppers work at the second harbor location. All four hoppers execute the same activity sequence: loading at their assigned harbor location, sailing loaded to the offshore dump site, unloading the material using bottom doors, and then sailing empty back to the harbor. This cycle continues until the required sediment removal from both harbor locations is fully achieved, satisfying the project's completion conditions. With this description of the dynamic components (1.1) in the considered maintenance dredge work, the OBS looks like A.1b. If this operation describes the ABS, then according to De Boer et al., [2022], the ABS would be structured as depicted in A.1c.

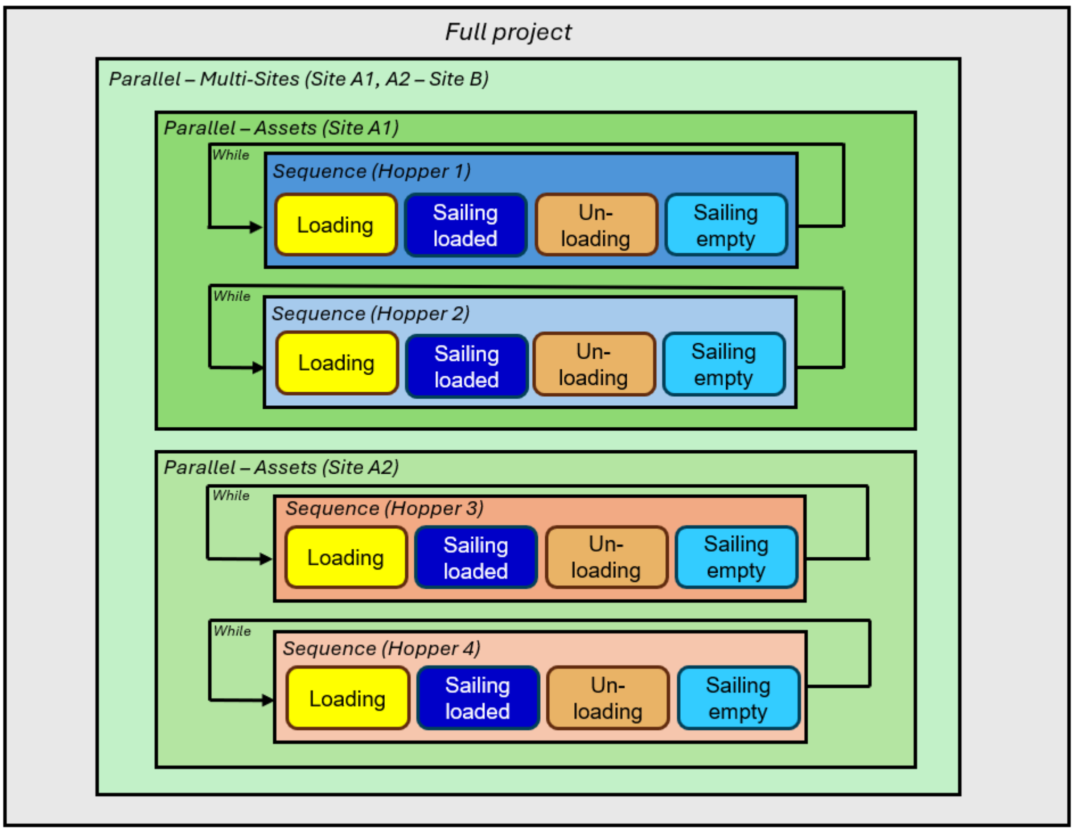


Object/Activity	Sites	Processor-Transporter	Processor-Transporter	Sailing Loaded	Sailing Empty
Parameters	A1: Harbor A2: Harbor B: Discharge	1: Hopper (A1-B) 2: Hopper (A1-B)	3: Hopper (A2-B) 4: Hopper (A2-B)	To discharge	To harbor

(a) Legend used in the schematic figures. Symbols indicate sites, assets (hoppers), and activity sequences, which are combined in the Object Breakdown Structure (OBS) and Activity Breakdown Structure (ABS).



(b) OBS: Harbor with two distinct locations (Site A1 and A2), Hoppers 1 and 2 dredging Sita A1 and Hoppers 3 and 4 dredging Site A2, one dump location (Site B)



(c) ABS: Full project consists of two parallel Sites (A1 and A2), at each Site two parallel Assets work (Hopper 1,2 and 3,4) until condition is met (*While*), each Hopper has a Sequence (Loading, Sailing Loaded, Unloading, Sailing Empty)

Figure A.1: Illustrative schematization of a dredging project using OpenCLSim. Legend of symbols (A.1a). (A.1b) Object Breakdown Structure (OBS) (with dynamic components 1.1) and (A.1c) Activity Breakdown Structure (ABS) of Work Breakdown Structure (WBS) of Hoppers dredging in a harbor.

B

Expert Elicitation: Protocol, Notes, and Transcript

B.1. Purpose and Context

This appendix documents how expert judgments were collected and translated into simulation inputs for the Malmporten case (Chapter 4). It complements the risk inventory and parameters reported in Tables 5.1, 5.2, 5.12, and 5.13.

B.2. Participants and Logistics

- **Expert 1 (E1)**: Lead tender engineer (dredging contractor consortium). Focus: work method, equipment, logistics.
- **Expert 2 (E2)**: Production engineer. Focus: turbidity constraints, regulatory windows.
- **Interviewer (I)**: Researcher (author).
- **Format**: Multiple shorter interviews with Expert 1 and Expert 2.
- **Artifacts**: Tender dossier (drawings, volumes, constraints), internal concept method statement, historic ops logs from an earlier phase at Luleå.

B.3. Elicitation Protocol (overview)

The interview followed the method from Chapter 3:

1. **Tender scan** → confirm scope, KPIs, constraints.
2. **Risk identification and categorization** (no numbers yet).
3. **Impact level assignment** (Activity uncertainty / Sequence delay / Delay across Project).
4. **Quantification** (occurrence basis, distribution type, min–mode–max).
5. **Mitigation brainstorming** (measures, costs, revised parameters).
6. **Validation** (unit check, reasonableness, consistency across sites).

B.4. Transcript (edited for clarity)

Part A — Tender scan and KPIs

I: Before we dive into risks: what would you say is the single hardest constraint here? **E1:** Time window. We *must* hit about 20 weeks because of ice. That drives everything else. **E2:** And turbidity. The discharge area is sensitive; if we cross the limit we have to stop. Those stops can be a day or stretch into a week if weather keeps stirring things up. **I:** Good—so KPIs we'll track are time, cost, and emissions, reported at P80.

Part B — Identify and group risks (no numbers yet)

I: Let's list a short-list of risks across all layers and categories you feel that could influence the impact of the dredge work and is interesting to simulate. **E1:** For the backhoes: crane breakdowns. It's not frequent, but when it hits, production on that site stalls. **I:** That sounds like a *Sequence* level delay on the backhoe asset. **E1:** Correct. **E2:** On the transport side: mooring can be a pain. With wind or traffic, you can lose minutes every cycle. **I:** That's an *Activity* uncertainty inside sailing/mooring. **E2:** Finally, turbidity exceedance at the pontoon. When we breach, we stop the whole show until readings are back in range. That's project-wide. **I:** So a *Delay across Project* risk. These three cover different layers—perfect for the model.

Part C — Quantification (occurrence, distribution, bounds)

I: For each risk, I'll ask for (i) occurrence basis, and (ii) impact distribution (min, mode, max). We'll encode triangular unless you want another shape.

C1. Backhoe crane breakdown (Technical / Sequence delay). **I:** Occurrence basis? **E1:** Use mean time to failure around ~ 120 net operating hours (NOH) per crane. **I:** Great. For impact duration once it happens? **E1:** Minimum 2 h if it's a minor fix, mode around 3 h. Worst case can be a week if we wait on parts. **I:** So Triangular(2 h, 3 h, 168 h). We'll convert MTTF to probability per loading event using the activity duration. *(Note: $t \approx 12{,}600\,\mathrm{s}$, $\lambda = 1/432{,}000\,\mathrm{s}^{-1} \Rightarrow P\_occ = 1 - e^{-\lambda t} \approx 2.87\%$.)*

C2. Barge mooring duration (Logistical / Activity uncertainty). **I:** How do we express mooring variability? **E1:** Every cycle you have it—it's inherent. Sometimes quicker, sometimes slower. **I:** Let's set occurrence to "per cycle" (100%). Bounds? **E1:** It can be faster than nominal by a few minutes; say -3 to $+10$ minutes, with mode 0. **I:** Triangular(-3 min, 0, $+10$ min).

C3. Turbidity exceedance (Env/Social / Delay across Project). **I:** Frequency basis? **E2:** Roughly once a month on projects like this, depending on weather and regulations. **I:** We'll map that to a Poisson rate per project and let the model trigger multiple events. Impact per event? **E2:** A day is typical; worst seen is a week. Use 24 h min/mode, 168 h max.

Part D — Mitigation brainstorming

I: Let's capture practical mitigations with rough costs and how they change the numbers.

D1. Spare parts on site (for backhoe breakdown). **E1:** If we mobilize critical spares, we cut the extreme tail. Say worst case down to two days. **I:** So the max goes from 168 h to 48 h. One-off cost? **E1:** €50k for the stockpile and logistics.

D2. Experienced captains (for mooring variability). **E1:** Better boat handling trims the spread: minimum -4 min, max $+5$ min. **I:** Cost basis? **E1:** €1,000/week/barge.

D3. Silt screen at discharge (for turbidity). **E2:** Screen around the outfall roughly halves exceedance frequency. **I:** So frequency basis "once per 60 days" instead of per 30. One-off cost? **E2:** €500k including installation and removal.

Part E — Wrap-up

I: I'll encode these exactly as we agreed, then I will review the first simulation outputs. Anything we missed? **E1:** That covers the key drivers given the time window. **E2:** Yes—let's verify turbidity behavior after a first run.

B.5. Follow-up Validation

I: Quick check: units and assumptions consistent with the method. **E1:** MTTF in NOH is fine; probability per loading event makes sense. **E2:** Total simulated project time looks good, we estimated it around 19 weeks, so with only three risks present the results seems in the right order of magnitude. For turbidity, Poisson is acceptable for now; note seasonality isn't captured—OK for tender phase.

Outcome. Experts confirmed the parameterization reported in Table 5.2; mitigation settings and costs as in Tables 5.12 and 5.13. Minor clarifications: "mooring" is modeled as an additive activity-level time variation; project-wide turbidity delays pause all activities.

B.6. From Elicitation to Model Inputs (traceability)

Occurrence conversion examples

- **Backhoe breakdown (Sequence):** MTTF $= 120\,\mathrm{NOH} \Rightarrow \lambda = 1/432{,}000\,\mathrm{s}^{-1}$. Loading activity duration $t \approx 12{,}600\,\mathrm{s} \Rightarrow P$_occ $= 1 - e^{-\lambda t} \approx 2.87\%$ per loading event.
- **Mooring (Activity):** Occurs every cycle; triangular variation applied to mooring/approach portion of sailing.
- **Turbidity (Project-wide):** Expert frequency "once/30 days" $\Rightarrow$ Poisson rate over project duration; model draws a count and samples event durations per triangular(24 h, 24 h, 168 h).

Mitigation mapping

- **Spare parts:** Reduce breakdown impact max to 48 h (cost €50k).
- **Experienced captains:** Narrow mooring spread to $[-4, 0, 5]$ min (cost €1,000/week/barge).
- **Silt screen:** Halve exceedance frequency basis from 30 to 60 days (cost €500k).

B.7. Notes on Uncertainty and Limitations (as raised in the sessions)

- Expert inputs reflect prior phase experience at Luleå; no formal calibration against fleet-wide statistics was available at interview time.
- Frequency assumptions for turbidity does not account for seasonality; acceptable for tender-phase, to be refined in later design.
- Triangular distributions were used to keep encoding simple and transparent for experts; other shapes may fit specific phenomena better (e.g., Weibull for wear-out).

B.8. Link to Main Tables

For the final, model-ready numbers, see:

- Risk set and impact level: Table 5.1.
- Occurrence bases and impact distributions: Table 5.2.
- Mitigations and costs: Table 5.12.
- Mitigated parameters: Table 5.13.

C
Analysis on Statistical Stability

In this Appendix, an analysis on the statistical stability is presented to determine the number of simulations required for reliable project time estimates. The study uses an unmitigated scenario where all risks are present, focusing exclusively on the impact of the risks and uncertainties that cause delays on total project time. Because costs and emissions are dependent on project duration (as explained in 3.3.1), they are not considered in this analysis. The simulation generates random time samples based on specified probabilistic distributions, such as from the triangular distributions derived from expert elicitation. For each drawn time sample, the simulation calculates the total project time. For example, for 5 runs, the simulation draws 5 random time samples from the probabilistic distributions, which results in 5 different total project time values. From these 5 results, an estimate can be taken in the form of a certainty value, the P80, P50, and P20.

The accuracy of these results is important to consider. Even with a large number of runs, there will always be a degree of variation between different simulation outcomes. This analysis provides an order of magnitude of accuracy, giving a sense of the expected range of project outcomes.

This analysis is designed to investigate whether the P80, P50, and P20 values for total project time achieve an acceptable level of stability after 200 simulations. The study aims to demonstrate this by evaluating the variation of these values, expressed as the standard deviation, to see if the spread consistently remains below an assumed threshold of 1.5%. This will investigate if 200 runs are sufficient to produce robust and reliable simulation outcomes.

The steps to correctly calculate the spread are as follows:

1. For each case with an amount of simulation runs, the calculated P80, P50, and P20 values are collected. This is done for scenario with all unmitigated risks and uncertainties included. Only the total time values of the case study project are depicted in Table C.1.

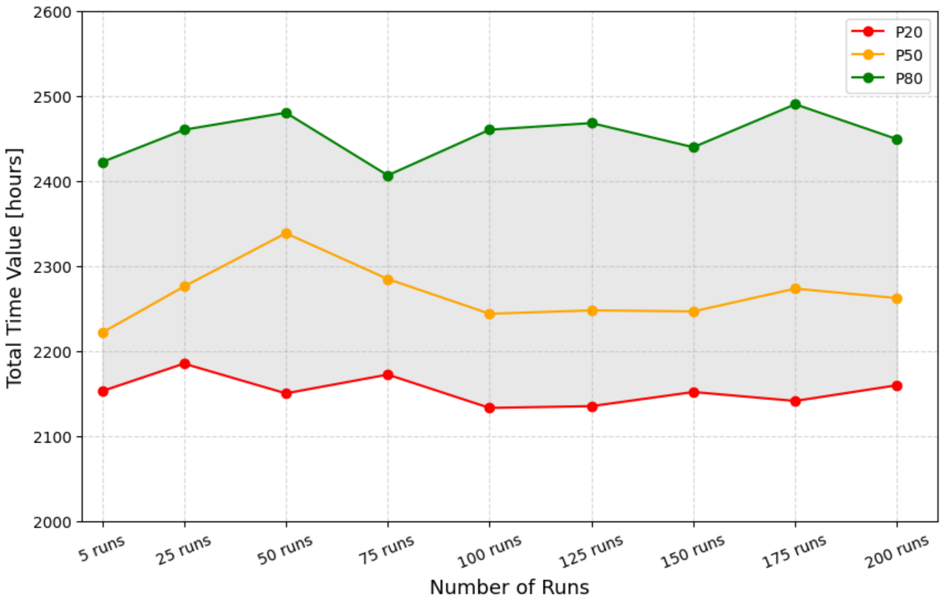


Figure C.1: Total Project Time values per case of running different amount of runs

Amount of Runs	P80 [hrs]	P50 [hrs]	P20 [hrs]
5	2422.4	2221.8	2153.0
25	2462.0	2275.8	2185.2
50	2480.3	2383.6	2150.2
75	2406.6	2284.7	2172.3
100	2439.7	2246.6	2151.8
125	2468.1	2247.8	2135.2
150	2439.7	2246.6	2151.8
175	2490.2	2273.4	2141.3
200	2449.1	2262.2	2159.8

Table C.1: Total Project Time All Risks Present Scenario (Unmitigated) Across Different Runs in Hours

2. The spread is then calculated as the variation of these values across the different runs. A common method for this is to use the standard deviation (σ), which measures the extent to which the values in a dataset deviate from the average. Therefore, the average values of each column must be calculated:

Calculate the average value of P80 over the N = 9 cases:

$$\mu_{P80} = \frac{2422.4 + 2460.2 + 2480.3 + 2406.6 + 2460.3 + 2442.4 + 2439.7 + 2451.8 + 2449.1}{9} = 2450.1$$

Calculate the deviations from the average value for each run:

$$(2422.4 - 2449.1)^2, (2460.2 - 2449.1)^2, \ldots$$

Same must be done for the average values of P50 and P20.

3. The formula for the standard deviation is:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{C.1}$$

Where:

- σ stands for the standard deviation
- x_i stands for the value (P80, P50, or P20) of each case (value in each row C.1)
- μ stands for the average value of P80, P50, or P20 across all runs (average of each column C.1)
- N stands for the number of cases simulated (amount of rows in C.1)

Calculate the standard deviation of P80:

$$\sigma_{P80} = \sqrt{\frac{1}{9}\sum_{i=1}^{9}(x_i - \mu_{P80})^2}$$

Repeat this process for P50 and P20.

Value	μ	σ	σ
P80	2450.1 hrs	25.5 hrs	1.04%
P50	2262.4 hrs	31.9 hrs	1.41%
P20	2155.5 hrs	16.3 hrs	0.76%

Table C.2: Average and Standard Deviations of each case in hours and percentage

Based on the analysis, the standard deviations for the P80, P50, and P20 values all fall consistently below the established 1.5% threshold. This outcome demonstrates that the simulation has achieved a state of statistical stability, meaning the results have evened and are no longer subject to significant variation with additional runs. The accuracy and order of magnitude of the results are thus considered sufficient and robust for the study's purposes. Consequently, it can be concluded that a total of 200 simulation runs is a sufficient number to yield reliable and trustworthy estimates for the total project time, providing a solid foundation for the risk and impact assessments in the main body of this research.