



NTNU – Trondheim
Norwegian University of
Science and Technology

Risk Management in Shipbuilding Projects

Using Monte Carlo Simulation for Scheduling

Kristian Bergem Odland

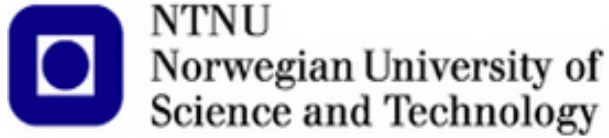
Marine Technology

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Risk Management in Shipbuilding Projects; Using Monte Carlo Simulation for Scheduling

A Master Thesis by Kristian Odland

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Problem definition

MASTER THESIS IN MARINE TECHNOLOGY

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FOR

Kristian Odland

Risk Management in Shipbuilding Projects; Using Monte Carlo Simulation for Scheduling

Background

DNV GL has established a new service for consulting customers on risk management in scheduling of all types of shipyard projects, such as new building, modification, maintenance and repair. Using Monte Carlo simulation, DNV GL quantifies risk of time overruns and estimates the total duration of a project. Further, DNV GL identifies the most critical activities in a project through sensitivity analysis and advises the customer on possible actions for monitoring and mitigating risk.

In this context, DNV GL wants to verify that their method is a reliable way of managing risk in project scheduling. They view their method as an easy and applicable way of estimating risk, thus making it easy to communicate to a customer. However, the method has been subject to criticism. Opponents of the method argue that simulations are time consuming and that the system will often require data far beyond the understanding of the user, like establishing correlation coefficients between input parameters. With a thorough investigation of the method, DNV GL seeks to identify potential improvements of their method in order to provide the “best practice” possible.

Main objective

The main goal of the thesis is to identify potential improvements of the DNV GL method so that it is best fit for identifying risks of time overruns. The following questions are to be answered:

- What is the theoretical framework underlying the DNV GL method, and how suitable is it for use in time estimation during project scheduling?
- What are the limitations and potential pitfalls when using the method in time estimation during project scheduling?

The results are to be used as input to a recommended practice for running the simulation. The aim is to improve the communication of results, particularly focusing on how realistic and reliable they are.

Scope and Main Activities

The following tasks will be conducted:

General Introduction

- Explain the importance of risk management
- Explain the concept of uncertainty
- Describe the early phase of shipbuilding projects

Scheduling Methods

- Describe different scheduling methods for estimating project duration
- Explain the Critical Path Method and its limitations
- Explain how a numerical simulation of a schedule works

Quantification of Input Data and Monte Carlo Simulation

- Show how uncertainties can be quantified and how a Monte Carlo simulation is run
- Explain important aspects of the methods that requires special attention
- Use illustrative examples to clarify points made

The DNV GL Method

- Describe the DNV GL approach for managing risk inherent in initial time estimate for the duration of a shipbuilding project
- Show a stepwise process of the DNV GL method
- Describe how DNV GL present the results from a risk analysis

Evaluation

- Use a case study to evaluate the DNV GL method
- Discuss strengths and weaknesses with the DNV GL method and point out limitations
- Discuss potential improvements of the method

Supervisor : Professor Arnulf Hagen, NTNU
Advisor : Tor Aarseth, DNV GL
Start : 16.01.2014
Deadline : 10.06.2014



Arnulf Hagen
Supervisor
Trondheim, 21.05.2014

Preface

This Master Thesis was written during the final semester of the 5th year MSc. Program in Marine Technology at the Norwegian University of Science and Technology (NTNU), in corporation with Det Norske Veritas - Germanischer Lloyd (DNV GL). The workload is equivalent to 30 credits.

Over the course of this past semester, I have learned a great deal about risk management in project scheduling. I started this semester without any knowledge on these subjects. The risk management process to DNV GL also required me to learn several software packages that were more or less new to me. Consequently, the work has been challenging, but rewarding.

I would like to thank my supervisor, Arnulf Hagen, for guidance during project execution. Throughout the semester, he has given me valuable feedback on my thesis. Tor Aarseth has been my adviser at DNV GL, and I would like to thank him for teaching me about the DNV GL risk management process. Aarseth has also provided me with useful material and a case study for my thesis.

Lastly, I would like to thank all employees at the Department of Maritime Advisory at DNV GL, in Bergen. During the past semester, my workplace has been in their office. I have truly had a wonderful time there.

Bergen, 10.06.2014



Kristian Odland

Abstract

The main objective of this thesis was to identify potential improvements of the risk management process to DNV GL so that it is best fit at identifying risk of time overruns and estimating project duration. Focus was placed on studying the following three aspects of risk management: 1) Scheduling method used to estimate project duration, 2) Quantification of uncertainties and 3) Monte Carlo simulation.

The theoretical framework underlying the DNV GL method was identified by comparing the theoretical framework of stochastic scheduling and the DNV GL method. The findings suggest that DNV GL uses a static stochastic scheduling method in order to estimate project duration, which is well suited when uncertainties are inherent in projects. A Bayesian estimation method is used to quantify uncertainties by establishing three-point estimates that define the best, worst and most likely case for uncertain input variables. This method is efficient when there is limited amount of data available to base estimates on.

Four risk analyses were carried out for a case study of a navy vessel. The main finding was that the estimate for project duration is likely to be too optimistic, because the schedule is approximately deterministic. When stochastic uncertainties were added to the deterministic input variables in the baseline model, the outcome was stochastic input variables with a variance, which was far too small. This also limited the impact of integrating correlation coefficients into the model. However, the establishment of uncertainties was effective as it caused the project to have a mean delay of about 10,7 months.

The sensitivity to choice of probability distributions used to characterize uncertainties was found to be low, with the exception of the Trigen distribution. Sensitivity to errors in three-point estimates was found to be significant for extreme values. Due to subjective errors in the assessment of three-point estimates, a Trigen distribution was suggested to characterize these estimates. This probability distribution generated the highest standard deviation amongst the distributions in the case study.

DNV GL runs an efficient risk management process with a theoretical framework well fitted for identifying risk and estimating project duration. However, the following recommendations are given:

1. Recommend the customer to establish a stochastic baseline schedule
2. A Trigen distribution (P10/P90) should be used to characterize the three-point estimates
3. Introduce a 15-minute exercise in estimation technique in the workshop
4. Consistency in establishment of correlation coefficient should be a requirement
5. Establish a database and compare estimates to actual results

Sammendrag

Hovedmålet med denne avhandlingen var å identifisere potensielle forbedringer av risikostyringsprosessen til DNV GL slik at den er best mulig skikket til å identifisere risiko for tidsoverskridelser i prosjekt og for å estimere prosjektets varighet. Fokus har vært på følgende tre aspekter: 1) Metode som brukes for å estimere prosjektets varighet, 2) Kvantifisering av usikkerhet og 3) Monte Carlo simulering.

Det teoretiske rammeverket som DNV GL-metoden bygger på ble identifisert ved å sammenligne teoretisk rammeverk av stokastisk tidsplanlegging og DNV GL-metoden. Funnene tyder på at DNV GL bruker en statisk stokastisk metode for å anslå prosjektets varighet. Denne metoden er meget anvendelig i prosjeter med betydelige usikkerheter. En Bayesiansk estimerings metode brukes til å kvantifisere usikkerheter ved å etablere tre-punkts estimater som representerer beste, verste og mest sannsynlige utfall for usikre input variabler. Denne fremgangsmåten er svært effektiv når det er lite eller ingen informasjon tilgjengelig til å basere estimatene på.

Fire risikoanalyser ble gjennomført for et case studie av et militært fartøy. Det viktigste funnet var at estimatet for prosjektets varighet sannsynligvis er for optimistisk fordi tidsplanen er tilnærmet deterministisk. Når identifiserte stokastiske usikkerheter ble lagt til den deterministiske utgangsplanen resulterte dette i en modell med stokastiske inngangsvariabler som hadde altfor liten varians. Dette gjorde også at effekten av å integrere korrelasjonskoeffisienter i modellen ble liten. Etableringsprosessen av usikkerheter var derimot nyttig, og resulterte i en gjennomsnittlig prosjekt forsinkelse på 10,7 måneder.

Følsomheten til valg av sannsynlighetsfordeling for å definere usikre variabler ble funnet å være liten, med unntak av Trigen-fordelinger. Følsomhet til avvik i tre-punktestimater var betydelige for ekstremverdiene, men ikke for modalverdien. På grunn av subjektive avvik i tre-punkts estimater ble en Trigen-sannsynlighetsfordeling vurdert passende til å representere disse estimatene. Denne fordelingen gav høyest standard avvik i resultatet blant de studerte fordelingene i case studiet.

DNV GL har en effektiv risikostyringsprosess med et teoretisk rammeverk som er godt egnet for å identifisere risiko og estimere prosjektets varighet. Imidlertid er følgende anbefalinger gitt:

- 1) Anbefal kunden å bruke en stokastisk utgangsmodell for å anslå prosjektets varighet
- 2) En Trigen-sannsynlighetsfordeling bør brukes til å karakterisere tre-punkts estimater
- 3) Bruk 15 minutter av en estimeringsprosess til å øke deltakerenes estimeringsferdigheter
- 4) Vær konsekvent i etablering av korrelasjonskoeffisienter
- 5) Etabler en database for å sammenligne estimater med faktiske resultater

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Nomenclature

BAE - British Army Equipment

CPM = Critical Path Method

DNV GL = Det Norske Veritas Germanischer Lloyd

FS = Finish to Start

HAT = Harbor Acceptance Test

IPMS = Integrated Platform Management Systems

MC simulation = Monte Carlo Simulation

MS Project = Microsoft Project

PERT = Program Evaluation Review Technique

$\rho(x,y)$ = Pearson's correlation coefficient

P1 = Percentile indicating 99 % certainty that actual value is above estimated value for this percentile

P10 = Percentile indicating 90 % certainty that actual value is above estimated value for this percentile

P50 = Percentile indicating 50 % certainty that actual value is below estimated value for this percentile

P70 = Percentile indicating 70 % certainty that actual value is below estimated value for this percentile

P85 = Percentile indicating 85 % certainty that actual value is below estimated value for this percentile

P90 = Percentile indicating 90 % certainty that actual value is below estimated value for this percentile

P99 = Percentile indicating 99 % certainty that actual value is below estimated value for this percentile

TRR = Test Readiness Review

1. Introduction

Risk Management is becoming increasingly recognized as a necessary measure for ensuring that projects are delivered on time and within budget limits. In shipbuilding projects, the need for proper risk management is significant. A rule of thumb is that 80 % of project costs and risks are connected to the pre-contract phase (Hagen, 2014). Making key decisions with a high degree of uncertainty often leads to significant losses for shipyards due to cost overruns, contractual penalties for not delivering on time and a weakened reputation. Currently, the word “Risk” is used more in research papers than the word “Cost” for the first time in history, as seen in figure 1.

This thesis deals with the high level of uncertainty inherent to scheduling of shipbuilding projects. Using DNV GL’s risk management method as a basis point, methods for quantifying uncertainties and estimating the duration of a project are investigated. DNV GL divides the risk management process into five stages: 1) Risk management planning 2) Risk identification, 3) Risk analysis 4) Risk response planning and 5) Risk Controlling & Monitoring. The two final stages are not studied in order to limit the scope of this thesis. However, these stages are just as important as the others are.

Three elements of the risk management process are given special attention in the thesis:

1. Scheduling techniques used to estimate project duration
2. Quantification of uncertainties
3. Risk Analysis with Monte Carlo Simulation

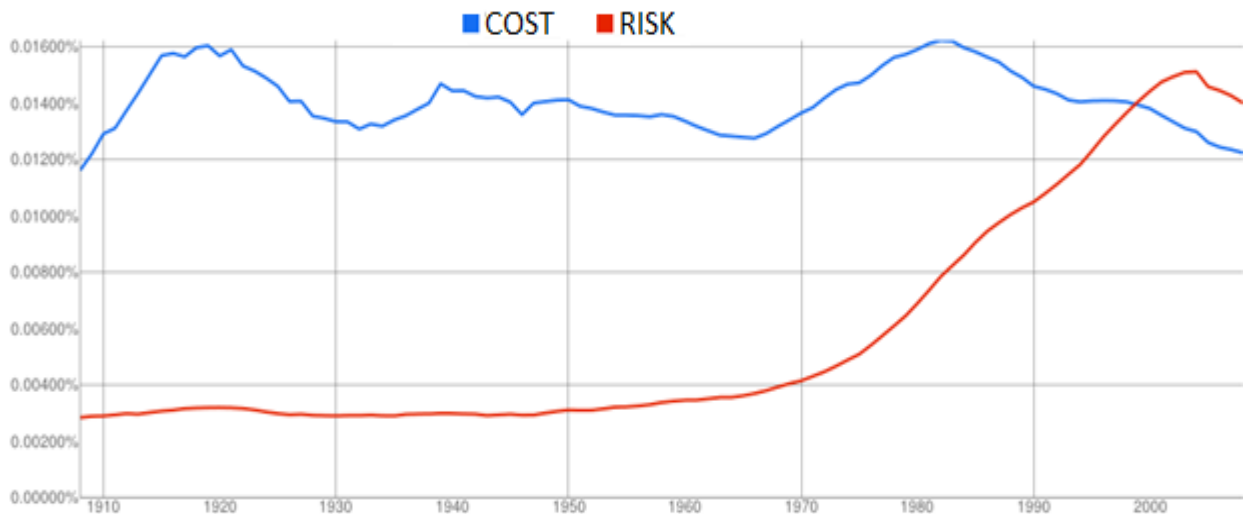


FIGURE 1 - HISTORICAL USE OF THE WORDS "COST" AND "RISK" (GASPAR ET AL, 2013)

1.1 Background

DNV GL has established a new service for consulting customers on risk management in shipyard projects, such as new building, modification, maintenance and repair. In a meeting with representatives from the project, DNV GL identifies uncertainties, gathers input data from experts and quantifies uncertainties in order to estimate project duration and to establish risk mitigation measures. This thesis seeks to verify that the DNV GL method is a reliable way of managing risk in shipbuilding scheduling. With a thorough investigation of the method, DNV GL wants to identify potential improvements of their method in order to provide the “best practice” possible. An important aspect of the method is that it needs to be time efficient and easy to communicate to a customer, because the customer takes part in the risk management process.

1.2 Why is Risk Management Important?

Many shipbuilders operate in a non-standardized segment where all projects have some degree of novelty or innovation. In the project development phase, there is a high degree of uncertainty related to the estimation of cost and duration. This causes errors that are often extremely costly when discovered “down-stream”. The most catastrophic failures in shipbuilding are not caused by errors in production on their own, but rather by poor preparations preceding the production stage (Hagen, 2014). Austeng et al (2005-i) states that the lack of correspondence between a planned schedule and the actual results only to some extent can be blamed on factors like low productivity, lack of quality and failing production management. Two main reasons for delays are unrealistic scheduling and improper management. Figure 2 illustrates the importance of considering costs and risks at an early stage in a shipbuilding process.

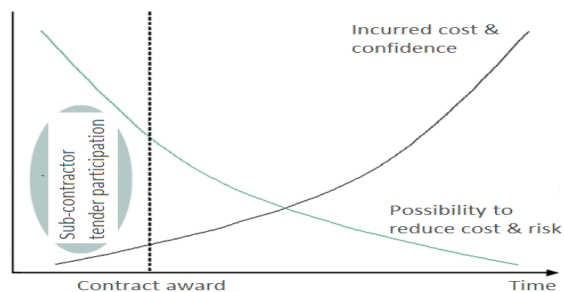


FIGURE 2 - RISK OVER TIME (ROY, 2003)

By identifying potential risks at an early stage of a project, it is possible to integrate risk mitigation measures in order to control these risk factors (Austeng et al, 2005-iii). The outcome of a process like this is a robust project that is more likely to be delivered on time. A risk management process brings people from different departments, like design, procurement, production and management, together in a meeting to discuss uncertainties and risk mitigation measures. These meetings are very useful, because the

participants get insight into each other's challenges and concerns (DNV GL, 21012). The outcome of a risk management process is risk mitigation measures that reduce risks (ibid). Sometimes, these measures enable activities to be executed faster than originally planned. Thus, new opportunities are also an outcome of the process.

One example of a useful risk management process can be seen at Navantia Shipyard in Spain. Here, the navy vessel "Canberra" was built for the Royal Australian Navy. The ship was planned to be loaded onto the "Blue Marlin", a semi-submersible heavy lift vessel, in order to be transported to Australia. The navy vessel had to be ready for the planned sail away date, because there were few transport vessels like "Blue Marlin" that could handle a vessel of this size. Not reaching the sail away date was not an option for the shipyard, because it could be months or even years before there was an available vessel like this one again. Figure 3 shows the "Blue Marlin" transporting the navy vessel "Canberra" from Spain to Australia.



FIGURE 3 - BLUE MARLIN TRANSPORTING THE NAVY VESSEL "CANBERRA" (ELLIOT, 2012)

1.3 Objectives

The main goal of the thesis is to identify potential improvements of the DNV GL method so that it is best fit for identifying risks of time overruns. The following questions are to be answered:

- What is the theoretical framework underlying the DNV GL method, and how well fit is it for use in time estimation during project scheduling?
- What are the limitations and potential pitfalls when using the method in time estimation during project scheduling?

By describing aspects of the risk management process and using illustrative examples, the goal is to make DNV GL aware of limitations and potential improvements of their method. In addition, the aim is to improve the communication of results, particularly focusing on how realistic and reliable they are. The customer plays an important role in the risk management process, and it is crucial that the customer understand how the method works and how to evaluate the results of the process.

1.4 Literature Review

Delays in shipbuilding projects occur ever so often. In addition to proper management in the project execution phase, it looks like the choice concept for identifying uncertainties and estimating project duration is decisive for the project outcome (Austeng et al, 2005-i). A static stochastic scheduling method seems to offer the most promising results for estimating project duration (Jørgensen, 2000; Austeng et al-2005-ii; Lichtenberg, 2000, Osmundsen, 2005). Several authors argues that deterministic scheduling method are too optimistic about their estimates (Elmaghraby 2005; Jørgensen,2000; Osmundsen, 2005), while a dynamic stochastic scheduling method requires too much data capacity to be commercially feasible even though the method is most accurate (Jørgensen, 2000). The Monte Carlo method seems to be a promising way to estimate project duration for stochastic simulations (Austeng et al, 2005-ii; Vose, 2000). However, the challenge of providing reliable input data using this method is widely discussed (Austeng et al-2005-ii; Austeng et al, 2005-iv; Vose, 2000). According to Lichtenberg (2000), the method requires input data that goes beyond the user's understanding. Further, uncertainty inherent in each input variable must be established. A Bayesian estimation method looks promising in order to establish estimates with little or no available reference data (Austeng et al, 2005-ii; Lichtenberg, 2000). However, several authors argue that subjective errors using this type of estimation method is inevitable (Austeng et al, 2005-ii; Austeng et al, 2005-iii; Jørgensen, 2014). Based on the research carried out on this field, it should be possible to identify the theoretical framework that the DNV GL method is based.

1.5 Structure of the Thesis

The remainder of this thesis is divided into six main chapters. Chapters 2-5 present the theoretical framework for stochastic scheduling, on which the DNV GL method is based on, while Chapter 6 presents the DNV GL method for dealing with uncertainties and estimating project duration. By doing so, a comparison between Chapters 2 -5 and Chapter 6 can be made to identify potential limitations and improvements of the DNV GL method. The findings from the comparison forms the basis for the case study presented in Chapter 7, which is used to clarify points made. The primary audience for this thesis is the employees at DNV-GL with basic knowledge about scheduling techniques, quantification of risk and risk simulation analysis. The rest of the thesis is structured as follows:

Chapter 2 introduces the reader to the concept of uncertainty and defines the terms risk, opportunity, estimation uncertainty and event uncertainty. Further, the chapter briefly presents challenges in estimating project duration in the early phase of ship building projects. Finally, the correspondence between the detailing level in a schedule and the level of uncertainty in a project is discussed.

Chapter 3 presents three concepts for project scheduling: 1) deterministic scheduling, 2) static stochastic scheduling and 3) dynamic stochastic scheduling. The limitations regarding the Critical Path method (CPM) are discussed, and a description of how numerical simulation can be used to avoid these limitations is outlined.

Chapter 4 describes the workshop process where a Bayesian estimation method is used to identify and quantify uncertainties. The use of three-point estimates to describe uncertainties is presented, and the challenge of establishing the likelihood of occurrence for events is discussed. Common errors in subjective estimates are described, and five probability distributions used to represent the uncertainties are presented. Finally, the sensitivity regarding errors in the three-point estimates and in choice of probability distribution is discussed.

Chapter 5 describes how a Monte Carlo simulation works and how to incorporate correlation between input variables. The use of sensitivity analysis carried out to study the input variables impact on the output is also discussed. The chapter ends by discussing how to interpret and communicate result from a risk analysis.

Chapter 6 presents the risk management process of DNV GL. The method for quantifying uncertainties, running a risk analysis and presenting results are explained. Finally, the DNV GL method is compared to the methods described in Chapter 2 - Chapter 5. Potential improvements and pitfalls of the DNV GL method are identified.

Chapter 7 presents a case study and four risk analyses used to illustrate the points made in Chapter 6. The first analysis shows the impact of adding uncertainties to the baseline model without uncertainties. Then, the impact of integrating correlation coefficients into the model is shown. Lastly, the sensitivity to errors in input data and choice of probability distribution for a risk analysis is demonstrated.

2. Uncertainty in Projects

It is important to have a clear perception of what uncertainty is before executing a risk management process, because there are numerous ways to define it. Table 1 describes the terminology used in this thesis, and it is based on the characterization given by Klakegg (1994). The rest of this chapter introduces the reader to the concepts in table 1 and the early phase in shipbuilding projects. Finally, the importance of developing a schedule that reflects the level of uncertainty in a project is discussed.

TABLE 1 - TERMINOLOGY USED ABOUT UNCERTAINTY (KLAKEGG, 2003)

| Term | Definition |
|------------------------|---|
| Uncertainty | Lack of knowledge about the future. The difference between necessary information required to make a certain decision and available information at the time of decisions. Possible outcome is potential loss or profit related to expected result. |
| Risk | Negative outcome of uncertainty |
| Opportunity | Positive outcome of uncertainty |
| Estimation Uncertainty | Uncertainty about elements or factors that affect the project's costs/duration. The consequence of the element is described as a continuous distribution. |
| Event uncertainty | Situations that either happens or do not. It is measured as the probability of an event occurring times the consequence of this event occurring |

2.1 Estimation Uncertainty and Event Uncertainty

Estimation uncertainty is a continuous uncertainty that reflects the variance in estimates for uncertain variables. The total variance for all activity durations reflects the *estimation uncertainty* inherent in the project. Estimation uncertainties occur when values for future events in a project must be assessed with a lack of knowledge. In project scheduling, it is challenging to estimate the duration of future events. A way to handle this is to use three-point estimates for uncertain input variables that represent the best case, worst case and most likely case. These three-point estimates are then used to define continuous probability distributions. The outcome is stochastic input variables that can take a set of possible different values, each with an associated probability. Assessment of three-point estimates is discussed in Chapter 4.

Event uncertainty exists when the likelihood of an event happening is less than one. Thus, the uncertainty is discrete, reflecting an event happening or not. The measurement of this uncertainty is the likelihood of an event occurring times the consequence of such an outcome happening. When the consequence is presented as a stochastic input variable it is important to distinguish between the likelihood of an event happening and the probability that a specific outcome of a consequence occurs. Establishing the likelihood of occurrence for an event can be demanding, especially if this likelihood is conditional. Chapter 4 describes the assessment of the likelihood of occurrence.

2.2 Risk and Opportunity

The outcome of uncertainty can be divided into risk and opportunity. Risk reflects unwanted events that lead to a potential loss, while opportunity, which is the opposite of risk, reflects positive events that lead to potential profits (Austeng et al, 2005-i). Shipbuilding projects are exposed to a significant number of risk factors that may cause delays. Lee et al (2009) conducted a survey analysis on 252 experts from 11 major Korean shipbuilding companies (2007) in order to determine common risk factors in shipbuilding projects. Some of these risks are seen in table 2. Note that risk is divided into *internal risk*, which exists within the interior of the yard and *external risk*, caused by external factors outside the yard.

TABLE 2 - RISK EVENTS IN SHIPBUILDING PROJECTS (LEE ET AL, 2009)

| ID | Risk Category | Risk Items | Remark |
|----|---------------|--|----------|
| 1 | Natural | Typhoon, flood, earthquake and other uncontrollable events happen | External |
| 2 | Political | Regulation against shipbuilders tighten or are amended | External |
| 3 | Legal | Classification's rules change and influence shipbuilders | External |
| 4 | Social | Incendiary fire or injuries occur | External |
| 5 | Economic | There is difficulty in supply of raw materials | Internal |
| 6 | Economic | There is a difficulty in meeting labor demands for production | Internal |
| 7 | Economic | There are shortages in design manpower | Internal |
| 8 | Economic | There is difficulty in supplying production equipment | Internal |
| 9 | Technical | Changes in design occur | Internal |
| 10 | Technical | Introduction of new technologies incur new risks | Internal |
| 11 | Technical | Failures in production equipment incur | Internal |
| 12 | Technical | Instances arise where the specification of the shipbuilding contract cannot be met | Internal |
| 13 | Managerial | Productivity does not improve | Internal |
| 14 | Managerial | Problems in quality management arise | Internal |
| 15 | Managerial | Problems arise due to strikes at headquarters | Internal |
| 16 | Managerial | Problems arise due to strikes at subcontractors | Internal |

Opportunity is the converse outcome of uncertainty. It may be argued that “risk management” should be called “uncertainty management”, because risk is only one outcome of uncertainty. However, in this thesis the term “risk management” is used because it is the terminology currently used by DNV GL. Olsson (2007) executed an empirical study, showing that current methodologies for risk management in a wide range of industries focus mainly on risk instead of opportunity. Jordanger (2005) claims that improved opportunity management is one of the most important challenges of the future within project management.

Opportunity is connected to flexibility and requires a dynamic management process with re-optimization of the model, because the initial objectives are based on imperfect information. (ibid). For instance, if activity A finishes sooner than planned at a production stage, more resources can be allocated to activity B. In this way, there is an opportunity to finish the project earlier than planned. Opportunities arise in the process of establishing risk mitigation measures for identified risks, either by reducing the risk of delays

or by making it possible to execute an activity faster than planned. Opportunities become evident in the evaluation phase of a risk analysis. A tornado plot from a sensitivity analysis (Chapter 5) shows how the mean output value changes for different values of stochastic input variables. Figure 4 shows how changes in stochastic input variables, which represent activity durations, affect the total duration for a project where a cofferdam is installed on a ship. Relative to the mean value, the sea trial can delay the project by about three days, but there is also an opportunity that the sea trial goes quicker than planned, leading to a project duration of about 43 days. See Jordanger (2005) for further studies of opportunity management.

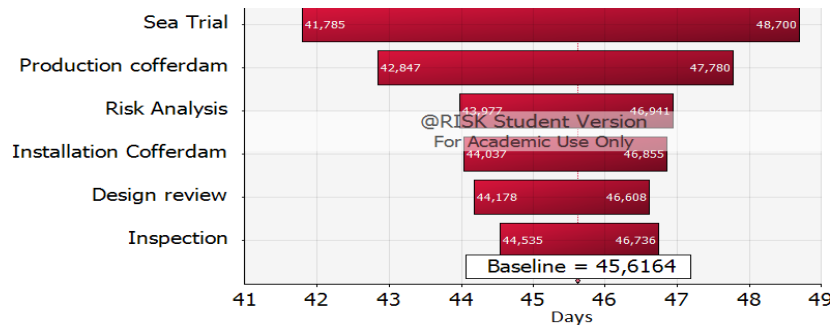


FIGURE 4 - RISK AND OPPORTUNITY FROM SENSITIVITY ANALYSIS

2.3 The Early Phase of a Shipbuilding Project

A typical shipbuilding process is seen in figure 5. Generally, a shipyard develops a response to a *Request for Tender* (RFT) issued from a customer (Hagen, 2014). In this process, an estimate for project duration must be carried out. The key challenge is to establish a competitive estimate in order to win the bidding round, while obtaining a realistic estimate for project duration. Contractual penalties apply if the shipyard fails to deliver a vessel at promised date, which may lead to significant losses for a shipyard.

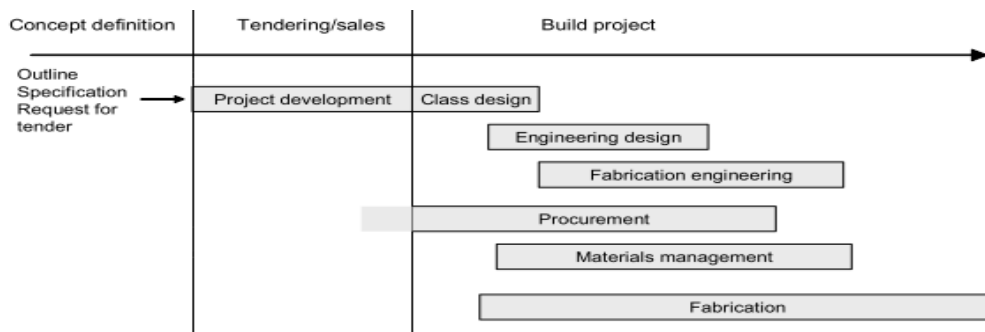


FIGURE 5 - A TYPICAL SHIPBUILDING PROCESS (HAGEN & ERIKSTAD, 2002)

The level of uncertainty in the estimate for project duration depends on factors like novelty, phase, complexity and size of the project. In a standardized serial production, it is likely that the duration of each

activity is somewhat known. In contrast, if a shipyard has little or no experience with a project, uncertainty in estimates may be significant. If the shipyard is allowed to develop a project using their own experience and best practice, there is less chance of delays and it is easier to estimate project duration.

In order to estimate the project duration it is important to know where it comes from. Sources of uncertainty can be divided into four categories (Austeng et al, 2005-i). *Conceptual uncertainty* reflects the uncertainty in the choice of an analysis model and parameters. For instance, the choice of detailing level in a schedule cause conceptual uncertainty. *Operational uncertainty* reflects the internal uncertainty about the efficiency in project execution. A project with a high degree of novelty is subject to this uncertainty. *Contextual uncertainties* are external uncertainties that are often hard to affect and predict. Weather is a significant cause for external uncertainty. For example, hull treatment and painting may be subject to this uncertainty. *Scenario uncertainty* occurs when changes in the future cause the targets of a project to be changed. This type of uncertainty is almost inevitable and is especially common for projects with a long time horizon (Austeng et al, 2005-i). The customer will often require changes to be made to throughout the shipbuilding execution.

The main formal document that marks the end of the project development phase and the beginning of the building project is the *build contract* (Hagen, 2014). This contract regulates price, delivery terms, penalties and more. If the shipyard has estimated a realistic execution time of the project, there is less chance that contractual penalties will backfire at the shipyard at a later stage.

2.4 Schedule and Uncertainty

A key concerning conceptual uncertainty is to develop a schedule that reflects the level of uncertainty in the project. There is no standard way to decide the detailing level in project scheduling, but a rule of thumb is that every aspect of a project should be included in an analysis and then be detailed according to need. On a project development stage with significant uncertainty, a rough analysis should be executed (Austeng et al, 2005-iv). A question that is useful to consider is “Does the detailing level reflect the knowledge of the estimators/experts?”

A schedule can be developed using a top-down approach or a bottom - up approach. In a bottom-up process, each task is broken down into smaller components that are given individual estimates. Then, the individual components are aggregated to develop a larger estimate for the task as a whole. The top-down approach means that the preliminary total estimate starts at the top level (Lichtenberg, 2000). Then, the top level is subdivided into lower level activities, and new estimates replace the former estimates.

Lichtenberg (2000) explains that this process continues for as long as the quality and the stability of the

total estimate are reasonably improved. If the estimators become uncomfortable with giving input values for the risk analysis, there is no point in increasing the detailing level. In ship building project, a “Work Breakdown Structure” can be helpful in the process of defining activities on a certain level. It shows a hierarchal system with the top-level items on top and their subgroups below (and so forth).

Even though it is hard to establish a general practice for choice of detailing level, the following statements should be considered (Austeng et al, 2005-ii):

- Total uncertainty is always bigger than the variability in the biggest input variable. Internal and external factors affect the uncertainty of the project. If these factors cannot be controlled, there is no point in increasing the detailing for the rest of the schedule.
- Roughly speaking, the number of input variables in a risk analysis should not exceed 25 - 30 activities.
- Choose a level of detail where control and overview of the project are obtained. A detailed level will not give better estimates if one fails to consider all activities and dependencies.

Table 3 shows arguments for a detailed level versus a rough detailing level (Austeng et al, 2005-iv).

TABLE 3 - ARGUMENTS FOR THE CHOICE OF DETAILING LEVEL (AUSTENG ET AL, 2005-IV)

| Arguments for a detailed level | Arguments for a rough detailing level |
|--|--|
| Need for specific knowledge, assuming that this detailed knowledge exists | Obtain an overview and avoid overlooking activities or factors affecting the project, by using a rough dividing. |
| Easier to estimate time and cost to a specific and recognizable activity. | Prevent uncertainty from being wrongly removed due to ignored correlation. |
| Avoid making causes for uncertainty invisible for the decision maker. With a rough detailing level, it may be hard to explain these reasons. | No point in going into details in some activities in a project if others are unknown. |
| By obtaining a detailed level, it is less chance that the same uncertainty is considered more than one time. | With time constraint, it is favorable to obtain a rougher schedule. |

2.5 Chapter Summary

Uncertainty is described. The difference between *estimation uncertainty* and *event uncertainty* is that the first is a continuous uncertainty that reflects the variance in estimates for identified uncertainties, while the latter is discrete, reflecting an event happening or not. Event uncertainty is measured as the product of probability of occurrence times the consequence of this event happening (Austeng et al, 2005-i). *Risk* and *opportunity* are negative and positive outcomes of uncertainty, respectively.

In the project development phase of a shipbuilding project, estimated duration must be established with a high degree of uncertainty. Sources to uncertainty are often conceptual, operational, contextual and scenario uncertainty (Austeng et al, 2005-i). The tender must be competitive, but must be balanced by the risk of contractual penalties for violate the contractual delivery date.

The basis for estimating project duration is to match the detailing level in the schedule to the level of uncertainty inherent in the project. This relates to the conceptual uncertainty and is very important to consider. A schedule can be developed using a *top-down approach* or a *bottom-up approach*. The first is often less time consuming as it starts by giving a preliminary estimate at the top level (Lichtenberg, 2000). The number of activities in the final schedule should generally not exceed 25 - 30 activities (Austeng et al, 2005-ii).

3. Scheduling Methods

Three scheduling techniques are presented in this chapter: 1) deterministic scheduling, 2) static stochastic scheduling, and 3) dynamic stochastic scheduling. The difference between these techniques is shown using illustrations. Further, the Critical Path Method (CPM) is presented, and two analyses are carried out in order to show potential problems with this method. Finally, a numerical simulation method that handles these potential problems is briefly described. Table 4 explains important terms used in this chapter in order to define scheduling methods. These terms should be studied before continuing to read.

TABLE 4 - DESCRIPTION OF TERMINOLOGY USED IN SCHEDULING

| Term | Description |
|------------------------|---|
| Deterministic variable | Single point value generally represented by the mean - or mode value. Contains no stochastic value |
| Stochastic variable | Random variables that can take on a set of possible different values within a range, each with an associated probability |
| Reactive schedule | Update schedule during project execution, re-runs a static model, approximation method to dynamic schedule |
| Proactive model | Anticipates future decisions and events and adjusts the schedule according to these assumptions |
| Static schedule | Generates a plan rather than a strategy. All decisions are made before uncertainty is revealed, resources allocated before the project starts. No flexibility in the schedule (Jørgensen, 2000). |
| Dynamic model | Different decisions can be made in different states, while the project is in process. Model often referred to as a strategy, rather than a plan. More involved than a static model, due to flexibility (Jørgensen, 2000). |

3.1 Deterministic Scheduling

The “traditional” approach for scheduling is based on deterministic input variables that represents the duration of each activity in a project. A deterministic input variable is a single point estimate, generally presented by the mean - or median value. People in favor of this method argue that the variance related to a variable will converge towards a central value (Osmundsen, 2005). When the number of outcomes is large and the variation is small, the central value is representative. However, this is only true when the central value is symmetric and the effect of variance is small. The extra effort needed for stochastic modeling may exceed the benefit of extra information that an estimate will provide, and sometimes there is a lack of experts required to estimate stochastic input values and to execute a stochastic simulation.

The problem with deterministic modeling is that it assumes that the future is predetermined. It only considers a few discrete outcomes, ignoring thousands of others. It also gives equal weight to each

outcome, and the interdependency between inputs is ignored completely. “What if” – analyses show results with different combinations of input variables. A deterministic scenario analysis with worst, most likely and best-case scenario is often used. However, the variance between these results may be unfeasible for practical use, and there is no knowledge about the chances of these events occurring. The illustrative example shown in Section 3.2 demonstrates that a deterministic scheduling approach will generally give a too optimistic result for project duration.

3.2 Static Stochastic Scheduling

The counterpart to deterministic modeling is stochastic modeling. Because a stochastic variable varies by coincidence within a sample space, the result in an output with as much as 500 – 100.000 scenarios where the probability of each outcome is integrated (Osmundsen, 2005). Based on this, a stochastic model can provide answers to important questions such as; “What is the probability of time overruns?” and “What is the likelihood of loss? There are two categories of stochastic scheduling: static stochastic scheduling and dynamic stochastic scheduling. Static stochastic scheduling is most commonly used today and is discussed in this section, while the latter is discussed in Section 3.3.

3.2.1 Deterministic Model vs. Static Stochastic Model

To illustrate the difference between a deterministic and static stochastic scheduling model, consider a project with two activities A and B in series. Most likely, the duration of each activity is 10 days. In a deterministic view, this leads to a project duration of 20 days. However, the duration of both activities may be shorter with a duration of 8 days, but also longer with a duration of 13 days. Integrating this uncertainty into a stochastic variable with a triangular distribution, the expected (mean) duration of the project is 20,7 days. Figure 6 shows the cumulative probability distribution that is the outcome of a stochastic simulation with 5000 iterations. The output distribution indicates that there is about 33,5 percent chance of that the project will be finished within 20 days, and there is a 50 percent chance that the project will use more than 20,6 days. The results indicate that there is a significant difference between the two methods and that the deterministic method is overly optimistic.

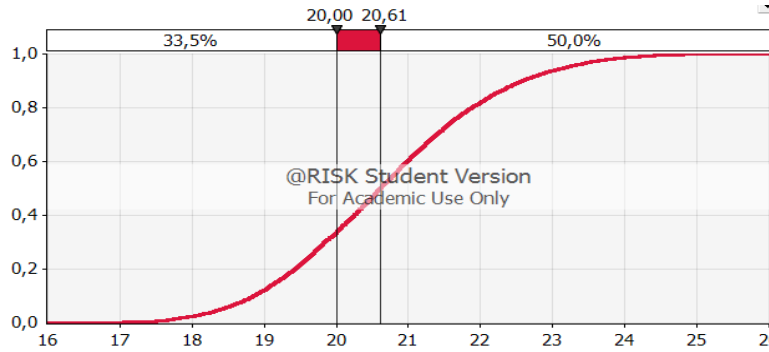


FIGURE 6 - DURATION USING A STATIC STOCHASTIC APPROXIMATION

3.2.2 Reactive and Proactive Scheduling

In static stochastic scheduling, there is reactive and proactive scheduling. Reactive scheduling revises or re-optimizes the baseline schedule when unexpected events occur. This method works as an approximation method to dynamic stochastic scheduling that integrates flexibility into the schedule (see Section 3.3). Proactive (robust) scheduling uses statistical knowledge of uncertainties with the objective to make the schedule more robust. A schedule is robust if it absorbs anticipated disruption without affecting the duration of activities. A way of creating robustness is to increase the allocation of resources. In a proactive stochastic schedule, significant risks are identified, and risk mitigation measures are established in order to mitigate or control the risk. A reactive and proactive scheduling technique can be combined, making the schedule both robust and flexible. For more studies of reactive and proactive methods, see Herroelen & Laus (2014) and Herroelen et al (2010).

3.3 Dynamic Stochastic Scheduling

Dynamic stochastic modelling is a “state of the art” technique for cost - and time estimation. Jørgensen (2000) explains a dynamic model as follows: *at each activity node there is a decision maker, which has local information about the state of the project. When all activities ending in the relevant node are finished, resources are allocated to the activities starting in that node. Based on how early/late the event took place, the allocation is set. Each decision maker is aware of other decision maker’s policies, but cannot observe the decision maker’s actual decision.* A dynamic model is more involved than static models and integrates the flexibility that the management can employ (ibid). A static model fails to consider this flexibility. Unfortunately, improvements in computer processing are required before this method is feasible from a commercial point of view, due to the number of iterations that have to be run in the simulation (ibid). The method is presented here in order to make the reader aware of what a deterministic and static stochastic models fail to consider, and to describe what future methods might look like. Jørgensen (2000) provides the following statements about deterministic and static models:

- 1) *The optimal objective function value of a deterministic and static model (with emphasis on expected value) is too optimistic. Using such models will, on average, lead to cost/time overruns*
- 2) *A static stochastic model gives an optimal objective function value, which, on average, is larger than cost/time estimates when applying the optimal dynamic strategy.*
- 3) *In practice, project managers apply dynamic strategies because they “update” their schedules during the execution of the project, often by re-running the static model (called reactive scheduling). This “updating” is done to reduce costs and is referred to as the “value of flexibility” which is the key difference between a static and dynamic model.*

Two effects that pull in opposite directions are observed from these statements: 1) using expected values for estimating activity durations results in an overly optimistic estimate for project duration and 2) neglecting managerial flexibility results in a pessimistic (too high) value for the project duration. The total effect is an optimistic estimate for the project duration (Jørgensen, 2000). Statement 3) indicates that a reactive static stochastic solution may serve well as an approximation method for dynamic scheduling.

Jørgensen (2000) demonstrates the value of flexibility by using a simple example from software engineering, where the flexibility inherent in the project is the possibility of using overtime in order to meet the deadline. The rest of Section 3.3 describes Jørgensen’s (2000) example. Figure 7 shows six activities in a software engineering project, which are all stochastically independent. The required work in all activities takes two equally likely values; $w = 5$ or $w = 15$ working days, giving an expected amount of work equal to 10 working days. The exception is activity 5, which takes either the value $w = 10$ or $w = 30$ man-days, with an expected value of 20 man-days. This generates 64 possible outcomes.

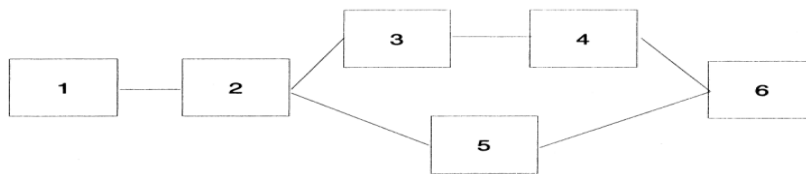


FIGURE 7 - ACTIVITY ON NODE NETWORK USED IN EXAMPLE (JØRGENSEN, 2000)

The following premises are given for Jørgensen’s (2000) experiment:

- Tardiness cost for violating the deadline (per days late) is ten times normal salary rate
- The cost per unit of time (salary rate) of allocating “ r ” units of resources is proportional to $c(r) = r^2$, i.e. allocating twice as much resources costs four times as much
- $r = 1$ means normal activity and $r = 2$ means maximum use of resources (100 % overtime)
- Work in an activity is equal to the duration that the activity takes using normal amount of resources ($r = 1$)

- Duration = $d(r) = w/r$, where “w” is amount of work needed for task and “r” is amount of resources allocated
- Total salary cost for an activity becomes $c(r) * d(r) = r * w$
- The deadline is set at the 55th day

Table 5 shows the results of running optimization algorithms using a deterministic model, a static stochastic model and a dynamic stochastic model (terms are defined in table 4). The rows in table 5, distinguish between a static solution (no updating of model), a reactive solution (model updated after an executed activity) and a solution with perfect information. For further investigation of the optimization models, see Jørgensen (2000). The results from Jørgensen’s analysis clearly demonstrate the difference between the different methods. Note that managerial flexibility is defined as the expected value for the reactive or proactive method minus the expected value of the static approach. Comments are given to the total cost results only.

Deterministic approach - using a static deterministic approach, the error of evaluating cost without considering managerial flexibility is about 22 % of actual expected cost. The error of using a deterministic static solution is 33 % compared to the case of perfect information. *Static stochastic approach* - the results indicate that a static stochastic approach is far more accurate than both the static deterministic approach and the reactive deterministic approach. The value of flexibility using a reactive approach is 6 %. In this example, this indicates that improving the static model by introducing stochastic variables reduces the value of flexibility. The error of using a reactive static stochastic model compared to having perfect information is roughly 8 percent. *Dynamic stochastic approach* - the results indicate that this approach gives the best estimation for the case, with an error of about 6 percent. However, an interesting observation is that the expected total cost is only slightly lower than the reactive static stochastic approach, which indicates that a reactive static stochastic approach serves well as an approximation method. In addition, the effect of using a reactive approach for this method is relatively small.

TABLE 5 - RESULTS FROM DETERMINISTIC, STATIC - AND DYNAMIC STOCHASTIC SCHEDULING (JØRGENSEN, 2000)

| | Deterministic | | | Static Stochastic | | | Dynamic Stochastic | | |
|---------------------|---------------|-------------|----------------|-------------------|-------------|----------------|--------------------|-------------|----------------|
| | Total cost | Salary cost | Tardiness cost | Total cost | Salary cost | Tardiness cost | Total cost | Salary cost | Tardiness cost |
| Static Solution | 112.2 | 70 | 42.2 | 87.5 | 81.8 | 5.7 | 82.1 | 82.1 | 0 |
| Reactive approach | 92.1 | 76.6 | 15.5 | 82.3 | 82.3 | 0 | 81.0 | 81.0 | 0 |
| Perfect information | 75.5 | 75.5 | 0.0 | 75.5 | 75.5 | 0 | 75.5 | 75.5 | 0 |

3.4 Critical Path Method versus Numerical Simulation

This section presents two popular methods for estimating project duration, typically used in the shipbuilding industry: 1) the Critical Path Method (CPM) and 2) numerical simulation. Concerns regarding the *Merge Event Bias* and the *Student Syndrome* are discussed briefly, and two analyses are used to illustrate the problem.

3.4.1 Critical Path Method

The CPM is a popular scheduling technique for projects in the construction industry used to estimate project duration. The method assumes that only the longest path (critical path) through a network structure affects the duration of the project. This implies that only the critical path needs to be considered for estimating project duration. Any task on a critical path is critical because a change in these activities affects the project's duration. Thus, there is no slack in the activities, and the project delay corresponds to the delays of a critical task. The method is efficient for schedules with few parallel paths and when there is good knowledge about activity durations, meaning that the standard deviation is small. However, the potential shortcoming is illustrated by figure 8. When using stochastic input variables, it is hard to evaluate which of the two activities in a parallel network structure that is critical. What if near - critical paths turn critical, like in activity B?

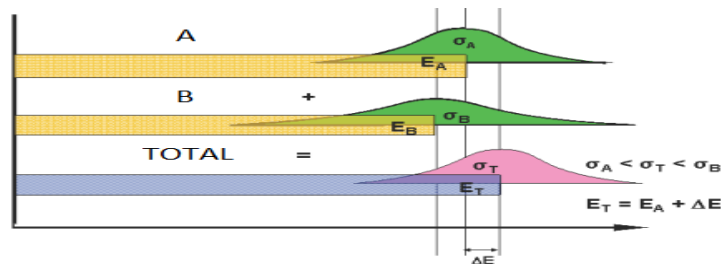


FIGURE 8 - PARALLEL ACTIVITIES AND TIME ADDITION (KLAKEGG, 1994)

The only time the CPM is accurate, is when everything goes as planned. This is rare in real projects, and the method is thus generally too optimistic. The *student syndrome* and the *merge event bias* explain why. Consider the following case related to the student syndrome; if a task is estimated to take 20 days and has 5 days of slack the project always tends to have a duration of 25 days. The people involved tend to be more inefficient when they know that the activity has a slack (Rand, 2000). A consequence of this is that every task becomes critical, greatly increasing the likelihood of schedule overruns. A recognized problem with the CPM is the so-called merge event bias (Lichtenberg, 2000). If the start of an activity depends on more than one preceding activity to be finished before starting, the expected start date of the activity is delayed due to *stochastic time addition*. This occurs because of the possibility that a non-critical activity becomes critical, as figure 8 shows.

3.4.2 Impact of Parallel Paths and Length Ratio

Two important factors that affect the merge event bias are; 1) the number of parallel paths through a portion of a network and 2) the closeness of the expected finish times at the merge event of parallel paths. In this section, two experiments are carried out to study these factors. The uncertainty inherent in estimates for activity duration is represented with three point estimates in a triangular probability distribution. Activities have an expected duration of either 2 days, 4 days or 6 days, as seen in table 6. The standard deviation varies for each expected duration and will affect the outcome of the analysis.

TABLE 6 - INPUT DATA FOR PROBABILITY DISTRIBUTIONS IN ILLUSTRATION

| Expected days - 2 | | Expected days - 4 | | Expected days - 6 | |
|-------------------|-------|-------------------|------|-------------------|------|
| Days | Prob. | Days | Days | Prob. | Days |
| 1 | 0,25 | 2 | 0,25 | 4 | 0,25 |
| 2 | 0,5 | 4 | 0,5 | 6 | 0,5 |
| 3 | 0,25 | 6 | 0,25 | 8 | 0,25 |

Figure 9 show the two network structures used in the analysis to illustrate the impact of number of parallel paths. ID1 has two parallel paths, while ID2 has three parallel paths. The number within the boxes represents the expected values of each activity.

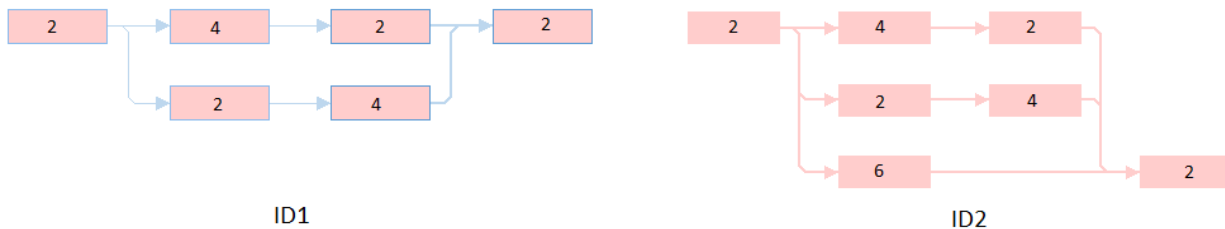


FIGURE 9 - ERROR WITH INCREASED NUMBER OF PARALLEL PATHS

The effect of slack on a Merge Event bias is demonstrated by figure 10, where the ratio between two parallel paths varies from 1/1, 3/4, 1/2 and 1/4. The activities in the analysis have an expected duration of either two days or four days or both (from table 6).

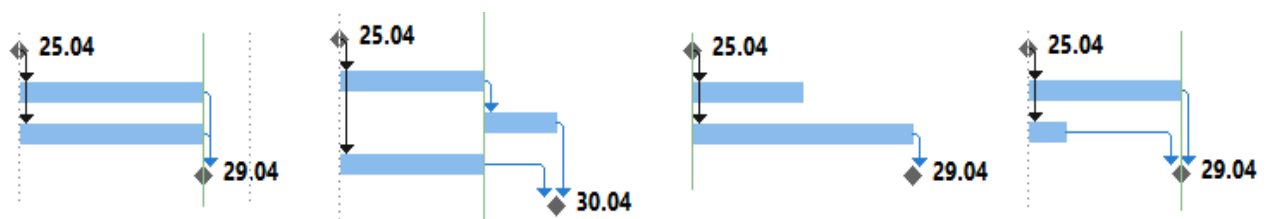


FIGURE 10 - THE EFFECT OF SLACK ON MERGE EVENT BIAS

3.4.3 Results from the Two Risk Analysis

Table 7 shows the results from the two analyses. The first analysis shows that the error related to the CPM increases as the number of parallel paths increase. The difference between the CPM - value and the exact value varies significantly. One could argue that these are extreme cases, because all paths are equally long. However, the impact is clearly illustrated. For the second analysis, the error of the CPM decreases as the length ratio decreases. A ratio of 50 percent, gives a insignificant merge event bias. However, the results are only credible for the specified input data and standard deviation in this analysis.

TABLE 7 - IMPACT OF SLACK AND NUMBER OF PARALLEL ACTIVITIES

| | Length Ratio | | | | Number of parallel paths | |
|--------------|--------------|------|-------|-----|--------------------------|------------------|
| | 1/1 | 3/4 | 1/2 | 1/4 | 2 parallel paths | 3 parallel paths |
| Length Ratio | 1/1 | 3/4 | 1/2 | 1/4 | 2 parallel paths | 3 parallel paths |
| CPM (mean) | 4 | 6 | 4 | 4 | 10,00 days | 10,00 days |
| Exact (mean) | 4,69 | 6,61 | ≈ 4 | 4 | 10,78 days | 10,94 days |
| Error CPM | 15 % | 9 % | ≈ 0 % | 0 % | 7,2 % | 8,6 % |

Moder and Phillips (1970) carried out a similar study and established a set of practical rules: 1) if the difference in expected finishing date is greater than the larger of their respective standard deviations for two merging activities, then the bias is small. 2) If the difference in expected finishing date is greater than two standard deviations for two merging events, then the bias will be less than a few percent and can be ignored. 3) If the rule of thumb indicates that a correction for the bias is required, then a method, like simulation, should be implemented to cope with this.

3.4.4 Numerical Simulation

In a simulation, a merge event is solved as follows: during the simulation, a random sample from each of two parallel activities is picked, and the activity with the longest duration is chosen as the starting point for the following activity. When the latest point in time is chosen for the two activities, with a sample process repeated over 500 times, the expected value for this distribution is even later than that expected value for the latest of the two activities (Austeng et al, 2005-ii). Stochastic theory recognizes that all paths through a project network could become critical. Consider the schedule in figure 11 with two parallel activities. Block B has an expected duration of two days more than block A. Three-point estimates (with P10/P90) with triangular distributions are given for all the activities, as seen in table 8. The uncertainty (variance) for each activity is significant, which is intentionally done to illustrate the difference between the two methods. Note that the CPM would only consider activities related to Block B. A simulation method recognizes that the activities in Block A may become critical.

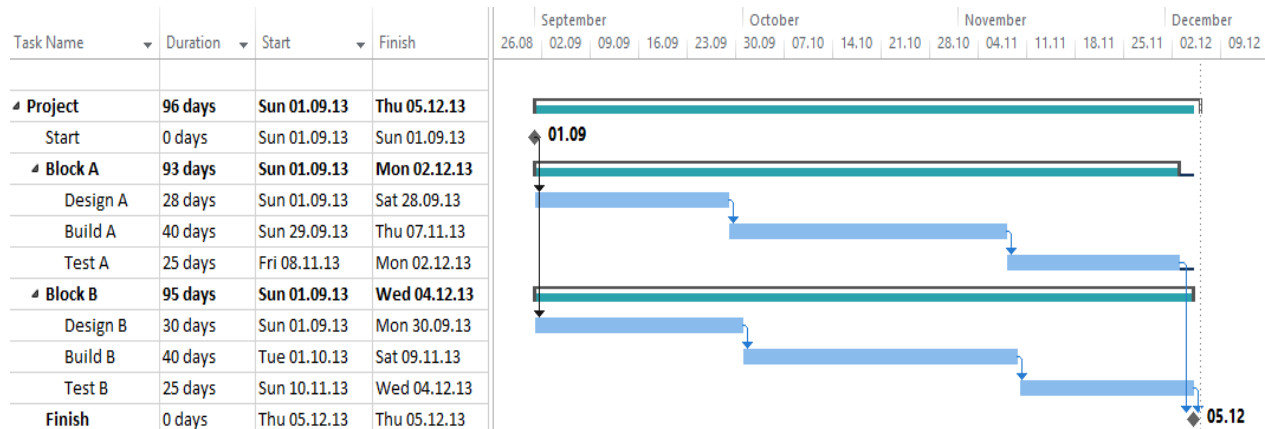


FIGURE 11 - GANTT CHART WITH TWO PARALLEL PATHS

Table 8 shows the input data for the stochastic input variables representing the duration of activities for Block A and Block B. Further, the critical index for each activity is seen.

TABLE 8 - INPUT DATA FOR TWO PARALLEL PATHS AND CRITICAL INDICES

| Block A | Duration (days) | P10 (days) | Most likely (days) | P90 (days) | Critical indices (%) |
|--------------|-----------------|------------|--------------------|------------|----------------------|
| Design A | 28 | 18 | 28 | 58 | 74,2 |
| Built A | 40 | 30 | 40 | 50 | 74,2 |
| Test A | 25 | 18 | 25 | 50 | 74,2 |
| <i>Total</i> | <i>93</i> | | | | |
| Block B | Duration (days) | P10 (days) | Most likely (days) | P90 (days) | Critical indices (%) |
| Design B | 30 | 25 | 30 | 40 | 25,8 |
| Built B | 40 | 35 | 40 | 50 | 25,8 |
| Test B | 25 | 20 | 25 | 30 | 25,8 |
| <i>Total</i> | <i>95</i> | | | | |

The expected finishing date varies significantly for the two methods. As expected, the duration of the project is longer when considering both parallel paths. Table 9 shows that the effect of considering both paths gives an increased duration of 8 days for the median (P50) value. For the P85-percentile, there is a difference of 15 days between the two methods. The critical index in table 8 explains the difference in results. Observe that the activities related to Block A are on the critical path about 25 percent of the time.

TABLE 9 - DURATION USING CRITICAL PATH METHOD AND STATIC STOCHASTIC METHOD

| | Start date | P10 finishing date | P50 finishing date | P85 finishing date |
|------------------------|------------|--------------------|--------------------|--------------------|
| Critical Path Method | 01.09.2013 | 05.12.2013 | 08.12.2013 | 13.12.2013 |
| Monte Carlo Simulation | 01.09.2013 | 08.12.2013 | 16.12.2013 | 28.12.2013 |

3.5 Chapter Summary

There are three main scheduling methods: Deterministic, Static Stochastic and Dynamic Stochastic Scheduling. A static stochastic scheduling method is the best way to estimate project duration when significant uncertainties exist. Deterministic scheduling methods are generally too optimistic and only consider a few scenarios, neglecting thousands of others. Dynamic stochastic scheduling gives the most realistic picture of a project, because it integrates flexibility into the schedule. However, improvements in computer processing are required before this method is feasible from a commercial point of view. A reactive scheduling method updates the model throughout the project execution and works as an approximation method to dynamic scheduling. Proactive scheduling means that potential risk and opportunities in the future are evaluated. By integrating measures to prevent negative outcomes, the schedule is more robust against unexpected events. A reactive approach means that a static model is updated throughout the project execution.

The Critical Path Method (CPM) has shortcomings compared to a stochastic numerical simulation that considers all paths through the network of a schedule. The CPM estimates the project duration by considering the path with the longest duration through the network, thus, parallel paths are not considered. However, by introducing stochastic input variables to represent activity durations, the longest path through the network can change for each iteration. Analyses in this chapter shows that as the number of parallel paths increases and the duration ratio between two parallel paths is close to one, significant errors in the CPM occurs in terms of giving a far too optimistic estimate. A stochastic numerical simulation choses the parallel activity with the longest duration as the representative for each iteration, which leads to what is called *stochastic time addition*. In this way all paths through the network is considered, thus, avoiding the shortcomings of the CPM.

4. Quantification of Uncertainties

Uncertainties are quantified using one of two options: 1) subjective evaluation of input variables or 2) historical data. In shipbuilding projects, there is generally a lack of historical data available. Thus, Chapter 4 will focus on describing the subjective evaluation technique for estimating activity durations. The reader is introduced to basic statistics required in a quantification process and six probability distributions that are used to describe the quantified data. Finally, errors in subjective evaluations are described, and comments on how to avoid these pitfalls are given.

4.1 Basic Statistics

The section starts by repeating some fundamental statistical formulations. Measures of central tendency, characteristics of a probability distribution, Frequentative statistics, Bayesian statistics and conditional probability are important concepts in risk management.

4.1.1 Measures of Central Tendency

There are three common measures for central tendency: *the mode, the median and the mean* (figure 12). The *Mode* defines the most probable value, thus, it represents the x - coordinate for the vertex on the distribution. The *Median* defines the midpoint number in an ordered line of numbers. In a continuous distribution, it is defined as the 50 % percentile. Finally, the *Mean* represents the average value.

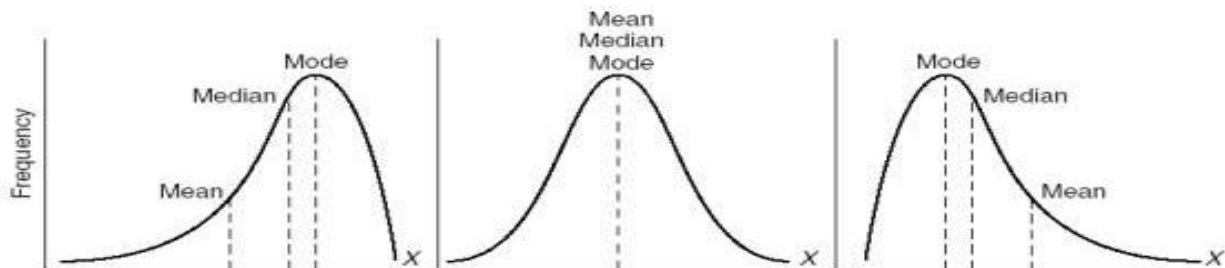


FIGURE 12 - THE MEAN, THE MODE AND THE MEDIAN

4.1.2 Characteristics of a Probability Distribution

Table 10 shows a list of important formulas needed for estimating the duration of a project. The outcome of a risk analysis is commonly presented by the expected value, $E(x)$, where the x-value is the center of gravity (1). The spread of the estimated total duration of a project is measured by the variance (5) or standard deviation (7), and it is the sum of the different variances from each activity. The premise for this condition is that all activities are independent of each other. In some cases, “uncertain” values are required to be multiplied in order to get the total expected value and variance, thus, equation 3 and 6 must be used. Skewness and kurtosis are used to characterize a distribution. Skewness (9) defines the lack of symmetry.

Negative values of skewness indicate that the curve is bent to right (left in figure 13) and opposite for positive values (right in figure 13). Kurtosis describes whether the distribution is flat or has a high peakedness related to a normal distribution, which has a kurtosis equal to three. A high kurtosis indicates a distinctive peak, which descends quickly and has a “fat” tail.

Finally, percentiles represent the area under the normal curve (increasing from left to right), and these are used to define where a certain value is located on the probability scale. The 10th percentile (P10) reflects the value where there is 90 percent certainty that the actual value will not occur below this value. “P85” reflects an 85 percent chance that the actual value will not occur above estimated value.

TABLE 10 - STATISTICAL FORMULAS

| | | |
|--------------------------------|--|----|
| Expected Value | $E(X) = \int_{-\infty}^{\infty} x f(x) dx$ | 1 |
| Total expected value (Sum) | $E_{TOT} = E_1 + E_2 + \dots + E_n$ | 2 |
| Total Expected Value (Product) | $E_{TOT} = E_A \cdot E_B$ | 3 |
| Variance | $VAR(x) = \int_{-\infty}^{\infty} [(x \cdot E(x))^2 f(x)] dx$ | 4 |
| Total Variance (Sum) | $VAR(X_{TOT}) = VAR(X_1) + VAR(X_2) + \dots + VAR(X_n)$ | 5 |
| Total Variance (Product) | $VAR(T) = \sigma_A' \cdot \sigma_B' \cdot \sigma_{A-B}'$ | 6 |
| | <i>where:</i> $\sigma_A' = \sigma_A \cdot E_B$, $\sigma_B' = B \cdot E_A$, $\sigma_{A-B}' = \sigma_A \cdot \sigma_B$ | |
| Standard Deviation | $\sigma = \sqrt{VAR(X)}$ | 7 |
| Range | $R = X_{max} - X_{min}$ | 8 |
| Skewness | $\sum_{i=1}^N \frac{(Y_i - \dot{Y})^3}{(N-1)\sigma^3}$, $\dot{Y} = \text{Mean Value}$ | 9 |
| Kurtosis | $\sum_{i=1}^N \frac{(Y_i - \dot{Y})^4}{(N-1)\sigma^4}$, $\dot{Y} = \text{Mean Value}$ | 10 |

4.1.3 Frequentative Statistics vs. Bayesian Statistics

According to Rolstadås (1997), each project is unique and is only carried out once. Thus, the amount and reusability of available data is often limited (Austeng et al, 2005-i). Past data may also be irrelevant due to technological changes or too expensive to obtain. *Frequentative statistics* and *Bayesian statistics* are two approximation methods established to make evaluations about the future.

Frequentative statistics - By running a high number of random trials, the objective of this method is to find out how often an event occurs, i.e. its frequency within a period. The sample space defines all possible outcomes of a random experiment, and an event is defined as a particular subset of the sample space. For each event there is a possibility that it occurs or it do not, and the probability of an event occurring will be approximately the relative frequency of number of trials where a specific event occurred, divided by the total number of trials run. As the number of trials approaches infinity, the relative frequency will converge towards the true probability.

Bayesian statistics - In contrast to frequentative statistics, where estimates are based on observations, a Bayesian estimation method assumes that the estimator has knowledge and experience about elements of the project and that the estimator is capable of making reasonable argumentations. The estimates are not necessarily based on similar projects done in the past, and the knowledge about an event does not have to be very high (Austeng et al, 2005-ii). The evaluations are expressed in terms of “degrees of believes” and “likelihood”, while frequentative statistics talks about probability. In order to establish the probability of an event occurring, statistical data is often required. Unfortunately, the statistical groundwork is often poor or not documented at all. Thus, subjective evaluations forms the basis for establishing the probability of occurrence with estimates based on experience, knowledge and insight amongst experts within the field.

4.1.4 Conditional Probability of an Event Occurring

Conditional probability must be considered when deciding the likelihood of an event occurring. Table 11 shows how to calculate the probability of an event occurring for different conditions. Formula 1 and 2 shows the criteria for activity A and B being independent. Two events are independent if the occurrence of one does not affect the probability of the other. Formula 3 shows a disjunctive event where activity A and B exclude each other, and formula 4 shows that the conditional probability of activity A occurring if activity B has occurred. Finally, formula 6 is called Bayes’ theorem, and it is a logical extension of formula 4 and 5.

TABLE 11 - FORMULAS FOR CONDITIONAL PROBABILITY OF EVENTS

| ID | Formula | Description |
|----|---|--|
| 1 | $P(A \cap B) = P(A) * P(B)$ | Formula express independent events. “ $A \cap B$ ” expresses event A and B occurring. |
| 2 | $P(A \cup B) = P(A) * P(B) - P(A \cap B)$ | Formula express independent events “ $A \cup B$ ” expresses event A or B occurring. |
| 3 | $P(A \cap B) = 0$ | Activity A and B exclude each other, called disjunctive event. |
| 4 | $P(A B) = \frac{P(A \cap B)}{P(B)}$ | Conditional probability that event A occurs if event B occurs. “ $A \cap B$ ” expresses event A and B occurring. |
| 5 | $P(A \cap B) = P(B \cap A)$ | The order of event does not affect the outcome |
| 6 | $P(A B) = \frac{P(B A) * P(A)}{P(B)}$ | Bayes’ theorem is a logical extension of the observations described in formula 4 and 5 |

4.2 Assessing the Values for Uncertainties

According to Austeng et al (2005-ii), subjective evaluations are the best way of getting reliable input to a risk analyses. Research has identified two important aspects of the subjective evaluation technique (ibid). The first observation is that people are bad at making subjective evaluations, and the second observation is that this skill can be significantly improved through knowledge and practice. If the estimates are executed by groups of experts rather than by individuals, there is a higher chance that potential pitfalls are neutralized. The group should consist of 4 - 15 experts and have an experienced facilitator to run the process (ibid). Because members of a project team are generally positive to their own projects, at least one person outside the project or organization should participate in the process. Øien et al (1996) defines a list of demands for using expert evaluations, which are the following:

1. Documentation
2. Objectivity
3. Empirical control
4. Completeness
5. Simpleness

Using expert opinions, criterion 5 is fulfilled, while criteria 1 - 4 are more difficult to handle. However, objectivity can be obtained from subjective evaluations by gathering input data in a systematic and structured way. Table 12 describes the differences between an unstructured data gathering process and a structured input gathering process. A significant drawback with a structured process is its high cost and

complex level. *The Delphi method* and *the Scenario method*, in the following section, are two methods that seek to gather input data from experts in an easy and systematic way.

TABLE 12 - FORMALISTIC EVALUATION VS. ENGINEERING EVALUATION (AUSTENG ET AL, 2005-II)

| Factors | Structured Input Gathering | Unstructured Input Gathering |
|--------------------------------|--|--|
| Structure | Systematic and structured process | Unsystematic and unstructured, "discussion over the table" |
| Specification of information | Well specified, based on information | Imprecise, assumptions not specified |
| Documentation | All steps well documented | Small amount of documentation |
| Extent of gathered information | Limited, only information from predefined question available | Broad, many aspects unveiled |
| Evaluation of experts | Objective evaluation | Subjective evaluation |
| Simpleness | Complicated and high cost | Very simple |

4.2.1 The Delphi Method

The Delphi method is a structured communication technique that consists of 1) an observation team that develops a questionnaire and chooses the respondents and 2) a panel of experts, anonymous to one other, which responds to questions. According to Øien et al (1996), it is the most common method for treating expert evaluations. The following bullet points describe the procedure briefly. See Lindstone & Harold (2002) for further studies of the method.

1. Observation team defines targets and sends out a questionnaire to respondents
2. Respondents give comments on the questionnaire and observation team adjust it
3. Observation team sends questionnaire once again, and respondents answer the questionnaire
4. The observation team analyze the answers and develops median values and percentile estimates (25% and 75 % estimates)
5. Results are sent to respondents that may revise their answers. Experts answering outside the 25 – 75 % percentile have to justify their estimates
6. Observation team analyzes answers and "far off" estimates are explained. Then, point 5 may be repeated up to three times.
7. Final median values are used as estimate. An indication of consensus among the respondents is a smaller variance in the final stage than at the start of the process

An advantage with this method is that the process is executed with the experts anonymous and separate to each other. In this way, there is a less chance that one person influences the other participants. The method

is also flexible as no meeting is required. Compared to the Scenario method, the Delhi method does not have an open communication process, which often generates solutions to problems.

4.2.2 Scenario Method

The Scenario method consists of three phases; 1) a preparation phase, 2) a questioning phase and 3) an evaluation phase (Austeng et al, 2005-ii). In the preparation phase, the problem is described and an evaluation of available resources is performed. Further, the choice of experts needs to be considered, as well as the estimation - and interview method. Questions often consists of words like who, what, how, where, when and why.

In the questioning phase, the objective is to extract as much knowledge as possible from the experts (ibid). Available information is given to the experts, who are questioned and asked to give three-point estimates that define the worst, best and most likely case for an activity. Afterwards there is a discussion about the results, and if the experts consider the results unreasonable, the estimates can be changed. The questioning process also needs to be considered. Are questions answered individually or in groups?

The results from the questioning phase may require a calibration. For instance, systematic “under/over estimation” from experts would be a reason to calibrate an experts. Weighting of experts are used to reflect the level of estimation skills among the experts. The weighting may be done accordingly; control questions mixed with real questions form a basis for evaluating the experts. Moreover, experts may weight each other’s opinion by filling in a form/matrix, or experts can fill in their knowledge profile and thereafter observe who has the most relevant knowledge.

The advantage of this method is that experts from all types of fields, like design, procurement, production and management attend an open meeting, which seldom happens. All the participants in the process get insight into each other’s concerns and suggestions. In this way a wide range of topics are discussed and an increased level of awareness of project risks is established. A drawback of the method is that participants may be influenced by dominant people who affect their estimates.

4.3 Errors in Assessment of Three-Point Estimates

In this section, five significant errors related to subjective estimation are presented. Knowing about these errors, the coordinator can make the participants aware of these pitfalls in order to improve their estimation skills, or the facilitator calibrates the estimates after a workshop process. The errors presented here are:

1. Confusion of what an estimate is
2. Overconfidence and ignorance to confidence level
3. Lack of self-enlightenment
4. Ignorance to historical data
5. Anchoring

4.3.1 Confusion of What an Estimate is

Before starting a workshop process with experts, it is important to establish what the objective of the estimate is (Jørgensen, n.d.). If the objective is to obtain a “realistic” estimate of number of working hours in a project, the estimate could be established from a “P50” - estimate. In order to establish a price for a “Request for tender”, the estimate could be a “P70” - estimate. Different objectives should give different estimates. It is impossible to have realism and competitiveness as the same objective. Realism often suffers when mixing these objectives (ibid). What the estimate represents must be made clear.

4.3.2 Overconfidence and Ignorance to Confidence Level

People are generally overconfident in their estimates with far too narrow ranges of uncertainty (Jørgensen, 2004). In addition, people are bad at considering extremes. Jørgensen (2014) found that project leaders, who are 90 percent sure that an estimate will be within a maximum-minimum estimate, were actually within the range only 60 percent of the time. He found that there was an *ignorance of the confidence levels*. The project leaders gave the same minimum-maximum interval for all cases of confidence intervals; a certainty of 60 percent was equal to a 75-, 90-, 99- percent certainty. Based on this, Jørgensen states that one should not ask for the minimum-maximum range for an activity. A question like: “how often have similar elements been delayed by more than 20 %?” are much easier to relate to. By doing so, improvements in realism are surprisingly big (ibid).

Another problem is that leaders associate narrow uncertainty ranges with a high degree of confidence, even if this overconfidence is revealed at a later stage. Consequently, participants often have an eagerness to say the right thing in front of the boss. It is important to work against these assumptions. Even though a narrow estimate seems more credible, it is likely to be wrong.

4.3.3 Lack of Self-Enlightenment

The “Central tendency of judgment” is a concept that states that the less we know, the more we push towards the middle (Jørgensen, n.d.). Thus, two factors pull towards a narrow range estimate: 1) overconfidence and 2) lack of knowledge. People are also focused on analyzing well-known areas, rather than unknown problems. Adjusting hours for one activity, while adjusting weeks for another is useless.

The focus should be at analyzing the areas that are poorly understood. Lastly, being eager to start a project, there is a high chance that estimates are too optimistic. Generally, at least a few people outside a project should participate in the estimation process. The ROSING equation describes this type of error:

$$RO = S * IN + G \quad 1)$$

Where:

RO = Relative cost overrun,

S = Selection bias (focus on low price)

IN = Inaccuracy

G = General estimation over-optimism

Imagine that a shipowner has chosen a shipyard that promises to deliver a project that is 30% lower than the average ($S = 0,3$) with a correlation between actual and estimated cost equal to 70 % ($IN = 1 - 0,7 = 0,3$). If suppliers are 20 percent optimistic on average in their estimates ($G = 0,2$) this gives an expected cost overrun of 29 %.

4.3.4 Ignorance to Available Reference Data

Available reference data is essential for good estimates. However, Jørgensen (n.d.) found that even if data were available, there is no certainty that the people will use this knowledge. In a study performed, he found that all the participants used available data for deciding minimum values (P10), while only half of the data were used to set the maximum (P90) values. The conclusion was that people believe that a project will be far better than earlier projects (ibid).

People overestimate how much they have learnt from previous projects. Jørgensen (n.d.) undertook an experiment where seven experienced system developers were asked to estimate sixty activities for a project that were clearly specified. Six of the activities were estimated two times with, at least, one month in between. Historical data were unavailable, but the experts had good knowledge of the system. The average difference between the estimates for the same activities was as high as 71 percent, even though the same system developers provided the estimates. This indicates that people should not trust their capability to remember historical data, but control it by written documentation (ibid).

4.3.5 Anchoring

Daniel Khaneman (2012), a winner of the Nobel Prize in economics, executed an experiment where a group of students was told to write down the number from a wheel of fortune with numbers ranging from 1 - 100. The students were unaware that the wheel of fortune was rigged and gave a value of either 10 or 65. Then, they were asked two questions; 1) is the percentage of African nations among UN members

larger or smaller than the number you just wrote? 2) What is your best guess of the percentage of African nations in the UN? The objective was to see if the number from the wheel of fortune, useless for establishing an estimate, affected the participants. The results showed that average estimates of those who saw the value 10 and 65, were 25 % and 45 % respectively.

The point of this experiment was to show that 1) people have a tendency to be anchored to a value given, and 2) people are easy to manipulate. By beginning to estimate a most likely value, the estimator tends to be anchored to this value when establishing the maximum and minimum value. A facilitator in a workshop process should ask questions that will not affect the participant's estimates. In addition, a dominant person in a workshop process may cause the estimates to be anchored. A smart way of preventing this is to ask the participants to write down their estimates before a discussion begins. In this way, a wider range of suggestions may be considered (Kahneman, 2012).

4.3.6 Sum Up and Recommendations

The statements below, sums up some of the recommendations given in Section 4.2 and 4.3,

1. Estimation skills can be improved significantly through practice.
2. The group should consist of no less than 4 people and be run by an experienced facilitator
3. The Delphi method and the Scenario method can be used to obtain more objective input data
4. At least a few people outside the project should participate in the estimation process
5. Explain that a narrow range for an estimate does not necessarily reflect their level of knowledge
6. Do not ask for minimum and maximum values, but rather ask for “more than.., less than...”, as people ignore the confidence levels.
7. Ask for a lower and upper limit value separately to avoid anchoring.
8. Do not trust the participant's ability to remember available reference data
9. Establish a database to evaluate the accuracy of the estimates.

4.4 Probability Distributions for Uncertainties

A Bayesian method with establishment of the three-point estimates is generally superior to any other estimation method (Austeng et al, 2005-ii). It works by identifying the most likely, worst-case and best-case value for uncertain input variables. These estimates are then represented in continuous probability distribution that defines stochastic input variables. The best and worst case value are based on percentiles of either P1/P99 values or P10/90 on the probability distribution, while the most likely value defines the peak of the probability distribution. Table 13 shows both empirical non-parametric distributions and model-based parametric distributions. Vose (2000) describes a model-based distribution to be a

distribution where the shape is born of the mathematics describing a theoretical problem, i.e. a normal distribution. An empirical distribution is a distribution where mathematics is defined by the shape that is required. A distribution that is confined to lie between to determined values are bounded, while an unbounded distribution theoretically extends from minus infinity to plus infinity (ibid).

TABLE 13 - FIVE COMMON PROBABILITY DISTRIBUTIONS

| Distribution | Category | Bounded | Level of knowledge |
|--------------|------------------|-----------|--------------------|
| Uniform | Non - parametric | Bounded | Low |
| Triangular | Non - parametric | Bounded | Low |
| Trigen | Non - parametric | Unbounded | Low |
| PERT (beta) | Non - parametric | Bounded | Medium |
| Normal | Parametric | Unbounded | High |

4.4.1 Uniform distribution

In a uniform distribution, the probability of occurrence is the same for all values in the interval. This non-parametric distribution is used when two extreme points (P1/P99) are known, but the variation between these points is uncertain. Generally, it is rare that experts will define a best and worst case value, but have no opinion about the most likely value (EpixAnalytics, n.d.). EpixAnalytics (n.d.) argue that it is a poor model since the density falls sharply to zero at the minimum and maximum in an unnatural way. The distribution is sometimes referred to as a “no knowledge” distribution.

4.4.2 Triangular distribution

The *triangular* distribution is popular due to the intuitive nature of defining a best, worst and most likely value. It also offers flexibility in its shape with possibility of skewness. Absolute worst and best case values (P1/P99) are used, which reflects 98 percent certainty in that the actual value occurs in this range. A potential shortcoming is that absolute extreme values are often hard to estimate (Vose, 2000).

4.4.3 Trigen distribution

The *Trigen* distribution offers the possibility of open-ended tails, by establishing best and worst case values for percentiles P10/P90. In this way, the concern of estimating absolute extremes values is less critical, compared to a triangular distribution. Management consulting companies, like Terramar, Holte Consulting and Dovre generally use 10/90 percentiles in a Trigen function to establish worst and best case values (Austeng, 2005-ii).

4.4.4 PERT distribution

The PERT (Program Evaluation and Review Technique) is derived from the Beta - distribution, which covers a wide variety of skewness types and is mathematically simple to use. As for a triangular distribution, it requires a value for best case, worst case and most likely case scenario. The difference compared to a triangular distribution is seen in figure 13. The PERT formula has been subject to a lot of criticism, because it uses a weighted factor to calculate expected values (Elmaghraby, 2005). Elmaghraby argues that it draws similarities to a deterministic method where the expected value is used as an estimate.

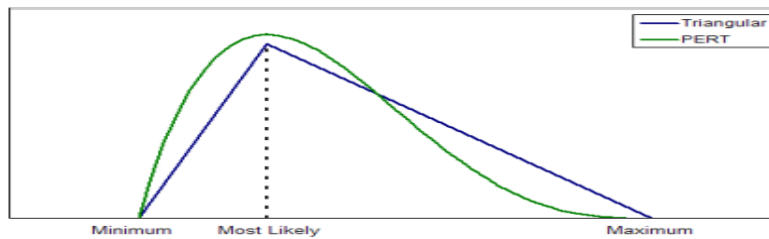


FIGURE 13 - PERT DISTRIBUTION VS. TRIANGULAR DISTRIBUTION

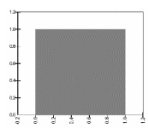
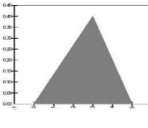
4.4.5 Normal

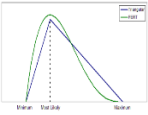
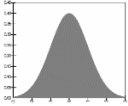
Normal distributions occur in many situations, especially for distributions of outcome (Austeng, 2005). Most observations are located near the average value, though some may deviate significantly. The Central Limit Theorem states that if many independent distributions are added together, then the resulting distribution is approximately normal distributed. The normal distribution is a parametric distribution, which means it requires sufficient amount of statistical data. The mean and standard deviation, which is symmetric around the mean, are entered to define the distribution.

4.4.6 Summary of Input Probability Distributions

Table 14 presents the five probability distributions in this section as well as their characteristics.

TABLE 14 - SUMMARY OF FOUR PROBABILITY DISTRIBUTIONS

| Distribution | Illustration | Properties | Expected Value |
|-----------------------|---|-------------------------|-------------------------------------|
| Uniform |  | Equal probability | $E(x) = \frac{Min + Max}{2}$ |
| Triangular and Trigen |  | Possibility of skewness | $E(x) = \frac{Min + Mode + Max}{3}$ |

| | | | |
|-------------|---|-------------------------|---------------------------------------|
| PERT (beta) |  | Possibility of skewness | $E(x) = \frac{Min + 4 Mode + Max}{6}$ |
| Normal |  | No skewness possible | $E(x) = \mu$ |

4.5 Assessing the Likelihood of an Event

If there is less than hundred percent chance that an event occurs, the likelihood of an event occurring must be established. A Bayesian estimation method can be used to establish the likelihood of an event occurring. The establishment of these estimates follows the process of establishing three-point estimates. The facilitator must go through each element to start a discussion amongst the experts to obtain estimates. The likelihood of occurrence is often divided into simple categories, as seen in table 15. A range of values is assigned to each phrase in order to maintain consistency between estimates of each uncertainty (Vose, 2000). The classification depends on the level of knowledge in a project. Throughout the project, a re-assessment of the likelihood of occurrence should be carried out. By multiplying the likelihood of occurrence with the consequence of this event occurring, event uncertainty is integrated into the model.

TABLE 15 - A WAY TO STRUCTURE PROBABILITY OF OCCURRENCE

| Degree of certainty | Probability of event occurring | Center of gravity |
|---------------------|--------------------------------|-------------------|
| Very likely | 50 % - 100 % | 75 % |
| Likely | 20 % - 50 % | 35 % |
| Less Likely | 5 % - 20 % | 12 % |
| Not likely | < 5 % | 3 % |

Events are usually considered independent. Austeng et al (2005-ii) separates between three types of events that may arise: one-time events, periodical events and unpredictable events. The first can be explained by a rock fall that occurs once. The likelihood of this event must be defined setting a certain time span, i.e. from risk analysis to project completion. The second is simpler to handle (ibid), because it is a direct consequence of time. For example, a hundred year wave has a return period of 100 years, which means that it will occur once every 100 year on average. The latter is hard to predict, because there is unawareness of the hazard. A stroke of lightening is within this category.

Conditional probabilities are a challenge to estimate, but it must be assessed if they exists. Event trees offer a simple illustrative way to obtain conditional probabilities, as seen in figure 14. A logical process works by tracing forward in time through a causal chain. It does not require a known consequence. The red nodes are binominal and the conditional outcome probabilities are seen in blue.

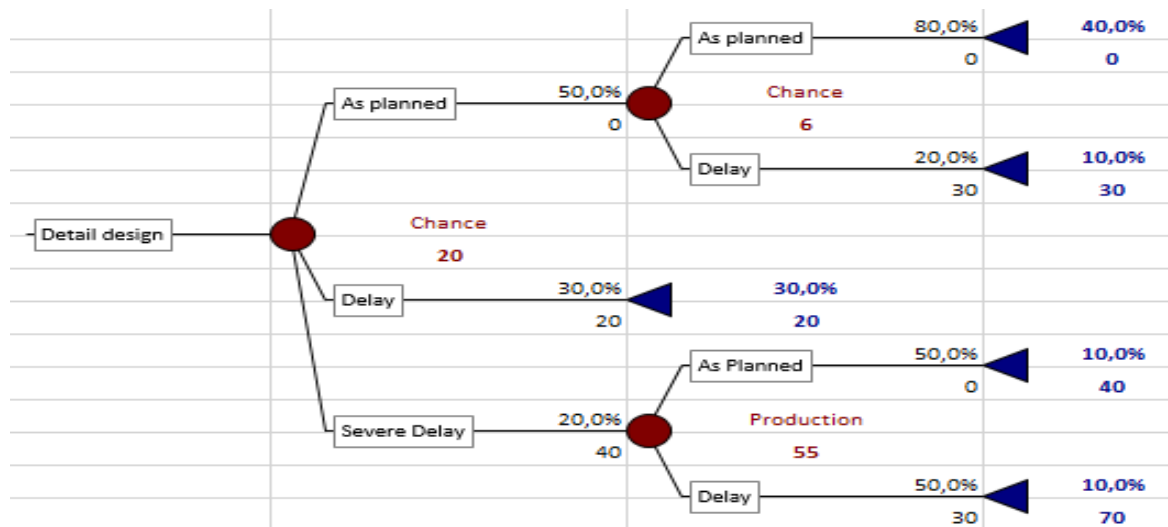


FIGURE 14 - CONDITIONAL BRANCHING USING EVENT TREES

4.6 Sensitivity to Errors in Input Variables

As mentioned, the output from a risk analysis is often limited by the quality of the information that is fed into the system (Lichtenberg, 2000). It is important to distinguish between sensitivities caused by subjective errors in the input data, and the methodical sensitivity analysis (explained in Chapter 5) used to observe which of the input variables that have the largest impact on the output. A simple example is used to illustrate the sensitivity for choice of input values and probability distributions. The case study in Chapter 7 discusses the subject in detail. Thus, there is no elaboration on the assumptions made in this section, and results are discussed briefly. Table 16 shows three-point estimates for six activities. These are represented by Trigen probability distributions (P10/90). By changing the characteristics for these values, as well as the probability distribution, it is possible to observe the sensitivity in the total duration of these activities.

TABLE 16 - DURATION OF ACTIVITIES USED IN ILLUSTRATION

| Minimum (P10) | Most Likely | Maximum (P90) |
|---------------|-------------|---------------|
| 4 days | 5 days | 6 days |
| 4,8 days | 6 days | 7,2 days |
| 4,8 days | 6 days | 7,2 days |
| 8 days | 10 days | 12 days |
| 3,2 days | 4 day | 4,8 days |
| 11,2 days | 14 days | 16,8 days |

4.6.1 Sensitivity in Choice of Three-Point Estimates

The value for each of the three-point estimates is changed individually, while the others are locked to their original values. In order to study the sensitivity, the minimum values are multiplied by a factor of 0,9 while the most likely value and the upper value is multiplied by a factor of 1,1. Figure 15 shows the results from the analysis. The curves indicate that errors in the 10/90 percentile - estimates have a significantly larger impact on the output than the errors in the modal value.

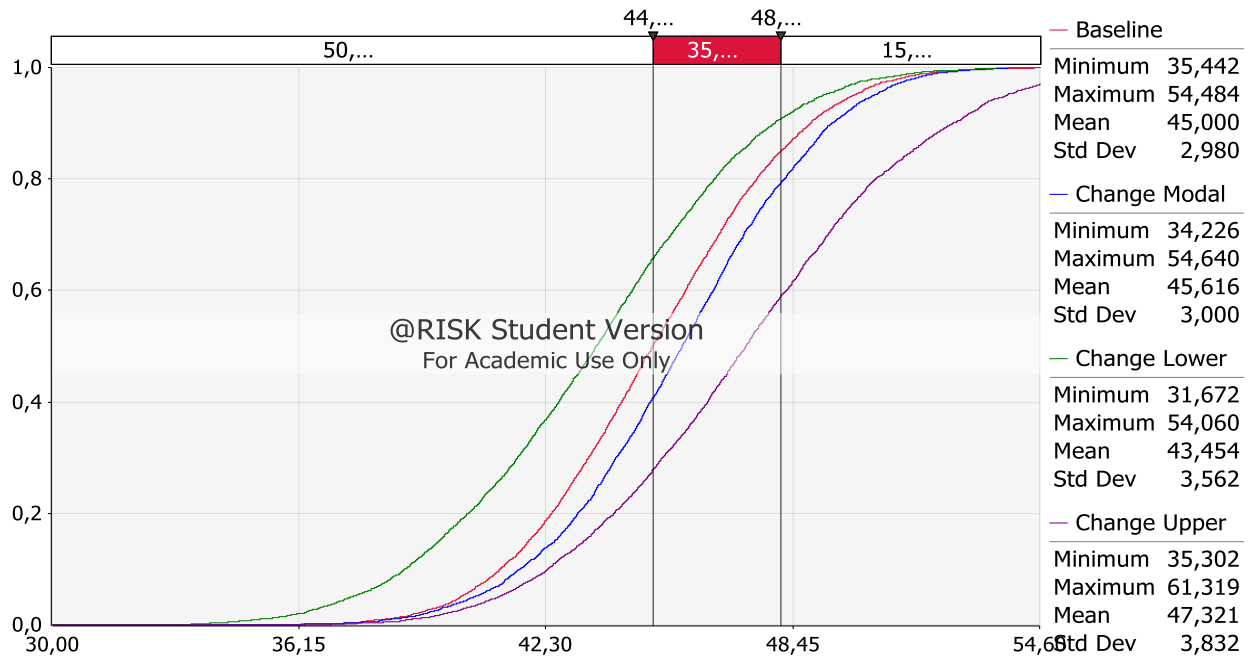


FIGURE 15 - SENSITIVITY IN TOTAL DURATION WITH CHANGED LOWER, - UPPER - AND MODAL VALUE

4.6.2 Sensitivity in Choice of Probability Distributions

Four non-parametric probability distributions are used to describe the input data; a uniform distribution, a triangular distribution, a Trigen distributions and a PERT distribution. Figure 16 shows that the differences between the probability distributions become evident in the lower - and upper percentile range.

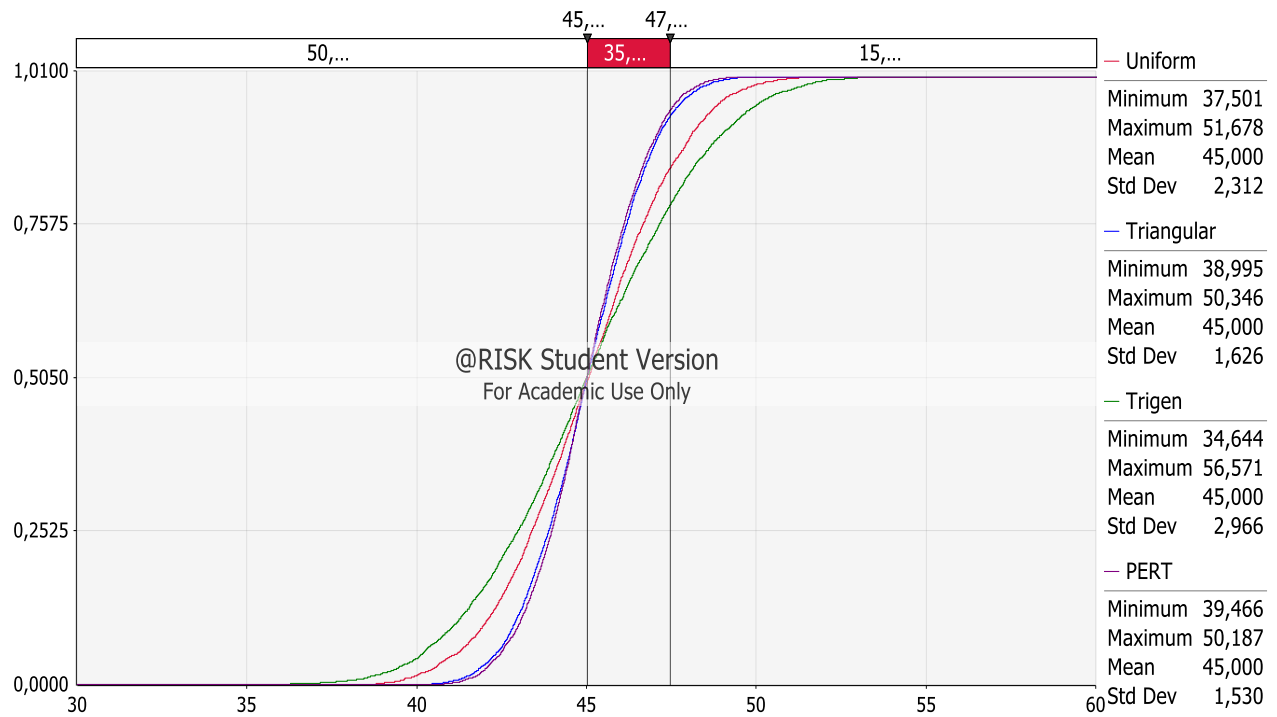


FIGURE 16 - SENSITIVITY IN TOTAL DURATION USING DIFFERENT PROBABILITY DISTRIBUTIONS

4.7 Chapter Summary

Assessing the values for uncertainties is challenging, as the reusability of available data is often limited in projects (Austeng et al, 2005-ii). A Bayesian estimation method assumes that the estimator has knowledge and experience about elements of the project, thus, the method trust the estimator to establish credible estimates. Three-point estimates for best case, worst case and most likely case can be used to define stochastic input variables, like activity durations for future events. In order to obtain objectivity in these estimates, a structured process like the Delphi Method or the Scenario method can be used.

Errors in subjective estimation of three-point estimates are inevitable. Ignorance to confidence levels, internal people being too optimistic and confusion of what an estimate represents are some sources of errors. There is an unwillingness to consider extremes, and the central tendency of judgment states that the less we know, the more we push towards the middle. People also believe setting a narrow range for uncertainties are associated with a high degree of confidence. Kahneman (2012) found that people are easy to manipulate and tends to be anchored to given values. Thus, one should ask for extreme values separately, before establishing the modal value. Fortunately, estimation skills can be improved significantly through practice.

Continuous probability distributions are used to characterize uncertainties. Distributions like a uniform, triangular, trigen distributions are generally used to define three-point estimates. The choice between these distributions depends on the level of knowledge about the uncertainty. A Trigen distribution has open-ended tails, meaning that extreme values are given for the P10/P90 percentiles, instead of P1/P99. Compared to a triangular distribution, this function has a higher variance.

The likelihood of an event occurring must be established for event uncertainties, which is a product of likelihood and consequence. This is done using a Bayesian estimation method. Usually, events are considered independent events. However, if conditional probabilities exist, event trees can be very helpful in order to obtain these estimates.

Finally, the sensitivity to errors in three-point estimates and to choice of probability distribution is investigated in two small risk analysis. The first analysis indicates that the values chosen for the extreme values are more important to consider than the value for the most likely case. The latter analysis shows that the PERT and Triangular distribution has more confidence in the value of most likely estimate, while the uniform and Trigen distribution gives more emphasis to the tails of a probability distribution.

5. Risk Analysis with Monte Carlo Simulation

The transition from qualitative risk analysis to a quantitative expression is challenging, but it must be done in order to evaluate, prioritize and manage risk (Osmundsen, 2005). The chapter starts by describing the different steps of the Monte Carlo method before important aspects like correlation between input variables and sensitivity analysis, used to establish risk mitigation measures, are discussed. Finally, a discussion of how to communicate present results from a Monte Carlo simulation is given.

5.1 Monte Carlo Simulation

The Monte Carlo (MC) method offers an efficient way to carry out a stochastic simulation. The method consists of three phases, as seen in figure 17, and each of these is described below.



FIGURE 17 - THE THREE STEPS OF THE MONTE CARLO METHOD

5.1.1 Model

The first step is to make a *model* that represents the system. Generally, a static model is used, which means that there are no time-dependent variables. The model must incorporate the network structure of a schedule, because activities are often carried out in parallel having lead or lag time relative to each other. The model must also include estimates and probability distributions for stochastic input variables, and correlation between input variables must be established. The defined number of iterations in a simulation has to be high enough to ensure that the simulation converges, i.e. a high number of input variables require a higher number of iterations. A good model is essential, because the results are limited by the quality of the information that is fed into the system (Lichtenberg, 2000).

5.1.2 Simulation

The method generates a numerical simulation using a random generator that randomly picks values from the stochastic input variables in each iteration. Thus, for each iteration, the sum of a deterministic path the schedule is recorded and reported as a numerical output probability distribution. The final outcome is a probability distribution showing thousands of possible outcomes from the model. A stochastic simulation recognizes that all paths through a network can become critical. The output distribution reaches an approximately normal distribution. This is due to the *Central Limit theorem*, which states that the sum of a large number of stochastic values with random distributions tends to be normally distributed. The criterion is that each of the variables is independent and that none of the values significantly dominates the others.

5.1.3 Evaluation

The risk analyst should evaluate the results from a risk analysis critically. For instance, uncertainty for an output variable may be far too small due to neglected uncertainty and there may be a lack of integrated correlation coefficients. So-called “Black boxes” in a simulation makes it difficult to perform a necessary overall quality control of the results (Lichtenberg, 2000). It is hard to tell if a simulation violates statistical laws or if the model is structured incorrectly. Austeng et al (ibid) suggest that the following questions are answered by the risk analyst carrying out the tests:

1. Should new factors be considered or should existing factors be changed?
2. Is all available information considered?
3. Does the result correspond with the presumed situation?
4. Is the plan sufficiently detailed and reliable?
5. Are the results and presentation suitable as a foundation for making a decision?

The approximate normal probability distribution uses standard deviations to represent areas under the curve. The areas are bounded one, two or three standard deviations on either side of the mean and contains approximately 68 %, 95 % and 99 % of the normal distribution, respectively. This is seen in figure 18. Compared to variance, standard deviation has the advantage of using the same unit as the output. Results from a risk analysis are often presented by the output’s mean value and the standard deviation. A range equal to the mean value plus/minus one standard deviation contains approximately 70 percent of the distribution.

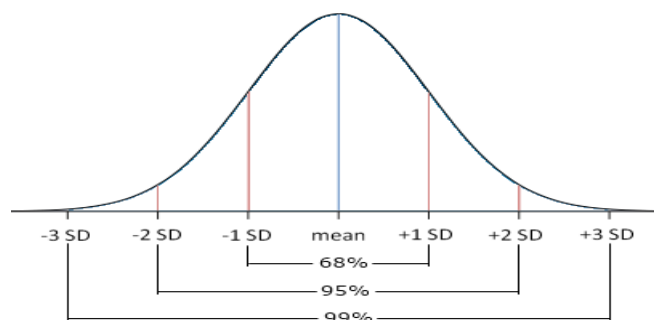


FIGURE 18 - ILLUSTRATION OF STANDARD DEVIATION

The shape of the cumulative distribution to the outcome distribution should also be discussed. A steep curve indicates that there is little uncertainty in the output variable. A flat part in the upper interval of a cumulative distribution indicates that there is a high chance of project delays. A high standard deviation will cause the cumulative distribution to be relative flat, while a small standard deviation causes a steep curve.

5.2 Correlation between Input Variables

One of the most common sources of error in a MC simulation is that input components are assumed independent (Touran & Wiser, 1992). There are two ways to cope with correlation between input variables; 1) make a schedule without dependencies between activities or 2) use correlation coefficients to adjust the result for this influence. Wall (1997) states that it is more important to establish correlations between construction elements than to choose the best-fitted distribution to represent variables.

5.2.1 What is Correlation?

Correlation measures the relation between two variables. It does not have an impact on the total expected value, but it does *have an impact on total variance and standard deviation* (Austeng, 2005-iv). The extra variance that occurs due to correlation is called covariance. In contrast to covariance, Pearson's correlation coefficient, $\rho(x,y)$, is dimensionless and has a value between -1 and 1. A value of zero indicates that no dependencies between input variables exist. If the value for one variable increases and causes the other variable to increase, there is a positive correlation ($\rho > 0$). If the second variables decrease, there is a negative correlation ($\rho < 0$). Formulas for Covariance (2) and Pearson's correlation coefficient (3) for two input variables are seen below:

$$COV(X, Y) = 2 \cdot Cor(X, Y) \cdot \sigma_X \cdot \sigma_Y \quad 2)$$

$$\rho(x,y) = \frac{COV(x,y)}{\sqrt{VAR(X) \cdot VAR(Y)}} \quad [-1 \leq \rho \leq 1] \quad 3)$$

5.2.2 Integration of Correlation Coefficients

Establishing correlation coefficients are time-consuming and often goes beyond a user's understanding (Lichtenberg, 2000). In a project risk analysis, there is seldom enough empirical data available to obtain the correlation coefficients analytically (Osmundsen, 2000). Osmundsen (2005) states that correlation should be taken into account, even if there is a lack of knowledge about the correlation. He suggests that correlation can be divided into correlation groups, as seen in table 17. Estimates like this, will give a more realistic picture of the situation even if the accurate value for the correlation coefficients is unknown (ibid). It may be efficient to run the analysis with - and without the correlation coefficient to see the impact on the output.

TABLE 17 - A DESCRIPTIVE WAY TO DEFINE CORRELATION COEFFICIENTS

| Grade | Negative | Positive |
|-------------------------|----------|----------|
| Perfect correlation | -1 | 1 |
| Significant correlation | -0,75 | 0,75 |
| Good correlation | -0,5 | 0,5 |
| Mild correlation | -0,25 | 0,25 |
| No correlation | 0 | 0 |

5.2.3 Impact of Correlation

The following simple illustration shows the impact of neglecting correlation in a simulation. The duration of a sandblasting job is set to have an expected duration of 30 days with 27 days and 33 days as best case and worst case scenario, respectively. The duration of the painting job is set to have an expected value of 25 days, with 20 days as best case and 33 days as worst case. PERT probability distributions are used to characterize the input values for all activities in the following illustration.

The results in table 18 show that standard deviation changes as correlation coefficient changes, while the mean value is the same. Integrating a correlation coefficient equal to 1, there is a difference in standard deviation of 1,4 days compared to without a coefficient. A positive correlation will increase the standard deviation. Neglecting this type of correlation will lead to a conclusion that the estimate is more precise than they really are. In contrast, neglecting negative correlation leads to an overestimation of variance (Chou et al, 2008). Negative correlations are always potentially useful, because it helps controlling the variation and reduces overall uncertainty (Wallace & King, 2012).

TABLE 18 - IMPACT OF CORRELATION

| | Sandblasting & Painting | | | | |
|--|-------------------------|------|------|------|------|
| Correlation [-] | 0 | 0,5 | 1 | -0,5 | -1 |
| Mean [days] | 55,5 | 55,5 | 55,5 | 55,5 | 55,5 |
| Standard Deviation [days] | 2,7 | 3,2 | 3,6 | 2,1 | 1,3 |
| Difference in standard deviation[days] | - | 0,5 | 0,9 | 0,6 | 1,4 |

Figure 19 shows the cumulative distribution for the example. Without a correlation coefficient, there is 85 % chance that the duration of the sandblasting and painting job will be less than 58,5 days. A correlation coefficient equal to 0,5 gives 81,5 % chance of using less than 58,5 days, while a correlation coefficient of 1 results in 78 % chance of using less than 58,5 days. Notice that the steepness of the curve decreases as positive correlation coefficients increase, due to increased standard deviation.

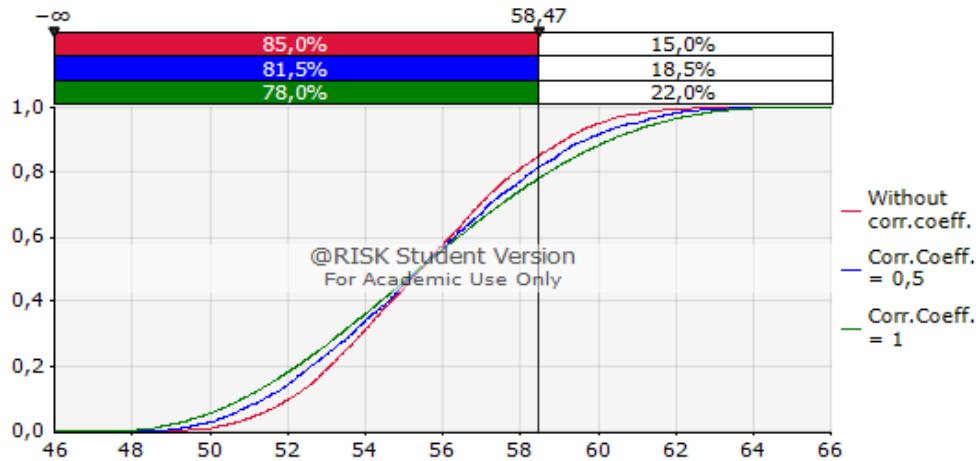


FIGURE 19 - CUMULATIVE DISTRIBUTIONS WITH DIFFERENT CORRELATION COEFFICIENTS

5.3 Sensitivity Analysis

A sensitivity analysis is applied to determine whether the output depends critically on the input parameters (Wallace & King, 2012). If input parameters vary significantly without affecting the outcome, a stable solution exists. An unstable solution exists if small changes in input variables affect the output variable. The latter is a concern since the input parameters are estimates with errors. What-if analysis, scenario analysis and stress tests generate a set of possible future outcomes. Sensitivity analysis is equivalent to these analyses, as all these methods are used to generate a set of possible solutions (ibid). A tornado chart is a graphical presentation of a sensitivity analysis, and it is described in the next section.

Sensitivity analyses are generally performed using *Spearman rank order correlation coefficients*. The coefficient is a statistic used for quantifying correlation relationship between two variables (Vose, 2000). Correlation coefficients are calculated between the output variable and the samples for each input. The higher the correlation between the input and the output, the more impact the input has on the outputs value. A rank order analysis is carried out by replacing “n” observed values for two variables X and Y by their ranking (Vose, 2000). The largest value for each variable has a rank of 1, the smallest a rank of “n”. A simplified Spearman rank order coefficient, where u_i and v_i are the ranks of the i^{th} pair of the X and Y variables, is calculated as:

$$\text{Spearman Rank Order Correlation Coefficient} = 1 - \frac{6 \cdot \sum_1^n (u_i v_i)^2}{n(n^2 - 1)} \quad 4)$$

A potential shortcoming of sensitivity analyses is that they cannot propose any kind of solution that addresses variability. Decisions based on sensitivity analysis can only find solutions that are optimal for some fixed (deterministic) settings of the uncertain parameters. Wallace and King (2012) argue that

sensitivity analysis does not connect very well to the setups for modeling uncertainty in a stochastic process. For more studies on this topic, see (Wallace and King, 2012).

5.4 Presentation of Results

Figure 20 shows the two main results from a Monte Carlo simulation in a risk analysis:

1. A cumulative distribution (left) shows the likelihood of finishing a project within a chosen date.
2. A tornado plot (right) from a sensitivity analysis shows how output uncertainty is affected by the uncertainty for each of the input variables

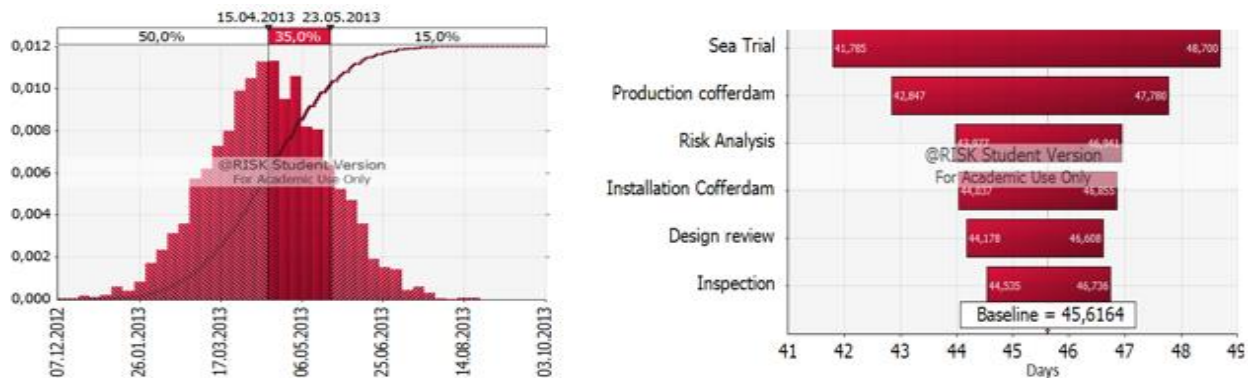


FIGURE 20 - PRESENTATION OF RESULTS FROM RISK ANALYSIS

The figure to the left shows a histogram, which is produced by grouping, generated output data into a number of bars. The number of values in any class is its frequency. By dividing the frequency by the total number of values, an approximate probability is given to an output variable within a class range. The histogram is overlapped by its ascending cumulative distribution. This distribution is useful for reading of quantitative information about the distribution of the variable. In contrast to the histogram, which shows the relative frequency on the y-axis, the probability for an x-value can be read directly of a cumulative graph. Thus, the probability of exceeding a value or the probability of lying between two percentile values can easily be found.

In risk management, the estimated project duration is often presented with the mean value and the P70 - percentile. *Holte Consulting*, a management consulting company in Norway, argues that values should be presented as an interval, rather than a deterministic value because people often fail to consider variance (Austeng et al, 2005-iii). For example, the value can be presented as an interval of 90 days - 110 days, rather than a deterministic value of 100 days.

The outcome of a sensitivity analysis is often presented as a tornado plot. The tornado plot in figure 21 (right) shows that the stochastic input variable “Sea trial” has the most significant impact on output. Relative to the mean value, the sea trial can delay the project by about two days, but there is also an opportunity that the sea trial goes quicker than planned, leading to a project duration of about 43 days. A “Top 10” list of uncertain input variables forms the basis for establishing risk mitigation measures. It is important to communicate that not necessarily all uncertainties in the “top ten” list can be reduced. In this way, useless time consumption is prevented.

5.5 Chapter Summary

Modeling, simulation and evaluation are the three stages of the Monte Carlo (MC) method. The model must provide reliable input data, incorporate the network structure and integrate the dependencies in a schedule. The MC method is efficient for running a stochastic simulation, because it uses a random number generator to generate thousands of scenarios that are presented in a probability distribution. However, “Black Boxes” in the simulation makes it difficult to perform a quality check and evaluate results.

Correlation measures the relation between two variables. In a Monte Carlo simulation, correlation coefficients must be integrated to adjust for correlations, because the method assumes that stochastic input variables are independent. Pearson’s correlation coefficient is used to adjust for linear dependencies. It is dimensionless and has a value between -1 and 1. It is difficult to establish these coefficients, and the coefficients can be divided into simple categories, each with a qualitative description of the value.

A sensitivity analysis determines whether the output depends critically on the input parameters (Wallace & King, 2012). An unstable solution exists if small changes in input variables affect the output variable. This a concern since the input parameters are estimates with errors. With the Monte Carlo method, a sensitivity analyses are generally performed using *Spearman rank order correlation coefficients*.

The presentation of results usually consists of a histogram with its cumulative probability distribution and a tornado plot. A cumulative probability distribution is useful to obtain the probability of reaching certain value, like the finishing date for a project. A tornado plot, from a sensitivity analysis, can be used to establish risk mitigation measure. The mean value and the value from a percentile in the upper range (P70-P85) are often used to present results in numbers. It is also important to communicate the variance in the result, as a customer tends to focus on the specific value given.

6. The DNV GL Method

The chapter describes how DNV GL consults their customers in risk management. By comparing their method to the theoretical framework described in Chapter 2 - Chapter 5, the goal is to identify potential improvements and pitfalls of the method. The findings from this chapter form the basis for the case study in Chapter 7. The following elements are discussed in this chapter: 1) scheduling technique used to estimate project duration, 2) workshop process for providing input data and choice of probability distributions and 3) risk analysis and presentation of results. The description of the DNV GL method is mainly based on a meeting 12th of March 2014, with Jannicke Juvik and Tor Aarseth, which are both DNV GL consultants in risk management.

6.1 Description of the Process

DNV GL divides the risk management process into five phases; 1) Risk Management Planning, 2) Risk Identification, 3) Risk Analysis, 4) Risk Response Planning, 5) Risk Monitoring and Control, as seen in figure 21. The process starts by outlining the overall project schedule using the management software program “Microsoft Project” (MS Project). DNV GL creates a deterministic model in MS Project, where activities are linked together to create a network structure. Then, uncertainties are identified and quantified by establishing three-point estimates in the workshop process. By importing the schedule into @RISK, uncertainties are added to the baseline model leading to stochastic input variables.

@Risk generates a static stochastic simulation while MS Project does the schedule calculations. By running the analysis, it is possible to estimate the total project duration, identify significant uncertainties and suggest risk mitigation measures in order to make the project more robust. “EasyRisk Manager” is a software program used to log and monitor risk and mitigation actions. Figure 21 illustrates the interactive process between @Risk and Easy Risk Manager. Over the project duration, @Risk continuously updates the project risk through the model as it gets feedback from the communicative Easy Risk Manager tool.



FIGURE 21 - STRUCTURED RISK MANAGEMENT PROCESS (DNV GL, 2012)

Studying the whole DNV GL risk management process is too comprehensive for this thesis. Stage 4 & 5 of the risk management cycle (figure 21) will therefore be left out of the thesis, including the use of “EasyRisk Manager”. The scope of this thesis is to investigate phase 1, 2 and 3 of the DNV GL cycle and the following subjects:

1. The scheduling techniques used to estimate project duration
2. The workshop process for identifying and quantifying uncertainties
3. The Monte Carlo simulation in @Risk

6.2 Scheduling Technique

Before the workshop takes place, DNV GL requires one or two weeks for preparing and planning the meeting. The objective of this phase is to get an overview of the company’s and the employees’ responsibilities. The customer provides organizational charts, information about the company and their current projects and the contract schedule with milestones. The Master Plan is used as a starting point for making a simplified schedule focusing on main activities and milestones. The Master Plan often consists of thousands of activities, while the simplified plan may range from 10 - 40 activities depending on the size of the project. A simple schedule makes it easier for the participants in the workshop to relate to the project plan and maintain control and overview.

The schedule and risk analysis are updated from the awarding of the contract until final delivery from yard to customer. Actual dates for finished milestones are included, and uncertainties are removed when activities have finished. This is done in order to continuously obtain a realistic view of the project advancement. When uncertainties have been identified, the resources are allocated to project activities. Table 19 compares DNV GL’s risk management planning phase to the theoretical framework and methods described in previous chapters.

TABLE 19 - COMPARISON OF DNV GL METHOD AND THEORETICAL FRAMEWORK - PHASE ONE

| Description | DNV GL method | Theoretical framework | Identification of potential pitfalls and improvement |
|-------------------------------|---|--|--|
| Establishment of schedule | Master Plan used as a starting point for making a simplified schedule | Bottom up approach | May be time consuming compared to top-down approach |
| Level of detailing in a model | Schedule contains 10 - 40 activities depending on size of project | Number of activities should not exceed 25 - 30 | |
| Resource allocation | Allocation decided before project execution | Static approach | |

| | | | |
|-------------------|---|--------------------|----------------------|
| Scheduling Method | Schedule continuously updated throughout the project | Reactive approach | Approximation method |
| Scheduling Method | Risk mitigation measures for future events to make the project robust | Proactive approach | |

6.3 The Workshop Process

6.3.1 The Workshop Structure

DNV GL uses subjective evaluations in order to establish estimates. The number of participants in the workshop process ranges from a handful to 20 people. DNV GL aim at including participants from all the different departments, like Design, Procurement, Production and Management. The workshop is an open process where a discussion between people from all departments takes place. A concern for DNV GL is that the participants in the workshop are afraid to speak freely if the management is present.

Consequently, the participants are sometimes split into sub-groups. DNV GL often hires a local DNV GL surveyor that has knowledge about the company and the culture in the country. The surveyor is used to ask the right critical questions in the workshop and is sometimes crucial. Generally, the workshop process has a duration of 2-4 days. It starts with a meeting where DNV GL outlines the workshop process and presents the simplified project schedule with the model baseline.

6.3.2 The Questioning Phase

In the questioning phase, the participants are asked to identify uncertainties and schedule risks. The identified uncertainties are integrated into the baseline model by using three-point estimates that represents the worst, best and most likely case. DNV GL starts by asking what the worst case would be, i.e. the case where everything goes wrong. In their experience, the participants are generally too optimistic about the worst-case estimate. There is an unwillingness to consider the extremes and an expectation that the current project will be better than previous projects. In order to prevent this, DNV GL asks them critical questions and suggests potential delays. The same process is carried out for the best-case scenario before the establishment of the most likely value is set.

DNV GL have usually identified and established values for uncertainties before the workshop takes place for two reasons: 1) to generate a discussion regarding the presented values and 2) to help the participants to identify and establish values for uncertainties. Participants quickly raise objections if they disagree with the estimates presented. In this way, a discussion is effectively generated. Getting input from an external source, like DNV GL, that has good experience in risk management is very valuable. Often, there is only one participant with knowledge about a specific uncertainty. Thus, the estimate will have a low degree of objectivity. By combining estimates from an external source like DNV GL and an internal source, this

may be prevented. The probability of occurrence is also established for event uncertainties, and is carried out in parallel to the mentioned process. A table that combines a qualitative description of likelihood to a probability range is used to categorize and structure the estimates. DNV GL often uses a risk matrix consisting of five categories for probability of occurrence. However, this level depends on the level of knowledge in a project, i.e. lack of knowledge requires few categories and so forth.

6.3.3 Management of Subjective Input Data

The three-point estimates are mainly characterized by a triangular probability distribution where percentiles of “P1/P99” represent the extreme values. Uniform, Trigen and PERT probability distributions are only used on rare occasions. Since the group provides uniform estimates, there are no weighting of the experts, and there are no calibration of the results. DNV GL does not provide a database in order to evaluate and compare the accuracy of the estimates to actual values for projects carried out. Table 20 compares DNV GL’s process for identifying and quantifying uncertainties to the theoretical framework and methods described in previous chapters.

TABLE 20- COMPARISON OF DNV GL METHOD AND THEORETICAL FRAMEWORK - PHASE TWO

| Description | DNV GL method | Theoretical Framework | Identification of potential pitfalls and improvement |
|--|--|---|---|
| Estimation method | Subjective estimates | Bayesian estimation method | |
| Workshop structure | Open workshop process. Group may be divided into subgroups | Scenario Method | Facilitator must prevent dominating participants |
| Number of participants | A handful to 20 people | Group of 4 - 15 experts | |
| Number of people giving estimate for each activity | Participants with knowledge about the activity and DNV GL | Group of experts should establish each estimate | Estimates from more than one person decreases chance of subjective errors |
| External People | Local DNV GL surveyor and DNV GL risk experts | At least a few external participants | |
| Workshop duration | 2-4 days | | Time constraints |
| The level of practice in estimation | Participants do not necessarily have any practice in establishing estimates. | A brief “estimation test” with known answers | People are generally bad at making estimates, but the skill can be improved through practice. |
| Questions asked | Values for three point estimates asked for separately | Ask for three point estimate separately | |
| Questions asked | DNV GL suggests estimates before the workshop takes place | | Potential anchoring errors |

| | | | |
|---------------------------------------|--|---|---|
| Questions asked | Asks for value for extreme values first, than the most likely case | Ask for: “more than.., less than...”, not minimum and maximum values | Ignorance to confidence levels. |
| Estimate for likelihood of occurrence | Subjective evaluation, simple categorization with qualitative description often used | Simple categorization with qualitative description. Event trees for conditional probability | Conditional probabilities hard to estimate without event trees. |
| Probability distribution | Mainly triangular probability distribution (P1/P99) | A Trigen probability distribution (P10/P90) gives higher standard deviation | People are generally bad at considering extremes |
| Calibration of results | No calibration | Systematic biases should be calibrated | Subjective errors are likely to occur |
| Database and documentation | No database | Database to evaluate the accuracy of the estimates compared to actual ones | A database will provide insight into subjective errors |

6.4 Monte Carlo Simulation Using @RISK

Uncertainties are characterized by probability distributions that represent both event uncertainty and estimation uncertainty (see Section 2.1). These uncertainties are added to the deterministic model. Thus, variances in input variables are introduced. Table 21 shows formulas for expected value and variance for a triangular distribution (P1/P99).

TABLE 21 - FORMULAS FOR A TRIANGULAR DISTRIBUTION USED TO INTRODUCE UNCERTAINTY INTO MODEL

| Description | Formula |
|--|---|
| Expected value for individual activity | $E(x) = \frac{Min + Mode + Max}{3}$ |
| Total expected values | $E_{TOT} = E_1 + E_2 + \dots + E_n$ |
| Variance for individual activity | $VAR(X) = \frac{1}{18} (Max - Min)^2 + (Max - Mode) \cdot (Min - Mode)$ |
| Adding of variance | $VAR(X_{TOT}) = VAR(X_1) + VAR(X_2) + \dots + VAR(X_n)$ |

@RISK generates a stochastic simulation process using a random generator, while MS Project does the schedule calculations. At each iteration, @RISK puts the random values in the cells with probability distributions, and then, MS Project calculates this schedule. The result from the simulation is a probability distribution with all the possible scenarios of project duration. By using the @RISK function “Probabilistic Gantt chart”, it is possible to obtain the percentage of time an activity fell on the path that

defines the duration during the simulation of the project. This is useful for deciding which risk mitigation measures that should be established and to evaluate if the CPM method can be used as an approximation method. See Appendix 2 for illustration.

6.4.1 Adjusting for Correlation in @RISK

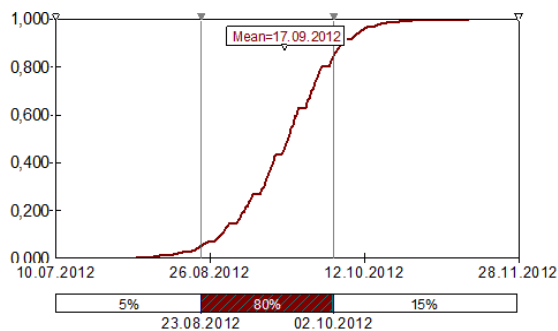
Correlation coefficients are not consistently integrated into stochastic model, because it depends on the person in DNV GL carrying out the risk analysis. In contrast to the difficult process of defining correlation coefficients between input variables, it is easy to integrate dependencies between activities into a model by using a correlation matrix. @RISK uses Pearson’s correlation coefficient that can only be used for linear relationships.

6.4.2 Sensitivity Analysis

DNV GL runs a sensitivity analysis in @RISK in order to establish which input variables that have the most significant impact on the project duration. This is a good starting point for identifying mitigation measures and prioritizing these. @RISK uses Spearman rank order correlation coefficients (section 5.3) to run the analysis. The higher the correlation between an input variable and the output, the more sensitive the output is to this variable.

6.4.3 Presentation and Communication of Results

Figure 22 shows a typical presentation of a DNV GL risk analysis. A cumulative distribution shows the probability of finishing a project at a chosen date. Delivery dates for the baseline case without uncertainty are presented together with the mean value and the P85-percentile from the risk analysis. The presentation also includes a tornado plot from the sensitivity analysis, which is considered an efficient way to convince the customer to establish mitigation measures. The tornado plot usually consists of a “Top Ten” list of uncertain input variables that are recommended to evaluate further. The report does not say anything about the standard deviation in the risk analysis result.



| No. Update | Milestone/Uncertainty | Planned | Mean | 85% |
|---------------|-----------------------|----------|----------|----------|
| February 2012 | Lanch | 23.11.12 | 23.11.12 | 24.11.12 |
| | Sail away | 23.12.13 | 12.03.14 | 28.03.14 |
| Sept 2011 | Launch | 23.11.12 | 27.11.12 | 05.12.12 |
| | Sail away | 23.12.13 | 15.03.14 | 01.04.14 |
| May 2011 | Launch | 23.11.12 | 08.12.12 | 31.12.12 |
| | Sail Away | 23.12.13 | 26.03.14 | 21.04.14 |

FIGURE 22 - TYPICAL DNV GL PRESENTATION OF RESULT FROM RISK ANALYSIS

Table 22 shows a comparison of the theoretical framework from previous chapter and the DNV GL method presented in this chapter.

TABLE 22 - COMPARISON OF DNV GL METHOD AND THEORETICAL FRAMEWORK - PHASE THREE

| Description | Description of DNV GL process | Theoretical Framework | Potential Pitfalls |
|---|---|--|---|
| Schedule structure for simulation | MS project models the schedule's network structure | All paths in network structure should be considered in risk analysis | |
| Simulation | @RISK generates a static numerical simulation with a random generator | Static stochastic simulation | Ignores the flexibility that is integrated in a dynamic simulation model |
| Correlation | Correlation modelled occasionally, using Pearson's correlation coefficient. | Correlation must be modelled, unless insignificant. | Correlation must be modelled. Pearson's Corr. Coeff. only considers linear correlations |
| Correlation | Correlation often modelled in the network structure | Correlation modelled in coefficient matrixes. | Possible misunderstanding of the correlation |
| Visual Presentation of Results | Tornado plot and Cumulative distribution | Tornado plot and Cumulative distribution | |
| Values presented for project duration | Baseline case, P50 and P85 values | P50, P70 and standard deviation | Emphasis the standard deviation in the result |
| Clarification of what the estimated values represents | No general clarification | Clarify what estimates like P50, P70 and P85 means | The customer may base important decisions on a P50 - estimate |

6.5 Chapter Summary

The scheduling technique that DNV GL uses combines the software tools *MS Project*, which models the schedule network, and *@RISK*, which generates a static stochastic simulation and introduces the model to uncertainties. In addition, proactive and reactive measures are used to provide a robust and realistic model throughout the project. The level of detailing in a schedule is established using a bottom-up approach with the Master Plan as a starting point. The outcome is generally a schedule with 10 - 40 activities.

In the workshop process, a Bayesian estimation method is used to assess three-point estimates, while the Scenario method is used to obtain objectivity in these estimates. The use of an external DNV-GL surveyor is very useful in order to evaluate how the workshop should be carried out and to ask the right questions. Subjective assessment of three-point estimates may cause errors. Anchoring errors are likely to exist, because DNV GL establishes three-point estimates before the workshop takes place in order to start the discussion. A triangular distribution (P1/P99) is generally used to define the three-point estimates, instead of a Trigen distribution (P10/P90) with open-ended tails that generates a wider range.

The Monte Carlo method consists of three stages: modeling, simulation and evaluation. *@Risk* uses Pearson's correlation coefficient to adjust for dependencies between stochastic input variables in the model. However, whether correlation coefficients have been integrated or not, seems to depend on the person carrying out the risk analysis in DNV GL. A sensitivity analysis is run using Spearman Rank Order Correlation Coefficient. DNV GL presents and communicates results using a cumulative probability distribution with values for the mean value and the P85 - percentile. In addition, a tornado plot is shown to illustrate input variables that have a large impact on the outcome variable. DNV GL does not have a strong focus on presenting the standard deviation in the presented results. As the customer tends to focus on a specific value instead of the range, this is a potential pitfall.

7. Case Study

Chapter 7 presents a naval shipbuilding project used to investigate important aspects of the DNV GL method. Four risk analyses are carried out to study: 1) impact of integrating uncertainty into the model, 2) impact of integrating correlation coefficients into model 3) sensitivity to choice of probability distributions used to characterize uncertainties 4) sensitivity to errors in estimated three-point values for uncertainties. By performing these analyses, the objective is to create awareness of potential limitations and pitfalls of the DNV GL method. Further, the objective is to identify potential improvements of the method.

7.1 Description of Case Study

7.1.1 Background

The case study is based on a real shipbuilding project that took place around 2010. It is a navy vessel, 230 meters long and 28 meters wide. The shipyard was responsible for building and outfitting most of the ship, but final preparations were completed in another country. This required the vessel to be transported by a semi-submersible heavy lift ship, a trip that took about 50 days. It was crucial that the shipyard delivered the vessel at the contractual date, or else the yard would have had to cancel the planned transportation or deliver an unfinished vessel, giving significant costs for the company.

7.1.2 Model and Assumptions

The deterministic baseline schedule is seen in figure 23. The project was estimated to have a duration of about 3,75 years starting 23rd of September, 2008 and finishing 24th of May, 2012. The schedule was divided into 17 main activities, with the activities “Launching vessel” and “Sail Away” representing the two most important milestone activities. An important notice is that the shipyard had a working time of five days per week. Thus, additional delay was caused by weekends.

The column named “Predecessor” in figure 23 reflects dependencies between linked activities. The activity “Build Blocks” starts when the predecessor (activity 6) has run for 299,25 days. This is written as “6FS-299,25”, where “FS” means “Finish to Start” and the negative sign means lead time. “Control and IPMS test completion” is written as “11FS+15”. The positive sign represents a lag time. Thus, the activity will start 15 days after activity 11 has finished.

Figure 24 shows the schedule’s network diagram with the numbers corresponding to the numbers for the activities in figure 25. The network suggests that “Zone 8 design” (2 & 3) and “Data and Equipment for BAE” (4 & 5) can be done in parallel to “Detail design (zone 1-7)” (6) and “Building the blocks” (7). The first two mentioned have none following activities. The network indicates that “Pod arrival and Installation” (13) are in parallel with activity number 9, 10, 11 and 12. By running a stochastic simulation

of the schedule, it is observed that the activity “Pod arrival and Installation” has a critical index equal to zero. “Test and Readiness Review (TRR)” (15) are in parallel to “Harbor acceptance trial (HAT)” (16), where “HAT” has a critical index of 97,8 %, while “TRR” has a critical index of 2,2 %. Consequently, there is a single path that mainly dominates the schedule with the ID number: 1,6,7,8,9,10,11,12,14,16,17. Appendix 2 shows the output data from a probabilistic Gantt chart for this case study.

There is no elaboration on how DNV GL developed the network structure or the dependencies between activities. Investigations show that the schedule will have a dominating path that defines the duration of the project. Whether this reflects a real situation of the project is beyond the writer’s knowledge. The reader should bear in mind that an incorrect modeling of the network structure and the dependencies would cause errors in estimates for project duration. As discussed in Chapter 3, basing the project duration on the Critical Path (single path) Method may cause the project to be overly optimistic.

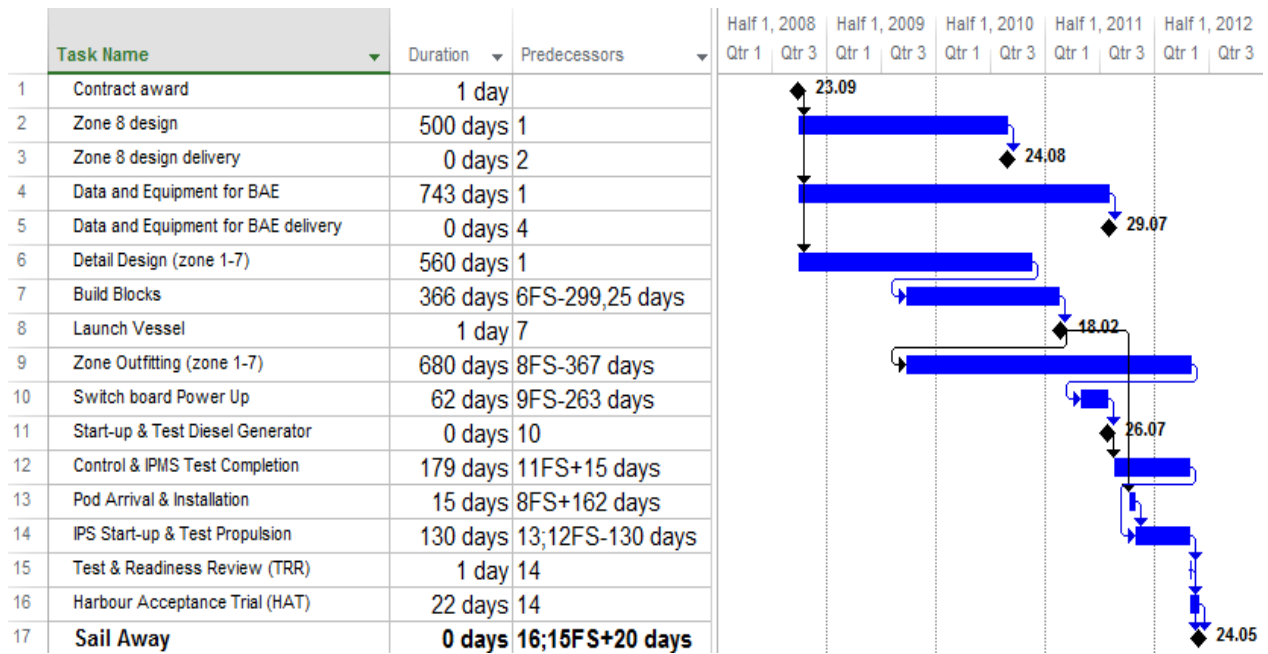


FIGURE 23 - PROJECT SCHEDULE FOR NAVAL SHIPBUILDING PROJECT

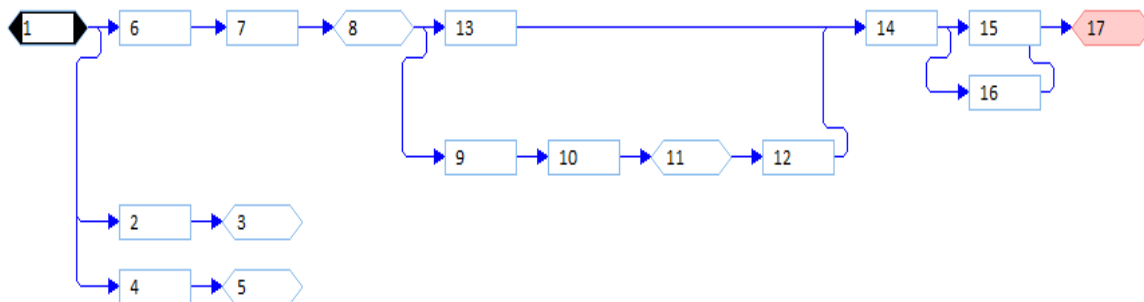


FIGURE 24 - NETWORK DIAGRAM FOR CASE STUDY SCHEDULE

7.1.3 Identified Uncertainties

Table 23 shows the outcome of one of the workshop processes that DNV GL carried out for this case study. In total, 21 uncertainties that affects project duration were identified, all representing risk factors in terms of delaying the project. Notice that table 23 shows the likelihood that an event occurs. The probability that a certain outcome of a consequence occurs is defined by a continuous probability distribution, which is based on the three-point estimates seen in table 23.

A Bayesian estimation method is used to assess estimates for both the likelihood of an event occurring and the following consequence. One could argue that some consequences are generic. For example, if material from supplier is delayed, the consequence is the same wherever the project is carried out, but the likelihood of this event happening varies from place to place. However, the reusability of available data is assumed limited. The likelihood of an event occurring is found using simple categories with a qualitative description of each category. Whether the likelihood in table 23 represents conditional or independent values is unknown, but event trees were not used to assess conditional probabilities.

TABLE 23 - INPUT DATA FOR IDENTIFIED UNCERTAINTIES FOR DURATION OF ACTIVITIES IN CASE STUDY

| Identified Uncertainties | Activity affected | Likelihood (%) | Consequence (months delay) | | |
|---|------------------------------|----------------|----------------------------|------|-----|
| | | | Min | Mode | Max |
| Development of zone 8 design | Zone 8 design | 5 | 1 | 1,5 | 2 |
| | Data Equipment for BAE | 20 | 2 | 3 | 6 |
| Lack of and/or insufficient data | Detail design (zones 1-7) | 10 | 1 | 3 | 6 |
| | Zone 8 design | 5 | 0,5 | 1 | 1,5 |
| Different contract interpretation and disputed contract changes (ECP) | Detail design (zones 1-7) | 5 | 1 | 2 | 3 |
| | Zone outfitting (1-7) | 10 | 2 | 4 | 6 |
| Use of class and possible delay | Zone outfitting (1-7) | 10 | 2 | 3 | 6 |
| | Detail design | 2 | 1 | 2 | 3 |
| | HAT | 20 | 2 | 4 | 6 |
| Design reviews and change proposals (QIRS) | Detail design (zones 1-7) | 2 | 1 | 2 | 3 |
| Lack of coordination due to project priorities | Zone outfitting (1-7) | 15 | 1 | 2 | 3 |
| Lack of production/outfitting resources to cover specific challenges | Zone outfitting (1-7) | 60 | 2 | 3 | 4 |
| Tight test and trials schedule (V&V process) | Test readiness review (TRR) | 30 | 1 | 2 | 3 |
| | Harbor acceptance test (HAT) | 30 | 1 | 2 | 3 |
| Management and engineering capacity (towards use of sub-suppliers) | Detail design (zones 1-7) | 10 | 1 | 2 | 3 |
| | Zone outfitting (1-7) | 2 | 0,5 | 1 | 1,5 |

| | | | | | |
|---|-----------------------|----|-----|-----|---|
| Insufficient project commitment using managing tools | Zone Outfitting (1-7) | 50 | 1 | 2 | 3 |
| Efficiency in engineering follow up of production problems | Zone Outfitting (1-7) | 20 | 2 | 3 | 4 |
| Production data and material is not brought to ship in time | Zone Outfitting (1-7) | 70 | 0,5 | 1,5 | 2 |
| Material has not arrived from the suppliers | Zone Outfitting (1-7) | 40 | 1 | 2 | 3 |
| Change of plan, completion of steelwork | Zone Outfitting (1-7) | 10 | 1 | 2 | 3 |

7.2 Impact of Identified Uncertainties

This section describes the identified uncertainties in table 23. Further, the objective is to evaluate if the integration of uncertainties into the baseline model has a significant impact on project duration.

7.2.1 Comment to Input Data for Uncertainties

The first notice about the uncertainties in table 23 is that only 6 out of 17 activities are affected by the identified uncertainties. An activity like “Build Block” with a duration of 366 days does not have any uncertainty. Further, estimates are given with “months” as unit, which is likely to give rough estimates compared to a unit of “days”. All uncertainties are event uncertainties, meaning that the likelihood that an event occurs is less than 100 percent certain. There are no identified opportunities in table 23, only risks of delay. DNV GL identifies opportunities during the process of establishing risk mitigation measures.

Table 23 shows that 17 of the 21 uncertainties identified are symmetrical about the modal value. Three uncertainties are skewed to the right and one uncertainty is skewed to the left. Using table 15 to describe the likelihood of occurrence, three uncertainties are described as “not likely” with a probability of less than 5 percent. Seven uncertainties are described as “likely” with probabilities in the range of 20 - 50 percent, and two uncertainties are described as “very likely” with probabilities in the range between 50 - 100 percent. Finally, nine uncertainties are in the range 5 - 20 percent with the description “less likely”. The majority of uncertainties are in the range of “less likely” to “likely”.

7.2.2 Impact of Identified Risks

The identified risks are added to the deterministic baseline model. This is done by inserting the three-point estimates into probability distributions. The probability distribution used for the case study is unknown. However, a Trigen distribution is assumed suitable. The likelihood of occurrence for an event is multiplied with this function. Finally, all the uncertainties are added together to their respective activity. Appendix 1 shows the model established to integrate uncertainties into the baseline model. @RISK runs a numerical

simulation to calculate the expected value and standard deviation for total uncertainty in each activities. There are six activities in the schedule, which are subject to uncertainties, in terms of delays. Table 24 shows that “Zone outfitting (1-7)” has the highest risk exposure.

TABLE 24 - RISKS ADDED TO SCHEDULE

| ID Number | Activity | Expected Value (Days Delay) | Standard Deviation (days) |
|-----------|----------------------------|-----------------------------|---------------------------|
| 2 | Zone 8 design | 3,8 | 0,78 |
| 4 | Data and Equipment for BAE | 23,2 | 8,93 |
| 6 | Detail Design (Zone 1-7) | 26,5 | 6,46 |
| 9 | Zone Outfitting (Zone 1-7) | 164,6 | 22,95 |
| 15 | TRR | 18 | 6,65 |
| 16 | HAT | 42 | 11,04 |

Table 25 shows the difference in estimated project duration using a deterministic baseline model versus a static stochastic model where uncertainties have been added to the model. The results indicate that adding the identified uncertainties to the baseline model causes a mean delay of about 10,7 months. However, remember that the yard has five working days per week, thus, an additional delay is caused by weekends.

TABLE 25 - INTEGRATION OF UNCERTAINTY INTO PROJECT DURATION

| | Minimum | Mean | 85 percentile | Maximum | Standard Deviation |
|----------------------------|------------|-------------|---------------|-------------|--------------------|
| 1) Baseline | 24.05.2012 | 24.05.2012 | 24.05.2012 | 24.05.2012 | - |
| 2) Static Stochastic value | 28.11.2012 | 15.04.2013 | 22.05.2013 | 09.08.2013 | 37 days |
| Difference | 6 months | 10,7 months | 12 months | 14,5 months | - |

Figure 25 shows the output cumulative probability distribution of the static stochastic simulation, which indicates that the mean finishing date is 15th of April 2013 with a standard deviation of 37 days. The P85-percentile indicates that there is 85 percent chance that the project will finish before 22nd of May 2013.

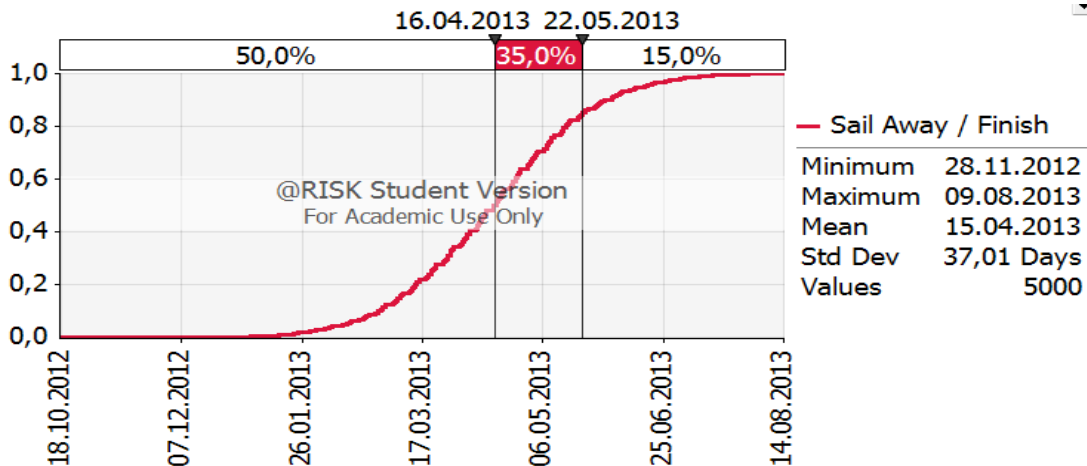


FIGURE 25 - DURATION OF CASE STUDY WITH STATIC STOCHASTIC SIMULATION

7.3 Integration of Correlation Coefficients

7.3.1 Background

One of the most common sources of error in a Monte Carlo simulation is that components are assumed independent (Touran & Wisser, 1992). In DNV GL, it seems that whether correlation coefficients are integrated into the model or not, depends on the person carrying out the risk analysis.

7.3.2 Objective

The objective of this analysis is to illustrate the impact of establishing correlation coefficients between stochastic input variables with linear dependencies. Further, the aim is to increase DNV GL's awareness about which output parameters that are affected. The focus of the analysis is not to represent the correct correlation coefficients between input variables.

7.3.3 Method

There are six stochastic input variables in the case study. However, only the relation with the presumably highest impact on output is considered. This is between "Detail Design (Zone 1-7)" and "Zone outfitting (Zone 1-7)", which are highly correlated. Osmundsen (2005) states that Pearson's correlation coefficient can be divided into simple categories, where each category has a qualitative description. Table 17 describes a value of "1" as *perfect correlation*, while a value of "0,5" is described as *good correlation*. These values are used in this risk analysis. MS Project and @Risk are used to obtain results.

7.3.4 Results

Table 26 shows the results of the simulation. By integrating a correlation coefficient, the standard deviation changes while the expected value remains the same. Integration of correlation coefficients between "Detail Design (Zone 1-7)" and "Zone outfitting (Zone 1-7)" have an impact on outcome for both a coefficient of 1 and 0,5.

TABLE 26 - IMPACT OF CORRELATION COEFFICIENT BETWEEN STOCHASTIC INPUT VARIABLES

| Activity dependencies | Correlation Coefficients | Standard Deviation | Minimum Duration | Maximum Duration | Mean estimated duration |
|---|--------------------------|--------------------|------------------|------------------|-------------------------|
| Initial Case | - | 35,6 days | 03.01.2013 | 30.07.2013 | 16.04.2013 |
| Detail Design (Zone 1-7) & Zone outfitting (Zone 1-7) | 1 | 42,1 days | 20.12.2012 | 16.08.2013 | 16.04.2013 |
| Detail Design (Zone 1-7) & Zone outfitting (Zone 1-7) | 0,5 | 39,2 Days | 14.12.2012 | 05.08.2013 | 16.04.2013 |

7.4 Sensitivity to Choice of Probability Distribution

7.4.1 Background

Observations in previous chapters indicate that DNV GL does not have a consistent way of choosing of probability distributions for uncertainties. Usually, a triangular probability distribution (P1/P99) is used, due to the intuitive nature of defining a best case, worst case and a most likely case value. In Chapter 4, it was argued that people are bad at considering extremes. Thus, a Trigen distribution could be used to compensate for this.

7.4.2 Objective

The objective of this analysis is to increase DNV GL's awareness about the implications of choosing a specific probability distribution to define three-point estimates for uncertainties. Emphasis is at studying the difference in results between a triangular and Trigen distribution.

7.4.3 Method

The probability distributions used in this risk analysis are a *uniform*, a *triangular*, a *Trigen* and a *PERT distribution*. These are suitable when the amount of historical data to base estimates is limited. The analysis is carried out by studying the identified uncertainties only. Thus, the output does not tell us anything about the project duration. It only gives an impression of the impact that the choice of distribution can have. It is much easier to illustrate the differences in output when using @RISK only. Time-consuming simulations are prevented because network structure and dependencies are neglected. Table 27 shows the three-point estimates used in the analysis, which is found by adding together all uncertainties that belongs to a specific activity in the case study. The minimum-maximum values represent the P10/P90 - percentiles for a Trigen distribution. In order to make a comparison between the distributions, this means that the P10/P90 - percentile values reflect P1/P99 - percentiles for the other distributions. Finally, the stochastic simulation is run with 5000 iterations.

TABLE 27 - THREE POINT ESTIMATES USED IN RISK ANALYSES

| Activity | Uncertainties (days) | | |
|----------------------------|----------------------|-------|-------|
| | Min | Mode | Max |
| Zone 8 design | 2,7 | 3,9 | 4,8 |
| Data and Equipment for BAE | 12,0 | 18,1 | 36,0 |
| Detail Design (Zone 1-7) | 18,3 | 25,2 | 35,2 |
| Zone Outfitting | 135,0 | 170,4 | 193,7 |
| TRR | 9,0 | 18,1 | 27,0 |
| HAT | 27,4 | 44,7 | 56,7 |

7.4.4 Results - Choice of Probability Distribution

Figure 26 shows the output distributions for the four distributions. The graph illustrates the effect of the *central limit theorem*, which claims that stochastic variables converge towards a central value. However, the relative frequency of the mean value varies significantly. A triangular and PERT distribution have a high relative frequency, compared to a Trigen and uniform distribution. As expected, the PERT distribution has a slightly higher peak than the triangular distribution, but the standard deviation is similar (see figure 28). The Trigen distribution is somewhat similar to the uniform distribution, which both emphasizes the tails of the distribution. The uniform distribution has the same probability of occurrence for the whole interval of the distribution, and the Trigen distribution sets input values for P10/P90 percentiles. This explains the high value for standard deviation, because open-ended tails sets the absolute extreme values (P1/P99).

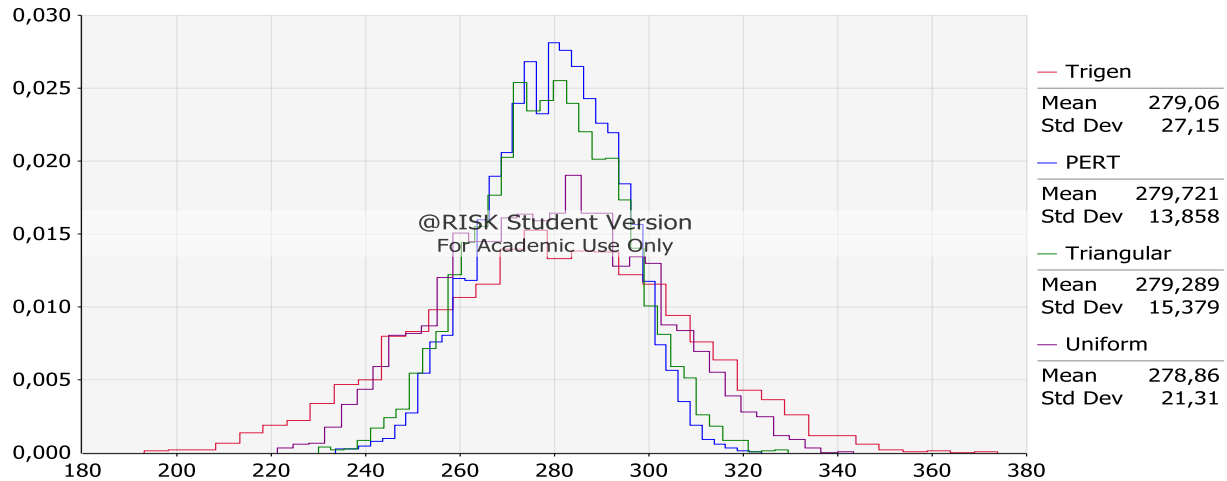


FIGURE 26 - OUTPUT PROBABILITY DENSITY FUNCTIONS

Figure 27 shows the cumulative distributions for the four distributions. The triangular distribution and the PERT distribution have a steep curve, indicating a small standard deviation. The trigen distribution has the smallest steepness, reflecting a high standard deviation. Observe that mean values are similar for all distribution due to the *central limit theorem*. The marked values in figure 29 shows the P85 - percentile estimate for the Trigen distribution. In this area, which represents the tails of the distributions, the differences between the distributions become are more evident.

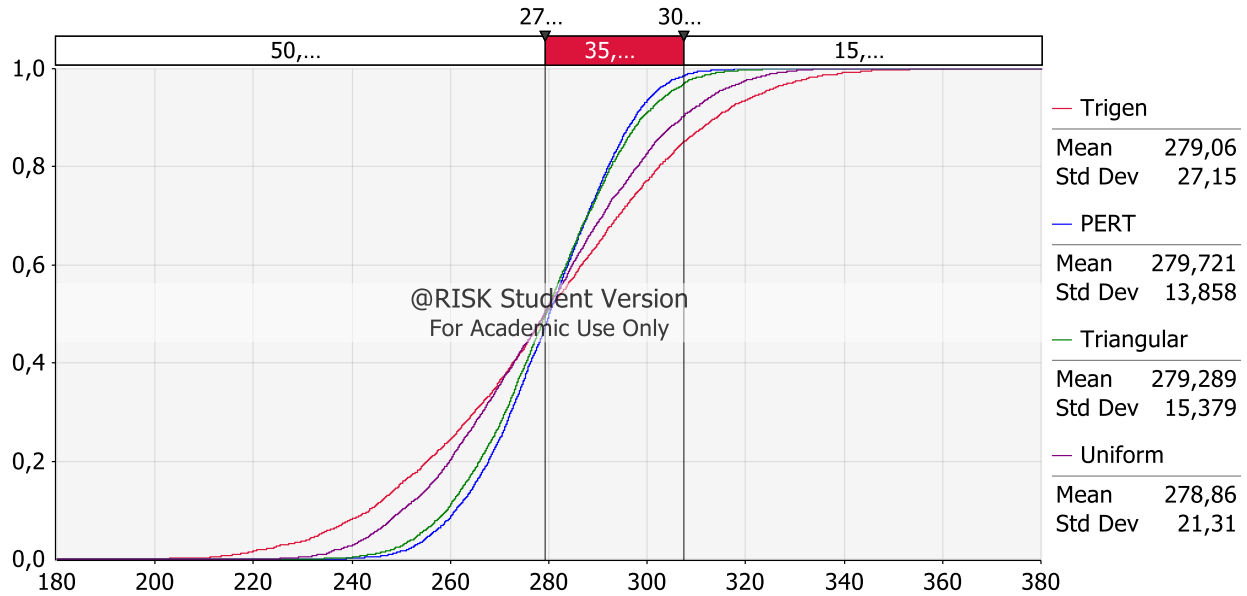


FIGURE 27 - OUTPUT CUMULATIVE PROBABILITY DISTRIBUTIONS

7.5 Sensitivity to Errors in Three-Point Estimates

7.5.1 Background

This section studies the level of error caused by estimation biases in the three point estimates. DNV GL uses a subjective evaluation technique where errors in the established three-point estimates are inevitable. Increased awareness about estimation errors can be used to shape the workshop process and questioning phase where three-point estimates are established.

7.5.1 Objective

The objective of this analysis is to create awareness of how errors in three-point estimates may affect the output. By running a sensitivity analysis for the three-point estimates, the goal is to 1) identify which of the three estimated values that affects the output the most and 2) compare the sensitivity in choice of input values to the choice of probability distributions.

7.5.2 Method

This section considers uncertainties only, as in Section 7.4. The input data is the same as for the previous analysis (table 27). Trigen probability distributions are used to define uncertain activities, because it is suitable for a Bayesian estimation method. Using another probability distribution would give a different impact on the outcome due to a different shape and weighting of the curve. Thus, the result from this illustration is only representative for this case scenario. The skewness and the relative standard deviation will also affect the output values. Finally, the number of iterations is set to 5000.

The risk analysis is carried out by changing each of the three-point estimates individually while the others are locked to their original values. In order to investigate the sensitivity in choice of input values, the mode and the upper value are increased by ten percent relative to initial value. The lower value is decreased by ten percent relative to initial value. By using subjective evaluations, it is considered likely that estimation biases of this size may occur.

7.5.3 Results

Figure 28 indicates that the consequence of estimating wrong modal value is small compared to consequences of estimating wrong extreme values. Not surprisingly, a change in the lower three-point estimate causes the most significant errors in the lower percentile area, while a change in the upper value causes the most significant errors in the higher percentile area. This level of deviation is illustrated in figure 28.

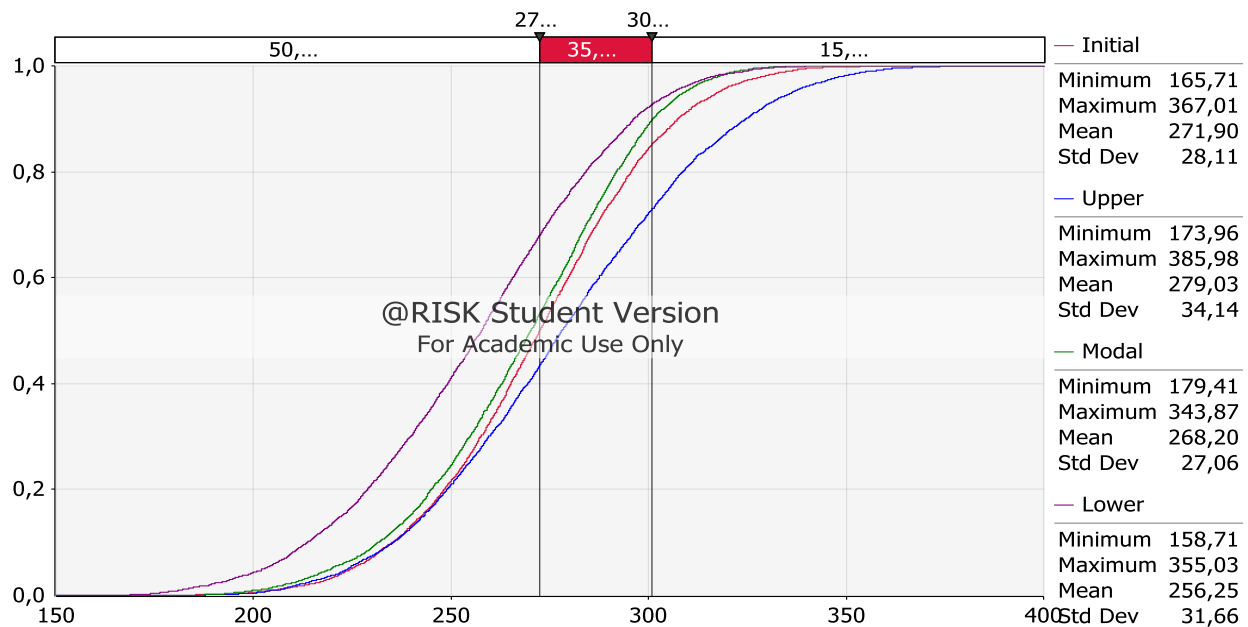


FIGURE 28 - SENSITIVITY TO A TEN PERCENT CHANGE FOR EACH OF THE THREE-POINT ESTIMATES

7.5.4 Comparison of the Two Risk Analyses

One of the objectives in the analysis was to compare the sensitivity to choice of probability distribution to sensitivity to errors in the three-point estimates. Figure 29 shows the percentage error in output values by choosing one of three distributions relative to a triangular distribution. As expected, the errors are most significant in the high and low percentiles, which represent the tails of the probability distribution. Due to the central limit theorem, errors are low around the mean value. Looking at the PERT and the uniform distribution, errors are below 4 %. The Trigen distribution has errors of about 12 % in the lower

percentiles and about 8 percent in the upper percentiles. The errors are not symmetrical around the mean due to skewness in the input distributions. The extreme values for the Trigen distribution are given for the P10/P90 percentiles with open-ended tails causing a wider range. This explains the significant deviation compared to a triangular distribution.

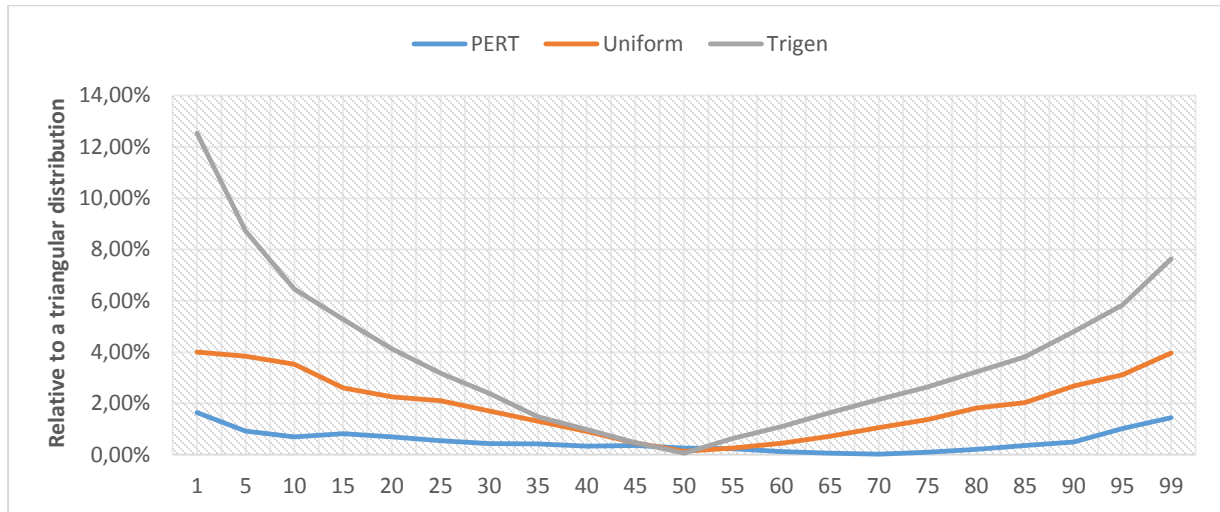


FIGURE 29 - PERCENTAGE ERROR RELATIVE TO USING TRIANGULAR PROBABILITY DISTRIBUTIONS

Figure 30 shows the percentage error in output values, relative to the initial values, for the three-point estimate. As expected, changes in the modal value do not cause significant errors, while errors become significant for the upper and lower percentiles, depending on which of the three-point values that are changed. The reason why errors are more significant for the lower extreme value, compared to the upper extreme value is due to skewness.

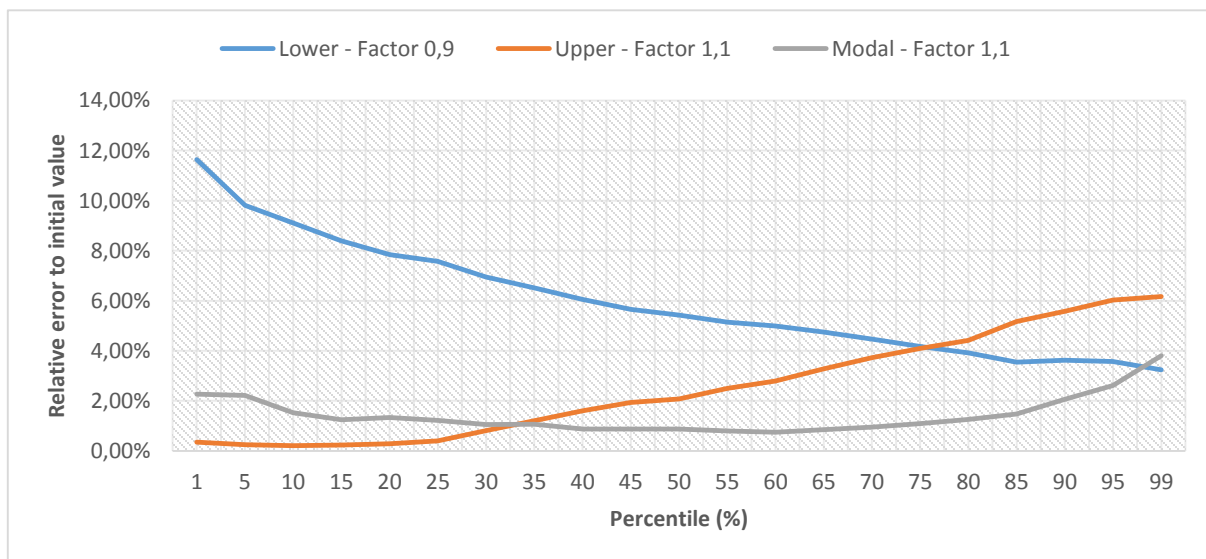


FIGURE 30 - PERCENTAGE ERROR RELATIVE THE INITIAL THREE - POINT ESTIMATE

It is difficult to state whether sensitivity to errors in the three-point estimates are more significant than sensitivity to choice of probability distributions. However, by comparing figure 30 and figure 31 it seems that sensitivity to errors in best-case and worst-case values are generally more significant than the sensitivity to choice of probability distribution, with the exception of the Trigen distribution. In the percentile range from P35 - 65 the errors are below 2 % for all the probability distributions due to the central limit theorem.

7.6 Chapter Summary

Four risk analyses are carried out based on a real case study of a naval vessel built around 2010. In addition, comments are given to three-point estimates for identified uncertainties, assessed during an actual workshop process.

The impact of adding identified uncertainties to the deterministic baseline model is significant and gives a mean project delay of about 10,7 months. Only 6 out of 17 activities have identified uncertainties. Thus, the majority of activities in the schedule represent deterministic input variables instead of stochastic. Finally, 17 of the 21 identified uncertainties are symmetrical about the modal value, and all uncertainties are event uncertainties.

The impact of integrating correlation coefficients is seen by studying the relationship between the activities giving, presumably, the most significant impact. The standard deviation changes, while the expected value remains the same. Compared to the initial case, a correlation coefficient of 1 and 0,5 gives a change in standard deviation equal to 6,5 days and 3,6 days, respectively.

Studying sensitivities to choice of three-point estimates, the effect of the *central limit theorem* is clearly demonstrated in the analysis. While values in the upper and lower range vary for different distributions, the mean value is the same. The Trigen distribution has the highest standard deviation and emphasizes the tails of the probability distribution more than a triangular distribution.

By studying the sensitivity to errors in three-point estimates, it is clear that the consequence of estimating wrong modal value is small compared to errors in extreme values. The sensitivity to errors in best-case and worst-case value (in the three-point estimates) is generally more significant than the sensitivity to choice of probability distribution, with the exception of the Trigen distribution. Errors in the percentile range from P35 - P65 are below 2 % for all the probability distributions, due to the central limit theorem.

8. Discussion

This chapter gives comments on the findings from in Chapter 7. Section 8.1 discusses the impact of adding uncertainties to the baseline mode from Section 7.2, Section 8.2 discusses the impact of correlation from Section 7.3 and lastly, Section 8.3 discusses the identified uncertainties in the case study and the sensitivity to subjective errors from Section 7.4 and Section 7.5.

8.1 Insufficient Variance for Stochastic Simulation

The impact of identified uncertainties from the workshop process causes the project finishing date to be significantly delayed. The analysis in Section 7.2.2 resulted in a mean delay of 10,7 months. This indicates that the workshop process plays an important role in order to obtain a more realistic picture of the project status. Knowing about these delays, the shipyard can establish risk mitigation measures to avoid contractual penalties for delays.

An important notice of the analysis is that the analysis does not compare a deterministic scheduling technique to a static stochastic scheduling technique, because uncertainties are *added* to the baseline schedule, instead of *replacing* deterministic baseline values with stochastic input variables. The consequence of this is that the variation in estimates for activity durations is small. Consider that the risk of delay for an activity is given by a three- point estimate with most likely, worst and best case equal to 30 days, 35 days and 25 days, respectively. A triangular distribution is used to characterize the stochastic input variable with formulas for variance and expected value seen in table 21. The baseline duration for this activity is 300 days. The outcome is an expected duration of 330 days with a variance of only 4 days.

This can be considered as a deterministic estimate, because the mean value will completely dominate in the stochastic input variable. Elmaghraby (2005) calls this the *fallacy of averages*. He argues that managers usually recognize the presence of uncertainty in estimates, but circumvent the required analysis by replacing random variables by their averages. Both Elmaghraby (2000) and Jørgensen (2000) have carried out experiments, which indicate that a deterministic scheduling technique is generally too optimistic. Thus, there is a chance that the DNV GL method will be too optimistic.

DNV GL explains that they have to be cautious about interfering with the baseline model created by the customer. However, one of their objectives is to consult the customer in estimation of project duration. It could be argued that the customer should at least know that there is a potential shortcoming in having a deterministic baseline model. The case studied in this thesis had a baseline activity duration of 15 days for “Pod arrival and Installation”. This activity was more than one year delayed, which indicates that the deterministic value was not certain at all.

8.2 Impact of Correlation

8.2.1 Comment to Results

The analysis carried out in Section 7.3 showed that integrating a correlation coefficient between zone outfitting (1-7) and detail design (1-7) had an impact on the outcome, in terms of increasing the standard deviation from about 35 days to 42 days. A rough calculation for the approximate normal distribution indicates that 70 percent of the area about the mean value corresponds to a project duration between 10th March and 22nd May 2013 without a coefficient. With a coefficient of 1, the same area is between 4th March and 28th May. This is not a significant change considering the relationship was considered one of the most significant in the case study. However, the result shows the potential pitfall of neglecting correlation coefficients. In a case where correlations and standard deviations are significant, the outcome of not adjusting for correlation would be far a too confident estimate with low variance.

8.2.1 Insufficient Variance

Formula 5 explains why the impact of correlation coefficients is relatively small. Covariance is the additional variance that occurs due to correlation, and it depends on the variance for the stochastic input variables (X, Y) and Pearson's correlation coefficient (ρ). If the variance for each of the input variables is small, then the covariance will be small even if Pearson's coefficient is one, which reflects perfect correlation. As discussed in Section 8.1, the activities in the case study have low variance, because the baseline values are deterministic. This can explain insignificant impact.

$$\sqrt{VAR(X) \cdot VAR(Y)} \cdot \rho(x,y) = COV(x,y) \quad , [-1 \leq \rho \leq 1] \quad 5$$

8.3 Subjective Errors and Mitigation Measures

8.3.1 Comments to Three-Point estimates in Case Study

The identified uncertainties for the case study in table 23 showed that 17 of 21 uncertainties are symmetrical around the modal value. This indicates an anchoring effect, which is supported by the fact that DNV GL establishes estimates before the workshop process takes place. By presenting estimated values to the customer, there is already a functioning anchoring effect. DNV GL also uses the Scenario method where potentially dominating people may cause other estimators to be anchored to this person's estimates. Khaneman (2012) suggests a simple solution to this problem; if estimators write down their estimate on a paper before the workshop takes place, there is a much bigger chance that anchoring effect are low. DNV GL is aware of the concern of dominating people, especially in cultures where workers are afraid to speak freely in front of the management team. The use of a local DNV GL surveyor that has to knowledge culture of the company is a very useful in order to evaluate how the workshop should be run.

The likelihood of occurrence is considered “less likely” or “not likely” for 12 out of 21 identified risks, compared to the qualitative description given in table 15. This may indicate that estimators are overly optimistic in their estimates. DNV GL argues that the participants in the workshop process are often too optimistic and think that the present project will be different from previous projects. This is supported by Jørgensen (n.d.), which argues that at least a few external people should estimate values to compensate for overly optimistic internal people.

Signs of overconfidence can also be demonstrated. Only 6 out of 17 activities are affected by the identified uncertainties. The activity “Build Block”, with a duration of 366 days, has none uncertainty inherent in the estimate. The activity “Pod arrival and Installation” had an initial estimated value of 15 days, but it was actually delayed by more than one year. This clearly demonstrates overconfidence. In addition, it seems strange that estimates for identified delays are given in the unit of “Months”, while an activity like “Build Block” is known to the specific day.

8.3.2 Assessment of Three-Point Estimates

The analysis of sensitivity to errors in three-point estimates in section 7.5 indicates that the output is much more sensitive to changes in extreme values, compared to changes in modal value. This is supported by an analysis carried out by Austeng et al (2005-ii). Knowing that people are generally bad at considering extreme cases (Jørgensen, 2014), this is a potential pitfall in subjective assessment of three-point estimates. A practical consequence of this is that extreme values should be considered first, which also minimizes the chance of anchoring effects. DNV GL starts by asking what the worst case would be. Then they ask for the best-case scenario before the most likely is established. Thus, DNV GL runs the process according to what the findings in this section suggest.

8.3.3 Choice of Probability Distribution

The analysis of the sensitivity to choice of probability distribution in Section 7.4 shows clear differences for the output values in the upper and lower percentiles. Because of the central limit theorem, the differences are small around the mean value. DNV GL uses the mean value and the P85 - percentile value in their presentation of a risk analysis. Table 28 shows the difference in these values using either a triangular or a trigen distribution in the risk analysis. The values are presented in “days” to clarify the differences. As expected, the difference is small for the mean value, while the difference becomes evident for the P85- percentile estimate with a variation of 8 days in output value. In addition, the difference in standard deviation is significant.

TABLE 28 - OUTPUT VALUES FOR A TRIGEN - AND A TRIANGULAR DISTRIBUTION

| | Mean (days) | P85 (days) | Standard Deviation |
|------------------------------|-------------|------------|--------------------|
| Trigen | 279,1 | 307,3 | 27,2 |
| Triangular | 279,3 | 299,0 | 15,4 |
| Difference (days) | 0,2 | 8,3 | 11,8 |
| Error relative to Trigen (%) | 0 | 2,7 % | 43 % |

The Trigen probability distribution uses the P10/P90 percentiles to define the best-case and worst-case scenarios. Thus, the open-ended tails in the distribution define the absolute extreme values. The consequence of this is an outcome with higher standard deviation compared to the other probability distributions. The cumulative distribution supports this, as the Trigen distribution present the curve with the smallest steepness. In Section 8.3.1, indications of subjective errors like anchoring, overconfidence and overly optimistic estimates were evident, and these errors tend to give estimates with far too small variance. In addition, Jørgensen (2014) has argued that people are bad at considering extremes. Consequently, it can be argued that Trigen distributions should be used to define three-point estimates instead of triangular distributions.

8.3.4 Estimation Exercise and Establishment of a Database

The Scenario method helps to neutralize the potential pitfall inherent in subjective evaluations by increasing the objectivity in estimates. However, section 8.3.1 identifies several potential errors even though the Scenario method is applied. According to Austeng et al (2005-ii), research has identified two aspects of subjective evaluations: 1) people are generally bad estimators and 2) the estimation skill can be improved through practice. DNV GL's risk management process is limited by the quality of the input data fed into the risk analysis model. Because of this, it could be efficient to start the workshop process with a 15-minute exercise session to improve the estimator's skill. The estimators could be asked to give three-point estimates for a known value, like the height of the Eiffel tower. Their minimum-maximum estimates should reflect 98 percent certainty of having the real height within this range, but Jørgensen (2014) has demonstrated that it is likely that only 60-70 percent of the outcomes are covered within the estimated range. Increasing the awareness about subjective errors could improve the estimator's skill.

Subjective errors could also accounted for by calibrating the estimated values. A database, where both estimates for uncertainties and project duration are collected and compared to actual values, would be invaluable. Subjective errors could be categorized and the frequency of each type of error could be found. This could be used to convince the customer to adjust their estimates or DNV GL could calibrate results. By comparing estimated project duration to actual duration for a wide range of projects, DNV GL could show the customer that deterministic schedules are generally too positive, as an example.

9. Conclusion

DNV GL uses a static stochastic scheduling method, which is currently one of the best ways to estimate project duration for projects with high uncertainty. The estimate for project duration is limited by a deterministic baseline schedule that violates the principle of stochastic scheduling. By adding identified stochastic uncertainties to the baseline model, the case study shows that the outcome is a model where stochastic input variables have a far too small variance. The low variance also limits the impact of integrating correlation coefficients into the model.

A Bayesian estimation method is used to identify and quantify uncertainties. In order to obtain objectivity from subjective evaluations, the workshop is carried out using the Scenario method. By combining these methods, the DNV GL method is very suitable for estimating risk of time overruns, especially in cases when there is little or no available data to base estimates on. The impact of identified uncertainties in the case study gives a mean delay of 10,7 months.

The findings from the analysis of the sensitivity to of errors in three-point estimates suggest that the best-case and worst-case estimates are most sensitive to errors. Further, subjective errors like anchoring, overconfidence and overly optimistic estimates are present in the identified uncertainties in the case study. The analysis of the sensitivity to choice of probability distribution shows that a Trigen probability distribution generates the highest standard deviation for the output value. Thus, a Trigen distribution can be used to compensate for the subjective errors that have been identified in the case study.

DNV GL runs an efficient and well-executed risk management process that considers most of the elements that should be considered in a risk management process. However, the following recommendations could potentially improve the method:

1. Recommend the customer to establish a stochastic baseline schedule
2. A Trigen distribution (P10/P90) should be used to characterize the three-point estimates
3. Introduce a 15-minute exercise in estimation technique
4. Consistency in establishment of correlation coefficient should be a requirement
5. Establish a database and compare estimates to actual results

10. Critique

The two risk analyses carried out to study the sensitivity to errors in three point estimates and errors in choice of probability distributions do not reflect an actual case. The identified uncertainties used in the model were simply added together. Thus, the output does not provide any information about the impact on the case study's project duration. It only gives a general impression of how output is affected by changes in stochastic input variables, which after all was the main objective. The simplification was done in order to obtain good illustrations that revealed the differences. By integrating the whole schedule into the model, time consumption would be significant, and it would be hard to present good illustrations of the output from the sensitivity analysis.

The assessment of correlation coefficients between stochastic input variables was not given much attention. The writer recognizes a poor knowledge about what coefficient values that should be given between different activities. Further, establishment of coefficients were only carried out for one case, because there were few activities with stochastic variables that would have an impact on the outcome. However, more relationships should be evaluated.

Finally, as it is argued that a deterministic schedule is more optimistic than a stochastic schedule, this should be investigated more thoroughly. It would be interesting to establish stochastic input variables for all input variables in the baseline model. The variance for each of the variables could be set to be a specific percentage of the duration for each variables. In this way, a comparison between an approximately deterministic model and a static stochastic simulation with sufficient variance could be carried out. However, the thesis does refer to Elmaghraby (2005) and Jørgensen (2000), which have carried out analysis on this subject showing that a deterministic schedule is generally too optimistic.

11. Further Work

Improvements of the DNV GL method can be done in the assessment of three-point estimates. These estimates affect the outcome significantly and are subject to subjective errors. Studying how subjective errors can be avoided is a very important aspect that should be considered. Magne Jørgensen, professor at *Simula Research Laboratory* at the University in Oslo, has done a lot of research in this field. He has tried to come up with a methodical way to improve subjective estimates. See reference to Jørgensen (2011), Jørgensen (2014) and Jørgensen et al (2006). Much of his work correlate well with Flyvbjerg's idea about a "reference forecasting" (Flyvbjerg et al, 2005) that works by predicting the future, through looking at similar past situations and their outcomes.

Another important aspect that has not been considered in this thesis is the choice of participants to a workshop process. Lichtenberg (2000) has written a lot on this topic. In his book: "*Proactive Management of Uncertainty using the Successive Principle*", he explains that in addition to experts representing key areas, the participants in the workshop process should include individuals that provide vital elements of creativity and breadth. The group should also have a person that functions as the "devil's advocate", as Lichtenberg explains it, in order to compensate for the over-optimistic atmosphere that sometimes exists. Establishing a group having broad competence can minimize estimation biases and potentially improve the DNV GL method.

Finally, the two last phases of the DNV GL processes, 4) Risk Response Planning and 5) Risk Monitoring and Control, should be evaluated. In phase four, establishment of risk mitigation measures is considered. A cost - benefit analysis have to be carried out, because many risk mitigation measures may be ineffective or too expensive to execute. Phase five deals with the follow up of phase four, and the software tools "EasyRisk" that DNV GL uses is an important tool to control and monitor this process. These two phases are just as important as the other stages and should therefore be evaluated.

12. References

- Austeng, K., et al. (2005-i). "Uncertainty analysis - Context and foundations." NTNU, Department of Civil and Transport Engineering (BAT). Trondheim: Concept-program.
- Austeng K., et al. (2005-ii). "Uncertainty analysis - Modeling, estimation and calculation." NTNU, Department of Civil and Transport Engineering (BAT). Trondheim: Concept-program
- Austeng, K., et al. (2005-iii). "Uncertainty analysis - Methodology." NTNU, Department of Civil and Transport Engineering (BAT). Trondheim: Concept-program
- Austeng, K., et al. (2005-iv). "Uncertainty analysis - methodological errors in data and analysis" NTNU, Department of Civil and Transport Engineering (BAT). Trondheim: Concept-program
- Chou, J.-S. (2011). "Cost simulation in an item-based project involving construction engineering and management." *International Journal of Project Management* 29(6): 706-717.
- Chou, J.-S., et al. (2009). "Probabilistic simulation for developing likelihood distribution of engineering project cost." *Automation in Construction* 18(5): 570-577.
- DNV - GL (2012) "New building risk assessment" from presentation to anonymous customer
- Erikstad, S. and Hagen, A. (2002) "Web base tendering collaboration in project-centric industries", COMPIT 2002
- Palisade Corporation, P. (2010). "Guide to using @RISK." from http://www.palisade.com/downloads/manuals/EN/RISK5_EN.pdf.
- Elliot, P. (2012). "First LHD hull arrives in Australia." from <http://www.navy.gov.au/news/first-lhd-hull-arrives-australia>.
- Elmaghraby, S. E. (2005). "On the fallacy of averages in project risk management." *European Journal of Operational Research* 165(2): 307-313.
- EpixAnalytics (n.d.). "Model Assist for @Risk." from http://www.epixanalytics.com/modelassist/AtRisk/Model_Assist.htm#Introduction.htm.
- Flyvbjerg, B., et al. (2005). "How (in) accurate are demand forecasts in public works projects?: The case of transportation." *Journal of the American Planning Association* 71(2): 131-146.
- Gaspar, H. et al. (2013), unpublished source
- Hagen, A. (2014). "Processes upstream to production." Compendium in TMR4125 Shipbuilding, Unit at Norwegian University of Science and Technology.
- Herroelen, W. and R. Leus (2005). "Project scheduling under uncertainty: Survey and research potentials." *European Journal of Operational Research* 165(2): 289-306.
- Jaafari, A. (2001). "Management of risks, uncertainties and opportunities on projects: time for a fundamental shift." *International Journal of Project Management* 19(2): 89-101.
- Jordanger, I. (2005) "Positive uncertainty and increasing returns on investments." NTNU, Department of Civil and Transport Engineering (BAT). Trondheim: Concept-program
- Jørgensen, M. (2011). "Contrasting ideal and realistic conditions as a means to improve judgment-based software development effort estimation." *Information and Software Technology* 53(12): 1382-1390.

- Jørgensen, M. (2014). "The Ignorance of Confidence Levels in Minimum-Maximum Software Development Effort Intervals." *Lecture Notes on Software Engineering* 2(4).
- Jørgensen, M. (n.d.). "Scientia." from https://www.simula.no/publications/Simula.simula.2332/simula_pdf_file.
- Jørgensen, T. and S. W. Wallace (2000). "Improving project cost estimation by taking into account managerial flexibility." *European Journal of Operational Research* 127(2): 239-251.
- Kahneman, D. (2011). *Thinking, fast and slow*, Macmillan.
- Klakegg, O. J. (1993). "Trinnvis-prosessen." NTNU, Department of Civil and Transport Engineering (BAT). Trondheim.
- Klakegg, O. J. (1994). "Tidsplanlegging under usikkerhet." NTNU, Department of Civil and Transport Engineering (BAT). Trondheim.
- Lee, E., et al. (2009). "Large engineering project risk management using a Bayesian belief network." *Expert Systems with Applications* 36(3): 5880-5887.
- Lichtenberg, S. (2000). *Proactive management of uncertainty using the successive principle*, Polyteknisk Press.
- Linstone, H. A. and M. Turoff (2002). "The Delphi Method." *Techniques and applications* 53.
- Moder, J. J. and C. R. Phillips (1964). *Project Management with CPM and PERT*. Project Management with CPM and PERT, Van Nostrand Reinhold Company.
- Olsson, R. (2007). "In search of opportunity management: is the risk management process enough?" *International Journal of Project Management* 25(8): 745-752.
- Osmunden, D. (2005). "Identifikasjon og kvantifisering av sammensatt risiko ved hjelp av Monte Carlo Simulering." *Praktisk økonomi & finans* nr. 3/2005.
- Rand, G. K. (2000). "Critical chain: the theory of constraints applied to project management." *International Journal of Project Management* 18(3): 173-177.
- Rolstadås, A. (1997). *Praktisk Prosjektstyring*, Tapir.
- Roy, R. (2003). "Cost engineering: why, what and how?" *Decision Engineering Report (DEG) Series*.
- Salling, K. B. (2007). "Risk Analysis and Monte Carlo Simulation within Transport Appraisal." Centre for Traffic and Transport, CTT-DTU, Build 115
- Salling, K. B. and D. Banister (2010). "Feasibility risk assessment of transport infrastructure projects: the CBA-DK decision support model." *EJTIR* 1(10).
- Touran, A. and E. P. Wiser (1992). "Monte Carlo technique with correlated random variables." *Journal of construction engineering and management* 118(2): 258-272.
- Vose, D. (2000). *Quantitative risk analysis: a guide to Monte Carlo simulation modelling*, Wiley Chichester.
- Wallace, S. a. K., Alan (2012). *Modelling with stochastic programming*, Springer.
- Øien et al (1996). "Inngangsdata til LCP og bruk av ekspertvurderinger." "Håndbok for gjennomføring av ekspertvurderinger, Prosjektstyring år 2000. Trondheim

Appendix 1

Table 29 and 30 shows how identified uncertainties (yellow) are quantified and added to the baseline model. Trigen probability distributions are defined in grey cells under the columns named “Sum”. The distribution represents the minimum, modal and maximum values seen in the figure. Event probabilities are multiplied with the Trigen functions, and the product is seen in grey cells under the columns named “Sum”. The products are then added together horizontally in the blue column “Sum Uncertainties”, representing total uncertainty for each activity. Depending on what the objective of the analysis is, these uncertainties can be included to the baseline in the blue column named “Summary Duration” by typing 0 or 1.

TABLE 29 - CALCULATED UNCERTAINTIES ADDED TO BASELINE - PART ONE

| ID | Task Name | Baseline Duration | Summary Duration | Included /not(0-1) | Summary Uncertainties | Development of zone 8 design | | | | | Lack of and/or insufficient information | | | | | Different contract interpretation/disputed contract changes | | | | | Use of class and possible delays | | | | | Design reviews and change proposals (QIRS) | | | | | Lack of coordination due to project priorities | | | | |
|----|-------------------------------------|-------------------|------------------|--------------------|-----------------------|------------------------------|-------------|-----|-----|-----|---|-------------|-----|----|-----|---|-------------|-----|----|-----|----------------------------------|-------------|-----|----|-----|--|-------------|-----|----|-----|--|-------------|-----|----|-----|
| | | (days) | (days) | | (days) | Sum | Event Prob. | Min | ML | Max | Sum | Event Prob. | Min | ML | Max | Sum | Event Prob. | Min | ML | Max | Sum | Event Prob. | Min | ML | Max | Sum | Event Prob. | Min | ML | Max | Sum | Event Prob. | Min | ML | Max |
| 1 | Contract award | 1 | 1 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2 | Zone 8 design | 500 | 504 | 1 | 3,8 | 0,075 | 5 % | 1 | 1,5 | 2 | 0,05 | 5 % | 0,5 | 1 | 1,5 | | | | | | | | | | | | | | | | | | | | |
| 3 | Zone 8 design delivery | 0 | 0 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 4 | Data and Equipment for BAE | 743 | 766 | 1 | 23,2 | 0,8 | 20 % | 2 | 3 | 6 | | | | | | | | | | | | | | | | | | | | | | | | | |
| 5 | Data and Equipment for BAE delivery | 0 | 0 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 6 | Detail Design (zone 1-7) | 560 | 586 | 1 | 26,5 | | | | | | 0,3 | 10 % | 1 | 3 | 6 | 0,1 | 5 % | 1 | 2 | 3 | 0,2 | 10 % | 1 | 2 | 3 | 0,04 | 2 % | 1 | 2 | 3 | | | | | |
| 7 | Build Blocks | 366 | 366 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 8 | Launch Vessel | 1 | 1 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 9 | Zone Outfitting (zone 1-7) | 680 | 844 | 1 | 164,5 | | | | | | | | | | | 0,4 | 10 % | 2 | 4 | 6 | 0,1 | 2 % | 2 | 3 | 6 | | | | | | 0,3 | 15 % | 1 | 2 | 3 |
| 10 | Switch board Power Up | 62 | 62 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 11 | Start-up & Test Diesel Generator | 0 | 0 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 12 | Control & IPMS Test Completion | 179 | 179 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 13 | Pod Arrival & Installation | 15 | 15 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 14 | IPS Start-up & Test Propulsion | 130 | 130 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 15 | TRR | 1 | 19 | 1 | 18,0 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 16 | HAT | 22 | 64 | 1 | 42,0 | | | | | | | | | | | | | | | | 0,8 | 20 % | 2 | 4 | 6 | | | | | | | | | | |
| 17 | Sail Away | 0 | 0 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

TABLE 30 - CALCULATED UNCERTAINTIES ADDED TO BASELINE MODEL - PART TWO

| ID | Lack of production/outfitting resources to cover specific challenges | | | | | Tight test and trials schedule (V&V process) | | | | | Management and engineering capacity | | | | | Insufficient project commitment using managing tools | | | | | Efficiency in engineering follow up of production problems | | | | | Production data and material is not brought to ship in time | | | | | Material has not arrived from the suppliers | | | | | Change of plan, completion of steelwork | | | | |
|----|--|-------------|-----|----|-----|--|-------------|-----|----|-----|-------------------------------------|-------------|-----|----|-----|--|-------------|-----|----|-----|--|-------------|-----|-----|-----|---|-------------|-----|-----|-----|---|-------------|-----|----|-----|---|-----|---|---|---|
| | Sum | Event Prob. | Min | ML | Max | Sum | Event Prob. | Min | ML | Max | Sum | Event Prob. | Min | ML | Max | Sum | Event Prob. | Min | ML | Max | Sum | Event Prob. | Min | ML | Max | Sum | Event Prob. | Min | ML | Max | Sum | Event Prob. | Min | ML | Max | | | | | |
| 1 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 3 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 4 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 5 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 6 | | | | | | | | | | | 0,2 | 10% | 1 | 2 | 3 | | | | | | | | | | | | | | | | | | | | | | | | | |
| 7 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 8 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 9 | 1,8 | 60% | 2 | 3 | 4 | | | | | | 0,02 | 2% | 0,5 | 1 | 1,5 | 1 | 50% | 1 | 2 | 3 | 0,3 | 20% | 1 | 1,5 | 2 | 0,899 | 70% | 0,5 | 1,5 | 2 | 0,49 | 40% | 0,5 | 1 | 2 | 0,2 | 10% | 1 | 2 | 3 |
| 10 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 11 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 12 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 13 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 14 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 15 | | | | | | 0,6 | 30% | 1 | 2 | 3 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 16 | | | | | | 0,6 | 30% | 1 | 2 | 3 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 17 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

Appendix 2

Table 31 shows output data for the probabilistic Gantt chart in the case study, which indicates that a one path defines the project duration. The only exception, where both parallel paths have an influence on calculated project duration, is the “Test Readiness Review” and the “Harbor Acceptance Trial”. The first has a critical index of 2,76 % , while the latter dominates with an index of 97,24 %.

TABLE 31 - DATA FROM PROBABILISTIC GANTT CHART FOR CASE STUDY

| ID | Task Name | Deterministic | | Probabilistic | | | | | | Critical Index |
|----|----------------------------------|---------------|--------------|---------------|------------|------------|-------------|------------|------------|----------------|
| | | Start | Finish | Start Min | Start 15% | Start Mean | Finish Mean | Finish 85% | Finish Max | |
| 1 | Contract award | tir 23.9.08 | tir 23.9.08 | 23.9.2008 | 23.9.2008 | 23.9.2008 | 23.9.2008 | 23.9.2008 | 23.9.2008 | 100 % |
| 2 | Zone 8 design | ons 24.9.08 | tir 24.8.10 | 23.9.2008 | 23.9.2008 | 23.9.2008 | 30.8.2010 | 31.8.2010 | 2.9.2010 | 0 % |
| 3 | Zone 8 design delivery | tir 24.8.10 | tir 24.8.10 | 26.8.2010 | 27.8.2010 | 30.8.2010 | 30.8.2010 | 31.8.2010 | 2.9.2010 | 0 % |
| 4 | Data and Equipment from BAE | ons 24.9.08 | fre 29.7.11 | 24.9.2008 | 24.9.2008 | 24.9.2008 | 1.9.2011 | 15.9.2011 | 4.10.2011 | 0 % |
| 5 | Data and Equip. for BAE delivery | fre 29.7.11 | fre 29.7.11 | 5.8.2011 | 18.8.2011 | 1.9.2011 | 1.9.2011 | 15.9.2011 | 4.10.2011 | 0 % |
| 6 | Detail Design (zone 1-7) | ons 24.9.08 | tir 16.11.10 | 24.9.2008 | 24.9.2008 | 24.9.2008 | 23.12.2010 | 3.1.2011 | 19.1.2011 | 100 % |
| 7 | Build Blocks | ons 23.9.09 | tor 17.2.11 | 30.9.2009 | 21.10.2009 | 31.10.2009 | 27.3.2011 | 6.4.2011 | 22.4.2011 | 100 % |
| 8 | Launch Vessel | tor 17.2.11 | tir 29.3.11 | 24.2.2011 | 17.3.2011 | 27.3.2011 | 28.3.2011 | 7.4.2011 | 25.4.2011 | 100 % |
| 9 | Zone Outfitting (zone 1-7) | ons 23.9.09 | ons 2.5.12 | 30.9.2009 | 21.10.2009 | 31.10.2009 | 25.1.2013 | 28.2.2013 | 15.5.2013 | 100 % |
| 10 | Switch board Power Up | fre 29.4.11 | tir 26.7.11 | 5.10.2011 | 19.12.2011 | 23.1.2012 | 18.4.2012 | 23.5.2012 | 7.8.2012 | 100 % |
| 11 | Start-up & Test Diesel Generato | tir 26.7.11 | tir 26.7.11 | 30.12.2011 | 14.3.2012 | 18.4.2012 | 18.4.2012 | 23.5.2012 | 7.8.2012 | 100 % |
| 12 | Control & IPMS Test Completion | tir 16.8.11 | man 23.4.12 | 20.1.2012 | 4.4.2012 | 9.5.2012 | 15.1.2013 | 19.2.2013 | 6.5.2013 | 100 % |
| 13 | Pod Arrival & Installation | tir 4.10.11 | tir 25.10.11 | 11.10.2011 | 1.11.2011 | 10.11.2011 | 1.12.2011 | 12.12.2011 | 28.12.2011 | 0 % |
| 14 | IPS Start-up & Test Propulsion | tir 25.10.11 | tir 24.4.12 | 29.3.2012 | 12.6.2012 | 17.7.2012 | 15.1.2013 | 19.2.2013 | 6.5.2013 | 100 % |
| 15 | Test & Readiness Review (TRR) | tir 24.4.12 | ons 25.4.12 | 27.9.2012 | 11.12.2012 | 15.1.2013 | 11.2.2013 | 19.3.2013 | 4.6.2013 | 2,76 % |
| 16 | Harbour Acceptance Trial (HAT) | tir 24.4.12 | tor 24.5.12 | 27.9.2012 | 11.12.2012 | 15.1.2013 | 15.4.2013 | 22.5.2013 | 9.8.2013 | 97,24 % |
| 17 | Sail Away | tor 24.5.12 | tor 24.5.12 | 28.11.2012 | 7.3.2013 | 15.4.2013 | 15.4.2013 | 22.5.2013 | 9.8.2013 | 100 % |