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Artificial Intelligence as a Tool for Project Decision-Making Support

Master's thesis in Engineering & ICT
Supervisor: Nils Olsson
June 2022

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Preface

This master's thesis is written during the spring of 2022 as the final delivery of the five-year master's program in *Engineering & ICT* at the Norwegian University of Science and Technology (NTNU). The thesis is written as part of the specialisation *Project and Quality Management* at the Department of Mechanical and Industrial Engineering and counts toward 30 credits.

We were first introduced to the topic of *Artificial intelligence in Projects* by our supervisor Nils Olsson in the spring of 2021. In the autumn of 2021, we wrote our specialisation report separately but under the same topic of artificial intelligence. As the lessons learned were many, collaborating on the master's thesis would give us new opportunities to further investigate the topic.

Our problem statement is "*Artificial Intelligence as a Tool for Project Decision-Making Support*". Digitalisation drives decision-making to enhance confidence and reliability in outcomes and predictions in all project management processes. Digitalisation is the "talk of the century", and the pressure to strive towards digital transformation increases. How may these technologies improve the industry's efficiency and effectiveness? The risk and opportunities of these technologies should be carefully studied, and the people expected to use these tools should not be forgotten when considering digital transformation.

The energy industry, for example, faces significant changes concerning business, operation and increasing demands. The operation in this industry has a history of fixed patterns and routines. It is exciting to be a part of the evolution of digital innovation and learn how to utilise and optimise this new technology in business areas such as project management.

As our study program has involved a hybrid selection of courses. It was therefore important for us to utilise both the knowledge of traditional engineering and our technical background. Therefore, it has been exciting to combine project management theory with the potential use of artificial intelligence and machine learning.

Acknowledgement

We would like to give special thanks to all the supportive persons who have made this master's thesis a great experience. This thesis would only become a qualitative literature research study without all the collaborative parties. We have been very fortunate to have had great follow-up and guidance throughout spring 2022.

First, we would like to give a big thank you to our supervisor, Nils Olsson. We have appreciated the guidance and support Nils has given us throughout our final year at NTNU. Nils' constructive feedback and valuable insight during our guidance hours have been very intuitive. If not for Nils' drive, we would not have been introduced and had such a good connection with the collaborating partners in this thesis.

Thank you for the contribution of Jon Lereim and Prosjekt Norge. Jon is a passionate driver of the digitalisation of project management and has given useful guidance into our thesis' problem statement and research questions. With his connection to Projekt Norge's research projects, we acknowledged helpful insight into the topic of digitalisation, project management and decision-making.

We would like to thank the collaborating companies, especially the main company that gave us project data and participated in valuable interviews. The company has shown great enthusiasm and interest in our thesis' progress and results, which has motivated us to do good work throughout this semester. We appreciate the time our main contact persons set aside for meetings and interviews to inform and guide us through their project data and system.

A special thanks to our families, that have given us nothing but love, support, and encouragement during our studies.

Finally, we would like to thank all our friends at NTNU for making the last five years a fantastic and unforgettable time for both of us.

Abstract

With the increased use of digitalisation in project management work processes, the pressure of utilising and implementing technologies to improve efficiency and effectiveness is rising. To fully benefit from digitalisation, digital transformation is desired; the transformation is done through the utilisation of new technology such as Artificial Intelligence (AI) and Machine Learning (ML). Digitalisation and digital transformation are strong drivers when evaluating and creating opportunities for improved project execution and operations.

The problem statement of this thesis is "*Artificial Intelligence as a Tool for Project Decision-Making Support*". The thesis aims to explore the current state of digitalisation in project decision-making and assess which decisions can be impacted by the implementation of AI technology. The thesis has limited its scope to investigate expectations around digitalisation and AI in the energy industry through three research questions. AI is discussed in regard to support and utilisation in corporate memory, and its benefits in evidence-based decision-making.

A triangulated study combining qualitative and quantitative research is performed to answer the research questions. The study combines the results from surveys and interviews conducted with employees from the energy industry. Simultaneously a data analysis utilising AI/ML technology on corporate memory data is conducted to test the theory in practice. The data analysis uses predictive neural networks to estimate cost and identify similarities between project data entities.

Based on the research methodology, the findings have concluded with positive expectations for the development of digitalisation and AI technology in the energy industry. The digitalisation survey and theory suggest that the industry is currently in an early phase of digitalisation, and a step in the right direction has been taken. The collaborating companies are all optimistic and excited about the future regarding digital transformation and the implementation of new technology.

The standardised corporate memory data used in the analysis show great potential for AI applications. The ML models show promising results when utilised in supporting project management. However, the models displayed varying performances on different projects. This variance is believed to be due to some cost factors not being represented in the data.

It is found that the people affected also play a significant role in the success of digital transformation. The respondents of the surveys and interviews pointed out digital maturity as the most significant challenge. Digital maturity includes the employees' data skills and understanding, which is crucial for the technology to succeed.

There is also scepticism towards AI machines making project management decisions, replacing the role of the project manager. The research currently suggests that human-machine collaboration is preferred. Where AI and ML models support human expertise, ensuring improved evidence-based project decision-making.

Sammendrag

Med økt bruk av digitalisering i prosjektledelsesarbeidsprosesser øker presset med å utnytte og implementere teknologier for å forbedre effektiviteten. For å få fullt utbytte av digitalisering ønskes digital transformasjon; transformasjonen gjøres gjennom bruk av ny teknologi som kunstig intelligens (AI) og maskinlæring (ML). Digitalisering og digital transformasjon er sterke drivere når man skal evaluere og skape muligheter for bedre prosjektgjennomføring og drift.

Problemstillingen i denne oppgaven er "*Kunstig Intelligens som et Verktøy for Støtte for Prosjektbeslutninger*". Denne oppgaven tar sikte på å utforske den nåværende tilstanden til digitalisering i prosjektbeslutninger og vurdere hvilke beslutninger som kan påvirkes av implementeringen av AI-teknologi. Oppgaven har begrenset omfanget til å undersøke forventninger rundt digitalisering og AI i energibransjen gjennom tre forskningsspørsmål. AI blir diskutert angående støtte og bruk i "Corporate Memory" systemet og fordelene med evidensbasert beslutningstaking.

En triangulert studie som kombinerer kvalitativ og kvantitativ forskning utføres for å besvare forskningsspørsmålene. Studien kombinerer resultatene fra undersøkelser og intervjuer utført med ansatte fra energibransjen. Samtidig utføres en dataanalyse ved bruk av AI/ML-teknologi på "Corporate Memory" data for å teste teorien i praksis. Dataanalysen bruker prediktive nevrale nettverk for å estimere kostnader og identifisere likheter mellom prosjektdataenheter.

Studien konkluderer med at det er knyttet positive forventninger til utviklingen av digitalisering og AI-teknologi i energibransjen. Digitaliseringsundersøkelsen og teorien tyder på at næringen nå er i en tidlig fase av digitaliseringen, og at et skritt i riktig retning er tatt. De samarbeidende bedriften er optimistiske for fremtiden når det gjelder digital transformasjon og implementering av ny teknologi.

De standardiserte "Corporate Memory" dataene som brukes i analysen viser et stort potensial for AI-applikasjoner. ML-modellene viser lovende resultater når de brukes som støtteverktøy i prosjektledelse. Imidlertid viste modellene varierende grad av nøyaktighet på de forskjellige prosjektene. Denne variansen antas å skyldes at noen kostnadsfaktorer ikke er representert i dataene.

Det er funnet at de berørte ansatte også spiller en betydelig rolle i suksessen til digital transformasjon. Deltakerne i undersøkelsene og intervjuene pekte på digital modenhet som den største utfordringen. Digital modenhet inkluderer ansattes dataferdigheter og forståelse, noe som er avgjørende for at teknologien skal lykkes.

Det er også knyttet skepsis til at AI-maskiner tar prosjektledelsesbeslutningene, og erstatter prosjektlederrollen. Forskningen tyder på menneske-maskin-samarbeid er å foretrekke, der AI- og ML-modeller støtter menneskelig ekspertise, og slik sikrer forbedret og evidensbasert beslutningstaking.

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List of Abbreviations

AFE	Authorisation For Expenditure
AI	Artificial Intelligence
ART	Accountability Responsibility & Transparency
CM	Corporate Memory
CPS	Cyber Physical System
CRISP-DM	CRoss-Industry Standard Process for Data Mining
CSF	Critical Success Factors
CVP	Capital Value Process
DG	Decision Gate
DSP	Decision Support Package
DSS	Decision Support System
EAD	Ethically Aligned Design
ECC	Enterprise Cognitive Computing
EDS	Engineering Design Specification
EPC	Engineering, Procurement & Construction
ESS	Energy Storage System
EU	European Union
FEED	Front End Engineering Design
FID	Final Investment Decision
IoT	Internet of Things
IMORL	Interactive Multi-Objective Reinforcement Learning

IPMA International Project Management Association

KM Knowledge Management

KMS Knowledge Management Systems

KPI Key Performance Indicator

LCI Life Cycle Information management

LogAcc Log Accuracy

MAE Mean Absolute Error

MAPE Mean Absolute Percentage Error

ML Machine Learning

MSE Mean Squared Error

NSD Norwegian Centre for Research Data

OBS Organisational Breakdown Structure

OMS Organisational Management System

PEP Project Execution Plan

PIMS Project Information Management System

PMB Performance Measurement Baseline

PMBoK Project Management Body of Knowledge

PMI Project Management Institute

PMP Project Management Process

PMS Performance Measurement System

PRINCE2 PRojects IN Controlled Environments

RFID Radio-Frequency Identification

ReLU	Rectified Linear Unit
RMSE	Root Mean Squared Error
ROI	Return On Investment
SeLU	Scaled exponential Linear Unit
t-sne	t-distributed stochastic neighbour embedding
VUCA	Volatile, Uncertain, Complex & Ambiguous
WBS	Work Breakdown Structure

1 Introduction

With the increased use of digitalisation in project management work processes, the pressure of utilising and implementing technologies to improve efficiency and effectiveness is rising in many industries. To fully benefit from digitalisation, digital transformation is desired. The transformation is done through the utilisation of new technology such as Artificial Intelligence (AI), the Internet of Things (IoT), and Machine Learning (ML). Digitalisation and digital transformation are strong drivers when evaluating and creating opportunities for improved project execution and operations.

The problem statement of this thesis is to investigate how "*Artificial Intelligence as a Tool for Project Decision-Making Support*". Digitalisation drives decision-making to enhance confidence and reliability in outcomes and predictions in all project management processes. Digitalisation is the talk of the century, and the pressure to strive toward digital transformation increases. How may these technologies improve the industry's efficiency and effectiveness? The risk and opportunities of these technologies should be carefully studied when considering implementing digital transformation.

As AI technology is emerging into several industries, it is still in an exploring and starting phase for the energy industry. The collaboration with the three energy industry companies has given insight into the needs and expectations of digitalisation and new technologies. This thesis aims to explore the current state of digitalisation in project decision-making and assess which decisions can be impacted by the implementation of AI technology.

The future objective is to use AI to achieve prescriptive analytics and encourage a more data-driven form of decision-making. A prescriptive form of decision-making will result in more precise, efficient and evidence-based decisions. The tools necessary to accomplish this form of decision-making may be developed from the data made available through Industry 4.0.

Gartner identifies technology trends every year that are critical to business. *Decision intelligence* and *AI engineering* are two out of twelve strategic trends that enable companies' CEOs to deliver growth, digitalisation and efficiency (Gartner, 2022). These two technology trends involve what this thesis will address. Data has become a valuable asset for many organisations, and it has great potential to utilise the data an organisation collects to its advantage.

The research structure of this master's thesis is three-parted. It involves digitalisation surveys, interviews and data analysis. The input from the literature study and digitalisation surveys were utilised to get background information about the relevant topics. Simultaneously, closer collaboration with a company allowed us to conduct data analysis on their corporate memory project data. The same company also participated in interviews to get further insight into the corporate memory system and the potential of AI and digital transformation.

The Research Questions

The three research questions (RQs) below were assembled to limit the thesis scope from the overall topic.

1. *What are the expectations of digitalisation in the Norwegian energy sector?*
2. *How can artificial intelligence, in particular, machine learning, support and utilise corporate memory?*
3. *How can artificial intelligence be beneficial for evidence-based decision-making utilising corporate memory?*

The Energy Industry

The energy industry, among other industries, is facing significant changes concerning the business, operation and increasing demands. Park et al. (2021) describe how important it is to recognise, prepare, and respond to the future trends of the energy industry's digitalisation and rapidly changing environment. The operation in this industry has a history of fixed patterns and routines concerning the collaboration between operators, system integrators, main contractors and suppliers. Development and operations in the past predominantly show a sequential approach, affecting the interfaces between the various development stages in value creation. The interface challenges are typical of technical, organisational and contractual nature. The plain sequential pattern challenges the technical interface in elements such as compatibility of information flow, integration of various data sources, and contextualisation of data.

Park et al. (2021) refer to how the energy industry is undergoing various changes such as the spread of renewable energy, Energy Storage Systems (ESS) and electric vehicles. There is also an expansion of the demand management market and consumer service innovation through digitalisation which converges with advanced technologies such as IoT and AI. The massive data generation and development of computing technology have increased the attention to forecasting methodology using big data. Therefore, there is a growing need to structure the unstructured text data utilised in big data to be used more effectively in future predictions.

Currently, technologies such as AI and IoT contribute to enhancing the sustainability of the energy industry. In terms of energy demand, digitalisation can reduce unnecessary energy consumption and optimise energy usage. Digital technology development can significantly change energy supply, transaction and consumption. The technology will increase efficiency, stability and safety. (Park and Kim, 2021)

2 Theoretical Background

The theory consists of nine sub-sections. To begin with, project management, breakdown, planning and performance are introduced. Then the project development in the energy industry is explained as it applies to all the cooperating companies. Decision-making and knowledge management is presented next as it is relevant for the RQs and data analysis.

Before the sub-sections about artificial intelligence and machine learning, the evolution of digitalisation and descriptive to prescriptive analytics are introduced. All the sub-sections define important terms and definitions before discussing the advantages and disadvantages of the topic regarding project management and the energy industry. Finally, the last sub-section Section 2.9 ties relevant theory all together.

The Sections 2.1, 2.2, 2.6 and 2.8, are inspired from the theory written in our respective specialisation projects, (Rasmuss, 2021; Tømte, 2021). The sections are combined, re-written and/or supplemented with new material.

2.1 Project Management

Project Management has been around for a long time. It was not before the 1960s that project management and the development of its techniques were recognised as a discipline (Kutsch and Hall, 2016). The first international associations, IPMA (International Project Management Association) and PMI (Project Management Institute) were founded between 1965 and 1969. These associations helped establish project management as a profession, creating clear guidelines, definitions and processes for good practice of managing projects (Rolstadås et al., 2020). As project management involves many different aspects and an unlimited amount of theory, the theory has had to be limited to cover the most important elements of this thesis.

During the 1960s, organisations and societies increasingly began to projecticise and organised themselves in terms of utilising time-limited sequences and project-based structures in their business operations (Kuura, 2020; Whittington et al., 2008). The term and concept "projectification" was introduced much later, in the middle of the 1990s (Kuura, 2020). This "projectification" of companies only intensified, and in 2004, PwC conducted a study on project management maturity in organisations. The report concludes "that it is hard to imagine an organisation that is not engaged in some kind of project activity." (Evrard and Nieto-Rodriguez, 2004; Jensen et al., 2016). As nearly all businesses have operations that can be defined as projects, the project manager is now a well-known and versatile profession. Project success is closely tied to managing the project, and having successful projects is highly important to businesses. Project management is therefore crucial for many businesses. It is also a continuous area of improvement as delays, and cost overruns are often the norm (Love et al., 2013).

By definition, no two projects are the same. They can vary immensely in cost, scale, and theme, making it difficult to determine best practices and approaches. However, PMI developed a primary book on project management - "A Guide to the Project Management Body of Knowledge (PMBoK)". The book defines basic project terms and describes the project life cycle and important practice areas of expertise and processes (Rolstadås et al., 2020). PMI focuses on ten competence areas, and for each area, they define several processes. It combines the competency within project management and the essential processes to satisfy the customer. PMBoK defines *project management* as the "application of knowledge, skills, tools, and techniques to project activities in order to meet or exceed stakeholder needs and expectations from a project" (PMI, 2017).

PMBoK has been the basis of the ISO standard for project management (ISO 21500) and the English PRINCE2 (PRojects IN Controlled Environments). PRINCE2 focuses on the project owner's perspective and shows the importance of a project rooted in an organisation's business processes. The PRINCE2 project model is less clear on competence areas but further in defining core processes on a higher level (Rolstadås et al., 2020).

Project management is no straightforward matter, and producing a successful project involves balancing competing demands such as:

- Scope, time, cost, and quality.
- Stakeholders with differing needs and expectations.
- Identified requirements (needs) and unidentified requirements of a project (expectations) (PMI, 2017).

The scope, time, cost, and quality are the most easily quantifiable from the bullet points above. In contrast, the other two points are harder to measure and subject to change even after the project period is over.

Traditional project management assumes that the project's scope is fully known in advance and often relies on delivering based on the requirements. It is a significant limitation, and it is clear that Olsson (2006) and Dyba and Dingsoyr (2008) believe the focus on traditional stability becomes challenged when managing projects today.

2.1.1 Project Success

There is a lot of research and literature on the topic *project success*. There is an obvious development in project management theory on defining project success. From a traditional view, focusing on stability, predictability and the project execution itself, often referred to as the "iron triangle" objectives of time, cost, and quality (Kutsch and Hall, 2016). In today's view, project managers focus more on the whole project life cycle and responding well to change and uncertainties. Key terms when discussing success includes *success criteria* and *success factors*. Success criteria determine whether a project is considered a success or failure when delivered. Johansen et al. (2019) refers to success criteria as parameters that are evaluated after project completion to decide whether a project has been successful. Success factors are defined as the set of factors and conditions that the project must comply with to increase the likelihood of success (Hussein, 2016; Johansen et al., 2019; Müller and Jugdev, 2012). The connection between the two terms is to identify the success factors required to achieve the defined project success criteria. The success factors also include the possibility to monitor and influence during the project execution (Rolstadås et al., 2020).

Several studies map Critical Success Factors (CSF), both for projects in general and more specific factors based on the project characteristics the project has. An example is an article by Müller and Jugdev (2012), which addresses the famous project management scholars Pinto, Slevin and Prescott's contribution to project success and related CSF in the 1980s. CSF may consist of clear objectives, a project manager with professional knowledge and insight, and the correct composition of a project team.

Hussein (2016) mentions two main challenges of defining success, the first one, how to *define* success and the other how to *measure* success. The challenge of defining success is to decide what criteria, dimensions and indicators to use and who will be responsible for evaluating them. One approach is defining the success criteria at the beginning of a project. Then it avoids discussing what the evaluations are based on at the end of the project. This approach creates a straightforward way to identify success factors, including the different stakeholders' perceptions of success and creating a shared vision and responsibility for the project. Martinez and Fernandez-Rodriguez (2015) writes about the importance of the different stakeholder's perceptions of success. What could be satisfactory for one could be unsatisfactory for the other. Another challenge with defining the success criteria in advance is assuming that the project scope and estimations are correct and will remain unchanged during the project life cycle.

The challenge of *measuring* success is deciding how and when to measure it. Hussein (2016) describes two approaches, and the first one is an objective approach to define the success criteria in advance and measure them at the end of the project. A second approach is a subjective approach, where success and failure are assessed by all stakeholders looking at the same project with different evaluation criteria. Challenges with the first approach are that it implicates that the time frame to determine success is immediately after the project-end. It presumes that not all the stakeholders will necessarily arrive at the same conclusion. Johansen et al. (2019)

describes success as always measured against goals, defining three sets of goals; project goals, business goals and societal goals. Where the project goals describe the project's final delivery within the "iron triangle". Business goals describe the outcome sought for the users of the project's result, e.g. if the planned competitive advantage was not achieved, the project might have failed according to the project owner's perspective. Finally, the societal goals involve the value and benefits the project should contribute to the society in the longer term.

The three goals Johansen et al. (2019) mentioned are very similar to the three perspectives Hussein (2016) described to evaluate project success.

- *Project manager success* - measures the extent to which the project has managed to meet the requirements of the traditional "iron triangle".
- *Process - success* - includes how the project participants have perceived or experienced the project execution. Focusing more on emotion and reason, because the project can have filled the requirements on time and budget, felt like a failure to other project stakeholders that feel ignored or run over.
- *Project success* - consider meeting the expectations of the purpose, outcome, customer satisfaction, achieving strategic economic goals, and increasing competitiveness.

2.1.2 Project Flexibility

The term *Flexibility* is frequently used in many different situations and disciplines. For an organisation to be flexible is "considered to have the ability to change itself so that it remains viable." (Bahrami and Evans, 2010, p. 18). Olsson describes flexibility as a "diverse property of a project"(Olsson, 2015, p. 5). The property or the opportunity to respond well to uncertainties due to scope changes and adjust to change based on iterative decision-making.

Uncertainty is "the primary need for project flexibility" (Johansen et al., 2019, p. 79). There are different nuances that highlight different aspects of uncertainty when discussing flexibility. Uncertainty is defined as the gap between the needed amount of information versus the available amount of information. It is where project flexibility can be used as an advantage to reduce the amount of required information.

Traditional project management would rather avoid flexibility and strive toward predictability and stability in projects. Instead, it is possible to renew this perspective and view project flexibility as a tool to manage uncertain and unpredictable situations that will always occur in a project. Olsson (2015) has developed a project flexibility framework to help organisations better understand, analyse and utilise project flexibility as an advantage.

Olsson (2015) introduced four strategies for managing project flexibility. The duration of a project is a flexibility driver to take into account. If a project has a long time frame, it is necessary to either decide to avoid or manage changes. The first strategy is "late locking of project scope and fast execution". By postponing the locking of the project scope, it gives the project more flexibility to gain more information before defining the final scope. The project will be more open to changes without high costs. After the scope is locked, fast execution is essential to avoid significant changes and high costs in later stages of the project.(Olsson, 2015)

The second strategy involves "shielding off areas of uncertainty". This approach is about project parts that is possible to define later than others when defining project scope. The uncertainty is identified and handled in later project stages. An example is splitting up a project to focus on the most important. The third flexibility strategy is about incremental commitments. It includes splitting a project into different stages, where each phase is executed, but at the end of the phase, the project can choose to continue, abandon or defer (Olsson, 2015). The possibility for decision-making opens up and has a connection to the different types of *real options* described by (Yeo and Qiu, 2003). The final approach to flexibility is called "absorption", which includes living with the changes. In this strategy, "slack" is often mentioned referring to having reserves, time-slack to manage the changes (Olsson, 2015).

2.1.3 Resilience in Projects

Projects are characterised by the achievement of unique goals with limited resources. In contrast to other business-as-usual activities, projects involve greater risk and uncertainty (Kutsch and Hall, 2016). *Project Resilience* is defined as the project's ability to survive adversity. The idea is to recognise the inherent fallibility of a project so it can successfully recover when confronted with disruptions. Disruptions could come in the form of significant, unforeseen events that create a sudden collapse in the project or a creeping erosion of performance, the latter being a more typical "death" for projects (Kutsch and Hall, 2016).

Traditionally, the way to address adversity in projects has been to transform uncertainty into risk and then manage this risk (Naderpajouh et al., 2020). It has resulted in the knowledge area of risk management. Risk management aims to reduce the impact of negative risks and take advantage of positive risks (Rahi, 2019). Risk management is concerned with the "known unknowns", the uncertainties that can be calculated and addressed. However, Pich et al. (2002) argues that some uncertainty will always stay unknown and therefore unmanageable. Mapping, analysing, and preparing for risks in highly uncertain environments becomes costly and near impossible. Projects in uncertain environments are likely to encounter unexpected influences that could not have been accounted for. Project resilience is the capacity to organise during disruptions in the form of shocks or stressors and thus also deals with the "unknown unknowns". Project resilience aims to increase awareness of changes in the environment and ensure that the project can adapt and recover when faced with disruptions.

Black Swans are "unknown unknowns" that significantly affect projects. They are defined as events that meet the following three criteria (Taleb, 2007):

- It is an outlier as it lies outside the realm of regular expectation.
- It carries an extreme impact.
- Humans nature makes us concoct explanations for its occurrence after the fact, making it seem explainable and predictable.

Black swans in a project setting are unforeseen events that come as a surprise with catastrophic consequences despite precautions. Taleb (2007) believes that the way to manage these events is to become robust and protected from adverse events, a description that fits well with the concepts of project resilience. Hajikazemi et al. (2016) proposes a more defined approach, proposing that the early identification of warning signs of an imminent possible black swan, combined with practical and proactive knowledge management, can prevent or lessen the consequence of these types of events. Black swans are also compatible with project resilience, which Kutsch and Hall (2016) views as the ability to notice, interpret, prepare for, and consistently contain and recover from adversity.

2.2 Project Breakdown, Planning & Performance

Projects are means to achieve an organisation's strategic goals, and it is the project manager's task to bring the project to completion on time, within the budget cost, and to meet the planned performance or end-product goals (Anantatmula, 2010; Dvir et al., 2003). A project manager needs to break the project down, create a good and manageable plan and then satisfyingly execute this plan.

2.2.1 Work Breakdown Structure

It is a fundamental prerequisite to breaking the project down into separate and defined tasks in larger projects. Breaking down work into separate manageable entities is called the Work Breakdown Structure (WBS). The WBS is a crucial part of creating an effective follow-up of the project execution (Rolstadås et al., 2020). PMI defines a WBS as "A hierarchical decomposition of the total scope of the work to be carried out by the project team to accomplish the project objectives and the required deliverables" (PMI, 2017). The WBS will work as a framework for planning and scheduling and establish a reference for tracking time, cost, and availability of resources. It will also serve as a base for tracking the progress and technical execution of the project (Globerson, 1994; Rolstadås et al., 2020). The WBS is hierarchical, meaning that the development of a WBS is done in levels with different ranks of scope. The first level, Figure 1 is created by separating the project as a whole into separate categories. Each of the items in this level is then divided into level two items. The process is repeated until the amount of work related to the items is small enough to be manageable for discrete tasks (Rad, 1999).

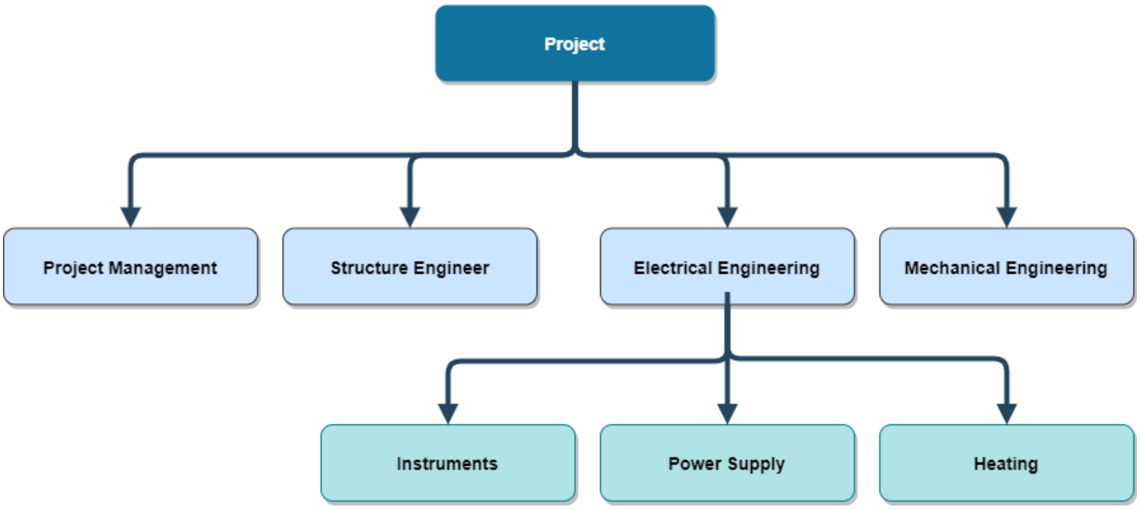

Figure 1: Example of the first levels of a WBS.

The scope of the lowest level items is important as these must have the following requirements (Rolstadås et al., 2020, p. 165):

- Status of the work can easily and unambiguously be decided.
- They have clearly defined start and end.
- They have a clear result.
- Time and cost can easily be estimated for the item.
- They have a finite and short duration.
- The work related to the item is independent of other elements when initiated.

These items are often referred to as WBS-items, tasks, or packages. The WBS-items and the levels of the WBS serve as a basis for the planning, scheduling, and cost estimation of the project going forward (Globerson, 1994).

2.2.2 Organisation Breakdown Structure

As the project is broken down into individual WBS-items, the organisation is broken down into an Organisational Breakdown Structure (OBS). Here the lowest level items are individual groups tasked with executing specific WBS-items (Golany and Shtub, 2001). The two structures are combined on these items, and the connection results in a "cost account" (Rolstadås et al., 2020). Figure 2 is an illustration of this relationship.

The cost accounts are items containing a specified amount of work and the people/resources associated with the work. The cost accounts act as the allocation of the organisation's resources to tackle the work in the project. These two structures and their integration provide a framework for project planning.

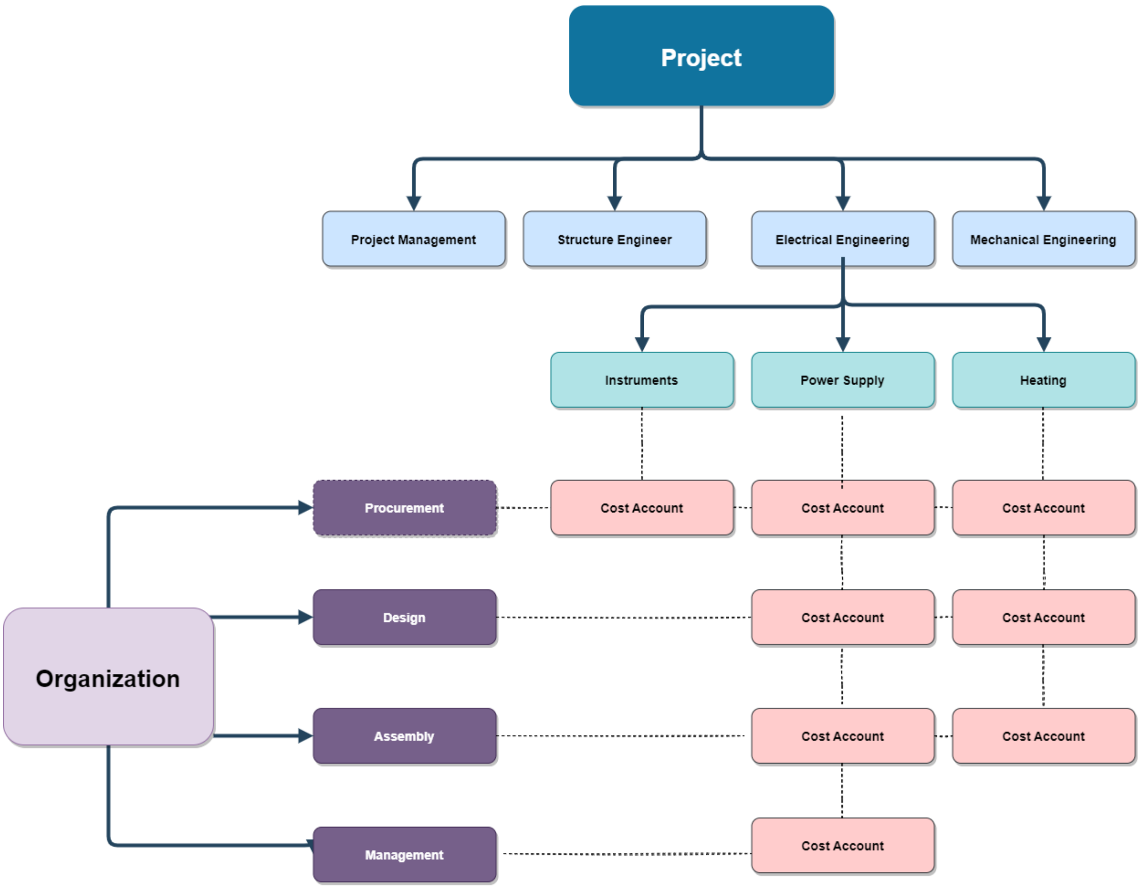

Figure 2: Illustration of integration between WBS and OBS as described in (Rolstadås et al., 2020)

2.2.3 Planning & Scheduling

The OBS and the WBS represent the "what" and "who" of a project. For a project, it is also necessary to decide "when". There are two terms related to the "when" in projects, planning and scheduling. Planning is deciding on the duration of each activity and what order they will be executed. Scheduling is to set the start and end times of activities in a project. An activity is here an operation that pushes the project further. (Rolstadås et al., 2020) lists three requirements for activity in this setting:

- It must be significant to the plan.
- The responsibility for the activity must be assignable to one person.
- Can be assigned a start and end time and scope of work.

An activity could be a WBS-item, a work packet, or the work related to cost account from these requirements. During scheduling, the activities are mapped based on the dependencies, duration, and available resources. The schedule is often represented in a Gantt chart or a network analysis. Gantt charts are simple to read and understand but do not typically portray dependencies and resource availability. Network analysis is used to show the dependencies between the tasks. The structure of the schedule is then an adjustment concerning what tasks have to be done sequentially and which can be done in parallel (Taylor, 2008). The network is typically created using a PERT chart or "critical path methods" to calculate the minimum time required to complete the project (Rolstadås et al., 2020).

2.2.4 Baseline

When the project has started, the project needs to be tracked to make sure "everything is going to plan". A baseline is set to measure the performance of a project. The baseline is critical for project success because it establishes the expectations of the project (Taylor, 2008). It models how the project progression will be made and acts as a reference point for deciding how the project is moving along. It is also an essential tool for communicating progression to the stakeholders in the project. According to Zafar and Rasmussen (2001), the baseline is essential for both contractors and owners to ensure that their long-term interests are guaranteed.

At the start of a project, the baseline represents the WBS and all approved changes. When established, it must be approved by the customer and key stakeholders. Any changes to the baseline must be done through a formal process approved by the customer and stakeholders. Revisions of the baseline are common but should be kept to a minimum. It is to ensure that the stakeholders in the project are as familiar with the baseline as possible. When changes are made to the baseline, it should only show changes from the current time forward; past performance cannot be changed. It is necessary to have this rule to protect the integrity of the historical data and ensures that the history of agreements and contracts is not altered. (PMI, 2017; Røberg, 2020)

The Performance Measurement Baseline (PMB) is the baseline for the project as a whole (Taylor, 2008). The performance measurement baseline represents the overall progression when the project has started. A study performed by Terry Cooke Davies on identifying factors that lead to project success found that one of two general factors that correlate to on-cost performance was maintaining the integrity of the PMB (Cooke-Davies, 2002). It is typical to refer to PMB when discussing "the baseline", but individual baselines can be created for different aspects of the project. Typically the PMB is split into the schedule, the cost, and the technical baseline (Taylor, 2008). The following section will further address the field *Performance Measurement*.

2.2.5 Performance Measurement

As mentioned in Section 2.1.1, project success requires some measurement to evaluate if the project is a success. The field of performance management has developed from providing general feedback and recommendations on improvement to introducing performance measurement frameworks and systems to implementing and using performance measurement systems (PMS) to manage organisational performance (Pavlov and Bourne, 2011). The history of performance and performance measurement has its origin from the term *productivity*, which was introduced with the industrial revolution. The revolution led to a change in demand with more focus on efficiency, and by adding labour efficiency and machine utilisation, the result became the term productivity (Andersen and Fagerhaug, 2002).

In the middle 1980s, the term *performance* replaced productivity, as the simple output/input relationship did not cover the development of market and business evolution. Similar to defining project success, "there is no generally accepted definition of performance." (Andersen and Fagerhaug, 2002, p. 15). The definition of performance varies over time, industry and person. It generally covers a wide range of aspects of an organisation, such as being innovative, attracting the best employees, maintaining the environment, and ethically conducting business. To measure performance is to get an understanding and instant feedback on how well various activities are completed to produce a certain level of performance. As Pavlov and Bourne (2011) states, "Managing through measures".

Managing performance has the potential for an organisation to generate value. Still, it is frequently seen as ineffective because it requires a significant investment of resources and cost and creates challenges for the organisation if implemented poorly (Guerra-López and Hutchinson, 2013). There are challenges concerning the employees' reaction to the impact of change, which is naturally received with uncertainty and perhaps resistance. In this situation, it is essential to analyse the uncertainty in the project, and the project flexibility, to identify the risks but also the opportunities for performance management (Johansen et al., 2019).

Why Measure Performance?

The purpose of performance measurements is to provide employees with feedback on the work they are performing. It generates several positive effects, such as improved motivation or the spurring of improvement initiatives. "If you cannot measure it, you cannot improve it." (Pavlov and Bourne, 2011, p. 102).

The article by Olsson and Bull-Berg (2015) identified primary groups for evaluating projects, one of them was performance measurement evaluations. The goal is *continuous improvement* and Andersen (2007) introduces a resourceful continuous improvement toolbox. Because every organisation will have to improve, some often, some now and then, but otherwise, it is hard to remain competitive.

With continuous improvement, every error or challenge is a "treasure", as it gives the opportunity for improvement (Andersen and Fagerhaug, 2002). This is in line with what Johansen et al. (2019) encourages. With the mindset change to not view uncertainty as undesirable but as an opportunity. As most people only perform their daily tasks, being involved in continuous improvement activities may be fun and motivational.

Performance measurement provides a general information basis that can be exploited for decision-making purposes, both for management and for all levels of employees. A PMS may become an instrumental panel used both for strategic manoeuvring, day-to-day running of the organisation and planning and implementing improvements and changes. The system also works as an early warning system and should not be underestimated. It has many benefits, such as helping alter behaviour and increasing motivation. The system can help with trend monitoring, improvement prioritisation and as a basis for *benchmarking*. (Pavlov and Bourne, 2011) states that performance measurement initiatives have the means to have a significant impact on the organisation and the organisation's processes.

Be aware of the psychological impact that being measured can have on people. As (Pavlov and Bourne, 2011) describe how the impact is unpredictable and often misunderstood. The power of performance measurement can often be described as a "black box" as the impact of performance measurement is separated from its intended outcome. A vital path to avoid is measuring on a personal level, using the measurements for punishment or other negative feedback. Measurements on an individual level need not be damaging if used correctly, but in the hands of manipulative or even "psychopathic" management will potentially ruin the work environment and create fear in general among the employees.

Bititci et al. (2012) highlight how rapidly changing industry affects the way organisations are managed, as well as the use of performance measurements. The shift from manual work to knowledge work builds on the need for an organisation to focus more on collaborative relationships, trust and leadership. One can also mention the disruptive and emerging focus on *project flexibility* that introduces different approaches to handle uncertainty and chase opportunities. Lean thinking is one approach to managing project flexibility by focusing on delivering a project while maximising value and minimising waste (Johansen et al., 2019).

Benchmarking

Benchmarking is a part of continuous improvement. Performance measurement as a basis for benchmarking involves collecting performance data that may be used as a reference point for taking measures against (Andersen, 2007).

Andersen et al. (1999) describes the essence of benchmarking as "learning from others". Key terms within benchmarking are *measurement*, *comparison*, *learning* and *improvement*. *Measurement* involves measuring the internal organisations' and benchmarking partners' performance level for both *comparison* and *improvement*. The comparison of performance level, processes and practice is done to achieve better knowledge and *learn* from own and others' performance. The *learning* step is essential for benchmarking to introduce *improvements* for the organisation, which is the main objective when conducting a benchmarking study. A benchmarking study is described as a structured process including a step-by-step process model. Benchmarking studies may take a longer time than expected, but the aim is for the organisation to recognise best practices for improvement (Anderson and McAdam, 2004).

There are several different benchmarking maturity levels (Anderson and McAdam, 2004; McAdam et al., 2008). From internal benchmarking to global benchmarking. Internal benchmarking refers to benchmarking within one's organisation. The next maturity levels expand the boundaries of whom one compares oneself, from close competitors to other industries until reaching a global level. Andersen and Fagerhaug (2002) and Anderson and McAdam (2004) describes three different types of benchmarking; strategic, performance or process benchmarking. The benchmarking depends on the organisation's purpose in conducting a benchmarking study. It could be to learn from benchmarking partners what strategic direction to pursue, compare performance levels or get a deeper understanding and learn from the processes to gain certain performance levels.

The most challenging task is finding benchmarking partners willing to participate in the benchmarking studies. Important factors to consider are that they are a close match, believed to be sufficiently better and willing to teach others by sharing their best practice. The organisation should use their network and associations to reach companies through different channels to map the relevant companies (Andersen et al., 1999). Companies participating in benchmarking studies appreciate a straightforward, systematic procedure and open communication to attract and know their expectations.

When conducting a benchmarking study, it is required to collect quantitative and qualitative information. Quantitative - the performance data is used to map the differences in performance levels, and the qualitative - business process descriptions are used to create the learning basis among the participants in the study. The challenge is getting the benchmarking partners to hand over confidential information that could involve financial information and/or intellectual property rights, which, understandably, many are unwilling to release. Give the partners enough time in advance to allow time to gather data and preparations. Exchanging all possible background information, to begin with, is useful to start straight on the interesting parts without wasting time. (Andersen et al., 1999)

2.3 Project Development & Execution in the Energy Industry

The Project Development and Execution process for a project addresses the whole project life cycle. It begins with an idea being created continuously until the results of the project are taken out of operation. Large dimensions and high budgets characterise energy industry projects and most operators in the industry have adopted a stage-gate project management process to manage these large investment projects. The project life cycle is split into different stages according to the maturity level of the project. The project stages have the objective of enhancing project performance and quality end-product (Johansen et al., 2019).

Individual organisations often refer to their project development process with different names and tailor them to their line of business. Different ways to structure the stages and manage the gates are also common. However, there is often much more similarity between the processes than differences among the systems (Cooper, 1990; Denney, 2006). The stages presented below translates well to the energy industry, although alterations also exist among companies there. Other names given for these kinds of systems (or similar systems) are Project Management Processes (PMP) or Capital Value Processes (CVP), stages are often referred to as phases and decision gates are often referred to as stage gates. In this thesis, they will be referred to as stages and decision gates.

2.3.1 The Stages

Stage-gate systems apply process management methodologies to project and innovation processes. (Cooper, 1990) explains the methodology in regards to innovation processes. However, the analogy applies to stage gates in project management, as innovation processes can be seen as projects. As products are built and produced in stages, the project is built in the same way. Work is divided into stages, and the products are controlled for quality between each stage. Only the products that pass the check are moved further to the next stage. The projects are managed in the same way, work is divided into stages, and quality is assured between the stages.

Each stage has different work activities, and a set of deliverables are specified for each phase. The stages are separated by a decision gate (or stage gates) that evaluates the deliverables of the phase and decides whether the project can move into the next phase. Whereas the projects are checked against a list of criteria, the gates in a project management process are governed by gatekeepers (Cooper, 1990). The decision gates are managed by gatekeepers that review the phase deliverables' quality and approve the project to continue into the next phase. These gatekeepers are typically senior managers with the authority to approve the resources needed to transition the project into the next phase.

Decision gates are moments in a project's lifespan that require a commitment to an investment or design decision that significantly affects the project. The earlier stages in the CVP are typically less expensive than the later stages, so the decision gate often signifies a commitment of company resources to the project. The decision gates can hold the project until it is ready to continue or kill it early if deemed unfeasible. It makes the decision gates a tool for risk management. The decision gate system ensures that information is gathered and analysed before making a big decision. As the project moves through the stages, information and expense increase with every stage transition. (Nitesh Gupta and Weig, 2017)

As the decision gate signifies a commitment of significant money or resources to the project, it incentivises all participants that the gate reviews are meaningful and important events in a project's lifespan. The project team is aware of the criteria of the deliverable needed to move the project into the next phase, and the gate review acts as a proof of quality for the project owners (Cooper, 1990).

Johansen et al. (2019) presents the following stages as an example of a project development and execution process, also illustrated in Figure 3:

- Stage 0: Identify
- Stage 1: Select
- Stage 2: Define
- Stage 3: Execute
- Stage 4: Commission

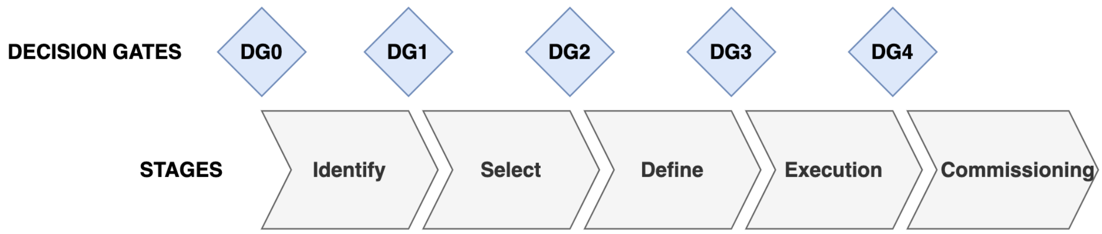

Figure 3: The stages and decision gates in the project development and execution process.

Identify

The Identify phase maps the need the project or business opportunity will address (Johansen et al., 2019). It can also be called a feasibility study, as the objective of the phase is to test the feasibility of pursuing an opportunity. This phase addresses fundamental questions on the feasibility of the project. Issues around how the project can technically be achieved need consideration and testing of different alternatives might be needed. The team must also decide whether the project aligns well with the organisational overall goals and strategy. During the identify phase, potential business opportunities are tested and developed to the point where they can be evaluated against each other. The team decides on a measure of success, prepares estimates for cost and schedule, and builds a preliminary execution plan for each identified business opportunity.

The deliverable of the feasibility phase is a Decision Support Package (DSP) that includes a description of the scope of the opportunity, the economic analyses, market benefits, the strategic fit and an execution plan (Johansen et al., 2019). Other outputs from the identify phase can be an overview of key stakeholders, an initial identification of risk factors and a plan for moving forward (Denney, 2006). The DSP is presented to the gatekeeper for deciding to revise, abandon or move on with the business opportunity.

Select

The project moves on into the *Select* phase when a business opportunity passes through the decision gate after the identifying phase. Different approaches for the business opportunity are evaluated during the select phase to identify the best development plan. Different concepts need to be identified, and thus information gathering and innovation are prevalent in this phase (Denney, 2006). As with the identify phase, alternative approaches are developed until they can be evaluated against each other. Resource requirements, risk factors and further project opportunities are identified, and the team also prepares estimates for cost and schedule, success measures and the execution plan. Again, this is gathered in a DSP and presented to the gatekeeper for revising. The result of the select phase is selecting an approach for the business opportunity deemed to be the best fit for the organisation.

Define

Define is the engineering phase of the project. It is often called the Front End Engineering Design (FEED) or Engineering Design Specification (EDS) phase. During this phase, the technological options and process design concepts have been chosen, focusing on the technical requirements and costs for the project. Project owners, operators and engineering contractors work closely to ensure that the project-specific requirements are met (Denney, 2006). During the FEED phase, main project costs are identified, and a price for the project's execution phase is established. Potential risks and opportunities of the project are further identified and evaluated. The main objective of the Define phase is to make the Execution phase run as smoothly as possible. Typical activities during this phase are to finalise the project scope, finalise the technology and process design, finalise the Project Execution Plan (PEP) and prepare risk management. Items subject to long lead times are also procured at this stage. Long lead items have long delivery times that can affect the overall completion time of the project. It is therefore important that these are procured ahead of time (Johansen et al., 2019). Along with a DSP, the team also prepares a request to approve the project budget and schedule estimates. This request comes in the form of an Authorisation of Expenditure (AFE) or a Final Investment Decision (FID). The phase also marks the end of the project's front end marking that the major part of planning is done.

Execution

The objective of the *Execution* phase of the project is to execute the project plan according to the scope and design determined in the previous phase and the PEP (Johansen et al., 2019). It involves everything from the tendering, procurement and construction of the defined plan. There are three central functions involved in this phase, engineering design, procurement of equipment and material, and physical construction of the facility, often called Engineering, Procurement and Construction (EPC). Most project owners do not have the resources or skills to complete all the EPC activities, which often leads to hiring contractors to execute this work. Executing the project likely involves hundreds of company staff and thousands of contractors and is an immense effort. The owner manages the services provided by these contractors, and the project management skills during this phase have long been considered unique and required (Denney, 2006). Typical activities during this phase are to complete the engineering design, procure the equipment and material used, construct the facility according to plan and perform checks to assure that the equipment and material have been installed according to the design specifications. Deliverables of the phase include the facility documents (plan to commission and startup the facility and an operating manual), and a DSP presented to the gatekeeper. The gatekeeper receives this DSP, and an inspection team ensures that the construction is built according to the plan, specifications, industry standards, and regulatory requirements from relevant authorities.

Commissioning

This phase is also referred to as Operation & Review. During this phase, the facility is commissioned, and operations on the facility are initialised. *Commissioning* ensures that all systems and components that went into the project are designed, installed, and operated according to the owners' specifications. The commissioning group verifies, tests and inspects all the operational components, assuring that the facility can do the processes it is built to do. It means checking that the facility can start to pump energy from the well, using the facility for energy companies. The project is then reviewed and evaluated. Documentation about the project is delivered to the owner, and contracts are closed. It is during this phase that much of the learning occurs, and firms use this phase to capture lessons learned in order to improve future projects (Denney, 2006). A final DSP is presented to the gatekeeper, marking the project's end.

2.4 Decision-Making

Decisions are taken all around at all times and levels, and as Lunenburg states, "it is fundamentally a *people* process." (Lunenburg, 2010). As a project manager, it is required to make big and small decisions every day. The choices and actions taken may greatly impact the prospects for the individual, the customer and the team. It is a large responsibility to identify the best path to make the right decisions and find the most optimal of all identified alternatives (Cohen, 2005).

Decision-making may be defined as "a process of making a choice from a number of alternatives to achieve the desired result." (Lunenburg, 2010). Regardless of how much or little information is gathered to arrive at a specific conclusion, it will leave a doubt concerning if it is the "best" decision. Kalantari (2010) refers to organisational decision-making as a complex process that is affected by many other factors in the organisation.

The complexity of decision-making has increased. Decisions are not considering the relevant variables, their future effects, or what happened in the rate would capture the opportunities and mitigate the risks for an organisation. White and Rollings (2021) have found that decisions today must be *connected*, *contextual* and *continuous* to establish a symbiotic relationship between humans and machines to generate the optimal action for a modern future-fit. They also believe that by 2023, more than 33% of large organisations will have analysts practising decision intelligence.

Cohen (2005) discusses the need for a framework that can be applied to a wide range of decisions having varying degrees of complexity. His proposal contains three steps; *defining* the question, *perfecting* the question and finally *answering* it. There are three dimensions to consider. If the decision should be answered based on facts, feeling or if the involved are in the position to make the decision independently. The whole process consists of developing a list of assumptions, classifying them as pros or cons, giving them weight or a score to calculate the total decision value. The framework will help people feel less anxious and feel recognised and valued. The quality of the decision will reflect the effort made to arrive at the specific decision, and therefore it may require time and patience.

Historically, there are two basic models for decision-making; the traditional rational model and the bounded rationality model. Elbanna (2006) discuss that decision-makers should consider combining both intuitive and rational processes to complement each other to achieve a balanced perspective.

2.4.1 The Rational Model

The rational model of decision-making is a step-by-step approach where the individuals use facts, information and analysis to reach a decision (Lunenburg, 2010; Uzonwanne, 2016). Commonly, the older generation leans more toward rational decision-making than the younger. The process involves taking into account all available information, probabilities of events, and potential costs when consistently determining the best choice of action (Uzonwanne, 2016).

From the literature found, there were various steps in the rational decision-making model. As a main outline, Lunenburg (2010) six steps involves:

1. Identifying the problem
2. Generating alternatives
3. Evaluating alternatives
4. Choosing an alternative
5. Implementing the decision
6. Evaluating decision effectiveness

After a problem is identified, the alternative solutions to the problem are derived. The evaluation step makes sure that the best alternative is carefully chosen for implementation. Lunenburg (2010) refers decision-making as an iterative activity. After the chosen alternative is implemented, it will also be evaluated over time to assure its present and continued effectiveness.

Uzonwanne (2016) advocates that rational decision making is the most promising, practical and functional process for leaders and managers when investments, stakeholders and high stakes are involved. He discusses the importance of decision-making models as an aspect of training for all executives, leaders, and managers in the governmental and entrepreneurial industry.

2.4.2 Bounded Rationality

When discussing rational decision-making, it indicates that the decision-maker is completely rational. If a person is entirely rational, the person would have perfect information knowing all the alternatives and consequences, leading up to selecting the optimal solution for each problem (Lunenburg, 2010). In reality, this is not the case. People are often limited by time, cost and the ability to collect and process information.

Herbert Simon is a well-known researcher and contributor to management on the topic of the human decision-making process and the evolution of the bounded rationality model (Kalantari, 2010). He stated that an organisation does make the decisions, but people do. Bounded rationality is the idea that rationality is limited because of the cognitive limitations of the mind and the time available to make decisions. Based on these criteria, decision-makers often act as satisfiers seeking a satisfactory solution rather than an optimal one. It may be more realistic to achieve objectives that are "good enough" rather than the "best" (Elbanna, 2006).

Simon advocates that rationality is the goal of organisational decision-making, but cognitive abilities and external factors limit the decision-maker. Hence as Elbanna (2006) addresses, "decision-makers are rational to the limits of their capabilities." (Kalantari, 2010).

2.5 Knowledge Management

Knowledge Management (KM) is the planned and continuous management of tools, processes, systems, structures, and culture to improve the utilisation of *knowledge* critical for decision-making and an organisation's competitiveness (Calitz and Cullen, 2017). The utilisation of knowledge concerns the creation, sharing, and utilisation, both internally and externally, of the organisation intending to meet the corporate objectives.

Salzano et al. (2016) encourage organisations to develop a robust strategy and structured approach to KM as KM enables organisations to make finer decisions faster and contributes to delivering higher-quality products more efficient. Organisations that manage KM strategically can have positive effects on innovation, efficiency and profitability (Calitz and Cullen, 2017).

A significant component of organisational knowledge lies in the form of *tacit* knowledge embedded into its members. Tacit knowledge is the knowledge that is "not explicated" (Spender, 1993). The knowledge that is hard to communicate and codify is regarded as tacit knowledge. A large portion of the experience the members of an organisation retain during work is not explicitly written down and is therefore regarded as tacit knowledge.

Opposed to tacit knowledge is *explicit* knowledge. Baumard (1999) stated that explicit knowledge rests upon the tacit knowledge, and people often cannot articulate more than a small fraction of the knowledge on which they rely. The majority of knowledge is gained by experience, created as tacit knowledge, but later made explicitly and shared by social interaction (Genç and Öykü İyigün, 2011). Calitz and Cullen (2017) describe the challenge of knowledge not being accessible to all employees in an organisation, especially tacit knowledge, resulting in valuable lessons learned may be lost. Lost knowledge leads to repeated mistakes and/or reinventing the wheel.

Calitz and Cullen (2017) introduced The Four Pillars of Knowledge Management framework, see Figure 4. The framework involves four Environmental Influences; Social, Political, Governmental and Economic. The four main pillars are; Leadership, Organisation, Technology and Learning. These pillars are the fundamental domains that are shown to have the potential to incorporate all the aspects of effective knowledge sharing.

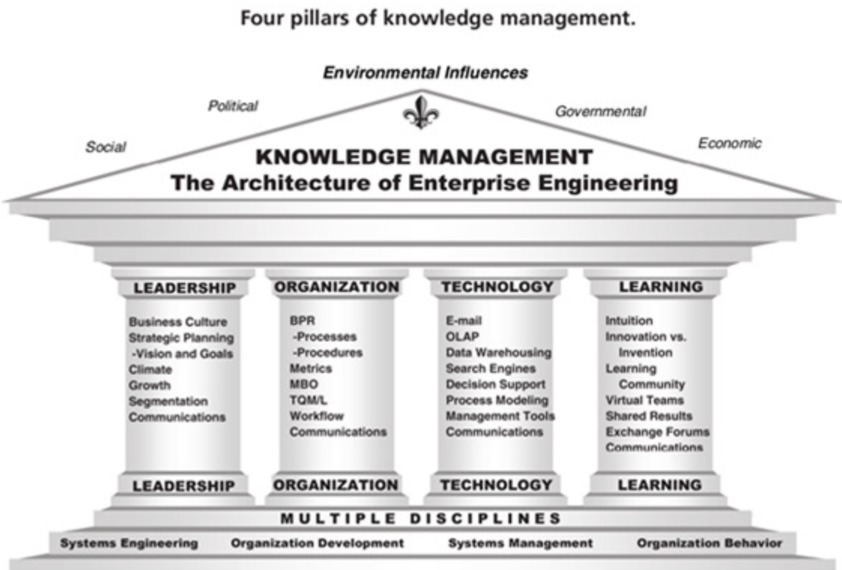

Figure 4: The Four Pillars of Knowledge Management, (Calitz and Cullen, 2017, p. 340)

Leadership consists of decision-making and the strategic alignment of KM and business objectives. The Organisation pillar indicates the strategic re-designing and alignment of operational processes and procedures to ensure the success of KM initiatives throughout the organisation. Enabling a technological infrastructure is the aim of the Technology pillar, which leads to improving the support of KM within the organisation. Finally, the Learning pillar relates to acquiring knowledge, skill, experience, or instruction, which emphasises that the organisation must address KM facilitating approaches. These KM facilitating approaches may involve internal communications, promoting cross-functional teams and shaping a learning community. In this master's thesis, the focus is primarily on the Technology pillar, but the synergy of the four pillars will also be taken into account.

From the literature found by van Heijst et al. (1997), KM has four basic knowledge processes, development, consolidation, distribution and combination. The development process is related to developing new knowledge. An organisation survives by continuously developing new knowledge from creative ideas, lessons learned, daily experience and R&D departments. Consolidating new and existing knowledge regarding the individual's knowledge should be accessible to the people in the organisation that demands it. The knowledge should be on hand at the right time and place. Further, the knowledge has to be distributed to those who can use it. Especially the turnaround speed of knowledge can be critical for an organisation's competitiveness. The final process of combining available knowledge is connected to the use of cross-functional teams. Combining the available knowledge areas when developing new products will increase the organisation's performance. (van Heijst et al., 1997)

By effectively utilising KM it will increase productivity by enabling the employees to;

- Locate and apply their available knowledge faster,
- enhance the quality of product development/client satisfaction,
- and minimise repeated mistakes by leveraging best practices and lessons learned.

2.5.1 Organisational Learning

Genç and Öykü İyigün (2011) define organisational learning as the *change* in the organisational knowledge. The change may come from adding new, reducing or transforming information to the present organisational knowledge. Organisational learning may be seen as an activity, a learning process in an organisation that exists without effort. The focus is on how an organisation learn, which exists naturally and increases with time. van Heijst et al. (1997) suggested that organisational learning is centred around the concept of communication. On the contrary, a learning organisation is a form of organisation which requires effort and activity. A learning organisation combines the collective knowledge and finds what approach the organisation should use to learn.

2.5.2 Knowledge Transfer

Another term closely related to knowledge management is *knowledge transfer*. It is described as being the process through which one unit is affected by the experience of another (Argote et al., 2000; Genç and Öykü İyigün, 2011). An example of knowledge transfer is how a franchise store may learn how to achieve greater customer satisfaction from another store. Alternatively, in the case of project management, one project team may learn from another team how to produce schedule and cost estimates more accurately. The ability to effectively transfer knowledge among parts of an organisation provides an advantage in performance over organisations that perhaps are more autonomous. These affiliated organisations would have the option to learn from a larger experience basis.

When discussing knowledge transfer, the term *strategic alliances* refers to the strategic relationship between separate companies with shared compatible goals and ambitious competitiveness. Establishing a strategic alliance will increase a company's knowledge base more efficient than outsourcing and contributes to the process of sharing, protecting and developing the knowledge base (Genç and Öykü İyigün, 2011).

Genç and Öykü İyigün (2011) state that there has been an extraordinary increase in alliances over the past decade. The cooperative relationships between organisations provide opportunities for knowledge transfer, as the primary motivation for entering a strategic relationship is to transfer organisational knowledge.

2.5.3 Intelligent Systems for Knowledge Management

Knowledge Management Systems (KMS) supports organisations to ensure organisational learning, flexibility and efficiency, and change management(Lehner and Maier, 2000). These tools can also be referred to as Organisational Memory Systems (OMS) and focus on organising knowledge as opposed to data or information (Becerra-Fernandez and Sabherwal, 2014). The main distinction between knowledge, information, and data is that while data is raw numbers and facts, knowledge is actionable, usable, and has more significant value than data alone. KMS are tools that provide the organisation with greater control and easier usage of their business knowledge that is built up over years of operating.

Systems that are designed to provide support for decision-makers, so-called Decision Support Systems (DSS), are becoming increasingly more critical to the daily operation of organisations (Nemati et al., 2002). DSS aims to provide key employees with the correct information and the means to utilise the information in a decision support context. Data Warehouses have been an integral part of modern decision-making since the mid-1980s. However, only a fraction of the required information needed is stored in these warehouses. The majority of the needed information is in the form of tacit knowledge in the mind of the employees. A new generation of knowledge enabled systems is therefore required, one where AI plays a part in the knowledge creation, storage, dissemination and management processes (Nemati et al., 2002).

The KMSs may provide the organisation with more decisive decision-making and make it more flexible when facing changing environments. As projects are instruments of change and a new project is a new environment, KMSs might benefit project-based organisations. KMS are effective for both tacit and explicit knowledge, and engineering documents and plans need to be captured, codified and documented. Lehner and Maier (2000) refers to KMS as a dynamic system which is supposed to support organisational learning and organisational effectiveness. Through specifications of mathematical models, AI can play a part in converting tacit knowledge into codified explicit knowledge. When the knowledge is converted and stored appropriately, it can be leveraged by making it available to others and analysed to produce new knowledge (Nemati et al., 2002). An example could be to track how an experienced employee works with a particular situation or problem. How the employee handles the problem would be stored and later used if other employees face similar situations.

Employees can often communicate only a fraction of the knowledge they rely on when making decisions. Therefore, it might be easier to track the procedure of an employee than to ask for documentation and reasoning behind the decision. AI can be used to prove the cause and effect relations that certain decisions have on the outcome through analytics, supporting an evidence-based approach to decision-making.

However, knowledge and information related to project management have been difficult to utilise for AI models as the environments are constantly changing, and cause-effect relations are difficult to document. Each project has its challenges and opportunities. Projects are a playground for innovation and are hard to standardise. A large amount of standardised data is needed in AI models, it is important to establish, codify, and structure project data to easily train the AI models.

2.5.4 Corporate Memory

There are several definitions of Corporate Memory (CM), as the notion has been around for more than a quarter of a century. The majority of definitions relate to the persistence of knowledge in an organisation (van Heijst et al., 1997).

CM is understood as information from the past that can be brought to bear on present decisions, and some of the memory is held in records within the organisation. CM depends on the collection, consolidation, storage, maintenance, search, and retrieval of information (M. Vogl, 2020).

The primary function of CM is to improve an organisation's competitiveness by improving how it manages its knowledge. From the four basic knowledge processes, stated by van Heijst et al. (1997), CM should support each of them in an interdependent way. CM can, for instance, support the development of new knowledge by recording failures and successes. By storing persistent and well-indexed knowledge over time, CM improves accessibility and helps consolidate new and existing knowledge. As knowledge must actively be distributed to the right people, CM also has to have the facility for deciding who should be informed about the specific knowledge. In total, CM will improve the accessibility of knowledge developed across the various parts of the organisation. Simon (1991) describes organisational memory as the "process of retaining unique traits within an organisation."

van Heijst et al. (1997) describe four types of CM. It is the combination of active and passive collection and distribution. Active collection is when an organisation actively searches for lessons learned. The passive collection is up to the employees to determine if a lesson learned should be added to the CM. For active distribution, the CM system actively informs the users about the new information relevant to them. Whereas passive distribution, the users have to consult the system to remain informed.

Knowledge is critical for the competitive advantage of an organisation. In a survey conducted by Leonard-Barton et al. (2015) leaders of large companies were asked to put estimates of the costs related to turnover rates. When asked about the costs related to new employees, most leaders reported less than 50 000 dollars for headhunting, training and relocation costs. Nevertheless, when asked about the costs of losing key employees (and thus knowledge), the estimates were much higher, 11% stating over 1 million dollars, and some simply responded incalculably. Simon (1991) also recalls that turnover of personnel is the greatest enemy of long-term CM. The losses related to delays, customer problems, and errors come from the loss of competent employees. Using and creating tools that retain knowledge and provide better information sharing in the organisation can mitigate these losses and provide better services.

Argote and Ingram (2000) split CM into the three essential elements of the organisation: its members, tools and tasks. Members are the human component of the organisation, the tools being the technical component and the tasks being the organisation's goals, intentions and purpose. These essential elements combine to form sub-networks mapping the relationship between the elements. For example, the members-task network maps the people in the organisation to the work that needs to be done. They further state that organisational performance improves both with the network's internal compatibility and external compatibility with other networks. A good performing member-task network allocates tasks to the most qualified members to perform them. Additionally, if the members-tools successfully allocate the right tools to the right members, the tools-task network subsequently performs well.

Calitz and Cullen (2017) describe knowledge loss as the phenomenon of "brain drain", which points to the result of experienced professionals' retirement, changing work behaviour of new and younger generations, and the general knowledge transfer. Organisations struggle with the knowledge transfer when replacing experienced employees, which has led to the realisation and growing interest in the concept of KM and CM.

2.6 Digitising to Digital Transformation

Digitalisation and digital transformation are strong drivers when evaluating and creating opportunities for improved project execution and operations. The development of today's industry and the emerging fourth industrial revolution (Industry 4.0) change how businesses operate and strategies. Anthony et al. (2017) describes this as "the circle of disruption", which changes markets in a disruptive way by making what used to be complicated, simple, and what used to be expensive, affordable. Business leaders are now challenged with keeping up with the constant change and increasing competition in the market due to digital innovation.

The terms *digitisation*, *digitalisation* and *digital transformation*, can be viewed as three stages of digital innovation, which Kane et al. (2017) refers to as an organisation's digital maturity. Digital maturity refers to how an organisation systematically prepares to adapt to ongoing digital change (Kane et al., 2017). Digitisation involves data conversion, changing from an analogue to a digital format. Digitalisation is applying digitising techniques to automate existing business operations and processes, which involves creating completely digital work processes. The last stage, digital transformation, is the transformation of organisational activities by changing the company's culture from how it works and thinks (Holmstrom, 2021; Savić, 2019). The development should mutually trigger an approach including real options and flexibility through the design and realisation stages for value optimisation and potential for opportunities.

As Wang et al. (2016) states, digital transformation is closely related to the evolution of data itself. Data is increasing in complexity, volume and velocity, and the immediate need for effective data analytics solutions. In terms of energy demand, the digitalisation of the energy industry may reduce unnecessary energy consumption and enable efficient use of energy (Park and Kim, 2021). The digital technologies mainly utilised in the energy sector include IoT to generate and deliver data required for remote devices and systems such as AI and analytical software.

(Gartner, 2022), introduced the top 12 technology trends of 2022 and described that each trend delivers one out of three main outcomes.

- Engineering Trust
- Sculpting Change
- Accelerating Growth

The outcomes can be related to the critical elements of digitalisation. The words "trust", "change", and "growth" are critical success factors when implementing digital transformation.

Industry 4.0

Industry 4.0 is the term used to identify the fourth revolution. It is defined as the global transformation of the manufacturing industry as it is introducing digitalisation and the internet. Burke (2021) describes how Industry 4.0 show how new innovative technologies transform the way power is generated, product manufacturing, data is communicated, and work is managed. The term originates from Germany in 2011 and is often related to other developments such as Smart Factories, Smart Industries, and IoT. Industry 4.0 has greatly impacted as it introduces new technologies, such as AI, ML, IoT and digital twins. (Silva et al., 2021; Kristoffersen et al., 2020).

In the same way as digitalisation, there is no complete or concise knowledge of implementing Industry 4.0 correctly. Here the Cyber Physical System (CPS) technology works as the connection between materials, sensors, machines, products, supply chain and customers. The exchange of information and control must work smoothly (Silva et al., 2021).

Internet of Things

The Internet of Things (IoT) is the primary communication technique linking all the smart devices to a central controller. From a project perspective, the smart devices are project components, and the central controller is the project manager and project office. IoT points out multiple "things" that are all connected to the internet (Burke, 2021). IoT provides advanced connectivity of various objects, systems and services, which enables data sharing (Silva et al., 2021). Radio-Frequency Identification (RFID) is an example of technology used in IoT to identify various objects and connect and interact with other objects or devices.

Digital Twins

One device closely related to IoT is digital twins. The data transferred from the IoT to a digital twin replica can help model and simulate a project and predict what-if situations (Burke, 2021). An example of digital twins is to use it as a virtual representation of a product combined with analytics for improved decision-making in complex project scenarios. Digital twins are then utilised to test various strategies in a virtual environment before applying a decision to the real-world (Kristoffersen et al., 2020).

2.7 Descriptive to Prescriptive Analytics

Prescriptive analytics seeks to find the best course of action for the future and has an increased research interest over the last decade. It is considered to be the next step towards increasing data analytics maturity and leading to optimised decision-making ahead of time for business performance improvement (Lepenioti et al., 2020, 2021). Prescriptive analytics is not yet an established field, but its characteristics have already been applied in business analytics and decision-making (Frazzetto et al., 2019; Lepenioti et al., 2020).

Within the business analytics field, there are three main phases, descriptive, predictive and prescriptive analytics. Business analytics can be defined as a set of information technologies to drive business planning using data about the past to achieve new insight about the future (Frazzetto et al., 2019). Finding a way to analyse the status and possible outcomes, business analytics also needs to bring value to the process. Based on this, the three business analytics stages should answer the following questions:

- Descriptive: *What happened?*
- Predictive: *What will happen?*
- Prescriptive: *How to make it happen?*

Lepenioti et al. (2020) highlights that business analytics aims to create business value by enabling organisations to make quicker, better, and more intelligent decisions. The three phases are interdependent, descriptive analytics is a sub-phase of predictive analytics, and predictive analytics is a sub-phase of prescriptive analytics. Therefore, prescriptive analytics is the highest level of support and value among the different phases. The focus has shifted from understanding (descriptive analytics) and forecasting (predictive analytics) to translating data into decisions and actions through optimisation (Brandt et al., 2021).

Descriptive analytics is the most known and established stage of analytics, as it focuses on collecting, categorising, and classifying data. It also involves identifying and visualising the relevant patterns found in the analysed data. Several articles also mention a fourth phase, diagnostic analytics, which is referred to as an extension to descriptive analytics (Brandt et al., 2021; Lepenioti et al., 2020; Sadat Mosavi and Filipe Santos, 2020; Sheng et al., 2021; Silva et al., 2021). Diagnostic analytics aims to understand "Why did it happen?" utilising exploratory data analysis techniques to look for insights. It is often difficult to distinguish both descriptive and diagnostic analyses of historical data as the job is often performed simultaneously by the same analyst. Therefore, it is natural to group all historical analyses (descriptive or diagnostic) into a single descriptive analytics category. Techniques that have been utilised for descriptive analytics applications are data visualisation, dashboards, statistical analysis, and data mining. With these techniques, frequently used methods are pattern matching and clustering to translate and visualise the information from the data in a simple way (Frazzetto et al., 2019).

Where descriptive analytics applications cannot perform predictions about future events, predictive analytics comes to use. Predictive analytics makes use of a large amount of historical data to extract and incorporate helpful information with the inspiration from machine learning, data mining and statistical techniques (Frazzetto et al., 2019; Silva et al., 2021). By utilising these techniques, it is possible to forecast the probability of certain events, find repetitive patterns in the future, and determine valuable relationships between the events. Predictive analytics supports planning and decision-making by using both what happened in the past and the future.

From Silva et al. (2021) quantitative research, they found that in the majority of papers regarding the three main analytics, predictive analytics had the most with a total of 80 applications. Descriptive and prescriptive analytics had 23 practical applications and 24 research works. The increase in the popularity of predictive analytics is linked to the growing interest in machine learning. The future of prescriptive analytics has huge potential for future research, as these analytics can "tell you what to do" and hold a more considerable business value for the industry. Wang et al. (2016) describes how predictive and prescriptive analytics will play a vital role in helping companies make effective decisions regarding the company's business strategy.

2.8 Artificial Intelligence

2.8.1 The History & Evolution of Artificial Intelligence

Artificial Intelligence (AI) is one of the upcoming and newest fields in *science* and *engineering* (Russell and Norvig, 2016). Burke (2021) defines AI as: "the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent human beings." (Burke, 2021, p. 46). People have tried to understand how human intelligence works for thousands of years. The field of AI takes the research even further by attempting to understand and build intelligent entities. AI consists of many aspects of intelligence, and there is no formal definition that covers it all. The *science* aspect of AI involves understanding the human brain's intelligence and discovering ideas about knowledge that may help explain the various sorts of intelligence. The *engineering* aspect is more about engineering actual intelligent entities and solving real-world problems by establishing ideas of representing and using the knowledge.

AI is perhaps seen as futuristic for an average person and only mentioned in science fiction movies and novels. In reality, philosophers such as Aristotle (300 B.C.) considered the idea that the mind in some way works like a machine and operates intelligently to decide what actions to take. Still, it was not before the summer of 1956 that at Dartmouth College, John McCarty and other researchers organised a two-month workshop that led to the birth of the AI research field (Adami, 2021; Russell and Norvig, 2016). Due to vast improvements in computing power and the rise of Big Data, it has become a highly relevant subject across various fields.

To explain what AI is, one can look at it in two dimensions. The first dimension concerns *thought* and *reasoning* versus *behaviour*. The other dimension defines AI related to *human* performance versus the *ideal* performance also referred to as *rationality*. Rationality means how a system does the "right thing" based on its knowledge. Four different approaches to AI are formed by combining the two dimensions; "thinking humanly, thinking rationally, acting humanly and acting rationally". A human-centred approach is a part of an empirical science based on observations and hypotheses about human behaviour. If taking a rationalist approach to AI, it involves a combination of mathematics and engineering (Russell and Norvig, 2016). The Turing Test, developed by Alan Turing, served as the first definition of how computers can be intelligent and act like humans. Turing's test involves a person (A), a computer (B) and an interrogator (C), all connected via the internet without seeing each other. The interrogator (C) asks A and B questions, and they both reply via the computer. If the interrogator (C) cannot distinguish the replies from A or B, it implies that the computer (B) has AI (Burke, 2021; Russell and Norvig, 2016).

The state of the art of AI includes many different activities in many different subfields. AI has advanced rapidly due to better scientific methods in experimenting and comparing approaches. Some well known AI applications include the Deep Blue chess computer that defeated world champion Gerry Kasparov, in chess in 1997 (Adami, 2021; Russell and Norvig, 2016). Other areas in which AI technology is implemented are robotic vehicles, speech recognition, and autonomous planning. People interact with intelligent systems in many day-to-day situations, such as online chat-bots, smart devices like robot vacuum cleaners, and the continuous monitoring of people's smart devices. The tracking of devices uses AI technology to predict and recommend different advertisements and products on our PCs and phones.

The progress in AI has often been evaluated in the form of playing board games. Even before AI was recognised as a field, efforts have been made to create programs that play games. It was done to test if it was possible to make computers solve tasks that seemed to require intelligence (Yannakakis and Togelius, 2018). In 1973 the British mathematician James Lighthill published a report criticising the potential of AI. He stated that "machines would only ever reach the level of an experienced amateur in games such as chess and that common-sense reasoning would be beyond their abilities" (Haenlein and Kaplan, 2019).

As affordable computing power has surged, AI is increasingly being utilised in many different fields and applications. In a survey conducted on business executives who had adopted AI into their business, 61% of respondents stated that AI would substantially transform their industry (Deloitte, 2020). However, in the survey, 95% of the respondents expressed concerns about the ethical risks of their AI initiatives.

Enterprise Cognitive Computing (ECC) is the use of AI to enhance business operations (Tarafdar et al., 2019). ECC applications can automate repetitive, formulaic tasks, which leads to considerable benefits in the speed of information analysis and reliability of service deliveries. ECC applications also free up employees to do higher-level work that requires adaptability and creativity, abilities that machines lack. ECC applications take many forms and can be used to service customers, process requests, and accurately predict further developments in markets.

AI needs much information to function correctly and is often used in enterprises where information has been stored for a long time, and work activities are consistent. In project management, this is not the case as the nature of projects is tied to change. This non-consistency can be used as reasoning for the lacking implementation of AI in projects and the low grade of digitalisation in the field. Computers work best when they can do the same task repeatedly, and they lack the human ability to be creative and adaptable. However, there have been promising attempts to apply AI in project management. These come in the form of systems and tools designed to assist the processes in projects and predictive models that help decision-making. In a study exploring how AI will affect PMBoK's ten knowledge areas in the following years, researchers concluded that AI would be an integrated part of future project management practice (Fridgeirsson et al., 2021). AI will have an influence on cost, schedule, and risk management, as well as monitoring and WBS management. Areas that require human leadership will be least affected by AI, areas that require soft skills such as team management.

2.8.2 The Ethics & Risk of Artificial Intelligence

Russell and Norvig (2016) identified six potential ethical threats and risks of developing AI technology. These include:

1. People might lose their jobs to automation.
2. People might have too much (or too little) leisure time.
3. People might lose their sense of being unique.
4. AI systems might be used towards undesirable ends.
5. The use of AI systems might result in a loss of accountability.
6. The success of AI might mean the end of the human race (Russell and Norvig, 2016, p. 1034).

The first issue refers to how modern industry and business have evolved and become more dependent on computers and technology. It includes the dependence on AI systems, e.g., how the United States use AI programs in the economy industry for credit card applications, charge approvals and fraud detection. The industry faces a big change as AI technology and computers replace thousands of human workers. Automation through AI and technology has also created more interesting and higher-paying jobs than discarded. It is important to ensure that unemployed workers are involved and utilised for other work. Making sure the unemployed people are transferred and followed up in other work areas will benefit the organisation. Perhaps the future may end up with the unemployed that serves as managers of their group of robot workers. (Russell and Norvig, 2016)

With too much or too little leisure time, some people thought technology would replace peoples' workload and that the future would involve shorter working weeks, more free time and potentially boredom. What has happened is that people are forced to expand their knowledge basis and work longer hours to keep up with the new technology systems. AI also pressures people to work harder and keep up with the increasing pace of technological innovation. In the future, it is possible that

AI also holds the potential to reduce some work as automated processes, agents, or robots will handle some parts of different functions (Russell and Norvig, 2016).

The third threat involves people losing their sense of being unique, as the thought of robots taking over creates the loss of autonomy or even of humanity. The issue may cause worry for some people, but the question of human uniqueness has come up previously in the form of Darwin's *Descent of Man*, which put humans at the same level as other species. The threat of success in AI is perhaps something people have to acknowledge, as done previously in the 19th century with Darwin's theory of evolution. (Russell and Norvig, 2016)

Using AI systems toward undesirable ends is a significant threat and desirable to be avoided. There are several examples where influential people have used advanced technology to overcome rivals or take advantage to misuse the technology's purpose. In a war situation, the possession and availability of powerful robots also create the risk of a nation becoming overconfident, leading to reckless decision-making in war. Another issue pointed out is the use of speech recognition technology which enables states to wiretap and perform surveillance of people, which results in the loss of privacy and civil liberties (Russell and Norvig, 2016). There are discussions on finding the optimal balance of privacy and security. The accountability and liability of AI systems are crucial if used in medical diagnosis. Vakkuri et al. (2020) conducted a study about where the industry is in terms of AI ethics, and they followed the ART principles representing Accountability, Responsibility and Transparency. Transparency involves understanding how the system works technically and following the development. Acting ethically and doing the right thing is harder to define, which consists of the responsibility in AI ethics.

One primary threat to consider is that the development of AI technology will lead to a different future than today. It will be a transition people might not like, but at one point, have no choice but to accept (Baker-Brunnbauer, 2020; Russell and Norvig, 2016). The question is whether an AI system will develop a more significant risk than the traditional software people are used to. Different risks such as the initial state of an AI system may be incorrect - causing it to make mistakes, or that an AI system's learning function may cause it to evolve into a system with unintended behaviour, potentially causing harm. More situations occur when the question is how much people can trust the AI programs, and the law has to catch up with technology to establish clear rules and regulations. Over the last few years, several institutes have published AI principles. For example, the European Union's (EU's) "Ethics Guidelines for Trustworthy AI" emphasises trustworthiness as the AI system's goal. Another prominent institute, IEEE, has also published a guideline, the "Ethically Aligned Design" (EAD) (Vakkuri et al., 2020). In parallel with implementing important policies, Ryan (2020) argues and shows scepticism to the EU's focus on the relationship between trust and AI. The thought of mixing trust with AI was a serious claim, as he states that trust is one of the "most important and defining activities in human relationships" (Ryan, 2020, p. 2).

To sum up, the development of AI has a significant impact. There are many important ethical factors to take into consideration. Today, the industry needs clear guidelines to follow, ensuring that AI systems do not take over humanity. Clear communication, transparency and documentation are necessary to learn from each other and take small steps at the time(Vakkuri et al., 2020). It is difficult to define the "right thing" to do, especially when people do not know what the future will bring.

2.8.3 Machine Learning

Machine learning (ML) is a buzzword often mentioned together with AI. ML is "a set of algorithmic techniques that build a statistical model from a sample of data, called the training set." (Rauzy, 2020, p. 163). In this thesis, ML will be utilised to predict costs related to projects and measure the similarity between projects and individual WBS-items. The purpose of the statistical model is to make predictions and improve decisions about future data based on the previously trained data. Rauzy (2020) states that the modern ML techniques can be seen as a black box because it is encoded into an internal data structure too complex for a human to understand. There are a fixed set of rules used to understand the models. By trial and error, this approach aims for the computer to learn the best way possible to achieve the given objectives (Burke, 2021).

Rauzy (2020) describes three immediate consequences to be aware of when using ML techniques these are; firstly, ML assumes the data analysed is sufficiently stable and does not change through time. Secondly, the quality of the data in the training set is very significant for learning the ML model. Thirdly, the training set must be of sufficient size and reflect the properties of the data under analysis as closely as possible.

ML technology allows for studying phenomena that are too complex to be studied by usual statistical means. As “Machine learning is in essence extremely data and calculation resource consuming.” (Rauzy, 2020, p. 164). There are three different categorisations of ML algorithms; supervised learning, unsupervised learning and reinforcement learning.

Supervised learning:

- The most widely used technique and also the most successful approach.
- The training set consists of pairs (i, y), where i is the input, i.e. values of features, and y is the expected result. The expected results are often referred to as labels. The algorithm learns from these pairs. For any values of features, it guesses the corresponding label y. Examples: image and speech recognition and medical diagnosis.

Unsupervised learning:

- The training set only consists of input values. The learning phase consists in finding clusters of similar input values. Then, when a new input value is presented, the algorithm guesses which cluster the value belongs to. The approach is referred to as “clustering”.
- Although proved to be useful in several fields, it has strong limitations since it barely looks for similarities and does not generate much information.

Reinforcement learning:

- The problem is represented by an environment consisting of states and actions and learning agents with a defined goal state. The agents can reach their goal state while maximising their rewards earned by selecting actions and moving to different states in the environment. Instructions do not steer the agents but learn by experience and discovering optimal sequences of actions. (Lepenioti et al., 2021)
- It is placed in between supervised and unsupervised learning. Alpha-GO's well-known program, which defeated the world's best GO-players, is based on this technology.
- Today, reinforcement learning is limited to a restricted set of applications.

In this thesis, the focus will be on supervised learning algorithms. The following section will present the ML model utilised in the data analysis, neural networks.

2.8.4 Neural Networks

A neural network is an information processing model that draws inspiration from how the human nervous system process information (Wang, 2003). In its most basic form, it is comprised of "densely connected" layers of processing elements called neurons. Densely connected means that every neuron in one layer is connected to every neuron in the next layer. Each of the connections between the layers is associated with a weight. Adjusting these weights is how the network recognises patterns and provides the correct output. These weights are adjusted by feeding data to the network in a training loop; this is done in two steps, namely *feedforwarding* and *backpropagation*.

During feedforwarding, data is evaluated by the network. Information is given as input to the first layer of the network. The input is then multiplied by the weights of the connections between this layer and the next. The result of this multiplication acts as input to the next layer. The process is repeated until the last layer is reached, and the output is measured against a label with the correct values. The error between the model output and this label is calculated after feedforwarding. This error is often denoted as loss, and there are different functions used to calculate this loss.

The performance metrics presented in Section 2.8.5 are often used as loss functions. After feedforwarding, the loss is backpropagated through the network. During backpropagation, the weights in the network are adjusted to minimise the error, which is how the network "learns". This thesis is rather technical, so it will not be relevant to forward- and backpropagation specifics.

Neural networks learn by examples and can, with enough data, learn to recognise complex patterns that humans and other algorithms cannot (Maind et al., 2014). There are a lot of different architectures and types of neural networks that specialise in different sets of problems and data structures. Silva et al. (2021) found in their research that neural networks were the most used approach in supervised learning.

Machine Learning Embeddings

Embeddings map high-dimensional discrete input to lower-dimensional continuous vector spaces (Boggust et al., 2022). The process of creating embeddings is illustrated in Figure 5.

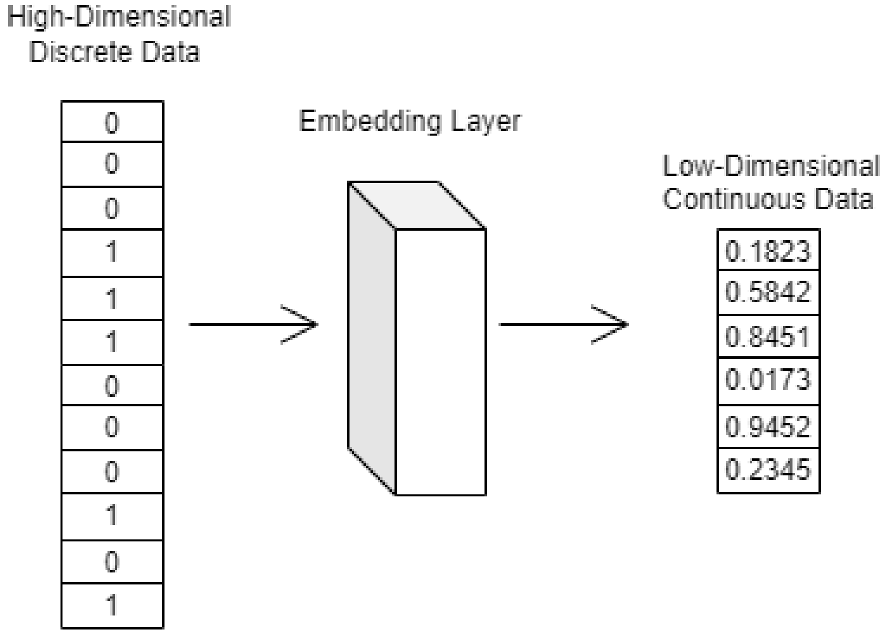

Figure 5: A Discrete Data vector of length 12 is mapped to a continuous vector of length 6.

This figure maps a data vector of length 12 containing discrete "sparse" categorical data to a "dense" continuous vector of length 6. The choice of length for the embeddings is arbitrary, but the vector is generally of lower length than the input data for downsampling. They are often used in language processing, where word-embeddings are frequently used to enable ML models to interpret their meaning. In word-embeddings, a neural network is trained on large text data to learn the associations between words. The network is trained to ensure that similar words or words with similar associations are mapped close to each other in the vector space. The similarity between different entities is not present for discrete categorical data, but a neural network can recognise the similarity between items through training. Comparing the embeddings returned from the network can reveal more about the data than directly comparing the input vectors. It can be utilised to create recommendation systems based on the nearest neighbours in the embedding space. Embeddings are often utilised in language processing, creating numeric representations of words, but any high dimensional data can be mapped to an embedding.

Embeddings are useful as they can be used to reduce the dimensionality of categorical variables. These mappings are meaningful representations of categories in the training context in the evaluated network. Compared to sparse discrete data, dense representations are advantageous for neural network training as higher dimensionality data mean more mathematical operations and slower training. In addition, as embeddings place similar entities closer together in the vector space, machine learning models can recognise this similarity and therefore converge faster. In essence, neural networks prefer dense vectors over sparse vectors for training purposes (Koehrsen, 2018).

Another interesting aspect of embeddings is that they can be manipulated using mathematical operations. A popular example with word-embeddings is that by subtracting the representation of "Man" from the representation for "King" and adding the representation for "Woman", the resulting vector is similar to the embedding representation of "Queen" (Goldberg and Levy, 2014).

In this thesis, embeddings will be utilised to create a numeric representation of projects from high-level project data in a predictive analytics model. In addition, a recommendation system based on calculating the similarity between learned embedding vectors will be created. These embeddings are created as a bi-product of the estimator model. The aim is to provide further insight into the data through comparisons of these learned embedding mappings.

By utilising embeddings in conjunction with predictions, the hope is to address the predictive and descriptive parts of the analysis. Further, to explore how these can help create prescriptive analysis establishing trust in the data and models to create the basis for data-based planning and decision-making.

2.8.5 Model Evaluation Metrics

After deciding which ML model(s) to test, it is important to evaluate how well the prediction and the model functioned. In the same way as performance measurement and benchmarking are tools for improving projects, ML model evaluation metrics are important to find out which model works best according to the objective and/or if further improvements are necessary. An evaluation metric is a way to quantify the performance of an ML model. It can also be defined as a number to compare the goodness of different models after they are trained (Anaconda, Inc. Maria Khalusova, 2019).

The models in this thesis are tasked with regression problems of cost. For regression problems, multiple metrics are frequently used. How these metrics are calculated and the pros and cons are essential to understanding the performance of the model (Agrawal, 2021). Presented below are the evaluation metrics used in this thesis. For all of the metrics presented, the lower the score, the better.

Mean Absolute Error

Mean Absolute Error (MAE) takes the absolute difference between the models' prediction, denoted as x_i and the target output, denoted as y_i. It is done for every prediction and divided by the number of predictions made to achieve a mean of the whole data set. The formula for MAE is:

$$MAE = (\frac{1}{n}) \sum_{i=1}^{n} |y_i - x_i| \tag{1}$$

An advantage of MAE is that the error is in the same unit as the output variable, which makes the performance of the model easy to communicate and understand. It is also the performance metric that is most robust to outliers (Agrawal, 2021).

Mean Squared Error

For Mean Squared Error (MSE), instead of taking the absolute value of the difference between the output and the prediction, the difference is squared. As with MAE, (1), this is done for every prediction and then divided by the total to get a mean for the data set. The formula for MSE:

$$MSE = (\frac{1}{n}) \sum_{i=1}^{D} (x_i - y_i)^2 \tag{2}$$

The main difference between MSE and MAE is that significant errors will be very prominent with MSE, as it squares the difference. It means that the model can perform well on the majority of the data set but perform very poorly on a select few outliers since the MSE will be high.

The output value is also not on the same unit as the target, as it is now squared, which means that communicating and understanding the result is not as straightforward as with MAE. This metric is often used as a loss function in ML as it is easily differentiable.

Root Mean Squared Error

By taking the root of the MSE, the values will transform back into the same unit as the target label. It is called RMSE, and the difference between the values of MAE, (1) and RMSE is that RMSE is still very sensitive to significant errors in the data set. The formula for RMSE is:

$$RMSE = \sqrt{(\frac{1}{n})\sum_{i=1}^{n}(x_i - y_i)^2} \tag{3}$$

RMSE will always be higher or equal to MAE, and by comparing the results from RMSE and MAE, one can get insight into where the model fails. If the RMSE is much greater than MAE, it suggests that the model has a large error on a few outliers. If they are closer together, the error for each data point is more constant.

Relative Error

To get a sense of the relative error of the model. To apply the metric, Log Accuracy refers to the size of the error to the size of the target. By using a relative error measure, one can give equal weight to errors of different magnitude in the data set (Morley et al., 2018). Consider the following: The model is tasked with predicting two values that range from 0 to 100. Target 1 has a value of 100, and the model output is 20. Target 2 has a value of 10. The model output gives 2. The average MAE of the model: $\frac{88}{2} = 44$. But the relative error is $\frac{1}{2}(\frac{2}{10} + \frac{20}{100}) = 0.2$. The MAE will not reflect the models' performance if it performs well on the small magnitude data points and if it struggles with the outliers, as few outliers will inflate the mean.

Mean Absolute Percentage Error (MAPE) expresses the error as a percentage of the target (Swamidass, 2000) and is typically used when a measure independent of scale is desirable. MAPE is calculated by finding the absolute difference between the output and the target value and dividing it by the target.

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - x_i}{y_i} \right| \tag{4}$$

However without the data set, the prediction will result in normalised values where some values are zero and some are close to zero. When the target is zero, MAPE is not defined and when the target is close to zero the MAPE inflates. Therefore, the Log Accuracy ratio is used. The metric is defined as:

$$LogAcc = \frac{1}{n} \sum_{i=1}^{n} \log \frac{y_i - x_i}{y_i} \tag{5}$$

In addition to these metrics, it is important to examine the fit of the model to ensure that the model follows the data closely. Examining line plots and comparing the model output and the target provides great insight into the performance of the model. The performance metrics supply a numerical value.

Evaluating the second part of the analysis in this thesis, namely finding similar WBS-items is less straightforward. It can be seen as an example of unsupervised learning as there is no defined correct answer and determining the quality of solutions in this space is a vital issue of the field (Spüler et al., 2015). Here the goal is to identify which tasks are similar in a cost context. An approach to determining the similarity between data is to compare the numerical values and calculate the differences directly. However, by training a neural network on cost and generating embedding representations from the data, the ML model can help identify similarities between projects and WBS-items that cannot be identified from the raw data alone. Evaluating the validity of these similarities is difficult without an experienced project manager evaluating the results. Although even for an experienced project manager, it would be difficult to give an exact metric for the recommendations from the network. Therefore, evaluating the similarity analysis is done through inspecting the results and evaluating their validity performed in this thesis.

2.9 Artificial Intelligence & Decision-Making in Projects

The increase in the complexity of projects makes project management a more challenging and complicated task. Several researchers elaborate on how the profession of project management has changed over the last decades. Kutsch and Hall (2016) mentioned how people treat projects and project management with a "mechanistic" approach. They describe projects as more "organic", living entities that last for a finite period, consisting of people, structures and processes. The development in project management has introduced different approaches to ease the difficulty of project management by using advanced techniques. AI technology is one of the new trends researchers have been intrigued by and studied within project management. For projects and organisations to maintain competitiveness, it is necessary to be up to date and follow digital innovation.

From literature found about AI and project management, the use of AI technology has been discussed in many, if not all, aspects of project management. When using AI techniques, the benefits to consider include improving monitoring data using real-time data that enables quick response and access to information. With faster access to information, it is possible to react to challenges or opportunities to increase productivity. The advantage of monitoring is access to data quicker, which results in more available data to base problem solving and decision-making, evidence-based decision-making (Burke, 2021). AI is replacing traditional statistical methods with ML methods that can deliver accurate analytics and insights from big data in a fast, structured and scalable manner. Using ML for decision-making has been one of the most important applications of AI (Lepenioti et al., 2021).

Huff (2016) introduced the term evidence-based project management. It is defined "as the ability to respond to new problems by adapting prescriptive knowledge from previous experience.". This definition links the fields of prescriptive analytics, decision-making and project management. Also, knowledge management can play an important role in enabling and motivating project managers to make the most of what they have previously experienced in the past. The combination of these fields is supporting the development of improved evidence-based decision-making.

Project managers need to keep up with AI technologies' characteristics, features, and capabilities to transform AI solutions effectively. The challenge is to identify the latest trend to understand the advantages of the new technology when necessary. The project manager's responsibility is planning and executing, and its main objective is delivering the project results (Johansen et al., 2019; Pedroso, 2017). A considerable amount of data can be gathered from the beginning until the end of a project, and it is said that AI models can decrease uncertainties in project management using logic reasoning and probability calculations (Davahli, 2020). The goal of implementing AI technology, such as ML, is to assist the project manager in developing better project plans, identifying and mitigating risks (Martinez and Fernandez-Rodriguez, 2015; Pedroso, 2017; Ruiz et al., 2021).

Ruiz et al. (2021) mentions that in less than ten years, AI may be applied to lessons learned from project history. An AI system can alert the project manager of possible risks and opportunities, which affect their decision-making. Davahli (2020) created an overview from his study of what different project management process groups, knowledge areas, and AI techniques were combined and applied. Of the papers he reviewed, the AI models widely used in various project management processes were neural networks, support vector machines, and genetic algorithms. The most common processes included effort predictions, project success factors and cost estimations.

The slow progress of AI in project management is primarily due to the lack of investment from private companies, which means progress is only made in the universities and public research organisations (Ruiz et al., 2021). Many organisations primarily focus on performance outcomes related to AI, but Holmstrom (2021) encourages that adaptability and performance should also be considered. Therefore, he introduced a framework to help organisations develop their AI business opportunity by first mapping their potential and opportunity for digital transformation, their "AI readiness".

Brethenoux and Karamouzis (2020) has recommended five steps to practically implement AI techniques within an organisation of any size. They describe the approach as a tactical way to introduce AI techniques.

1. Use cases - Have an impactful, measurable and quickly solvable portfolio of use cases.
2. Skills - Accumulate the applicable talent that is needed to solve the use cases.
3. Data - Collect the relevant data to the use cases.
4. Technology - Select the AI techniques linked to the use cases, skills and data.
5. Organisation - Structure the expertise and accumulated AI experience.

3 Methodology

This section describes the research methodology used in this thesis. The thesis is a combination of a qualitative and quantitative research study which is often referred to as a *triangulated* study (Fellows and Liu, 2009). Qualitative research is often referred to as soft data as it is difficult to quantify because it is related to a person's understanding and interpretation of the observed information (Holme, 1996). Qualitative methods involve characterising the quality properties of a specific topic (Repstad, 1993). If knowing the basic and distinctive features without the importance of the frequency of something or how normal something occurs, qualitative interview and observation is the approach to choose. Another characteristic of qualitative research is that it is flexible. Data gathered for quantitative research must follow the same strict and consistent structure to get the correct comparison and statistical analysis. Qualitative research aims to describe "how" something exists, not about comparing and finding "how often" something exists. (Repstad, 1993).

Quantitative research is applied when information is possible to quantify and transforms hard facts and data into numbers and quantities (Halvorsen, 2008; Holme, 1996). Later the numbers are often used in statistical analysis. As qualitative research focuses on more flexibility, quantitative focus on structure. For quantitative data, validity and reliability are essential. The reliability is decided based on the measuring procedure and the accuracy of further data processing. The validity depends on what is measured and the properties the problem statement is supposed to clarify (Holme, 1996).

Reliability and Validity are two central terms that must be remembered when conducting research. It is important that there is compliance between the different theories found related to definitions and concepts. With research, the actions and processes bring forth new knowledge and systematise it (Halvorsen, 2008).

When combining methods, the qualitative and quantitative information gets integrated to accomplish a comprehensive and nuanced understanding (Creswell, 2019). The multi-dimensional view, through the synergy of different methods, results in a broader database and a more secure basis for interpretation (Fellows and Liu, 2009; Repstad, 1993). A benefit of triangulation is the possibility of testing the method's validity, confidence, and the analysed result. If there is a large degree of agreement between data based on different methods, it indicates that the data collected is valid. If there are significant differences in the result, it could allow new interpretations and approaches (Holme, 1996).

In this thesis, we have received input from a qualitative survey about digitalisation answered by three different energy industry companies. These results were provided to us as preparation and insight into the industry's expectations and requirements relevant to the topic. One of the companies has also collaborated with us by providing project data and participating in interviews. Before conducting the interviews, our research project and interview guide were approved by the Norwegian Centre for Research Data (NSD). With respect to the contributing companies and NSD's interview standards, we have kept the interviewees and company names anonymous throughout the entire thesis. To differentiate between the three responding organisations, they will be referred to as companies A, B and C. Regarding data analysis and interviews, the company we have had the closest collaboration with is company A. Figure 6 is an overview of the composition of the research methodology.

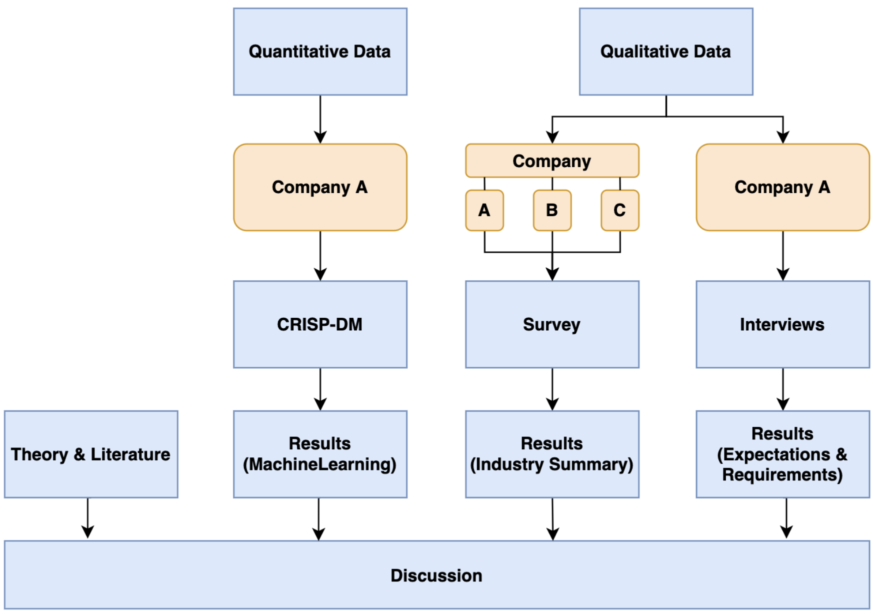

Figure 6: Triangulation of quantitative and qualitative data.

The three different companies' input resulted in a top-down and bottom-up perspective. The information gathered from the digitalisation survey and data analysis made up the top-down perspective. Together with the theory and literature study, the survey resulted in a mapping of the general status and expectations of AI in project management. The interviews of key users from company A resulted in a bottom-up perspective, providing an in-depth perspective to help answer the research questions. The interviews were also beneficial as they gave us a better understanding of the CM data used in the data analysis.

The following sections further describe the methodology used throughout this thesis. The theory and literature study are presented first, and information about the digitalisation survey is given. Secondly, the interview process and experiences are introduced before describing the data analysis process. The CRISP-DM approach will be followed with the given project data to analyse and implement ML algorithms on the data. The CRISP-DM approach is based on the same theory used in Rasmuss (2021) 's specialisation report.

3.1 Literature Search

To gather the relevant literature, a comprehensive literature research was carried out to provide sufficient input to prepare and answer the chosen research questions. The Norwegian digital search library, Oria, was mainly used to find the fitting articles, but also other digital libraries such as, Google Scholar and Scopus were used. The articles were selected based on their relevancy to the topics, and based on who, where, and when they were published. The various keywords used and combined in the searches are "project management", "artificial intelligence", "machine learning", "digitalisation", "decision-making", "descriptive to prescriptive", and "knowledge management".

Several of the sources of the literature have come from previously completed courses taken throughout our studies and some were recommended by our supervisor.

As mentioned in the introduction of the Theory Background section, Section 2, four sub-sections are inspired from our specialisation project. As we wrote separate specialisation projects on the same topic, it became natural to combine some of the relevant sections (Rasmuss, 2021; Tømte, 2021). The sections have all been combined, re-written and/or supplemented with new literature.

3.2 The Digitalisation Surveys

We have been fortunate to get insight into Prosjekt Norge's ongoing research projects concerning project management in the energy industry. Prosjekt Norge is currently working on establishing an energy industry cluster. The partners involved are the oil and gas sectors, traditional power producers and distributors, other infrastructure owners, developers, and producers in other forms of renewable energy, and large energy consumers (Prosjekt Norge, b). The overall theme of the projects is related to the possibility of adopting principles and methodology from Industry 4.0 and digital transformation. The research projects are currently mapping the current situation regarding the digitalisation of project models, management processes and identifying future potentials. In this regard, we have received the results of two surveys from three of the cooperating companies. These surveys are highly relevant for our thesis as they provide a good overview and understanding of the industry's current situation and future expectations.

Prosjekt Norge is a national competence centre working with the development of future project processes through research and knowledge sharing. The Norwegian university, NTNU, owns the competence centre but has useful academic partners such as BI, Sintef, and Oslo Met. In addition, all government development agencies are important contributors, together with contractors, consulting companies and the oil and gas sector. Their main objective is to initiate research and establish arenas for knowledge and experience sharing between academia, agencies as clients and the business community as suppliers within project-oriented activities. (Prosjekt Norge, a)

The results of the digitalisation surveys will be presented in Section 4.1. The information relevant to our thesis will be presented as a summary divided into appropriate headings. These headings were chosen in relation to how the questions and answers fit our problem statement. As mentioned above, to differentiate between the three responding organisations, they will be referred to as companies A, B and C.

As the world is in the middle of disruption and digitalisation, Prosjekt Norge has found the need to strengthen the energy industries companies, operators, system integrators and contractors, to improve their competitiveness internationally. There is a need to standardise project execution models, encourage collaboration across the industry, and look at performance and value creation from a life cycle perspective. Experiences over the last decades imply that the business and project environment in the energy industry consists of non-optimal and sub-optimal roles, connections, and relations that hinder potential opportunities. The sequential project development and execution processes are mentioned as a challenge, together with the lack of data sharing, affecting the information flow. Their ongoing research projects have the objective of improving these challenges.

New patterns of collaboration and value creation are key enablers for improving the business and project performance. By identifying and describing the integrated value-optimisation, with full use of digital tools, the movement from descriptive to prescriptive analytics is the future objective. Prosjekt Norge's research projects also aims to improve confidence and evidence-based decision-making. Desired effects utilise the features available with digital tools such as AI, machine learning, and big data in decision-making. Prosjekt Norge also aim to recommend when digitally based autonomous decision-making is a real option. Digitalisation accelerates decision-making and provides enhanced confidence and reliability, even in outcomes and predictions, in all project management processes. What are the impacts of digitalisation concerning roles and responsibilities in the project organisation? How can machine learning, Industry 4.0 linked data, or AI perform predictive analytics as a basis for decision-making? It is essential to determine the project success factors with the improved confidence, efficiency, reliability, and success by utilising digitally based decision support. It is necessary to map and define which decisions can be impacted by digitalisation and which may not.

3.3 The Interviews

As described in the methodology introduction, we had a closer collaboration with one of the three companies answering the digitalisation surveys. Company A has been very co-operative and participated in interviews to help gain a deeper understanding from a company perspective.

With the help of our contact person, we obtained the contact details of relevant employees, and we interviewed a total of six employees from company A. Some of these interviewees were working and had experience with the corporate memory system. We were also interested in interviewing employees involved in decision-making and who had opinions on digital transformation and AI technology. All the interviewees were chosen based on their experience and knowledge of the system, data, or work areas.

The interviewees were contacted by email containing general information about our master's thesis and the purpose of the interview. With the interview invitation, all the interviewees had to sign a consent form that contained the rights and properties following the NSD's standard for interviews. The interviewees also received the interview guide so they could prepare their answers. The interviews were conducted using Microsoft Teams, which ensured professionalism and security for the interviewees and resulted in a positive dialogue. See appendix Appendix A for the interview guide.

Most interviewees were well prepared, and the interviews lasted approximately one hour. The two of us took turns in asking questions and transcribing the answers, ensuring that there was one listener and one taking notes. All six interviewees were very positive to the topic of our thesis and had a lot of information and input to our questions. As they were all very enthusiastic on the subject and had a lot to say, the interview process went effortlessly.

After all the interviews were held, we read through all the interview notes to get an overview of the different feedback. We then chose to focus on the main points and differences mentioned. The results are presented in Section 4.2.

In retrospect, we feel that, because the interviews were conducted remotely through Teams and not "face-to-face" the interviews were less personal than we hoped. It is easier to get a personal connection and to read expressions and emotions by being present in the same room. It can also be easier to elaborate and bring out the essence of what is being asked and answered by physically present. Simultaneously based on time and efficiency, it was the most optimal option to have the interviews digitally, as the interviewees were all located in different locations from us. Overall, the interviews went very well, and the interviewees (and interviewers) were satisfied both during and after the interviews.

3.4 Data Analysis

The method used to analyse the data is the **CR**oss-**I**ndustry **S**tandard **P**rocess for **D**ata **M**ining (CRISP-DM) framework. The framework was introduced in the late nineties and is still the most widely used methodology for analytics, data mining and data science projects (Martinez-Plumed et al., 2021).

The CRISP-DM process consists of six iterative steps that are represented in a life cycle model from *Business Understanding* to *Deployment*, see Figure 7 (Schröer et al., 2021). It is important to be aware of the effect of each step and the interplay between them as they all contribute to the success of the analysis (Jaggia et al., 2020). To combine CRISP-DM with the structure of this thesis the *Evaluation* phase is discussed later in Section 4.3, *Results from the Data Analysis* section. The *Deployment* step, involves translating the knowledge gained from the data analysis into a set of recommendations, sometimes in the form of a user-guide which is later deployed into the business. As deployment of our findings is not fully applicable, it is still resourceful to our cooperating companies and energy industry. It is important to document the knowledge achieved and discuss limitations and future recommendations, which this thesis as a whole addresses.

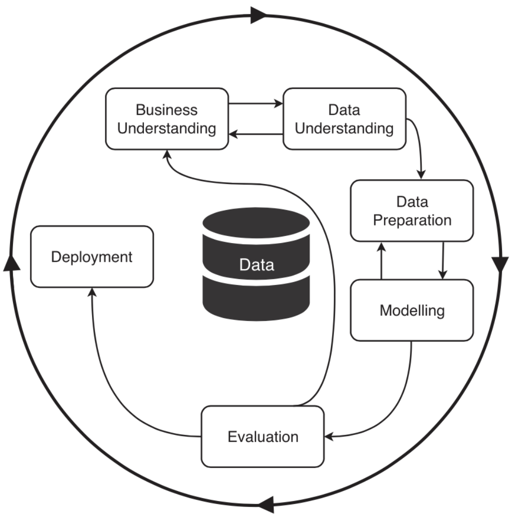

Figure 7: CRISP-DM process model (Martinez-Plumed et al., 2021, p. 3049)

3.4.1 Business Understanding

The first step is to understand the problem and what objectives and requirements should be met from a business perspective (Jaggia et al., 2020). Company A supplied us with data from their corporate memory system. The theoretical background regarding corporate memory is introduced in Section 2.5.4. During follow-up meetings after receiving the data set, we got a thorough introduction on how the corporate memory system is currently used, maintained and what future visions the company had for the system.

The company is currently in the process of developing their corporate memory system and setting up a culture of storing and utilising the data produced during their projects. For the system to work optimally, the company recognised the need of large amount of quality data, easy navigation, and user-friendliness. The company hopes to develop a system that helps them make evidence-based, precise and improved decisions, increasing the quality of their projects and success rate. Currently they are working on a initiative to include more granular, lower level data about each project into the system. Data such as the key dates, sanction dates and metadata for each project.

Additionally they are looking into ways of incorporating technical data together with the organisational data used during cost estimation and planning. By incorporating more data, company A hope to build a database with data from multiple disciplines involved when undertaking a project. All the way from conceptualisation, scheduling and cost estimation to engineering and execution. This basis could then be used as a reference for new projects as well as the development of AI/ML tools.

Company A voiced an interest in exploring new applications of the system using AI and ML technology. They also wanted to see how these technologies could improve the user experience and efficiency of the system. Hoping that AI can improve how the user navigates the data, connecting users to the right information more quickly.

It was therefore decided to train two neural network models on the cost estimation data from the CM system. One model tasked with predicting the cost of the project as a whole, basing its predictions on high level project data extracted from the database. Another model would be trained to predict the cost of the individual WBS-items that makes up the database. By utilising neural network models we can additionally generate embedding representations. The second to last layer of the networks is used as an embedding layer, generating a continuous vector representation of the project or WBS-item. The similarity between these embeddings can then be measured and used to create a recommendation system. This system would provide users with relevant previous cases based on input from the user. This input could be fully or partial information about a project or a WBS-item. The system would then recommend similar items based on what features the network deemed as relevant to the cost of the item.

The data analysis is therefore conducted in two connected parts, one at the project level and one on the individual WBS-item level. As the data set only contain 19 projects, it was decided to not evaluate the predictive capabilities of the models on this level, rather focusing on the predictions at the WBS-item level. The results of this part of the analysis is therefore only evaluated on the similarity study of the projects. Additionally the generated embeddings from the project level analysis is used as a part of the input for the WBS-item level analysis, connecting the two parts.

3.4.2 Data Understanding

The data understanding step involves collecting, describing, exploring and verifying the data (Schröer et al., 2021). The data is supplied from the corporate memory system used of company A, where the data is primarily used for cost estimation.

Data Description

The data set consists of 19 projects that has been approved in DG3. This means that all of the projects are ready for the execution phase with regards to the project development process presented in Section 2.3. The projects start dates range from 2016 to 2026. Therefore some of the projects are currently being executed, some are finished and others have not yet begun.

The data is structured into rows of WBS-items. Each WBS-item representing a piece of work, with associated features of information. In total, there are 50 features available for each row. These data features contain information such as what project the WBS-item is associated with, its position in the WBS hierarchy, its cost, its geographical location and its start and end date. The rest of the features will not be described in this thesis due to confidentiality concerns, but are utilised as input to the models.

In total, the 19 projects contain a total of 1322 WBS-items, with varying number of items per project. The number of items per project can be seen in Figure 11. The cost of the WBS-items range from values of thousands of NOKs to hundreds of millions of NOK. The cost of the projects as a whole range from hundred million NOKs to multiple billion NOK.

Not all of the 50 features per item were useful for data analysis. In the CM system 7 of the features are reserved for descriptions of another feature or could otherwise be deduced from other features. 13 of the features are used to denote costs across different currencies and three of the features contain no values. One feature was reserved for additional commentary regarding the WBS item. These features were therefore not included for training. This results in 26 unique data features for each row which contain information relevant for an AI model. Additionally a lot of these features were associated with specific products and therefore contained no information for majority of the rows. These were still included for training as they were considered relevant for costs although the data in them was sparse.

3.4.3 Data Preparation

After understanding and exploring the given data, it is easier to select which data will be selected for further analysis. "Specific tasks in this step includes data reduction, data wrangling and cleansing, and data transformation (e.g., creating dummy variables) for subsequent analyses and testing." (Jaggia et al., 2020, p. 614). Two types of models are to be trained and it was therefore necessary to create two separate data set, one for projects and one for WBS-items. These data sets are now referred to as the Project data set and WBS-item data set. The project data set will be created by extracting high level characteristics of the projects from the data set, the WBS-item data set will be the result of the cleaning of the data set. As the embeddings generated from the project analysis will be used as part of the input in the WBS-item data set, the project analysis needs to be completed before starting the WBS-item analysis. How the data sets are created as well as their relation to each other are presented in the flow chart, Figure 8, below.

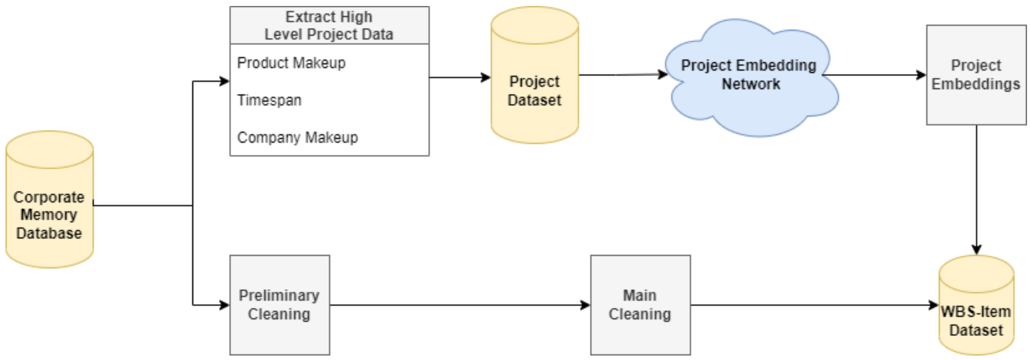

Figure 8: Data Preparation Flow Chart

3.4.3.1 Creating the Project Data Set

For training the project level model, high-level project data was extracted from the data set. A part of this data was different makeup arrays that characterised the project. Examples of these makeups are arrays displaying what contractor companies and activities were active in the project. These makeups were extracted by counting the occurrences of each within a project and dividing by the total amount of WBS-items, returning a weighted array representing the prevalence of each category, see Figure 9. This process was also applied for some of the features omitted from being described due to confidentiality concerns.

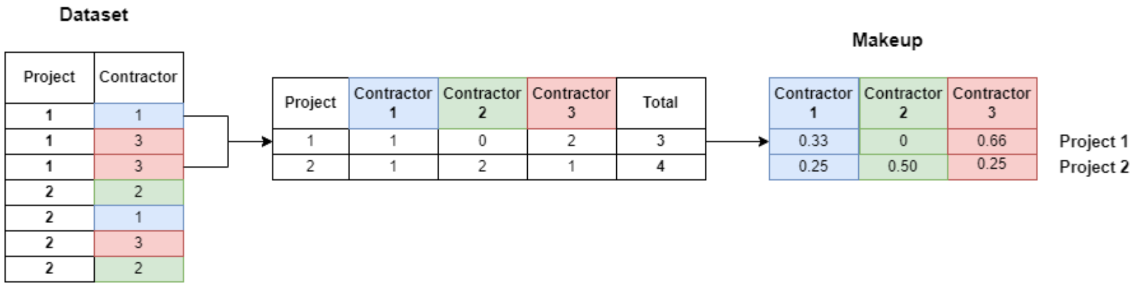

Figure 9: Creation of the makeup arrays used as part of the input into the Project model

Additionally, a time array representing the time periods the project is active was created. The array was created by attaching an index value to every quarter year from 2016 (the earliest start date of any WBS-item) up to the start of 2029 (the latest end date for any WBS-item). For each day the item is active, the value in the array corresponding to that day's quarter index is incremented. Summing the values from each item in a project, an array mapping the total project activity is achieved. The array is then divided by the total amount of increments made across all items in that project. Note that we are not dividing by the total amount of days the project is active. As some activities overlap, the number of increments is larger than the number of active days, and we want the array to contain values between 0 and 1. As some activities overlap, periods with a large number of activities will have a higher weighting than those with few activities, see figure Figure 10. Active dates of the projects range from 2016 up to 2029, and with four quarters for every year, the time array is of length $13 \cdot 4 = 52$.

WBS-Item	Q1_2016	Q2_2016	Q3_2016	Q4_2016	Total
1	16	91	92	27	226
2	67	22	0	0	89
3	0	57	64	0	121
4	54	16	0	0	70
5	0	0	92	91	183
6	10	91	32	0	133
7	0	0	0	16	16
Total	147	277	280	134	838

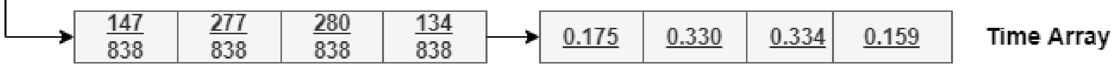

Figure 10: Example showing how the time array is created. In this example there is only one year, resulting in a time array of length 4, in the data set the array is of length $13 \cdot 4 = 52$

The product makeup for each project is collected by iterating over the WBS-items and collecting what products are present in the project. The product makeup is represented by an array with an index for each product. Each value in the array can be either (1) - success, meaning the product is present in the project, and (0) - failure, for not present.

After assembling the separate arrays for each project, they were concatenated into one final array that would be used as input to the model. The resulting array had a length of 177 features, meaning we had 19 rows, one for each project, with 177 individual data points for each row.

The cost of the project was calculated by iterating over each WBS-item in the data set, accumulating the cost of each project into one value, and normalising the resulting values according to the method presented below, using equation (7). A neural network model was then trained on the projects with the inputs presented above and the label being the project's total cost. The specifics of the network are described in greater detail in Section 3.4.4.

3.4.3.2 Preliminary Cleaning

The cost of each WBS-item will work as the label for the network during training. In the data set, the cost is split into different currencies and thus needed to be collected into one variable, representing the total cost of that WBS-item. Currency rates for each quarter between 2016 and 2022 were used to convert the cost of WBS-items to NOK. For WBS-items scheduled in the future, the rates for the 1st quarter in 2022 were used.

Handling Negative Cost

In the data set, there were WBS-items present that had a negative cost attached to them. These were regarded as special occasion items that did not follow the norm and were due to either an error when plotting the data into the system or a correction measure to make the budgets add up, fixing an earlier mistake. Items with negative costs were considered exception measures and removed from the data set. There were 11 WBS-items with negative cost in the data set and, when removed, brought the total amount of WBS-items down to 1311.

Handling Outliers

It was also discovered that some WBS-items had vastly larger pricing than the others. These are outliers, values in a data set that differ significantly from the rest of the observations (Ghosh and Vogt, 2012). Outliers tend to confuse machine learning models as they differ significantly from the norm, and it was decided to remove the most extreme outliers from the data set. To detect outliers in the data set, a method utilising the Z-score of the cost of each item was used. The Z-scores are calculated by the formula:

$$z = \frac{x_i - \mu}{\sigma}. \tag{6}$$

Where μ is the average value of the cost, and σ is the standard deviation. A Z-score of $\pm$ 3 would be an extreme value in a standard distribution and is typically used as a standard cutoff value for finding outliers (Mary, 2011). We then removed every row with a cost Z-score over 3. The removal of outliers affected 22 items, bringing the total number of rows to 1289.

Handling Duplicates

It was discovered that there were WBS-items in the data set with identical features but with different costs, meaning all the features of the WBS-item was identical except the cost. As the cost would serve as the target value for the model during training, these WBS-items would only bring noise to the training. A model can only be as good as the data it is fed, and a premise for the learning of a model is that similar input results in similar output. Having identical inputs resulting in different outputs breaks this premise as the model has no method of distinguishing between these. For handling the duplicates, it was decided to keep one instance and remove all other instances. In total, there were 75 duplicates, across 28 distinct instances. Therefore 47 items were removed from the data set, bringing the total amount of items to 1242. Figure 11 shows the distribution of WBS-items per project before and after the data cleaning.

		Projects																			
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Total
No. Items	Pre Cleaning	103	93	59	18	78	59	34	113	121	28	12	122	131	55	28	54	66	116	32	**1322**
	Post Cleaning	98	83	53	18	72	55	26	110	116	19	9	119	130	54	28	46	65	114	27	**1242**

Figure 11: Distribution of items per project before and after the data cleaning.

3.4.3.3 Main Cleaning

First, all the N/A values (No value is Available) in the data set were replaced with zero, as N/A values can not be utilised for mathematical operations. Another challenge was transforming the categorical data into numerical data, as most of the features in each WBS-item were categorical values. For the model to interpret this information, one-hot encoding was utilised for all categorical values except the value representing the project the WBS-item belonged. The project value is instead replaced by an embedding vector from the project analysis would replace this value.

One-hot encoding is the process of creating variables ("dummies") for each of the distinct variables in a feature. For example, if the feature represents the colour of a dog and the colour is any of the following: Brown, Blonde, Black or White. Then four dummy variables are created, one for each colour, assigned to each of the indexes. The index corresponding to the colour represented in the data is mapped to (1) while all the others are (0) as illustrated in Figure 12.

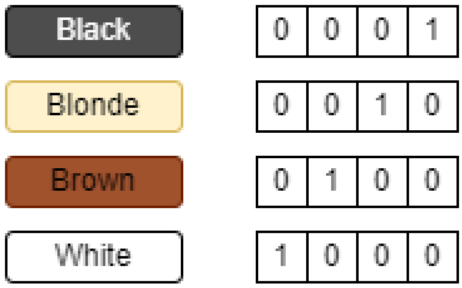

Figure 12: One-Hot Encoding of the color attribute of dogs

The Python library Pandas and its function get_dummies() was used to one-hot encode the data (Pandas development team). The resulting array after one-hot encoding is a sparse array, an array characterised by a large number of 0-variables, resulting in a significant increase in the number of features per row.

Due to the significant difference in scale between inputs and costs, all numeric values are normalised. Normalising the data ensures the model considers all inputs to a similar extent, providing faster and more stable learning. Normalising the data is also beneficial as neural networks converge faster on normalised data (Sola and Sevilla, 1997). Normalisation is done by Equation 7, This formula is also known as MinMaxscaling.

$$z_i = \frac{x_i - min(x)}{(max(x) - min(x))} \tag{7}$$

An array representing the time each item was scheduled for was created by a similar method as done with the project input in Section 3.4.3.1, attaching their active days to quarter years and dividing by the total amount of days the WBS-item is active. In addition, the total amount of days used for the WBS-items was attached as a separate feature.

Lastly, the generated project embeddings from the project analysis are appended to the data set. For each WBS-item the project embedding vector that item is associated with appended to the input representing that item. Appending the different arrays to the WBS-item row resulted in a final input array of length 320 for each WBS-item.

3.4.3.4 Cross-Validation & Train-Test Split

As we are not interested in the accuracy of the estimations from the project network, only the generated project embeddings, this network is trained on the complete data set. Therefore, a train-test split for the project data set is unnecessary.

For the WBS-item predictions, the specific entries for training and testing are rotated to cross-validate the training data. Cross-validation is a re-sampling method employed to measure performance more accurately, by evaluating on more data. It is one of the most widely used data resampling methods to estimate the true prediction error of models and to tune model parameters (Berrar, 2019). During cross-validation multiple models are initialised and trained on different parts of the data set. Each model is then evaluated on the portion of the data set not used for training. The evaluation of the model's accuracy is then based on the mean performance of these models. In this analysis, cross-validation is done by training a model on 18 projects and evaluating it on the remaining project. When the model has finished training on the training set, it is evaluated on the test project. The results are stored, another project is chosen for evaluation, and the other 18 projects are put in the training set. A new untrained model is initialised every iteration, and the process is repeated until every project is used for evaluation.

3.4.4 Modelling

In this thesis, machine learning is used to estimate costs and give insights into the data we analyse. Two networks are utilised, one network for estimating the total costs for a project based on high-level data and creating embeddings used for representing the project for further use in a lower level focused network for WBS-item estimation. Both models are tasked with predicting costs, which is a regression problem. Utilising embeddings, we were limited to choosing neural networks as our model type. The python library PyTorch was used to create the neural networks, and all layers are of the PyTorch Linear layer type, also known as a Dense layer (Torch Contributors, a,b).

Below in Table 1 are the architecture and parameters of the Project model.

Parameter	**Value**
Learning Rate	0.00001
Training Epochs	200
Layers	177x177x50x1
Loss Function	MSE
Optimiser	RMSE
Activation Function	SeLU

Table 1: Project model's architecture and parameters.

The parameters are explained in further detail in the appendix Appendix B. The layer structure 177x177x50x1 denotes the number of neurons in each layer. Therefore, this network consists of 3 layers—two layers with 177 neurons, one with 50 neurons and an output layer of one neuron. The activation function between the layers is the same for all layers.

For the WBS-item network the parameters are as described below in Table 2:

Parameter	**Value**
Learning Rate	0.0001
Training Epochs	50
Layers	320x320x320x320x320x50x1
Loss Function	MSE
Optimiser	RMSE
Activation Function	ReLU

Table 2: Parameter and values for the WBS-item model.

The main differences between the configurations are the number of epochs and the size of the network. Models are dimensioned according to the dimensionality of the problem, as larger models perform better on larger data sets (Bebis and Georgiopoulos, 1994). As the WBS-item data set is significantly larger than the Project data set, the WBS-item model is significantly larger than the project model. The project network has 19 projects to train on, whereas the WBS-item network has a total of 1242 WBS-items. The specific configurations used were found through a trial and error method and were configurations that seemed to work well for the different models and data sets.

Training the Models

The models are trained by forward propagating the inputs from the data set through the network and comparing the output to the target label. The error of this prediction is then calculated by applying the loss function, and this loss is propagated back through the network, updating the weights Section 2.8.4. The training loop is divided into epochs, one epoch equalling an entire run through the training set. Training for 50 epochs will mean the model has processed every item in the data set precisely 50 times.

The process of training the project model is presented in Figure 13 below. Input from the data set is forward propagated through the network, resulting in a prediction from the model. This prediction is then evaluated against the label, and the loss is calculated and propagated back through the network, updating the weights. Training the WBS-item model is done similarly but with the added layers and input from the WBS-item data set.

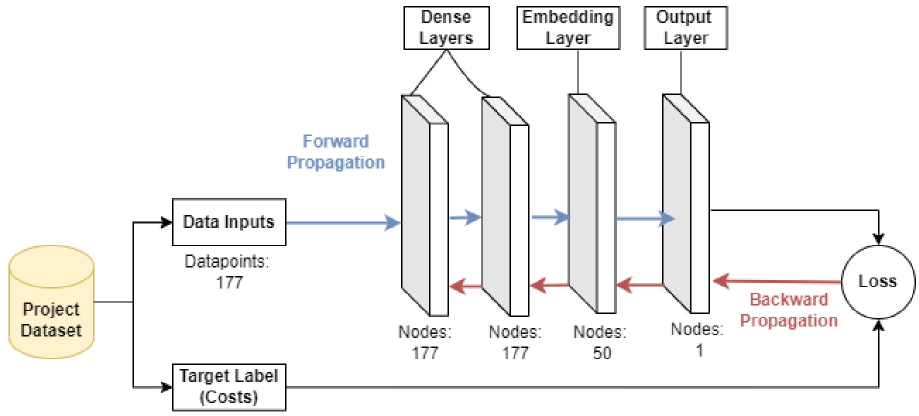

Figure 13: Training the Project Network. The first two layers have 177 nodes, the third layer is the layer the embeddings are extracted from. Last layer is used to predict the cost of the project as a whole.

Generating Embeddings

After training, the project inputs are propagated through the network again but stopped before the last layer and extracted. In Figure 14 below, the process of generating the project embeddings is illustrated. The figure illustrates how the sparse input data is propagated through the network and mapped to a dense continuous embedding vector of length 50. Embeddings for the individual WBS-items are generated in the same manner.

The embeddings were created with the almost the same configuration as the estimator. The only exception is the activation functions for the WBS-item model being changed from ReLU to SeLU. This change is due to the ReLU activation reducing the information in the embedding vectors, setting many values to "0". As a lot of the values in the vectors will be 0, the vectors will share these values, and the similarity between them is artificially inflated. ReLU and SeLU are briefly explained in Appendix B.

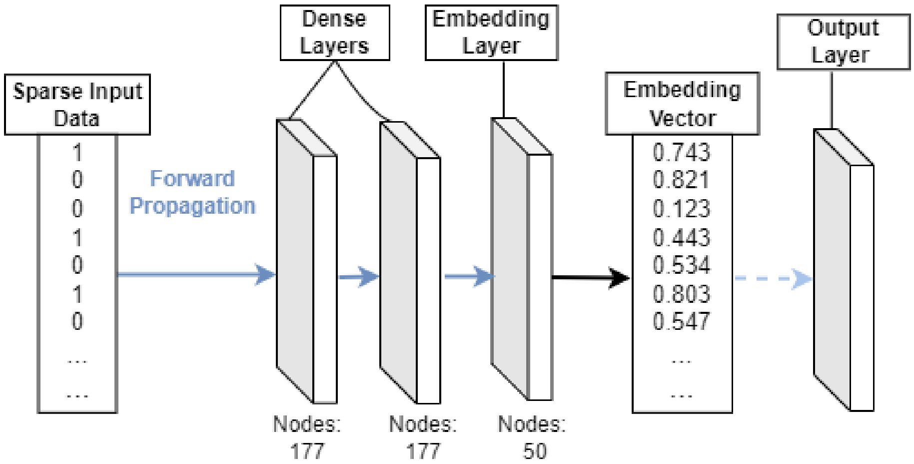

Figure 14: Creation of project embeddings by a trained network. Sparse input data is transformed to a dense vector.

Comparing Embeddings

In this thesis, embeddings representing the projects and the individual WBS-items are generated and measured on similarity. Both the WBS-item embeddings and the project embeddings are vectors of length 50. The similarity between the embeddings is calculated by two different methods: Cosine similarity and Euclidean Distance. Cosine similarity is the primary function used to evaluate the similarity between word embeddings (Intellica.AI, 2019), and this is why it is also chosen as a method in this thesis. Cosine similarity is calculated by the formula:

$$\cos(\mathbf{t}, \mathbf{e}) = \frac{\mathbf{t}\mathbf{e}}{\|\mathbf{t}\|\|\mathbf{e}\|} = \frac{\sum_{i=1}^{n} \mathbf{t}_i \mathbf{e}_i}{\sqrt{\sum_{i=1}^{n} (\mathbf{t}_i)^2} \sqrt{\sum_{i=1}^{n} (\mathbf{e}_i)^2}} \tag{8}$$

Doing this for each WBS-item we can use this distance value to measure how similar the embeddings are. The score ranges from [0,1], where "0" equals no similarity and "1" is identical.

Another measure of similarity between embeddings are Euclidean distance. The formula for Euclidean distance is defined as:

$$d(p, q) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \tag{9}$$

The Euclidean distance is the distance between the endpoints of two vectors in the vector space. The lower the distance, the more similar the two vectors are. This measure is not bounded like the cosine similarity, but can take on any positive value.

As there is only 19 projects, these similarity between these will be evaluated directly by using a heatmpap. However, using a heatmap for the similarity between WBS-items would not be appropriate as there are far too many items. It was rather decided to create a prototype of a recommendation system that would guide a user to relevant information. The system will take a WBS-item as input and return a set of similar items known as neighbours. Neighbours would be decided by defining a decision function based on the similarity values. As one measure is bounded and one is not, it was decided to base the decision function on the Z-score distribution of the values. The Z-score being calculated by the equation presented in Equation 3.4.3.2. A benefit of using the Z-score distribution is that the method for choosing which two vectors are regarded as neighbours is the same for both Euclidean distance and cosine similarity. The Z-score of the two different metrics was then used to decide whether two WBS-items were neighbours. Z-scores two deviations from the mean in the direction toward similarity were chosen as the cutoff point for neighbours. As cosine similarity is positively focused, e.g. the bigger the cosine similarity value is, the more similar, Z-scores above "2" is counted as neighbours. For Euclidean distance, the opposite is true; the smaller the distance, the more similar; therefore, Z-scores less than -2 are counted as neighbours.

4 Results

This section will first present the results from the digitalisation surveys and interviews with company A. In context with the CRISP-DM process, the *Evaluation* phase involves reviewing the results of the data analysis in the context of the first step, *Business Understanding* (Martinez-Plumed et al., 2021; Schröer et al., 2021). The three parted results will be evaluated together in the Discussion section, Section 5, together with the literature presented in the Theory Background section, Section 2.

4.1 Results from the Digitalisation Surveys

The following results are an overall summary of the responses from companies A, B and C of the surveys received by Prosjekt Norge, which was introduced in the Method section, Section 3.2.

4.1.1 Project Execution Model

All the responding companies practise a stage-gate based project execution model with clear decision gates (DGs) between each project stage. A requirements list for the DG is established for company A to develop sufficient maturity through the upcoming stages. The process is generated by the project management team led by a project manager. The model is customised to fit all types of the companies' projects. Companies A, B and C all practise with five DGs in their current project execution model, and the last DG representing the handover to operations. Companies A and B refer to the five DG's as DG0 to DG4, but company C practises with DG1 to DG5. Company B's project execution model contains three initiating decision gates concerning screening, bid/mandate, and negotiation. Company C's DG5 involves more than operation but also verifies that the delivered product aligns with the requirements agreed upon in the previous DG. Their DG5 works as a follow-up of the project and is scheduled for about a year into operations.

4.1.2 Project Decision-Making

The three companies are not utilising any digital tools specific for decision-making. Company A has an underlying data basis but does not utilise any digital tools in the interface towards partners. They have two systems they use internally as databases. The primary decision-making process is done through meetings, PowerPoints, and digital tools from Microsoft, such as Teams.

The two other companies agree with how internal decision-making is done, as company B also utilises Microsoft's interaction applications. Companies B and C also utilise the system License2Share, an information-sharing platform used between operators, partners, and authorities. The system is not purely used for decision-making but serves more as decision support.

There is an overall low degree of autonomy in strategic and stand-alone decisions regarding digital features and tools. Companies B and C correspond with a management team sitting physically in a meeting room or on Microsoft Teams to make these decisions. The projects get a "yes" or "no" at each DG before proceeding to the next phase.

The companies mentioned that digitalisation in decision-making creates the opportunity to do more with less. As easy access to information reduces the amount time spent researching, digitalisation can lead to fewer people and resources being necessary for decision-making. It may also lead to improved decision quality, as more information can be absorbed ahead of making the decision. When asked what is critical for making successful digital decision-making tools, Company B highlights the issue concerning industrial standardisation.

4.1.3 Status & Perspective on Digitalisation

Company A views digitalisation as a tool to enhance performance and predictability, not a process. Digitalisation development is reflected and implemented as new solutions are developed in the management or the specific subject area. The case company has established programs to coordinate digitalisation initiatives to improve the functional line and operations. They have different digitalisation programs, one governed by a business unit and the other by a large project.

Company C described how they utilise the project administration tool PIMS (Project Information Management System) together with in-house developed project execution and portfolio systems to follow up on their projects. PIMS is working well for the company, but they are currently looking for a new system to replace the existing portfolio management, as the system support of PIMS is running out.

When the three companies were asked to evaluate their digital maturity level from 1-5, where 1: Poor/Resistor and 5: Disrupter/Full utilisation of digitalisation, companies A and B considered themselves at levels 2-3: Explorer-Beginner. The companies mentioned that several initiatives are currently taking place in the company. Company C states that they would score high in project follow-up systems but have room for improvement when digitalising the information collected externally and integrating project execution systems internally. Based on these challenges, company C scored their digital maturity relatively low, which may be interpreted as a score of 2.

The survey asked about the benefits and experiences of using digitalisation in management and control regarding reliability and quality of project delivery, efficiency, transparency, and traceability. Company A states that the benefits experienced so far are traceability, efficiency, and transparency. Most of the company's project controls have been moved from Excel to PIMS, also used for other management processes. They also mentioned using PowerBI for cost reports and conducting meetings on Microsoft Teams. The company mentions a challenge that permanent deviations must be registered in project PIMS and then to a different database, resulting in double work. Here they see an obvious opportunity for improvement.

Company B agrees with company A regarding the benefit of transparency. They have also implemented Power BI to easily access and view information and data. In contrast, company B did not agree with the term efficiency. They believe that no significant efficiency is gained due to fewer hours, execution duration, or quality improvement. Company B expressed that new projects often struggle to achieve the benefits of digitalisation as the variety of project execution models and multiple contractors make it more challenging to implement.

Company C recalls that all the terms mentioned are essential to follow up on the various projects in different phases. Company C refers to individual projects and on a management level to get the status of the overall portfolio. Achieving this will lead to better experience transfer between the different projects. Currently, the digitalisation of governance processes in project execution is limited. Therefore the project organisation, roles, and responsibility are currently not affected. The interaction is the primary access to familiar sites, SharePoint, to exchange information about reports and action tracking.

The companies where questioned on how the project organisation, roles and responsibilities are currently affected by digitalisation in execution models. For company A, the project organisation will follow systematic steps in a transformation model. The involved stakeholders, roles, and responsibilities will be identified and defined based on how digitalisation will affect them. It is a complex stakeholder environment, but the whole value chain has enough representatives to define the digital opportunities.

Companies B and C point out that digitalisation will not remove the need for "traditional" competence but instead adds a new one. Company B describes that digitalisation has been met with optimism and chaos regarding responsibility and roles. Company C also mentions that the impact of digitalisation will lead to more process orientated organisations and create the need for multi-discipline teams.

The companies were asked how digitalisation enhances the capabilities of managing the VUCA world for projects. VUCA world as in a Volatile, Uncertain, Complex and Ambiguous world. In a VUCA world, nothing can be taken for granted, and this also applies to the projects. Specific capabilities are required for mastering such an unpredictable and turbulent environment. Company A states that it is possible that improving data management will lead to reduced costs driven by reduced working hours and improved decisions. Company C agrees with company A that more accurate and updated data management will improve the basis for decisions at different levels. For example, improve the capability for risk-based decision-making.

In company A, agile working methods will be introduced and created to help projects cope with VUCA, resulting in more robust/adaptable projects. Access to market data and its project data clarifies where the company has their most significant risks, this can be used for performance measurement. Once a project has passed DG2, it is not executed very differently from how projects have been executed before. Company A has also established alliances to increase robustness to help thrive in the VUCA world. They recognise that if digitalisation has a significantly positive effect on lead times, it will reduce uncertainty of investment decisions. Shorter lead times are preferred as it makes it easier to estimate the market price at the time of production. Company B believes that digitalisation may not reduce volatility in markets in the short term, but it will reduce complexity and ambiguity. Over time they are also convinced that it will reduce the uncertainty of project duration, cost, and quality.

Digitalisation will have benefits for projects and introduce new ways of collaboration. All the companies agree that digitalisation will reduce project control and engineering time. Collecting all the information in one place will be helpful and lead to more efficient collaboration due to the increased availability of data. It will limit the possibility of misunderstandings, thus preventing decisions from being made on the wrong basis. All three companies agree that where technology makes it possible to improve work processes, they see significant value creation.

4.1.4 Industry 4.0 Adaptation & Implementation

The three companies believe that the industry is at its early stage of adapting Industry 4.0 features. Company A thinks their current model-based process for system engineering is relatively immature. Many proprietary execution models, engineering tools, and deliveries still govern the industry. Today, company A utilises a standard engineering model. The system mentioned was LCI (Life Cycle Information Management) deliveries.

Company B describes how Industry 4.0 will lead to fewer decisions needing to be made. As the information is available, it will result in less fire fighting and make it easier to make the right decision when required. Improving the digital foundation for making decisions will also improve the decision. Company C is positive to step wise adapt and become more digitalised in their project execution. They are still beginners in Industry 4.0, but they believe that implementing Industry 4.0 features and characteristics may be a future goal for the organisation.

4.1.5 Digital Technology

Big data, IoT, AI, and ML technologies are insignificantly utilised for management and performance control in the three companies. The decisions and performance management are driven by data analysis, but the data flow and analysis are only automated to a small extent. For companies A and C, a large share of the project data is controlled and administrated by suppliers. Fundamental information is collected and reported automatically to company A, but not to the degree to which big data analysis can be utilised efficiently for performance management and control.

Company A is well acquainted with digital twin technology, but they think it is hard to define as the term digital twin can mean a lot. For company B, digital twins have been utilised to a low degree in project execution but are more frequently used in operation. Similarly, company C utilises digital twins for operation but not during project execution and control. Both companies A and B have experience using 3D models as digital twin technology.

From the question: "*How may digitalisation impact project control through monitoring & contextualisation of data, AI & ML, predictions & prescription, and real-time condition monitoring*?" Company A believes that digitalisation has great potential within project control. The first step is naturally to monitor and contextualise the data between different systems, vendors/suppliers, and projects. Both companies A and B believe that the contextualisation of data will lead to less time being spent on non-value-adding activities. Implementing this first step will give easy access to updated and structured information and increase transparency, improving performance management both on the project and portfolio level. Companies A and C state that the value from AI, ML, predictions, prescription, and real-time condition monitoring is most relevant in the production phase, such as forecasting and continuous improvements in operation. All the companies are aware of a robust digital foundation to make these improvements possible. Digital maturity in project development is essential.

The companies were also asked about their thoughts on cyber security and its impact. Company A considers cyber security a task handled by a team. This team secures the data from the sensors to the cloud. They thus consider this team to be a part of the digital value chain. The challenge is that many people involved in this process take all too little consideration for cyber security. The company admits that the cyber security risk is greater than the company would want in some areas. Company C worries that the security threat will always make restrictions on complete digitalisation. Cyber security will always have challenges related to what data can be shared and how unwanted access to data may threaten the business. Company B did not have a comment on this question.

4.2 Results from Interviews with Company A

The results are presented as a summary, referring to important points and arguments from the interviews. The interviewees had different roles and responsibilities, but all were involved or familiar with the system. Some still worked closely with the system, including system owners and developers. Others have taken part in establishing the system but currently worked with project and enterprise architecture development and digitalising projects.

Several interviewees point out that the company is very data-focused, so implementing new technology is already well integrated and understood. The company's CEO is data-centric and wishes to automate as much as possible. Therefore, the company invest a lot in digitalisation and new technology projects. Data skills and understanding are something the company focuses on when hiring new employees and developing current employees. The organisation carries out a quarterly evaluation of its employees' development and motivation. One of the questions asked refers to the level of data usage their department is practising. One of the interviewees wished that the score was higher regarding data usage but emphasised acknowledging intention. The intention of increased data and digital maturity is established as a work in process.

To remain competitive and follow marked trends, all the interviewees pointed out the need for research, academia and the collaboration between academia and the industry. Without these resources and input, the industry will struggle to think outside the box and get stuck in its habits and routines. By expanding their horizon, the utilisation of research and academia will enable the possibility to follow trends and what other industries do. One of the interviewees thinks, "we can achieve what we want, but it is up to the company to spend and know what they want.".

4.2.1 Corporate Memory

The corporate memory (CM) system is developed for the cause of a better understanding of project performance. One defined it as an IT platform for collecting knowledge and learning. Comparing projects against each other is beneficial to learn from the difference between good and bad projects. In this way, the company will achieve continuous improvement—a significant opportunity to learn by collecting quantitative data, such as costs and other project characteristics. Collecting data is fundamental to promoting organisational learning and, as an interviewee mentioned, will be essential for the company to become the world leader in their industry.

CM is mainly utilised and developed for company A's partners in different production areas. The partners complete their own cost benchmarking on their delivery before company A can conduct its benchmarking on a project level. From the CM system the partners can quickly get insight into the pricings of the projects they are currently collaborating on. All the interviewees emphasised the importance of good data quality, structure, and collection.

It was mentioned that the management in company A has access to the CM system, but very few are utilising it. The majority is familiar with its existence but let the primary users have control of its use. A CM developer wishes to scale the system so the whole company can benefit from the system. Today, the data and information in the system are too specific, as its functionality is only relevant to the users utilising it. An application that will direct the information to the right people would be optimal in the future. One also mentioned the wish to implement planning into the CM system. If the system could create a link between project activities and estimation, it would provide great insight into the projects.

Currently, they are focusing on establishing the road map and overview of the system and its future potential. The people working with the system are working to ensure good quality data concerning their roles and portfolio areas. Company A wishes that CM will hold more weight in decision-making processes and that it will prove and demonstrate the better and more predictive answers. The word trust is mentioned by several of the interviewees.

Today company A is working on a different IT system that will support the requirements of the CM system. The system will help transform the data to a suitable format and import it correctly into CM. It will serve as a link and help elevate the CM system. One of the interviewees pointed out the importance of learning from the CM system. The person clarified how CM and learning were connected in an ecosystem and advocated the awareness around knowledge sharing and transfer in the company. An example mentioned was that it is challenging to prioritise learning because people are often too busy to set aside time. The CM system is one initiative the company has active to gather knowledge and increase learning within the company. Such a initiatives need to promote a "one-team" mindset to get everyone involved and committed.

The main limitation mentioned by all interviewees was the digital maturity of the people in the organisation. The lack of data understanding, skills and resources were emphasised. The importance of understanding the use and value of data is hard to implement into the organisation's culture. Even though people have their work routines, they need to understand the importance of taking the time and trouble to enter the data, which may be of value to others in the future. As they struggle with data understanding, it is hard to get the employees to trust the data and the system. As many of the employees in the organisation have been around for a long time, it is natural to create personal barriers and forget that they are a part of the bigger picture.

Educating the organisation's employees and involving them in the process will encourage them to appreciate the work done and become more comfortable with the technology. Several of the interviewees highlighted the need to increase the company's digital maturity, knowledge and learning become critical aspects. The value of lessons learned during and after project execution is crucial for organisational learning. It is essential to share experiences and knowledge quickly and make sure it gets to the relevant people to increase project success. One of the interviewees emphasised the importance of presenting the results of the CM system in a simple and understanding way and, at the same time, having the opportunity to justify why the results turned out the way they did.

There is also the challenge of enough resources to develop the CM system. It is essential to collect the data and determine where and how it has value for the company. Following a standardised process, the company has found instances where the data source does not correspond. One dashboard gives one value, but another gives a different one. Getting inconsistent values makes the users confused and decreases their trust in the system. It proves the need for consistent sources with the right data foundation and tools, to increase the quality and success of projects.

Another technical issue mentioned was the need for more technical attributes so "AI can do its thing". The real power behind AI and ML technology is in numbers, and the key metrics are essential to get the correct correlations in the predictions. The challenge is to codify all the technical data, as a lot of the information is written in descriptive reports, maps, and designs. Soft factors performed by people are also complicated to translate into numbers. All interviewees emphasised the importance of good data quality, structure, and collection.

When asked about what was holding them back, one of the interviewees mentioned that the cause was variable. Some departments have the data available but do not see the opportunities, and others know what they want but do not have the data or know where to start. One of the interviewees was sceptical of the system's value, as of how far the functionality and development have been achieved to date. All the limitations mentioned are part of an ever-pressing market and the need to preserve or increase the competitiveness.

4.2.2 Artificial Intelligence & Machine Learning

All the interviewees are optimistic about the development of ML technology in project management. It was mentioned that it is a natural step to follow the industry's development regarding where it is heading. They were excited to see the correlation between human and computer decisions and see what type of insight it would give. Perhaps the output will reveal some currently unknown truths.

Several interviewees mentioned that it would be a great feature to use AI and ML to provide helpful analytics early in the project, based on minimal input. The feedback could reduce the work in feasibility and study by excluding some of the alternatives early and saving time and resources. The most crucial factor is that the people utilising and making decisions believe in what comes out of the predictions. One of the interviewees referred to the new technology as "a solution looking for a problem", which will affect many industries. It is where the consultant companies have an advantage as they can recommend new technology to areas the company may not have seen or identified as a need in the first place.

A CM developer pointed out that ML technology will surely be beneficial. As one of the interviewees is working with project benchmarking, ML predictions will lead to a faster turnaround in the person's assignments from weeks to days or hours. A few were more sceptical of AI technology, as this area is more unclear to them what it is all about.

The importance of having access to many well-structured data was mentioned several times during the interviews. One of the interviewees pointed out that most data is unstructured, as the data is saved in PDF and Excel files. The company is currently working on transitioning from document-based, unstructured data to storing structured data. After storing structured data, the next step will be to standardise the data. Data knowledge is essential for AI implementation to become a success and a net profit for the company, and this is often where the challenge arises.

It was mentioned that it is challenging to implement new technology as company A's projects are very different from each other. The company has large investment projects that last over several years. These large projects often operate as a company within the company and have their own organisational structure and associated systems and software. However, the company also has smaller, more repetitive projects. The smaller projects are repeated continuously and have characteristics more suitable for AI and ML. However, most innovations happen in large projects as they receive bigger budgets and can afford to spend resources on improvements, such as software tools. Ironically, the smaller projects may be more suited for AI solutions but generally have limited budgets and can not afford to invest in new improvements.

One of the interviewees pointed out that the sum of introducing AI and ML technology is less than if it goes wrong on a project. The future profits will be greater than the costs of developing and implementing the technology. A project or product delay will cost the company much more than the application of an ML model would cost to prevent the delay. The interviewees' perspectives on project scope and cost involved significant investments. If AI and ML technology can improve and increase the precision level of a decision, it may have a considerable impact.

4.2.3 Predictive Analytics & Decision-Making

Predictive analytics will make the company more efficient in deliveries and lessons learned, leading to improved project deliveries. Most of the interviewees focus on the financial benefits regarding cost analysis and estimates. One of the interviewees mentioned that it would make the company more "lean", which refers to the field of lean management. Lean management is all about maximising value and minimising waste.

Using predictive analytics as a tool will make the people in the company feel more comfortable with their decision as it is evidence-based, making the entire decision-making process more efficient. It will be a significant improvement to get the deliveries as planned with their intended value. Predictive analytics and real-time insight into ongoing projects will be a great combination and potential for further development. For example, it could give the results of who should do what.

Another area for predictive analytics is risk management. Identifying early risks is beneficial for optimisation and brings out positive risks and opportunities. Today, company A is cooperating with an external company helping them develop a platform to make data accessible and secure. With the platform's help, they have the opportunity to utilise the data further into functionality such as digital twins, dashboards, and intelligent maintenance management.

4.2.4 Impact on the Company & Way-of-Work

The interviewees suggest having a strategic approach when discussing the effects on the organisation. Securing the digital and overall strategy coincides with the organisation's relationship with its current roles, knowledge, and expertise. It is important to plan how to utilise the organisation's knowledge. If the knowledge of one role is not needed anymore, the resource should be adjusted, transferred, or further developed in another area. The strategy can change relative to the organisation's development, investment, and maturity.

As digital maturity was an issue, the organisation ensures that their employees are always on top of their field of expertise as they have a high volume of hired employees. The hired employees create a synergy as they come with experience and knowledge beyond the company and combining different fields of expertise gives more opportunity and flexibility. On the contrary, hiring many hired employees could also be challenging, as new trends and ideas may not be well acknowledged if their leader is not open to change.

One of the interviewees believes that new technology will make everyone work more efficiently and save much manual work. An example is that the organisation is currently entering a lot of the same data in different places. Implementing new technology will hopefully gather a lot of the data in one place. In the long run, it will make the employees more confident and ensure the organisation of its decisions and work processes. One employee mentioned that Facebook and Amazon have become so powerful today because they collect a large amount of data, and data is valuable.

All the interviewees agreed to establish a well-known project methodology and good standardisation, so the process will be easy to get acquainted with. Establishing a good structure in the organisation will make up for the stagnation when key people leave. Especially the process of codifying the knowledge is essential to replace a key person's knowledge. It was pointed out that the management is not the ones sitting on the knowledge. Their job is to facilitate, as the knowledge comes from further down in the company.

When asked how the new technology would affect their work, one of the interviewees immediately thought about data liberation. Make sure that data is accessible and of good quality. The demand for collecting, utilising, and accessing data will only increase. Company A is digitally progressive, so the limitations are up to the individual's interest and technical availability. At the same time, some pointed out that the need for the human aspect will always be there. New technology, such as using ML for predictive analytics, will not be able to handle unforeseen situations such as black swans. Instead of leaving it up to the machines, handling unforeseen situations comes up to the combination of experience and field expertise. It is not the technology driving the people but the people using technology as a tool for improvement.

4.3 Results from the Data Analysis

The data from company A was analysed by training neural network models to predict the costs of projects as a whole and for the individual WBS-items. The bi-product from the project analysis embeddings were used as input to the WBS-items to increase the level of context data for each item. The embeddings for both the projects and the WBS-items were then analysed by calculating the cosine similarity and the Euclidean distance between them, creating neighbourhoods for similar entities.

4.3.1 Training the Models

The models are trained on all the WBS-items from the projects they are currently not being evaluated. It is possible to see that the networks are training stable by plotting the loss after every epoch. Below are the loss plots for the models. The first plot, Figure 15, shows the loss for the project model. It is clear that the network is training steadily and gradually converging towards a minimum after 200 epochs.

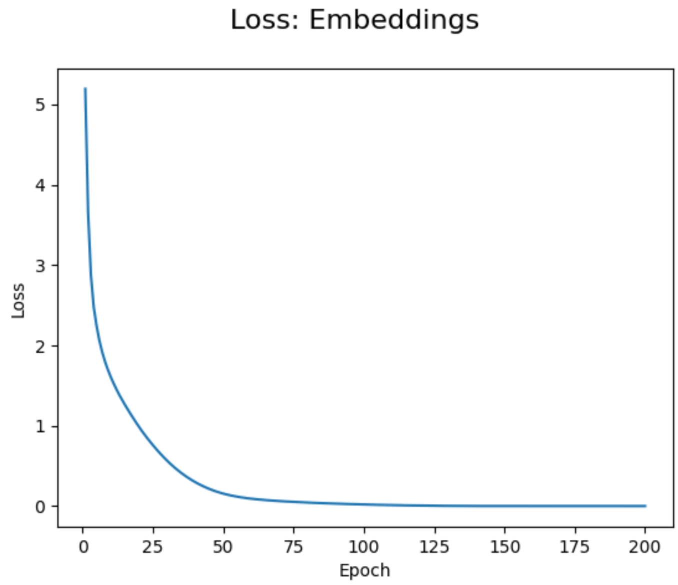

Figure 15: Loss plot for the project model

For the WBS-item model, the loss plot from one of the cross-validation iterations shows how the network is not converging as steadily as for the project model, which can be seen in Figure 16 below. Towards the end of the 50 epochs, the network fluctuates. It may suggest that the network is struggling to find a better fit for the data set.

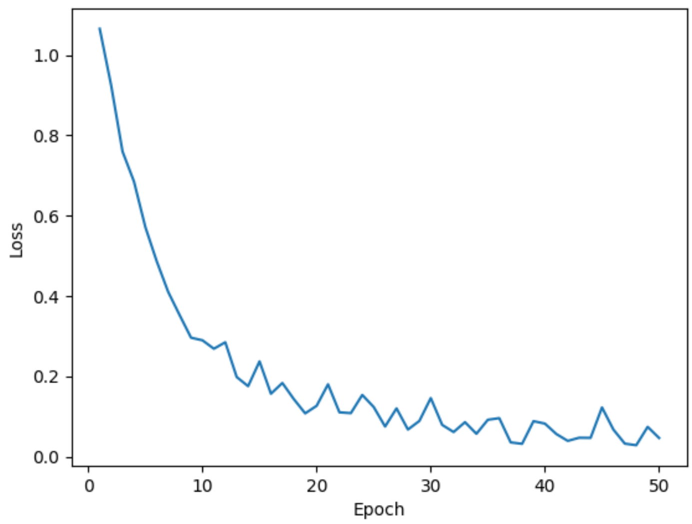

Figure 16: Loss plot for the 19th iteration of cross-validation

4.3.2 Results from Project Embeddings Similarity Study

t-distributed stochastic neighbour embedding (t-sne) is used to plot the embeddings to the 2-dimensional plane for visualisation purposes. As t-sne maps the high dimensional vectors to 2-dimensions, it could be used to evaluate the similarity and clustering of the WBS-items. As stated by (Boggust et al., 2022), the method is sensitive to hyperparameters and stochasticity, which may lead to different results. Therefore, it is possible to tune the method until one finds the optimal results. Based on this, it will not be used to measure similarity between projects but as a visualisation tool, converting the 50-dimensional vectors to 2-dimensions to be presented in a plot. Figure 17 shows this plot for the project embeddings. From the figure, it is possible to see indications of clustering between some of the projects, as projects seem to be gathering into six different groupings:

- Group 1: Projects 1 and 2
- Group 2: Projects 3, 5 and 6
- Group 3: Projects 4 and 19
- Group 4: Projects 7, 14, 15, 16, 17 and 18
- Group 5: Projects 8, 9, 12 and 13
- Group 6: Projects 10 and 11

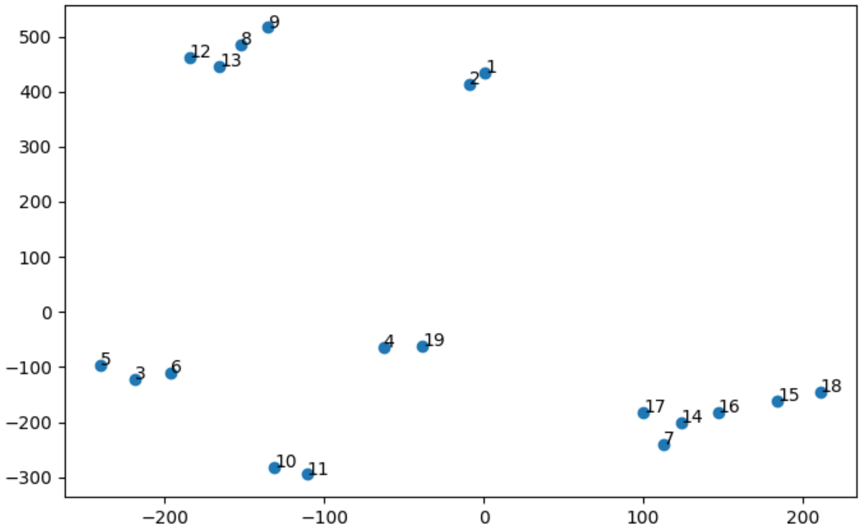

Figure 17: Plot of Project Embeddings mapped to a 2-dimensional space using t-sne. The project number is attached to its location in the plot

Figure 18 and Figure 19 show the cosine similarity and Euclidean distance between each project embedding. Notice that the colouring is according to similarity. Higher values translate to a higher similarity for cosine similarity and are therefore coloured lighter. For Euclidean distance, the reverse is true as lower values are coloured lighter, which equals a higher similarity. The diagonal is "1" for cosine similarity, as identical items are mapped to "1". The diagonal is "0" for the Euclidean distances as the distance between two identical vectors is "0".

From the heatmaps, it is clear that the methods largely agree on which projects are similar. Cosine similarity seems less restrictive than Euclidean distance as high scores (close to 1) are frequent. There are no bounds for Euclidean distance, but the range of values is more significant, resulting in more considerable contrasts in the heatmap. The matrices confirm a lot of the relationships hinted by the t-sne plot, Figure 17, illustrating that several projects have the same groupings. Projects 12 and 13 have the highest similarity for both methods, closely followed by projects 14, 16 and 17. The groupings presented from the t-sne plot are represented mainly in these matrices as the relationship between projects is generally above 0.9 for cosine similarity and below 0.7 for Euclidean distance.

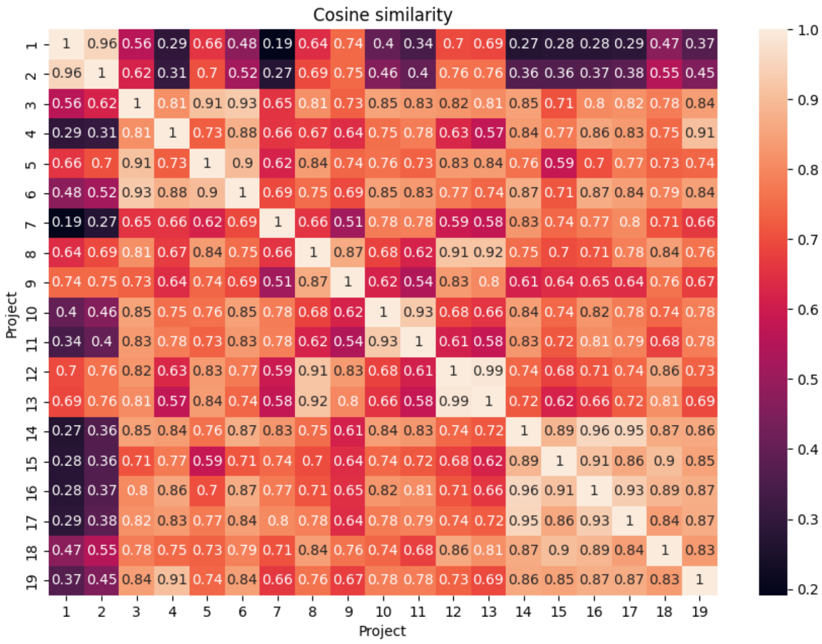

Figure 18: Cosine similarity between project embeddings, similar items are marked lighter in the heatmap.

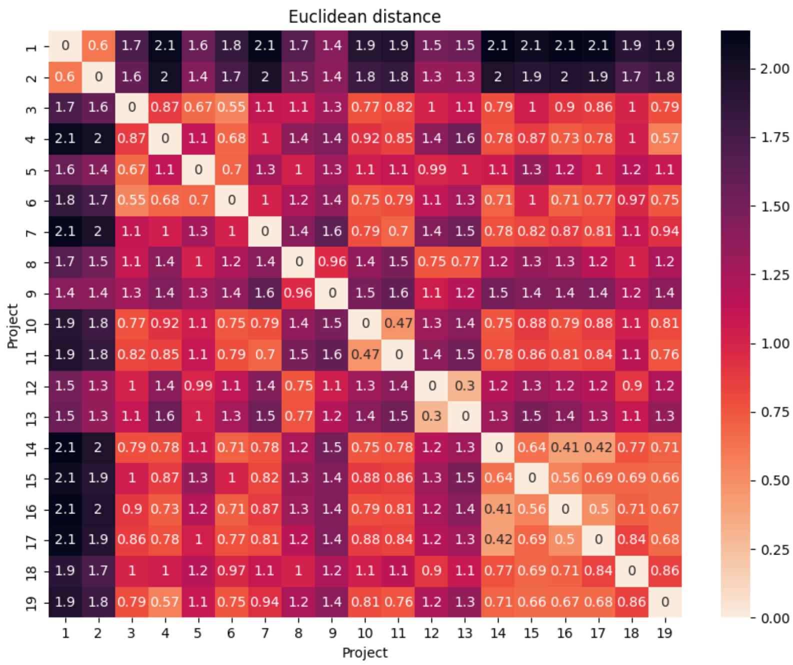

Figure 19: Euclidean distance between project embeddings, similar items are marked lighter in the heatmap.

4.3.3 Results from WBS-Item Embeddings Similarity Study

First, the plot for the WBS-item embeddings was plotted in the same manner as for the project embeddings results in Figure 20. In this figure, the identifying text has been disabled as it would only lead to clutter because of the large number of items. The figure shows some clustering between items. However, a good portion of the items is located alone, not near other items. The following sections present the results from the similarity analysis.

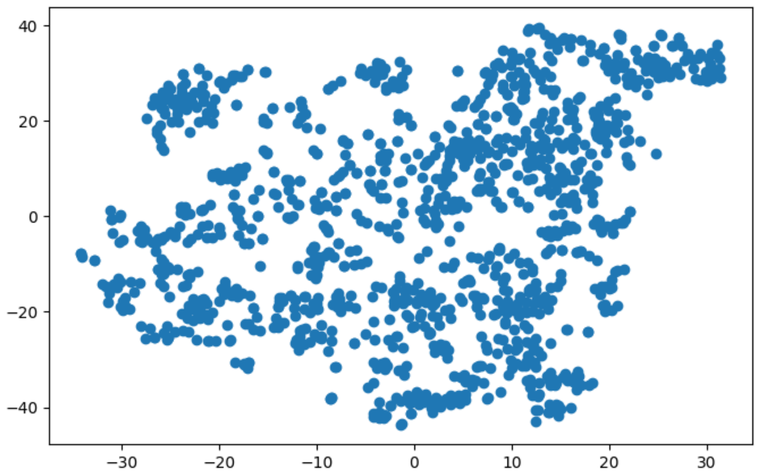

Figure 20: Plot of WBS-Item Embeddings mapped to a 2-dimensional space using t-sne

Cosine Similarity

The results for cosine similarity are presented below in Table 3. The table shows the mean cosine similarity between the WBS-items and a standard deviation. The table also shows the resulting mean number of neighbours per item, achieved by setting a decision rule regarding pairs of WBS-items with a Z-score above " 2" as neighbours. Here the cutoff point of $Z - Score > 2$ equals a cosine similarity of above 0.979.

	Mean	σ
Cosine similarity	0.331	0.324
Neighbours per Item	0.700	1.291

Table 3: Cosine similarity result with $Z - Score > 2$.

Below in Figure 21 is a plot of the Z-score distribution for the cosine similarity values. From this plot it is evident that only a small portion of the relationships between items are regarded as being neighbours.

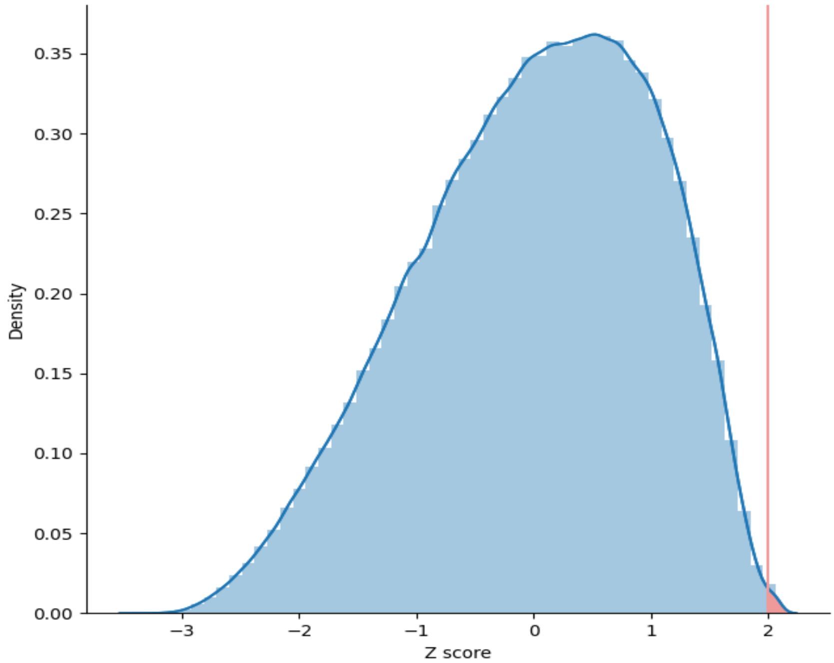

Figure 21: Z-score distribution for the cosine similarity between WBS-item embeddings. The red line marks the cutoff point for neighbours

Figure 22 is a plot of the amount of neighbours for each of the WBS-items. The figure reveals there is a large amount of items without a single neighbour.

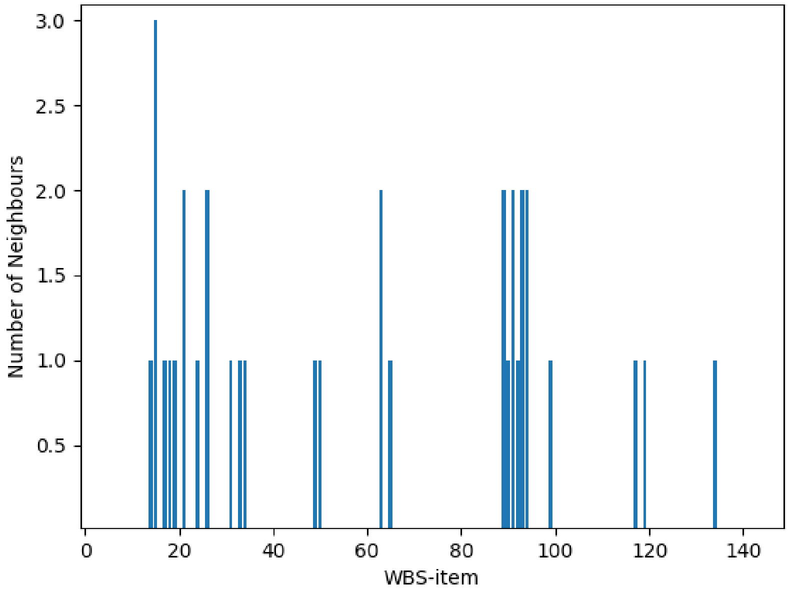

Figure 22: Section of the plot of neighbours per WBS-item using the cosine similarity method.

Euclidean Distance

The results for Euclidean distance with decision rule; Z-score below -2 to be regarded as neighbours are presented below in Table 4. Here the cutoff point of $Z - Score < -2$ equals a Euclidean distance below 1.053.

	Mean	σ
Euclidean Distance	2.988	0.967
Neighbours per Item	4.432	3.925

Table 4: Euclidean distance results with $Z - Score < -2$.

Figure 23 shows the Z-score distribution for the Euclidean distances.

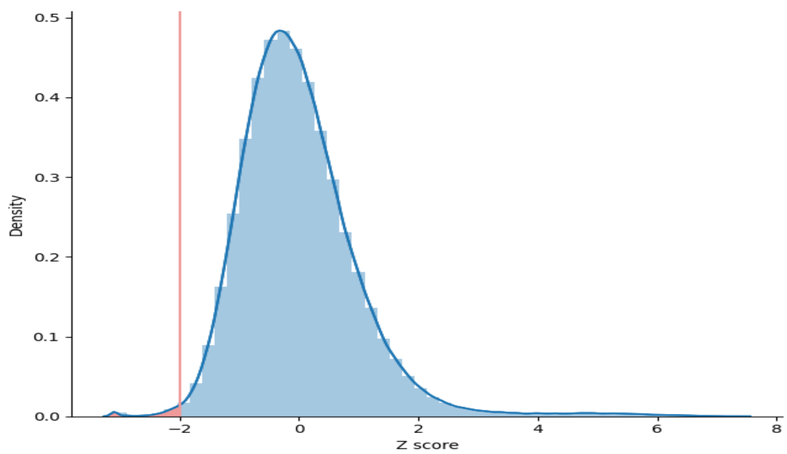

Figure 23: Z-score distribution for the Euclidean distances between WBS-item embeddings. The red line marks the cutoff point for neighbours.

The neighbour-per-item in Figure 24, illustrates the big difference in size of neighbourhoods. It also shows that although the neighbourhoods are generally larger, there are still a considerable amount of items without any neighbours in their neighbourhood.

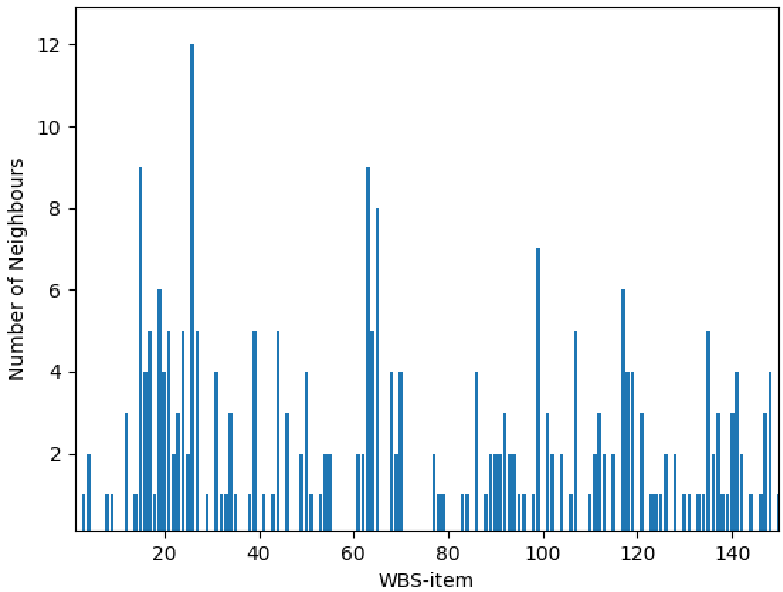

Figure 24: Section of the plot of neighbours per WBS-item using the Euclidean method.

4.3.4 Results from WBS-Item Cost Prediction

The results from the cross-validation are presented in Table 5, with the three metrics which were explained in Section 2.8.5, All values are min-max normalised to the range [0,1].

Project	**MAE**	**RMSE**	**Log Accuracy**	σ	**Nr. Items**
1	0.1109	0.4710	-0,6666	0.1589	98
2	0.0750	0.3783	-0.2778	0.1031	83
3	0.0268	0.2117	-0.0325	0.0445	53
4	0.0650	0.3606	-0.3302	0.1620	18
5	0.0393	0.2802	-0.3640	0.0809	72
6	0.0172	0.1855	-0.1456	0.0297	55
7	0.0325	0.2549	-0.4972	0.0546	26
8	0.0827	0.4067	0.0949	0.1125	110
9	0.1035	0.4549	0.2466	0.1556	116
10	0.0582	0.3414	0.0063	0.0717	19
11	0.0611	0.3495	1.1209	0.1129	9
12	0.0360	0.2684	-0.8361	0.0408	119
13	0.0423	0.2909	-0.7602	0.0556	130
14	0.0192	0.1961	0.0134	0.0231	54
15	0.0208	0.2041	-0.2653	0.0607	28
16	0.0178	0.1884	-0.0163	0.0235	46
17	0.0150	0.1731	-0.1215	0.0261	65
18	0.0402	0.2835	-0.1390	0.0572	114
19	0.0550	0.3316	0.6427	0.1006	27
Total	**0.0534**	**0.3255**	**-0.2464**	**0.0914**	**1242**

Table 5: Result from cross-validation with metrics

By plotting the model output against the actual cost label of each WBS-item it is possible to see how well the model performs for each of the WBS-items in a project. Below are plots from two projects, Figure 25 and Figure 26, chosen as they were projects where the model performed well. In Table 5, its shown that for project 12 and 13 has the lowest relative accuracy value (Log Accuracy) when compared to the other projects. Meaning that the predictions from the model is close to the target on most WBS-items. The line plots of project 12 and 13 illustrates this case as the yellow prediction line follows the blue target line rather closely. The rest of the project line plots are attached in Appendix C. All values in the plots are min-max normalised to the range [0,1].

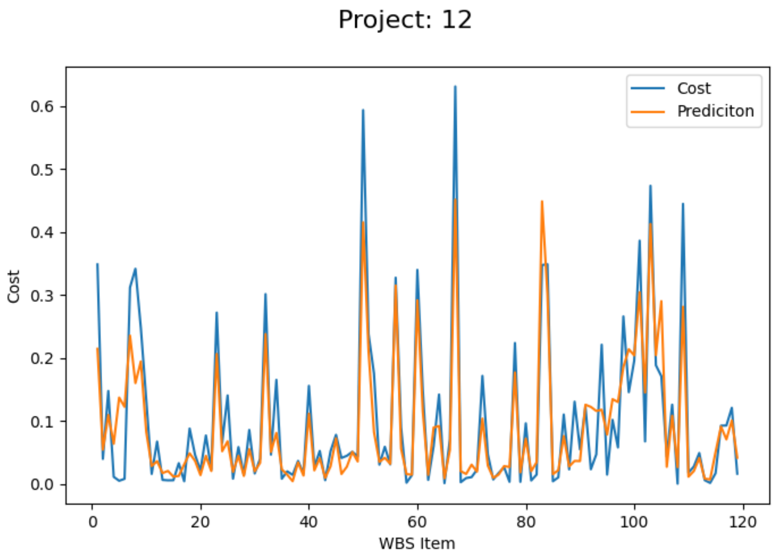

Figure 25: Line plot of the models performance on project 12. The orange line is the models output, the blue line is the target value

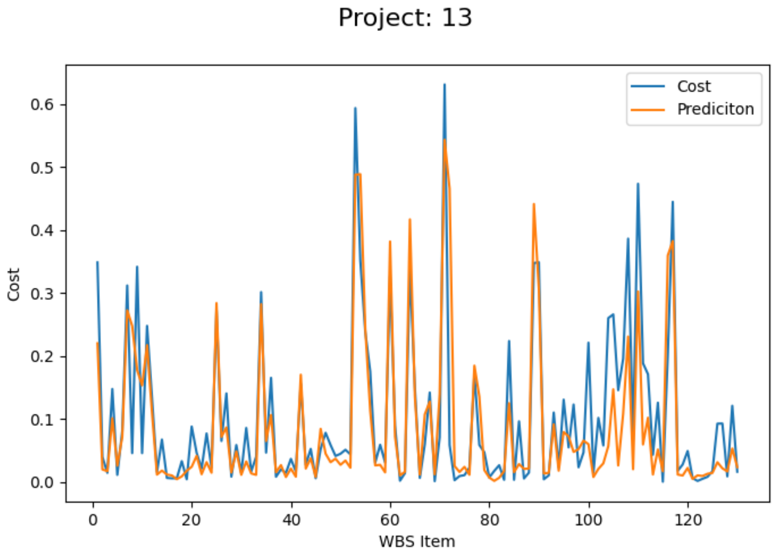

Figure 26: Line plot of the models performance on project 13. The orange line is the models output, the blue line is the target value

The next page illustrates examples of situations where the model performed poorly, Figure 27 and Figure 28. Performance on project 4 is good on a project level as the relative accuracy is low, but for the largest WBS-item in the project the model fails significantly to predict the right cost. These examples show how the how the dimensions of the projects affect the metrics used for accuracy. The costs of the WBS-items in project 16 (Figure 27) are rather low across the board, resulting in a low MAE and RMSE even though the yellow line prediction lies far from the blue target line. For project 4 (Figure 28) the reverse is true, the yellow line tightly follows the blue line for most items, but due to big errors in WBS-item 6, and 14 the MAE and RMSE is high, while relative accuracy is low.

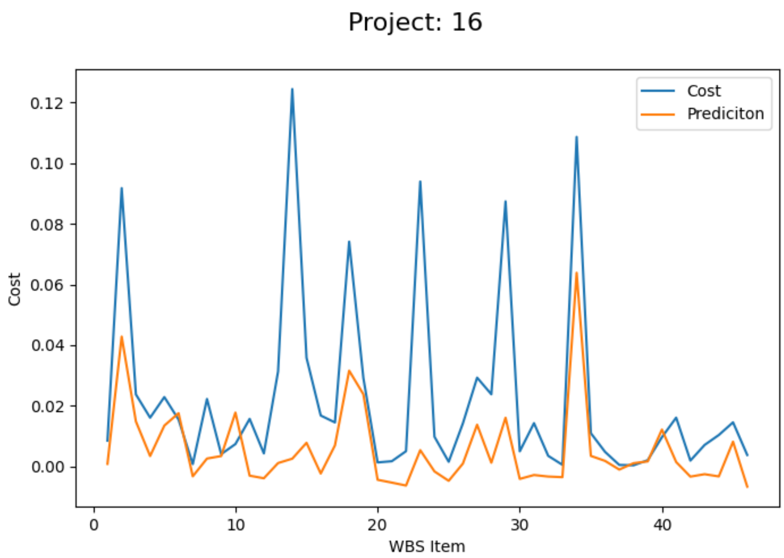

Figure 27: Line plot of the models performance on project 16. The orange line is the models output, the blue line is the target value

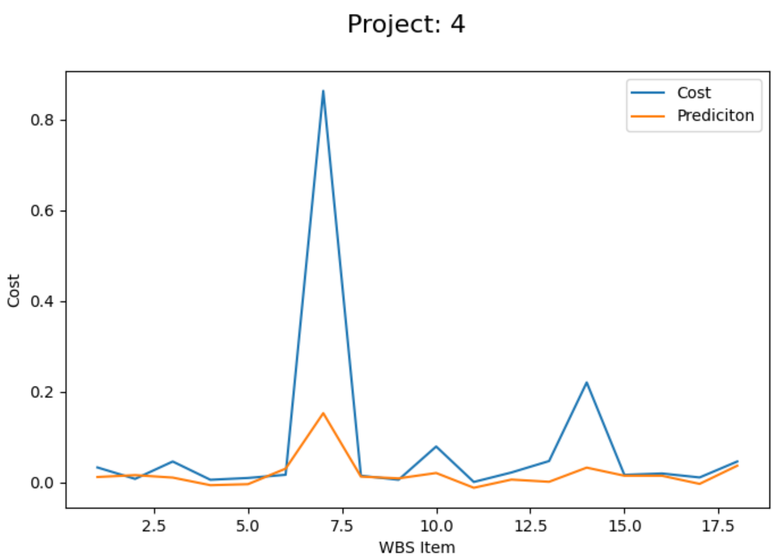

Figure 28: Line plot of the models performance on project 4. The orange line is the models output, the blue line is the target value

5 Discussion

The following section will tie all the research methods together. With the input from Theoretical Background, Section 2, and the Results from digitalisation surveys, interviews and data analysis, Section 4, are the following subtitles applicable concerning the research questions.

5.1 Digitalisation & Project Management

The complexity and development of projects are increasing as new technology, and digital transformation are trending. The development and changes also applies to the energy industry. The new value is created as processes such as energy production, delivery, and consumption are being digitalised, and the data is collected and analysed in real-time through digital technologies (Park and Kim, 2021).

From the digitalisation surveys, the companies rated their digital maturity between 2-3, where 5 was the maximum score, referring to total digital transformation. The maturity score corresponds to an explorer, beginner phase. Based on the company's digital maturity, one can consider that the energy industry is in the early stages of adopting digital technologies, such as Industry 4.0, big data, IoT, AI and ML.

From both the survey and interviews, it was mentioned that many work processes are still influenced by manual and repetitive work. Several interviewees pointed out that a digital, data-centric mindset is already established in company A. They were all clear that data was important and gave value to the business. Even though they identified many challenges and improvement areas, the message of data importance has come across. The shift in mindset is clear and agrees with the response Kane et al. (2017) got in their research, where 85% of the respondents agree that "being a digital business is important for the success of my company.". As it is not all up to the leaders of an organisation, the organisation also have to cultivate a culture and organisational structure that enable digital maturity.

A known challenge with digital transformation is the resistance to change. It was mentioned during the interviews that employees struggle to adapt to change, as they are used to their routines and habits. The uncertainty around change causes the issue, but as Johansen et al. (2019) encourages to not view uncertainty as undesirable but as an opportunity. Considering flexibility is a way to manage uncertainty and improve the organisation's ability to change in a way that it remains viable (Bahrami and Evans, 2010).

From the survey and interview results, the companies believe that digitalisation is a step in the right direction. It was mentioned that digitalisation could be an opportunity to improve efficiency and precision in project deliveries and control. Company A views digitalisation as a tool for improving performance and predictability, not a process. Digitalisation also strengthens organisations and projects to become more flexible and resilient.

Even though the interviewees mentioned several data challenges, they all pointed out the importance of the company's digital maturity and data understanding. The key is not to put all the responsibility on the technology but also focus on the people it affects. In this regard, the term *knowledge* and KM were mentioned. Storing an organisation's knowledge and expertise is critical for both the employees' and the organisation's development. Holmstrom (2021) refers to AI technologies having human-like cognitive capabilities, which include knowing, learning, communicating and reasoning.

Savić (2019) refers to the focus of digital transformation as knowledge leveraging. There is a natural link between digitalisation and KM. In this thesis, the focus on CM systems may be considered the right step toward introducing and implementing digital technologies. It confirms Salzano et al. (2016) statement about how "Knowledge management provides flexible approaches aimed to enhance knowledge gathering, sharing, application, and retention.".

Several articles mention *flexibility* concerning KM. Salzano et al. (2016) developed the KM framework for clinical development, but the framework is relatable for other organisations and industries as well. The article suggests implementing the framework as it provides flexibility and improves and collects the knowledge from the organisation and the project's lessons learned. The literature described how KMSs might provide the organisation with stronger decision-making and more flexibility when facing changing environment.

From the survey, it was stated that digitalisation would require cross-functional teams. Calitz and Cullen (2017) discussed how promoting cross-functional teams is a part of the "Learning" pillar in the KM framework. Cross-functional teams are helping to shape a learning community by combining the available knowledge, and this will all together increase an organisation's performance (van Heijst et al., 1997). Kane et al. (2017) also stated that 70% of digitally maturing organisations are using cross-functional teams to structure and prepare the teams.

As AI technologies create new opportunities for digital transformation, it also involves new challenges for managers of digital transformation processes. Holmstrom (2021)'s framework to understand an organisation's abilities to meet these challenges, "their AI readiness".

For the energy industry to remain competitive, it is critical to follow digital innovation. AI and ML are key drivers of digital transformation in today's organisations, and the advantages of their utilisation in decision-making when combined with data analytics. The interviewees mentioned the importance of research and collaboration between academia and industry. Getting external input widens the company's horizon and creates the opportunity to improve its performance continuously.

5.2 The Data Analysis

This sub-section will discuss the results from the data analysis presented in Section 4.3. The results from the project embeddings, estimation model and WBS-item embeddings will be discussed separately.

Project Embeddings

Company A was interested in comparing projects against one another to analyse if the model could identify any similarities between the projects. An embedding model was created and trained on all projects after extracting high-level data such as the product makeup and time span, among other features.

The generated embeddings were used as input for the project component of the WBS-items model. Embeddings are continuous dense vectors representing the projects. They contain more information that benefits the model more than discrete categorical values from a one-hot encoding. The embeddings contain information about each project concerning the others in the given context (the project's total cost). It was especially beneficial when cross-validating the model in a project-to-project manner. The model could then make sense of the vector regarding the vectors it has been subject to during training.

From Figure 17, it can be seen that the t-sne groups some projects. These relationships are confirmed in Figure 18 and Figure 19. From these heatmaps, it can also be seen that cosine similarity is less restrictive than Euclidean distance as it attributes a high value (>0.8) to a large amount of the project pairs. Interestingly there seems to be a similarity between projects with an equal amount of WBS-items. The cause of this similarity is likely due to similar projects being structured the same way in the CM.

WBS-Item Estimator

The model performance differs significantly between projects. Projects with low performance are likely due to the low correlation between WBS-items in the training set and the evaluation project. Projects with a high degree of "unique" WBS-items will be difficult to predict for any ML model. The projects 12 and 13 (Figure 25 and Figure 26) are projects where the model performance is high. For nearly all of the WBS-items, the model prediction closely follows the label, and the MAE, (1), never surpasses a normalised value of 0.150. These two projects are likely very similar as they have roughly the same amount and structure of WBS-items. When project 12 is evaluated, project 13 is represented in the training set and vice versa. Therefore, when the model is making predictions for project 12, it bases itself on the training examples of project 13.

In contrast, Figure 17 show projects 8 and 9 mapped together with projects 12 and 13 by the t-sne. The projects are also similar according to the cosine similarity and Euclidean methods, as seen in Figure 18 and Figure 19. However, the models' performance on projects 8 and 9 is some of the poorest when evaluating the model metrics RMSE and Log Accuracy during cross-validation. The reason for why the model did not perform well on these projects is not clear, but it could be that the way the high-level project data was extracted was not ideal. The extracted features could have been too abstract or not the most relevant project characteristics, leading to false similarities between the projects. Also, although the projects are similar concerning high-level information, they may differ significantly on the individual WBS-item level. Another reason could be that the model recognises many of the same WBS-items, but that the cost of these items is significantly different due to some parameters the model fails to recognise.

From the line plots, it is possible to identify two types of prediction errors. The first type of error is total misses, where the model undershoots or overshoots the cost of the item. An example of this is project 4 and 16 (Figure 28 and Figure 27), where the model predictions are way off the label multiple times. These have relatively few WBS-items, and the errors are easier to spot. It is likely due to the model encountering "unique" WBS-items that share a few similar features with those represented in the training set. Then it is possible to see that the model fails to predict the correct cost.

With larger volumes of quality data, models will have a larger base of data to train on, and occurrences of this type would be fewer. However, as no two projects are the same, new projects bring new challenges and procedures to handle. There will always be areas where the information origin is sparse. Therefore, the lack of data will be an everlasting challenge with this sort of technology and information-based decision-making.

Other errors are situations where the model approximately predicts the correct cost but under- or overshoots the target by a noticeable margin. As an example, project 13 (Figure 26), the model follows the same "profile" as the actual costs, creating spikes where the label cost spikes. However, for many WBS-items, it undershoots the target cost, predicting a value that is off the target cost by a good fraction. For these errors, the model predicts the correct "ballpark" cost, and it can be assumed that a WBS-item similar to this item exists in the training set. Possible reasons for the remaining error might be due to two things:

- Some factors affect the cost of the item that is not represented in the data.
- The model fails to recognise all the factors that affect cost in the data set.

During Preliminary Cleaning, Section 3.4.3.2, it was discovered that the data set contained duplicates with different costs attached to them. The duplications raised the suspicion that information affecting costs is not represented in the data. In the meetings with company A, it was confirmed that this was the case as the data set only contained a limited amount of technical data. Company A could inform that some of the biggest cost drivers were technical data, such as the material type for the construction. Therefore, it is likely that some of the errors may be attributed to these hidden factors.

During the training of the estimation models, the ReLU activation function performed significantly better than the SeLU activations despite being relatively similar functions. Models with ReLU as the activation function converged faster and achieved higher accuracy than the SeLU activations. Due to the high sparsity of the input data, ReLU was better at handling sparsity. An advantage with ReLU is that it produces true zeros, which is suitable for naturally sparse data, such as the features used as input to the model (Glorot et al., 2011). However, true zeros become an issue when creating the embeddings as they inflate the similarity between vectors as information is removed. It resulted in the dilemma where the preferred function for estimations differs from the preferred function for embeddings.

Ideally, the same activation function should be used for both areas. It would then be possible to utilise the same model for both the embeddings and the predictions. In this way, the predictions are directly correlated to the embeddings, and the embedding neighbours serve as the basis for the models' prediction. With different models, this relationship becomes fuzzy as there is no guarantee that the different models base their predictions on the same factors. One may be forced to assume this to be the case, trusting that the models base their predictions on the same drivers of cost.

Table 5 shows the performance metrics for each of the individual projects. The table shows that the model performance relies on the project it is evaluated. An MAE, (1), of 0.0543 across all the WBS-items may seem like a good score for the model, although it does not tell the complete picture. Because of the vast differences in cost for each item, an error of 0.0543 might be a total miss for smaller cost items, although it is a good result for the larger items. As smaller cost items are also hard to notice in the line plots, it is therefore challenging to deem the model's accuracy on these items. However, by inspecting the Log Accuracy, (5) of the model, one can get an idea of the performance across these items.

As Log Accuracy is defined as $log(\frac{error}{target})$, this metric measures the error in relation to the target value. A log accuracy close to zero means that the error is within the same magnitude as the target. Significantly negative values are preferred as standard, as errors of the same magnitude as the target is unacceptable. The relative accuracy differs heavily from project to project. The relative accuracy is negative for 13 out of the 19 projects from the cross-validation, although many are only barely negative.

It suggests a low overall accuracy, even in cases where the MAE is low such as for project 17.

Generally, it seems the model performs poorly on smaller projects. The projects with a small amount of WBS-items have a larger training since only some of the WBS-items are removed from the training set. It may indicate that the smaller projects are entirely dissimilar from the larger ones, and the added size in the training set has little effect.

The RMSE, (3) is considerably higher than the MAE, suggesting that the model performance does not vary significantly from item to item. It can also be seen from a high standard deviation. The model accurately predicts the cost of some items while missing largely on others, possibly due to some items being wildly dissimilar to others. Lack of precision negatively affects the models' usability, making it hard to trust the predictions.

WBS-Item Embeddings

From the t-sne plots, there are no obvious clustering of the WBS-items. However, when calculating the similarity between the embeddings there was considerable similarity between certain WBS-items. The two methods of calculating similarity gave very different results. Cosine similarity resulted in more significant neighbourhoods for the embeddings than Euclidean distance. However, measuring the "goodness" of this aspect of the models is difficult as the labels are not known. The amount of average neighbours for each WBS-item is dependent on the decision function, and the Z-score is used as a cut-off point. There is also no guarantee that the embeddings are mapped correctly together on relevancy. Via inspection of the WBS-items returned as neighbourhoods, it is possible to get a general sense of the goodness of this feature.

When inspecting the neighbourhoods of the WBS-items with the largest neighbourhoods of each method, it was discovered that the Euclidean method generally returned the WBS-items with a similar position in the WBS in different projects as neighbours. It was more challenging to find a pattern of relevancy with cosine similarity, often returning WBS-items that seemed to have no apparent connection to each other. Thus, the Euclidean method was the best as the position of the WBS and the product attached were the main drivers when deciding the cost of an item.

From the Z-score distribution plots, Figure 21 and Figure 23, there is a small portion of the connections between embeddings that qualify as neighbours. The number is somewhat larger for the Euclidean distance method, with an average of roughly four neighbours for each WBS-item. For cosine similarity, the result was 0.7, which is below one, and this method could benefit from a less restrictive decision function. An average of four neighbours per WBS-item might be too restrictive, although it is important to keep in mind that this tool will filter data based on relevancy for a human user. The user will likely be interested in only the most similar WBS-items, and not interested in being presented with a large number of items. The decision function can also easily be adjusted to be more or less restrictive interactively, giving the user the choice of including more distant neighbours if it seems appropriate. Another way to utilise the similarity scores could be to sort by this score, arranging the items in a descending manner on similarity, resulting in the most similar items being presented first.

In Figure 22 and Figure 24 show the differences in the size of neighbourhoods per WBS-item, which make it evident that many of the items have few similar items. Naturally, a model will struggle to predict these. Reasons for this may be that the items are, in fact, unique and have few similar attributes compared to the rest of the database. Another explanation is that the model has failed to recognise similar attributes, meaning that the model fit is not strong enough.

5.3 Data Usage & Decision-Making

From the digitalisation surveys, it can be considered that the use of digital tools in project decision-making is not fully implemented and utilised. The companies all mentioned they have digital tools for information storing and sharing but are still reliant on physical meetings and Microsoft applications such as PowerPoint and Excel sheets.

Many have the impression that AI techniques are still vague, fuzzy and as Brethenoux and Karamouzis (2020) called it, "shiny objects". The money invested by an organisation and the lack of Return On Investment (ROI) is often the case. Brethenoux and Karamouzis (2020) encourage organisations to complete the five steps to introduce AI techniques within an organisation to identify the gaps in skills, data and technology. The gaps in culture, readiness and general education about the AI field will also emerge by working through the steps in a few iterations. The five-step approach serves as an initiating process before the organisations should consider a more effective and long-term AI strategy.

During the interviews, it was mentioned that in order to ensure evidence-based decision-making, the users need to *trust* the data and the tools. By using embeddings, a measure of the models' confidence and the basis of prediction could be extracted to increase the trust in the ML models. If the model maps an item close to many other items in the embedding vector space, the model considers this item to be similar. In essence, the embeddings can give insights if the model is "shooting in the dark", identifying a new problem, or if it has seen this situation before.

A measure of the models' prediction confidence could be to investigate the size of the neighbourhood, with a larger neighbourhood meaning more confidence. Supplying the confidence score together with the prediction can serve as a heads-up for the user when utilising the tool, alerting the user that the confidence is low for this prediction. A user could then inspect the neighbourhood items and determine if the prediction seems reasonable or if further research is necessary. An obvious issue is if the model wrongly maps different situations close to one another. Therefore, the predictions should not be accepted blindly and should instead be used as a tool in conjunction with human expertise.

An important thing to note is stated in the article by Cohen (2005): "Once a choice is made, it is necessary to commit to it and move forward. A decision half-heartedly implemented is no decision at all." The statement may be linked to the importance of the ML models' precision and impact on decision-making. The organisations and users of AI technology have to develop the trust and skills to understand the ML models to use them as optimal as possible.

None of the interviewees were worried that the role of the project manager would be replaced by AI technology. They emphasised human expertise and the ability to adapt to unforeseen events why "human" project managers are preferred. For example, several interviewees regarded human expertise as instrumental in handling black swan events, stating that machines would not be capable of taking action sufficiently rationally in situations where prior experience and data are limited. However, AI technology can be used to assist human expertise and be utilised to gather information and analyse data. Some areas are most effective when AI systems are put aside humans, i.e., when AI complements human capabilities and augments the human's decisions and actions instead of replacing them. The application of human-machine collaboration shows several advantages (Lepenioti et al., 2021).

Utilising AI technology to assist project managers will ensure and improve the process of making the right decision when encountering unforeseen events. It confirms what Hajikazemi et al. (2016) proposed how black swans should be handled, referring to tools to identify early warning signs together with proactive knowledge management. As these subtle early warning signs can be challenging for a human to recognise, AI can play a role in recognising these patterns. AI can also be instrumental in transferring information to key employees in the organisation that can interpret the data and identify possible future outcomes. Fast data transfer enables the organisation to react appropriately to black swan events, resulting in better project resilience. In short, AI can increase the robustness of projects by providing faster analysis and information to human decision-makers.

Hajikazemi et al. (2016) also stated that the knowledge created through responding to black swans should be stored. Storing the knowledge is necessary for an organisation to improve and manage these events in the future continuously. For an organisation to manage its knowledge, especially lessons learned from black swans may help the organisation to identify its weak points. The next step involves understanding and evaluating the weak points, so the organisation can increase its robustness and provide flexibility when met with unforeseen events. The whole process is also linked to the process of performance measurement and benchmarking for continuous improvement (Andersen, 2007).

An interesting proposal from one of the interviewees was referring to AI technology as "A solution looking for a problem". The technology can be so powerful that it can give insights into areas a company has not even thought of as an issue yet. The rise of AI enables companies to manage large amounts of data in order to get predictions and gain meaningful insights (Lepenioti et al., 2021).

Business analytics was defined in Section 2.7 and is referred to as the data intelligence component and a vital ICT tool for Industry 4.0 (Silva et al., 2021). It confirms the notion about how data evolves to become information and then knowledge (Salzano et al., 2016). When the data behind the prediction is fully understood, it is possible to use the predictions and take the next step toward prescriptive analysis, which may define the way forward. Ruiz et al. (2021) states that AI technologies are more precise than traditional tools, but currently, they remain partly complementary to the traditional approaches.

Understanding the descriptive and predictive parts is essential before achieving prescriptive analytics, as this thesis utilises predictive analytics in its data analysis. The next step is to achieve prescriptive analytics, "how to make it happen". One interpretation is the argument of how predictive analytics serves as an assistive tool for the project manager. The combination of predictions and knowledge and expertise of the project manager will achieve prescriptive evidence-based decision-making. The connection between evidence-based decision-making and evidence-based project management is closely related when discussing Huff (2016)'s definition.

6 Conclusion

This master's thesis has covered important aspects of AI's trending and current development in projects. Based on this, the problem statement "*Artificial Intelligence as a Tool for Project Decision-Making Support*" was defined. The following research questions will be answered with helpful input from collaborative parties, thorough literature research, and data analysis.

RQ1: What are the expectations of digitalisation in the Norwegian energy sector?

Based on the digitalisation surveys from Prosjekt Norge and the interviews conducted with company A, all the corresponding parties agree that digitalisation is a natural step in the right direction. Currently, the limitations lie within the organisation's digital maturity and data understanding. Theory, surveys, and interviews state that it is not just up to the technology but also to the people affected.

Together with theory, it is found that the implementation of digitalisation is still in the starting phase for the energy industry. The response from our research process shows that the mindset has shifted, and digitalisation is not just a buzzword anymore. The organisations and employees are more aware of how the industry is developing and changing. The next step is to establish the foundation and prepare for digital transformation to succeed.

No specific areas within the companies that have accomplished total digital transformation were not mentioned. Currently, the companies have a broad corporate focus on digitalisation. The focus on data skills and knowledge is spread throughout the organisation's employees, preparing the employees for the future demand for data understanding. The companies are working on developing their current employees' data skills and taking data skills into account when hiring new ones.

From the digitalisation surveys, the companies were optimistic about the process of collecting information and data in one place. Storing information in one database and its accessibility will increase work efficiency and reduce misunderstandings as the information comes from the same source. The involved companies expressed their expectations that digitalisation will work as a tool, decreasing the time spent on project control and engineering and introducing new ways of collaboration.

Brethenoux and Karamouzis (2020); Holmstrom (2021) both introduced a framework for how to proceed when introducing AI technology into an organisation. The respondents all agree that a systematic approach is required when introducing digitalisation and new technology. Introducing new technology and work processes has been met with optimism and chaos regarding roles and responsibilities.

RQ2: How can artificial intelligence, in particular, machine learning, support and utilise corporate memory?

From the data analysis conducted on the project data received from company A, it is clear that AI, particularly ML, is applicable to support a CM system. Navigating the available data efficiently and effectively is crucial to utilising the CM system to its full potential. Automating parts of the analysis within the CM system has significant advantages as it can eliminate large portions of repetitive work that do not require human expertise. With the help of the system, it frees up resources that may be utilised in other required areas.

AI has a role in making the data easier to navigate and automating repetitive tasks. However, there are obvious obstacles to implementing these technologies into an organisation. Obstacles related to data handling, such as gathering, formatting, and understanding data, were mentioned during the interviews with company A. These obstacles were encountered during the data analysis, as decisions regarding the data handling would affect any applications built on top of CM. The introduction of AI technology will require the development of the organisation's competency regarding data handling and usage. It includes any areas of the organisation where data is gathered and used. These areas are potentially a large portion of (if not the whole) organisation.

For the technology to have any value to the company, it must be used frequently. This requirement sets a demand on the quality of the models and applications. The demand comes in the form of reliability, speed and practicality for the organisation to benefit from using it. As the tools are based on CM, their quality is dependent on the data. It creates a relationship where the better data quality, the more reliable the model is. It increases the organisation's trust in the model, making it more likely to put more effort into data handling. It can be viewed as a positive spiral, where all components influence each other's quality. The reversed scenario concerns poorly performing models, resulting in less effort into data handling, leading to worse models.

The project data extracted from the CM system has great potential. The cost estimation data used in this thesis has the apparent benefit of being standardised, serving as a sound basis for ML. However, the data set did not contain the full context of the projects. It was made clear from the interviews with company A that the CM system is not fully developed and that more disciplines and in-depth data will be implemented in the future.

The CM system can handle more diverse data from other organisational disciplines with further development. With the proper context between data points, the system can serve as a basis for compelling AI models. However, during the interviews, it was stated that a lot of the relevant project data is hard to codify. Much of the technical data is stored in individual reports and documents that were difficult to translate into numbers. Sharing information between disciplines is not trivial either, as it demands that employees from one discipline are familiar with the data types and structures of the others. To sum up, AI and ML show positive results in supporting CM systems but still have areas for improvement to achieve their fullest potential.

For a project manager to apply the insight available from ML models, a good understanding of how the model operates is required. ML models can often be viewed as a black box, spitting out results from inputs with few ways to see the reasoning behind the result. Little is known about the model's reasoning; it is hard to know if the output is accurate.

From the predictions on the WBS-items, the model developed in this thesis performed differently from project to project. For some projects, the model performed well, accurately estimating the WBS-items costs. For projects 12 and 13, Figure 25 and Figure 25, the model could be a useful tool for speeding up the cost estimation process. However, on other projects, the model was not that reliable, performing poorly on many WBS-items. For some of the projects, the general performance was good, but the model completely failed to predict the cost of specific items. When the model is used in production, the correct cost of the item is not known, making it difficult to know if the prediction is accurate.

Because projects are unique by nature, project managers often encounter situations with little applicable historical data. These are situations where AI models generally will perform poorly. It is crucial to identify these situations when the model is good and when it is not to utilise AI models in projects. Different approaches can be used to understand the reasoning behind the models' prediction. One approach is to investigate the embeddings created as a bi-product. This thesis has explored the use of embeddings to find similarities between project data. It is possible to get a sense of what the model is basing its predictions on by returning the items the network considers similar to the input. In turn, this can be used to evaluate the validity of the prediction.

RQ3: How can artificial intelligence be beneficial for evidence-based decision-making utilising corporate memory?

From tying all three research processes together with theory, it is possible to see a full circle of how digitalisation and AI can be linked with decision-making, CM, and project management.

AI is beginning to emerge into different industries, and most people are excited about the benefits it holds. AI is in an exploring phase for the energy industry and is not fully implemented or utilised in any project management processes. From the literature research, researchers are tying AI and business analytics and finding a lot of positive advantages. AI and ML are always mentioned when discussing the development from descriptive to prescriptive analytics. The future profits of implementing AI technology will be greater than the cost of developing and implementing it. If the technology can prevent a mistake or failure, it may have significant financial consequences and impact projects.

Currently, it is pointed out that the majority of research lies within predictive analytics, especially with the involvement of AI and ML (Frazzetto et al., 2019; Lepenioti et al., 2021; Sadat Mosavi and Filipe Santos, 2020; Silva et al., 2021). It is impossible to rely entirely on predictive models without understanding the data behind the predictions to achieve true evidence-based decision-making. Any ML model will lack the ability of human improvisation, a skill much needed when dealing with projects. Because of this, ML models cannot be relied upon to make decisions that can be trusted blindly. Instead, the effort lies in exploring the possibilities within ML. When faced with an unforeseen event, the project managers can quickly gather an accurate picture of the situation and develop an appropriate response. In this way, AI is used to increase the flexibility and resilience of projects, mainly through alerting and transferring data quickly to individuals to react appropriately. The models are thus autonomously analysing the situation, leaving the final decision to "human" project managers. With the trust and accuracy behind the predictions, the project manager has the evidence behind the decision.

7 Limitations & Further Research

This section will consider how this study can be improved, discussing future ideas and thoughts. The main takeaways from the digitalisation surveys and interviews are the challenge and lack of digital maturity in the industries. The terms digital maturity, data understanding, data skills, and data quality were mentioned repeatedly.

7.1 Project Management Implications

The project data received from company A contained project costs only from decision gate 3. In this thesis, the focus has not involved the details around the specific decision gate. It would have been interesting to conduct the data analysis regarding the specific decision gate.

During the interviews, some respondents mentioned how AI technology could serve as a tool in the project's Identify phase (presented in Section 2.3). During this phase, multiple concepts are explored to choose the most optimal solution for project development. The respondents saw an opportunity to utilise AI to limit the number of concepts requiring further investigation. The AI solution would quickly filter out the least feasible concepts from a few input parameters, saving time and cost otherwise wasted on researching unsuitable concepts.

7.2 Data Analysis

It is ambitious to believe that perfect data exists. Perfect data is data that does not need any cleaning or pre-processing, and this will likely never be the case for project data. However, it is an advantage to have formatted the data to minimise the amount of pre-processing needed and ensure the quality of the data. From the questionnaires and the interviews, it is clear that companies in the energy industry are taking the focus on data seriously. The quality of data is still important when utilised in new technology. This section will consider how this data analysis can be improved, discussing future ideas and thoughts.

7.3 Quality of Data

Poor data quality will have a negative effect on data processing. It is a challenge that will always exist and is important to detect and handle. The data quality issues mentioned in this report can be summed up in five bullet points;

- Access to data
- Enough data
- Correct data
- Sparse data
- Missing values

Several articles advocate the availability of data. For an organisation to implement AI technology, it is necessary to have access to data. Access to data is sometimes very costly and time-consuming, especially if the organisation does not collect data. "Access to good relevant data can be a challenge when evaluating projects" (Olsson and Bull-Berg, 2015, p. 491). An organisation may have access to data but do not have the knowledge or capability to utilise it. Using existing data will require fewer resources than introducing and collecting new data. For such an organisation, the resources would be spent exploring possible applications for the data and developing AI solutions.

It is not just about collecting data; it is also about collecting enough data and correct data. The data received from company A is not perfect; people manually enter it, increasing the possibility of mistakes. Often the data is also selected by humans, leading to biases being transferred to the AI systems (Baker-Brunnbauer, 2020). The trained algorithms should not be affected by human biases, so it is important to be aware of them.

Missing values occur for different reasons; one reason is that the information is not collected because people decline, skip or do not have a value to fill in. The explanation for missing values could also be that the attribute does not apply to the situation. It leads to a misrepresentation of the result. Another situation is the human fault of typing in the wrong value, which leads to "noise".

Ways of handling missing values are eliminating, estimating or ignoring. The approach used in this report is mainly "ignoring" and including the information that they are "missing". Categorical data have all been one-hot encoded, where "missing" is a distinct category. Missing values for numerical data have been replaced by zero. The motivation for this approach was to use as much data from the dataset as possible. Another option would be to eliminate the features with a large number of missing entries. The benefit of this method is that the data will be trimmed, making the relationships between the remaining features easier to learn. The argumentation for choosing this approach is that the model would likely struggle to find any meaningful relationship between these features and the cost, as they rarely are a part of the input. As the model would struggle to learn from these features, they would only serve as noise during training. However, the downside of this approach is that by eliminating these features, relevant data is potentially lost. Models can generally handle large amounts of features and quickly sort out the relevant ones. However, it could be beneficial to omit some sparse features and see if the model performed better. Currently, for the cross-validation, training 19 models took approximately 15 minutes, so the size of the model regarding computation time was not an issue.

Other data quality problems include noise and outliers, fake data and duplicated data. The difference between noise and outliers is that noise is an error measurement of a random component. However, outliers may concern legitimate data objects or attribute values that stand out from the majority (Tan et al., 2006).

Neural networks often behave like a black box. In this thesis, the model does not give out results along the way to identify which attributes are most important or what predictions and decisions influence each other. It would be interesting to change the ML estimator to a linear regression model for future studies. A linear regression model can give further insights into the correlations between features and the output.

One can calculate the weight each input feature contributes to the output and better understand what affects the outcome. The drawback of these models is that they are linear. That the model is linear does not necessarily mean that they produce linear lines but that the terms for calculating the output are in a linear form: A parameter multiplied by an independent variable (Fox and Weisberg, 2002). Nonlinear models are more flexible as they can take on different forms and fit more curves than linear models. As embeddings were utilised in the analysis, the model decision was limited to using neural networks. However, it would be interesting to see if a linear model could provide more insights into the data and explore how these insights could lead to a more prescriptive analysis.

Currently, the model serves as a prototype, showing the possibilities. For the company to utilise this model for projects, it needs more work. Most naturally, the model can benefit the company as an application on top of the CM system. The most straightforward use of the model would be for cost estimation, predicting the cost of WBS-items. The model would take the data of a WBS-item as input, estimate the item's cost, and return a set of similar items. The returned set of items could be beneficial for other aspects than cost as well as the user would be able to see all the details of the neighbours. For example, for a WBS-item regarding a specific product, the user could see where that product is typically manufactured and inspect if the choice of location changes for different projects.

As the model is currently just a prototype, making it into an application would require further work. To implement the application, one would have to create a framework for interacting with the model. This framework would include a graphical user interface (GUI), a connection to the CM data and software to present the results meaningful to the user. For the application to be pleasant to use, user testing is needed, testing its usability and user-friendliness. A method for updating the application when new data is added to the CM system would also be beneficial, ensuring the model is up to date with all the data available. When new data is available, the current model needs to be trained on the new data, or a new model needs to be trained on the entire updated data set.

The usage of embeddings can be further explored. It would be interesting to develop a confidence feature based on the neighbourhoods of WBS-items in the embedding space. Different measures of similarity could be utilised, and different methods of determining the model's confidence based on similarity to the rest of the database could be explored. One method could be to evaluate the confidence based on the size of the neighbourhood of the WBS-item embedding. Another approach could be to inspect the model's error on the items in the neighbourhood during the cross-validation. The results from the cross-validation on the neighbourhood can indicate whether it is difficult to estimate the cost of this type of WBS-item.

Martinez and Fernandez-Rodriguez (2015) conducted a thorough research which concluded with the recommendation of fusing different AI tools so they can take advantage of the strengths of one tool and cover the weaknesses of another. Based on this, it is possible to look into other approaches to implementing AI tools in projects.

Lepenioti et al. (2021) consider the third ML categorisation of reinforcement learning and decision-making as closely related themes. Reinforcement learning relies on interaction with the world and experiences to assist in decision-making. They proposed a generalised human-augmented prescriptive analytics approach using Interactive Multi-Objective Reinforcement Learning (IMORL). Using IMORL, it is possible to achieve an optimised human-machine collaboration in decision-making ahead of time. The human-machine collaboration conciders both the objectives and the human preferences derived from different users with various levels of expertise and strategies.

Another aspect not mentioned in this thesis is data security. Implementing new technology will also come with risks and uncertainties. In Section 2.2.5, *Benchmarking*, it was mentioned that it could be challenging to get the benchmarking partners to hand over confidential information. Cyber security is critical for organisations to trust that their data is safe and protected against information leakage, hacking etc., but to cover this issue, would be a whole thesis in itself.

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Appendix

A Interview Guide - Company A

Created by: Erling Tømte & Jemima EC Rasmuss 08.04.2022

Interview Questions

We are currently writing our master thesis and the problem statement: *"Artificial Intelligence as a Tool for Prescriptive Project Decision-Making"*. Digitalisation drives decision-making to enhance confidence and reliability in outcomes and predictions in all project management processes. Digitalisation is the talk of the century, and the pressure to strive toward digital transformation increases. New technology such as, artificial intelligence (AI), machine learning (ML) and the Internet of Things (IoT) is often mentioned when discussing this topic. How may these technologies improve the industry's efficiency and effectiveness? The risk and opportunities of these technologies should be carefully studied and not forget the *people* when considering digital transformation.

Role description:
Date/time of interview:

1. What is your role and responsibilities in your organisation?
2. How are you working with the corporate memory system today? Pros/Cons?
3. Are there any functionality/features in the corporate memory system today that you are missing or would like to improve to make their navigation better/easier?
4. What are your thoughts and expectations about introducing AI and ML technology into project management?
5. In what areas in your work is it possible to utilise predictive analytics models to result in more evident-based decision-making? Do you see any obvious benefits or limitations?
6. What type of project decision areas would be relevant?
7. How do you think this technology will affect your way of work?
8. How can this technology help you work more efficiently and make more accurate decisions?
9. How do you think implementing new technology will affect the project/organisation's design/structure? Do you think roles and responsibilities in the organisation will have to be changed/created?
10. Do you have anything else to add regarding this topic?

B Neural Network Parameters

A The Loss Function

The loss is used to update the weights in the network, and it can be calculated with different functions. As the model is trying to minimise the loss, the function that determines the loss has a lot to say about how the model performs. A typical loss function used is MSE, (2), a function described in the thesis. When using this function, a model might be more inclined to reduce the significant errors to a minimum instead of optimising its already decent predictions when compared to MAE, (1), as a loss function.

B The Learning Rate

The learning rate is often the most crucial parameter when training a neural network Bengio (2012). It is also highly listed in the importance factor graph. The learning rate specifies the rate at which learning happens in the network. A too high learning rate will cause the model to diverge as the optimising function overshoots the weight adjustments, and the network never manages to recognise anything. A too small learning rate will cause the model to train slowly, so slowly that it might get stuck.

C The Activation Function

The activation function is applied to the outputs of every layer in the neural network. The role of the activation function is to control the neuron firings in a neural network during forwarding propagation. The activation function is essential for the neural network by transforming the linear output of a network layer to non-linear output for further computation (Nwankpa et al., 2018). It enables the neural network to learn more complex data patterns. Activation functions can also be used in the output layer to produce outputs, such as the softmax function is commonly used in classification tasks (Nwankpa et al., 2018).

The activation function plays a major role in the success of training deep neural networks (Ramachandran et al., 2017). The most widely used and successful activation function currently is the Rectified Linear Unit activation function $f(x) = max(x, 0)$, which is plotted below in Figure 29. It is a rather simple function that sets all negative values to 0 and lets positive values stay unaffected. The activation function SeLU used in the embedding models is a modified version of ReLU that does not produce true zeros.

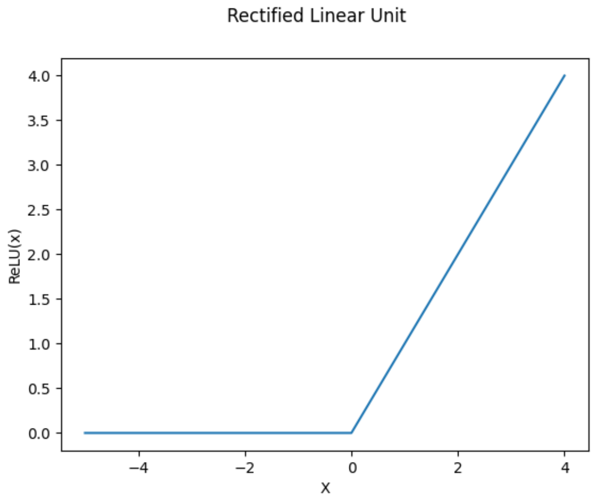

Figure 29: The ReLU function

D The Optimiser

The Optimiser algorithms are responsible for calculating the gradients used for updating the weights of the network (**?**). Gradient Descent is the most basic and frequently used, but many different optimisation algorithms are used. The optimiser algorithm used in this thesis is RMSprop, which scales the learning rate to the input magnitude to provide faster learning (Bushaev, 2018).

C Result Project Plots

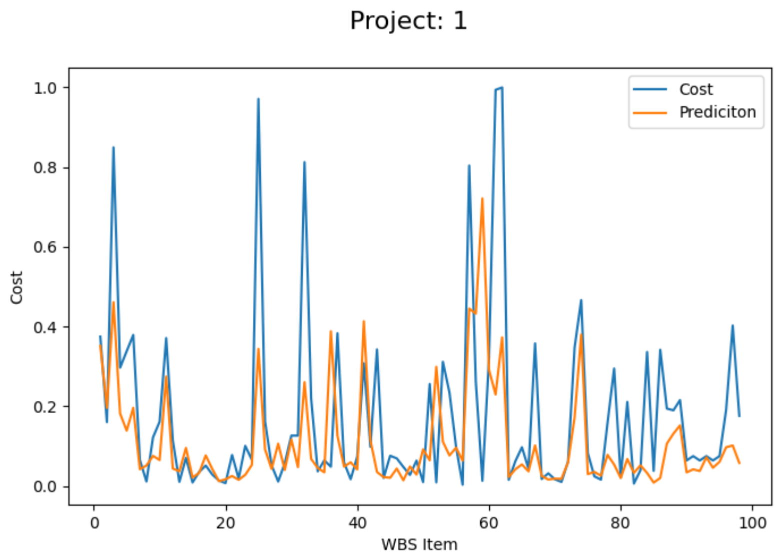

Figure 30: Line plot of the models performance on project 1. The orange line is the models output, the blue line is the target value

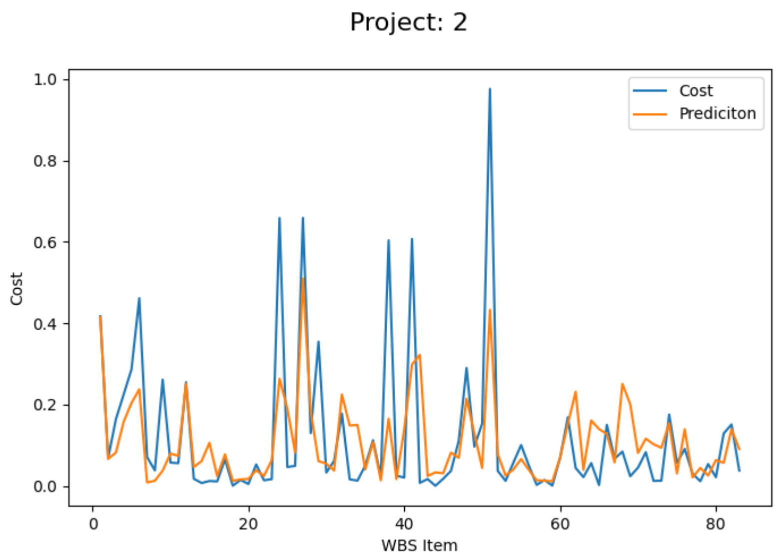

Figure 31: Line plot of the models performance on project 2. The orange line is the models output, the blue line is the target value

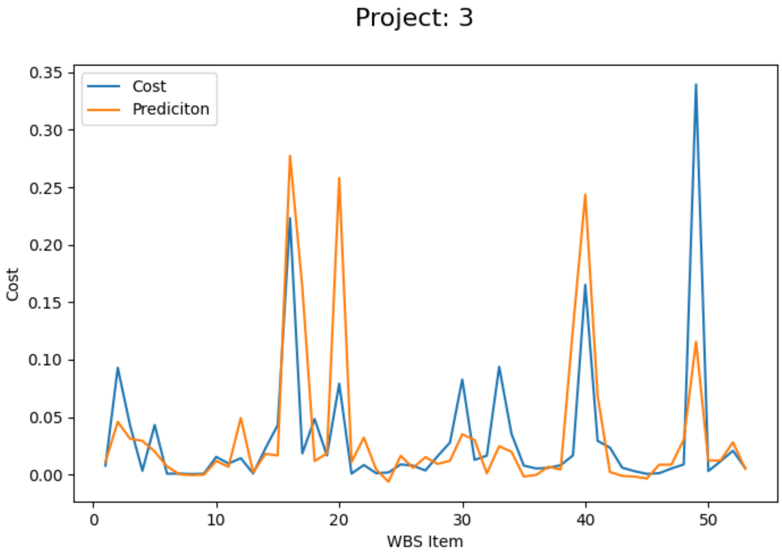

Figure 32: Line plot of the models performance on project 3. The orange line is the models output, the blue line is the target value

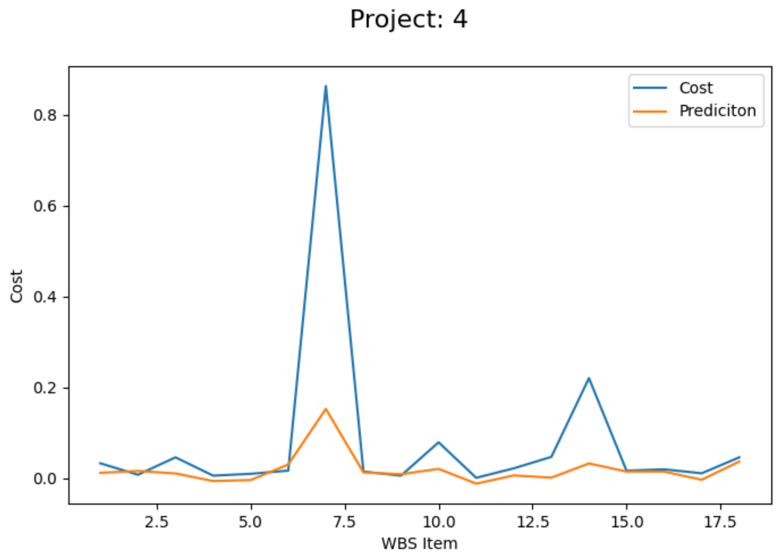

Figure 33: Line plot of the models performance on project 4. The orange line is the models output, the blue line is the target value

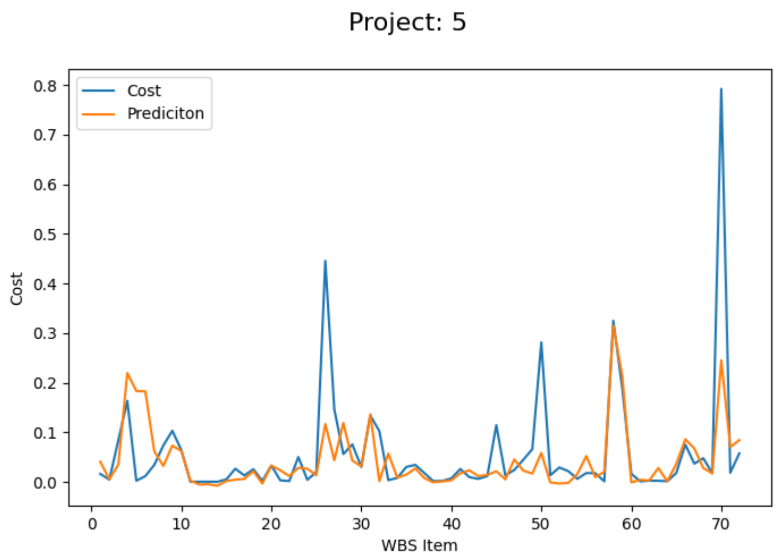

Figure 34: Line plot of the models performance on project 5. The orange line is the models output, the blue line is the target value

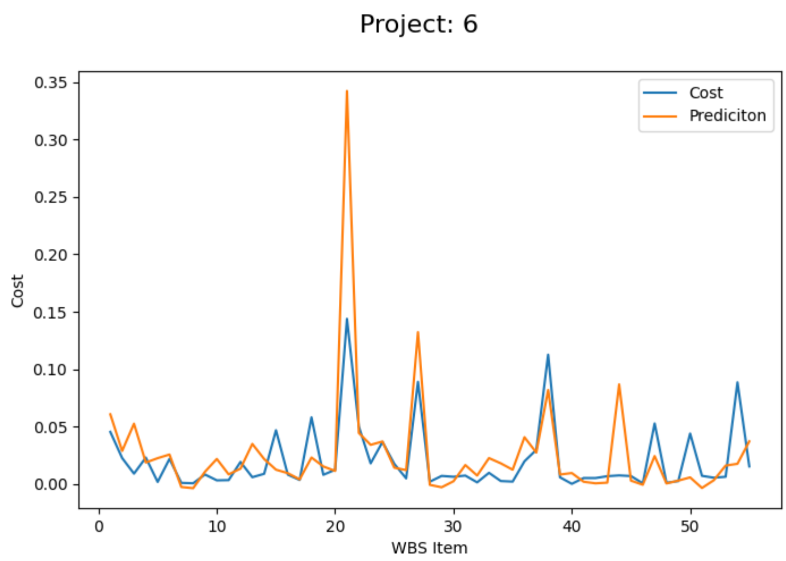

Figure 35: Line plot of the models performance on project 6. The orange line is the models output, the blue line is the target value

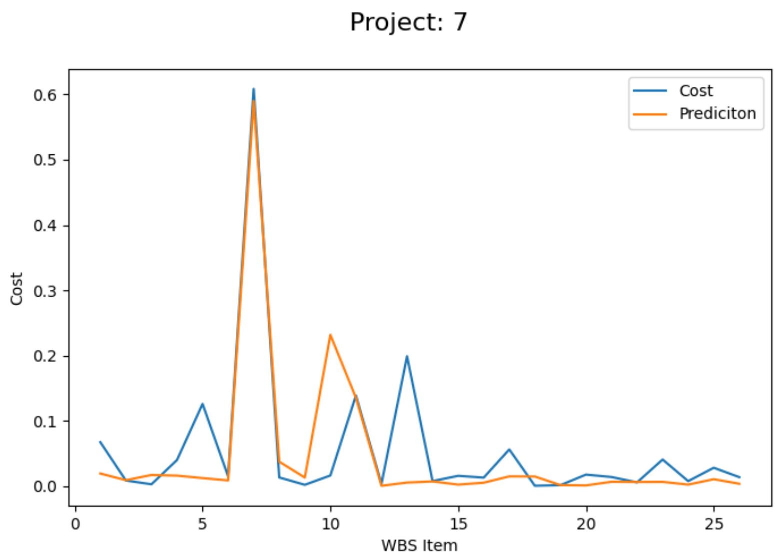

Figure 36: Line plot of the models performance on project 7. The orange line is the models output, the blue line is the target value

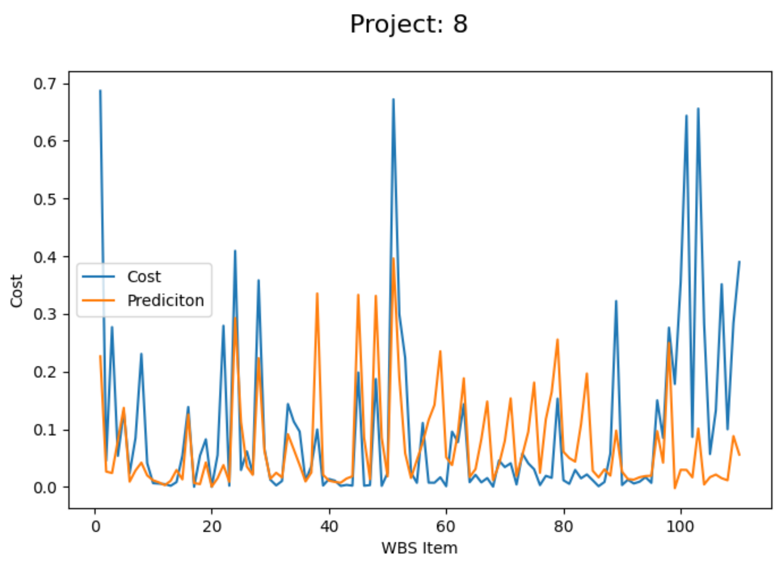

Figure 37: Line plot of the models performance on project 8. The orange line is the models output, the blue line is the target value

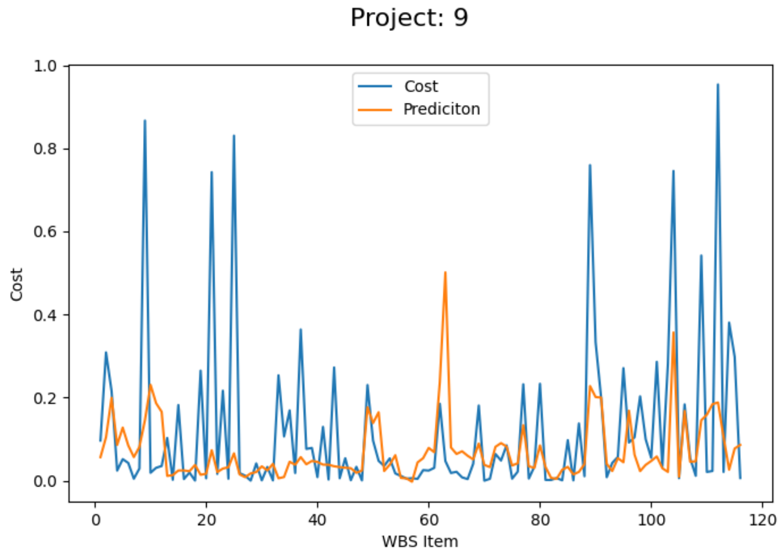

Figure 38: Line plot of the models performance on project 9. The orange line is the models output, the blue line is the target value

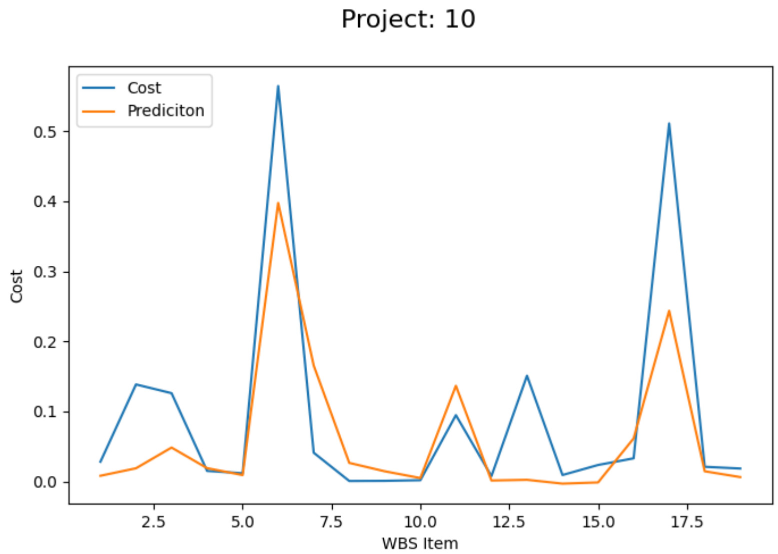

Figure 39: Line plot of the models performance on project 10. The orange line is the models output, the blue line is the target value

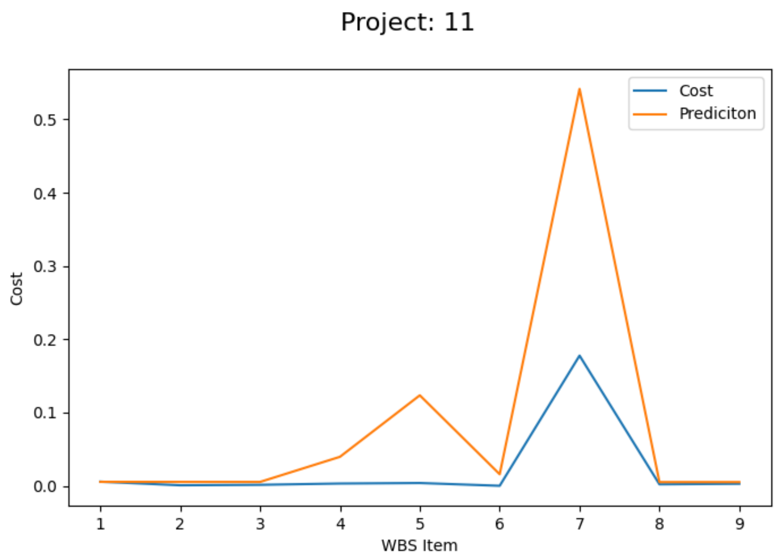

Figure 40: Line plot of the models performance on project 11. The orange line is the models output, the blue line is the target value

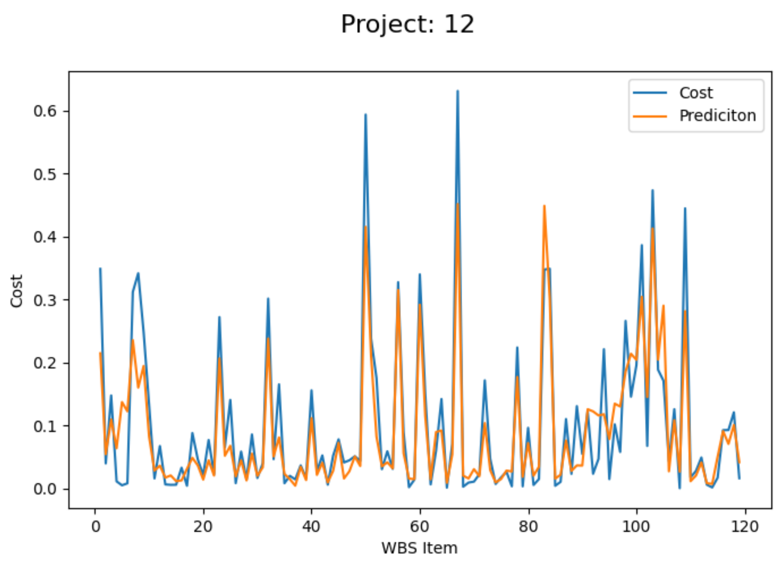

Figure 41: Line plot of the models performance on project 12. The orange line is the models output, the blue line is the target value

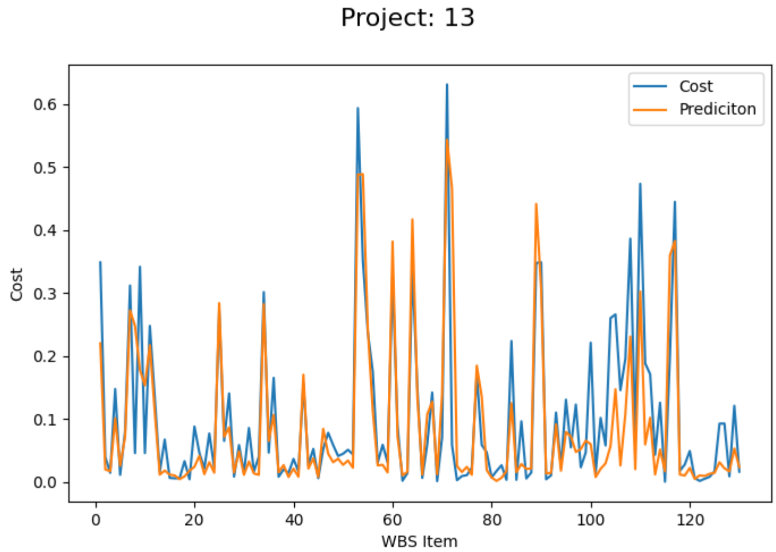

Figure 42: Line plot of the models performance on project 13. The orange line is the models output, the blue line is the target value

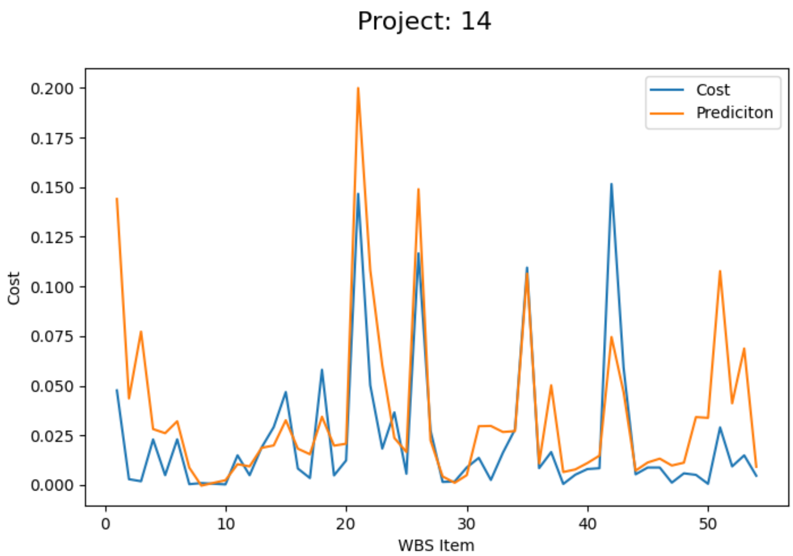

Figure 43: Line plot of the models performance on project 14. The orange line is the models output, the blue line is the target value

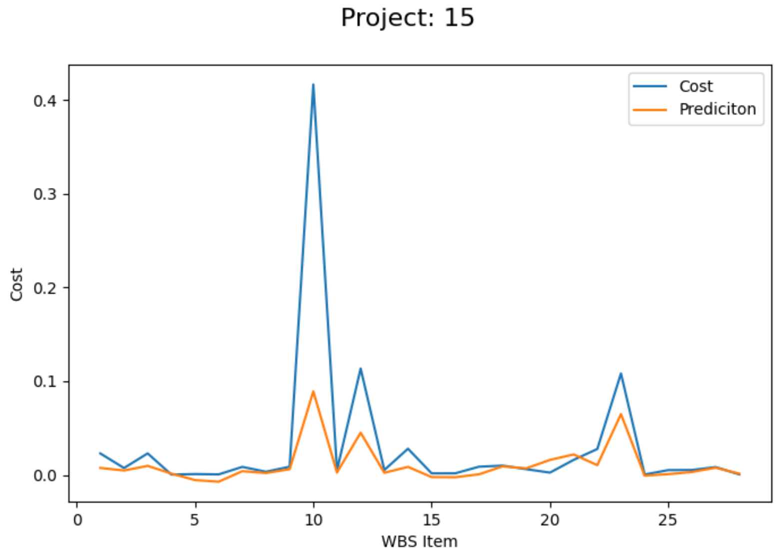

Figure 44: Line plot of the models performance on project 15. The orange line is the models output, the blue line is the target value

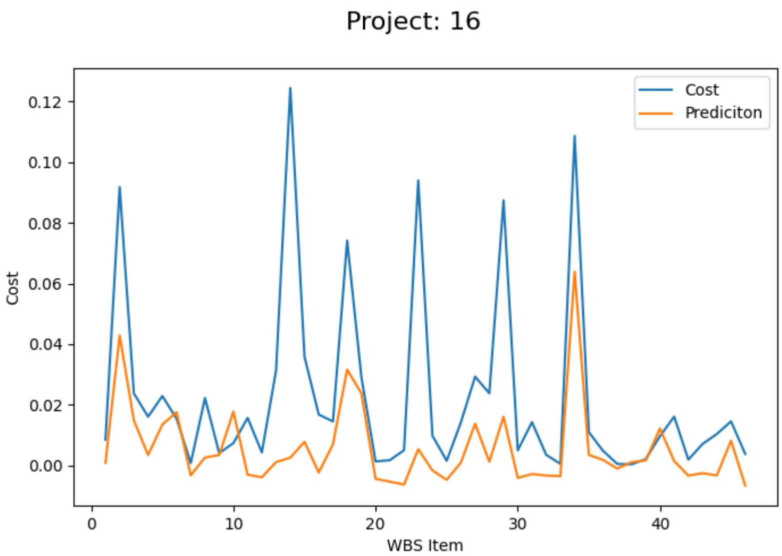

Figure 45: Line plot of the models performance on project 16. The orange line is the models output, the blue line is the target value

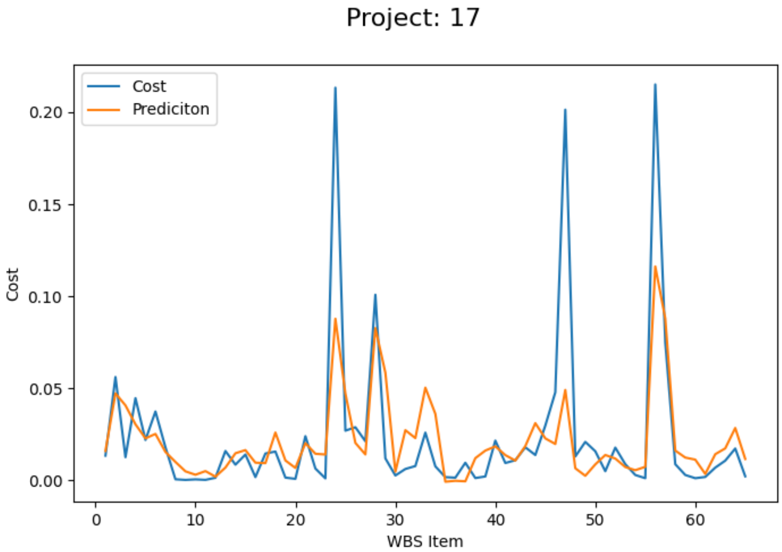

Figure 46: Line plot of the models performance on project 17. The orange line is the models output, the blue line is the target value

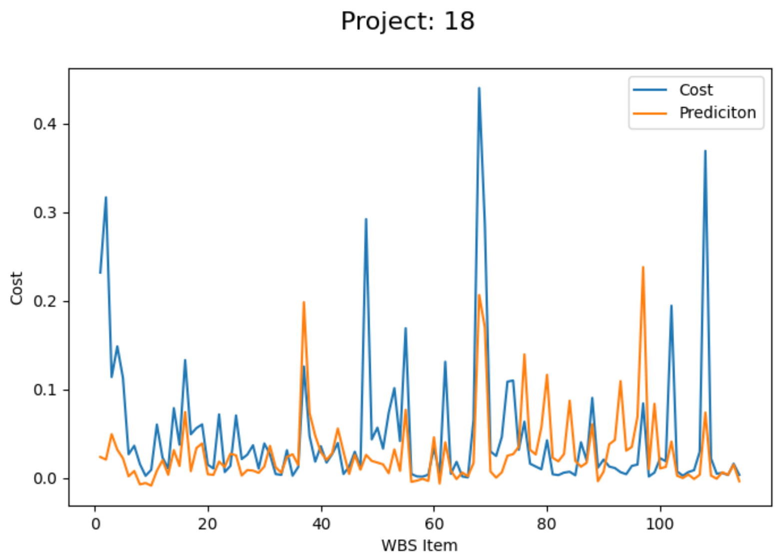

Figure 47: Line plot of the models performance on project 18. The orange line is the models output, the blue line is the target value

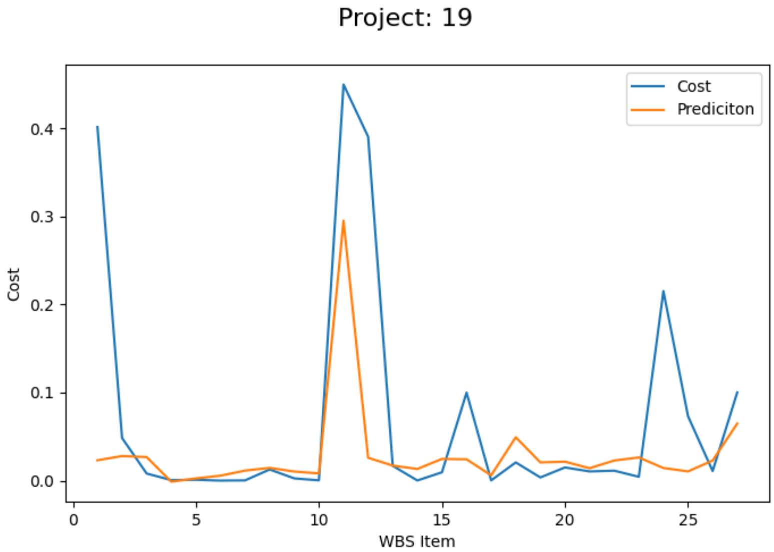

Figure 48: Line plot of the models performance on project 19. The orange line is the models output, the blue line is the target value

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