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AI in Construction Management: Preparedness and Potential

A case study on implementing a predictive machine learning framework for construction project scheduling

Master's thesis in Master Complex Adaptive System and Design and Construction Project Management

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Abbreviations

AI Artificial Intelligence

BIM Building Information Modeling

CPM Critical Path Method

CPU Central Processing Uni

GPU Graphics Processing Unit

KFold K-Fold Cross-Validation

ML Machine Learning

MAE Mean Absolute Error

MLP Multi-Layer Perceptron

MSE Mean Squared Error

RMSE Root Mean Squared Error

$\mathbf{R^2}$ Coefficient of Determination

PyTorch Python Torch Library (for ML)

Contents

Abstract

Persistent challenges related to project delays continue to plague the construction industry, an industry often characterized as outdated, low-productivity, and unpredictable. These challenges are amplified by the complexity of infrastructure projects, external pressures, and the historically slow adoption of digital technologies. Despite generating large volumes of data, the industry struggles with inconsistent data collection and effective utilization. To address these limitations and underline the importance of robust data management, this thesis explores the integration of ML-based predictive models to improve decision-making in project management. In collaboration with NCC, the complex Ingelkärr–Stenkullen transmission line project served as a case study. A hybrid forecasting model was developed, combining Monte Carlo simulations with a neural network-based ML approach. The Monte Carlo simulations generate a wide range of potential project completion timelines, incorporating variations in task durations and task-specific characteristics. These simulated outcomes serve as the foundational training data for the neural network. A key technical contribution of this work lies in the model's dynamic weekly updates with real-world progress data, enabling adaptive learning. Task dependencies were processed using GPU acceleration, and an attention mechanism allowed the neural network to capture task interactions, enhancing predictive accuracy. Interviews with NCC and Svenska Kraftnät project managers and engineers informed the model's user interface, ensuring transparency and improved decision-making. Results showed high predictive accuracy ($R^2 = 0.92$), which improved over time, highlighting the value of combining data-driven methods with traditional management strategies. Ultimately, this thesis demonstrates the critical need for next generation planning systems in construction, focusing on intelligence, adaptability, and transparency. The proposed framework shows strong potential to transform industry practices by significantly improving risk forecasting, optimizing resource management, and increasing responsiveness to uncertainty, thereby offering a pathway to more efficient and resilient project management in construction.

1
Introduction

1.1 Background

For years, the construction industry has faced significant challenges that stem from both external and internal factors [1]. On the side of external forces, these challenges include economic uncertainty, regulatory pressures and heightened competition that is demanding greater efficiency and innovation. Through the internal lens however, the industry contends with the ever-growing complexity of project scopes, tighter deadlines, and budget restrictions, creating formidable hurdles for project managers.

Traditionally, the industry has relied on intuition, experience and outdated risk management methods. Using these methods often left managers to struggle with meeting deadlines and stay within budget [1]. This challenge does not only affect the project or the company but the industry as a whole. It is reported that the construction industry productivity level and ranking are much lower, and that it is struggling behind other industries regarding efficiency improvements [2]. Countries like Australia and the U.S showed negligible productivity gains and it is clear that the construction industry has not taken advantage of the IT evolution during the early 2000s. Though this does not have to remain true, the construction industry can still evolve, especially now when artificial intelligence (AI) and machine learning (ML) can redefine how projects are planned.

This study is a testament to this statement where modern technologies are leveraged to support decision-making, risk management, and project forecasting. By integrating AI and ML, construction companies can move away from static, reactive planning and instead adopt predictive, data-driven approaches that offer greater transparency and adaptability throughout the project life cycle.

1.2 Problem Statement

The construction industry consistently meets with substantial difficulties in managing project delays, primarily due to the complex and interdependent nature of risk factors [3]. As stated previously, these risks come from various sources ranging from the owner-related issues, contractor inefficiencies, resources constraints and external influences. It would be beneficial if the construction industry could rely on risk analysis methods like Monte Carlo simulation and deep neural network models as it provides a systematic way to quantify and analyze uncertainties.

Applying these mathematical models has proven to be particularly challenging. While the construction sector generates significant amounts of data over a project's life cycle, much of it is unstructured, inconsistent, or incomplete [3]. Furthermore, the data are highly diverse, including images, schedules, economic records, and more, each requiring distinct processing methods [4]. The lack of standardization across these data types further complicates cohesive integration and analysis. Identification of gaps in construction project management processes, particularly in data utilization and stakeholder engagement. Emphasis on the need for a combined technical and user-focused approach.

1.3 Objective and Scope

As the construction industry remains in the early stages of integrating ML and AI into project management, this study aims to explore how such technologies can be applied to support decision-making and improve productivity through enhanced data monitoring and analytical capabilities.

This thesis is conducted in collaboration with NCC, one of the Nordic region's leading construction companies, and is based on a real infrastructure project, Ingelkärr-Stenkullen. The intention is to bridge the gap between academic research in AI and ML and their practical application in real-world construction environments. This objective forms the basis for the thesis' dual focus on both technical development and practical relevance.

On the technical side, the study involves the development and validation of a machine learning model capable of forecasting project progress and detecting trends that may signal emerging risks or delays. Key steps in the model development process include data preprocessing, feature engineering, model training, and validation to ensure both accuracy and applicability in a construction context. While the model is developed using data from a specific project, the aim is to design a solution that is adaptable and applicable across different construction projects and settings.

On the practical side, the research includes interviews and collaborative sessions with construction professionals, such as site managers and engineers from NCC, to gain a understanding of existing project management workflows, challenges in data usage, and the requirements for analytical tools that can support their daily decision-making.

To ensure focus and depth, the scope of the technical side is limited to data-driven forecasting and data pattern detection within the domain of scheduling and performance. The financial aspect is discussed briefly in the literature review, while environmental, and resource specific dimensions are recognized as important aspects construction project management, they are considered outside the core scope of this thesis.

1.3.1 Research Questions

In order to achieve the objectives, a set of research questions have been formulated to guide both the research process and the development of the ML model:

- How can AI and ML be implemented effectively and practically into construction management workflows?
- In what ways can predictive models contribute to data-driven decision-making, and to what extent does data management affect model performance?
- How do construction professionals perceive the use of AI and predictive models in their daily workflows?

1.4 Research Approach

This section presents the general approach taken to conduct the thesis and reach the final results. A variety of methods were combined to explore the topic from different angles and ensure the outcomes was grounded in both practical understanding and technical development.

1.4.1 Gap Analysis

To achieve the research objectives and address the identified questions, the thesis began with a gap analysis aimed at understanding the needs of construction project management and exploring how AI and ML could be meaningfully integrated into existing workflows. This process was done quickly and involved internal discussions, a review of current state of AI and ML through literature, and collaborative sessions with industry professionals from NCC and other stakeholders. Key challenges and opportunities were identified through meetings, semi-structured interviews, and an examination of existing digital tools and software standards used in the industry. This analysis guided the technical work in this thesis by shedding light on the needs in the industry as well as the practical limitations of current solutions.

1.4.2 Literature Review

The second part of the research approach is conducting literature review to better understand the current state of AI and ML within the construction industry. The review focused on academic publications, industry surveillance, case study to identify existing methods, common challenges and trends in the adaptation of data-driven tools in project management. Particular attention was given to research on the implementation of mathematical models in construction planning, as well as studies that applied various ML methods for forecasting and optimization purposes.

The findings from the literature reviews provided a foundation for the development of the model. Additionally, it also supported the identification of gaps between theoretical advancements and real-world application.

1.4.3 Case description: Ingelkärr-Stenkullen Project

To sustain the practical relevance of this thesis, a case study was conducted on the Ingelkärr-Stenkullen project, a collaboration between Svenska Kraftnät and NCC. This section introduces the project and its importance for the research in a real-world context. A significant portion of the thesis is based on data collected from this project including task schedule, progress updates and planning structures. The thesis was further supported by insights gathered through interviews with key stakeholders, offering technical inputs and user-oriented perspectives to guide model development.

Project description

Overview
Svenska Kraftnät and NCC have collaborated to construct a new 400 kV overhead transmission line, linking Ingelkärr in Ale Municipality to Stenkullen in Lerum Municipality [5]. This project's purpose is to strengthen Västra Götaland's electrical grid and increase the power transfer capacity to the Gothenburg area. The power line will also help facilitate the integration of new wind power production and alleviate transmission bottlenecks affecting electricity trade between Sweden, Norway and Denmark.

Background
The project stems from network studies that identified the need to reinforce the transmission grid between Skogssäter and Stenkullen to ensure a secure and reliable power supply. This in turn would help to prevent overload and risks of major power outages. Additionally, EU regulations require member countries to avoid internal transmission bottlenecks that could hinder cross border electricity trade.
Skogssäter-Stenkullen was the original planned project, however, due to environmental restriction in the Bredfjället-Väktor nature conservation area, the project was divided into two parts:

- Ingelkärr to Stenkullen (Current project)
- Skogssäter to Ingelkärr (Future project)

This thesis is only about Ingelkärr- Stenkullen project as the line is expected to enhance trade, supporting industrial electrification, and enabling the ongoing green transition in transport and industry.

Technical description:
Line Length: 18-20 km
Technology: Overhead alternating current (AC) transmission line.
Voltage: 400 kV
Supporting Structures: Steel portal + pylons requiring a 44 meter wide corridor in forested areas
Planned station: Ingelkärr- Stenkullen.

Project timeline:
2012-2016: Initial planning and consultation
2016: Application for a transmission line concession submitted
2019: Environmental restrictions led to splitting the project into two phases
2020-2023: Permitting process, environmental impact assessments and finalizing the route
October 2024: Transmission line construction completed and connected to Stenkullen station
2026: Expected commissioning once Ingelkärr station is fully operational

1.4.4 Interviews

Interviews are not only one of the common ways to collect qualitative data but it also extends beyond creating a comprehensive snapshot, analyzing languages and reporting detailed insight [6]. This method aims to learn new perspectives from different stakeholders and experts to gather real life information. The results from these interviews are presented in chapter 6 and further discussed in chapter 7. Appendix A presents the interview transcriptions along with the questions asked. To ensure transparency, the full content of each transcription is provided in the original language, Swedish.

Interviewees:
There are a total of three interview opportunities with six interviewees from Svenska Kraftnät and NCC, who have either worked on the Ingelkärr-Stenkullen project or possess expertise in the field. To protect the interviewees' identities, their names and roles have been anonymized.
From Svenska Kraftnät:

- Project leader: Interviewee A
- Trainee: Interviewee B

From NCC:s side on-site workers:

- On-site leader: Interviewee C
- On-site block leader: Interviewee D

In addition, there is an interview with NCC engineers to gain insight into how the company operates when starting a new project.

- Manager: Interviewee E
- Master Trainee: Interviewee F

Structure of the interview
For this thesis, the interviews were either conducted in person or via Microsoft Teams, each lasting approximately an hour with about 30 to 40 minutes dedicated to active questioning. To ensure an active conversation, the questions are open-ended while incorporating follow up questions to explore the responses. The interviews were designed to address different perspectives within the project.
By speaking with NCC's off-site managers and master trainee, Interviewees E and

F, the thesis gained detailed insights into production planning, execution, and challenges associated with large-scale construction projects. On-site managers, Interviewees C and D, contributed valuable perspectives on the specific difficulties faced during the Ingelkärr–Stenkullen project and how the team managed unexpected hurdles. From the owner's side, an interview with Svenska Kraftnät's project leader (Interviewee A) and trainee (Interviewee B) provided insights into project expectations and the challenges of coordinating with and communicating across various government agencies.
Each interview session was structured around similar themes such as risk management, timeline adjustment, project visibility, AI implementation and communication challenges.

Ethics of interviews
Conducting ethical interviews is fundamental to ensuring the integrity and credibility of research. Interviewers must obtain ethics approval before conducting interviews intended to gather data for researching findings [7]. Key ethical considerations include maximizing benefits while minimizing potential harm to participants, ensuring voluntary participation through informed consent and treating all interviewees with respect. Interviewer should also be mindful of the management of data to protect participant confidentiality.

In conducting the interviews for this thesis, several key ethical considerations were meticulously observed to ensure the integrity and credibility of the research process. Each interview commenced with mutual introductions and a clear explanation of the thesis objectives and the specific purpose of the interview. Prior to any recording, explicit consent was obtained from all participants for both audio and video, in line with ethical standards that emphasize informed consent and respect for participants' autonomy. The recordings were subsequently transcribed semi-verbatim to maintain accuracy and facilitate thorough analysis. To delve deeper into the insights gathered, the transcribed data underwent comprehensive discussions, allowing for a nuanced understanding of the information provided by the interviewees. This approach not only ensured compliance with ethical guidelines but also enhanced the depth and validity of the research findings.

2

Literature Review and Research

To get a clearer picture, this chapter focuses on the current workflow within construction industry by reviewing literature and articles, explore various scheduling methods and analyze the current state of AI and ML could in construction industry, its influence and the intricate factors involved.

2.1 Construction Management: Project Planning, Progress, and Risk

This section outlines current practices in project planning, explores common scheduling methods, and examines approaches to risk management within the construction industry.

2.1.1 Overview of Construction Project Planning

Effective planning is crucial to any construction project as they are complex and vulnerable to random external factors. In the late 1950s, the introduction of planning techniques based on schedule networks and bar charts became a standard industry practice and has remained so ever since [8]. However, the report by McKinsey explores the weakness of the industry as 98% of construction projects experience more than 30% cost overrun and 77% projects are at least 40% overdue [9].

According to PMBOK Guide [10], every project encompasses aspects of scoping, scheduling, budgeting and quality management. As one of the largest sectors worldwide, constitutes approximately 13% of the global Gross Domestic Product [9], the construction industry follows a similar working management process, incorporating additional knowledge areas such as risk, safety and environmental considerations.

Scheduling in the construction industry is one of the critical aspects of project management due to the unique nature of construction projects, which often involve distinct challenges and specific requirements [11]. Therefore, it is essential for both the contractor and the owner to establish a well structured construction project schedule that includes the selection of resources (e.g machines, workforce) and effective coordination. To develop an optimal schedule that meets the accepted criteria, the planner must account for specific project conditions and constraints.

Another fundamental component of construction management is resource allocation as it has a direct influence on the project's progress and result [12]. Resource allocation is also connected to project scheduling as the availability and distribution of resources directly influence task sequencing and project timeline [13].

Faniran et al (1999) argue that efficient resource allocation in construction planning should prioritize value addition and cost effectiveness when determining resource requirements [14]. The study also shows that increasing resource allocations to construction planning can enhance project performance, thus, it is crucial to determine the appropriate resource allocation to maximize efficiency and project success.

2.1.2 Construction Scheduling Methods

Examination of methods and tools used to monitor project progress and ensure adherence to schedules.

Scheduling methods:
Over the past decades, construction scheduling has become a focal point as there has been an excessive amount of methods and algorithms developed to address specific scenarios and problems [15]. Scheduling methods can be divided into two categories: Bar chart and network-based systems. Bar charts (e.g Gantt chart) are easy to understand and generally an acceptable communicating tool [16]. These charts are commonly preferred in the construction industry because they present schedules in a simplified and flexible format [18]. This clarity is especially beneficial, as employees often have varying levels of comprehension.

Gantt charts
The most recognizable bar chart is the Gantt chart, as it was a tool developed to plan and manage production [19]. It works by having production planning operate in a top-down approach, connecting end-item requirements to their components through time-phased production scheduling, ensuring parts are available when needed.

Gantt charts emphasize systematic solutions over algorithmic ones, with a simple layout that is easy to follow. However, their limitations in managing and processing information effectively posed significant challenges. They also required extensive data collection and planning, which was unnecessary for organizations where uncapacitated production methods worked well. Over time, Gantt charts fell out of favor as the complexities of large-scale production overwhelmed the techniques [19].

The revival of Gantt charts began with the advent of microcomputer based project management software. Their simplicity and effectiveness in visually displaying project activities, timelines, and progress made them appealing to managers as well as all level workers. Unlike complex network based schedules, Gantt charts offer an intuitive and easily understandable format for presenting schedules, making them accessible to a wide range of users. Another surge of popularity occurred by the development of interactive applications where Gantt charts were used to facilitate communication between users, allowing for better problem definition and solution. Today, Gantt charts remains a staple in modern project management [19].

Critical Path Method
Another well-known scheduling technique is Critical Path Method (CPM), which is a network based system [20]. It works by identifies the sequence of tasks and activities that determine the minimum project duration, also known as the critical path. Any delay in tasks on the critical path will directly affect the project duration. CPM is useful in production planning and control, helping managers prioritize tasks and allocate resources.

Despite its success in the project management sector, CPM has been accepted as a universal tool in the construction industry [17]. In the survey conducted by Galloway (2005), only 46 % of owners require CPM scheduling on their projects, and 72.5% specify it in contracts. However, only 55.9% require a baseline schedule. Project owners value CPM for its ability to conduct “what-if” scenarios and summarize schedules on a bar chart, but also express their concern about the complexity of CPM and the potential for contractors to manipulate schedules.

From the same survey, many contractors noted the rise of CPM popularity as their contracts often require CPM scheduling [17]. In projects that do not have a CPM scheduling requirement, many of them would still prepare one to plan and monitor their work. Contractors primarily use CPM for periodic control of work, developing look-ahead schedules, coordination of subcontractors, etc. They believed that there are many time-saving and financial benefits to using CPM with the majority achieving a moderate to high success rate in leveraging these advantages. Despite this, contractors also identified logic abuse as the primary setback of CPM scheduling. Other concerns include excessive work to implement, over-reliance on specialists, and lack of responsiveness to field personnel.

There are several ways to improve the use of CPM in construction projects. According to Kim et al (2005), universities should revise their programs to provide more practical and consistent CPM training for their students [18]. The article also emphasized on the need for standards for CPM scheduling to foster a more transparent environment. CPM is a valuable project management tool and its full potential is hindered by a lack of standardization, inconsistent training and complexity of software. By addressing above-mentioned issues, the construction industry can benefit greatly from embracing CPM scheduling [18].

2.1.3 Risk Management in Construction Projects

Risk management is one of the most important processes in construction, as risks can arise at any stage, from initial planning and design to execution and final project delivery. Therefore, effective risk management requires active participation from all stakeholders involved in the project. According to the article by Schieg (2006), risk management in construction is a structured and systematic process consisting of six key steps: risk identification, risk analysis, risk assessment, risk control, risk monitoring, and goal management [21].

Despite the structured nature of this framework, the most commonly used techniques in practice, such as brainstorming sessions, checklists, risk registers and sensitivity analysis, which tend to be largely reactive, semi-formal and often unstructured [22]. These methods, while useful, are generally not embedded into the broader project systems in a proactive or continuous way. Moreover, effective communication and information sharing are critical in managing risks, especially considering the wide range of stakeholders involved in construction projects. As highlighted by Serpella et al. (2014), these processes are often hindered by the limited variety and frequent misapplication of risk management approaches [23]. Another significant challenge is that traditional methods rarely allow for the systematic capture and reuse of risk-related data from past projects. This lack of knowledge retention makes it difficult to identify recurring patterns or anticipate future risks based on prior experiences. By promoting better documentation and reflection on past projects, organizations can improve their ability to foresee and mitigate risks, ultimately enhancing project outcomes. Leveraging historical data can help anticipate similar issues, enabling stakeholders to implement proactive measures [23].

In the context of mega-construction projects, the exposure to risks is amplified and extends beyond typical concerns. These large-scale projects often face heightened threats including political, economic and design-related risks [24]. Political risks, in particular, involve uncertainties and challenges stemming from changes in government regulations, political instability, and legal or regulatory processes, all of which directly impact project financing, approval procedures and overall project momentum. Despite the significance of these risks, current risk management strategies in mega projects tend to treat each risk individually, overlooking the ways in which different risks interact and amplify each other. Furthermore, existing classification methods do not adequately group risks according to their sources or underlying causes, making it difficult to trace their origin and assign clear responsibility to the relevant stakeholders. As a result, effective risk ownership and accountability are often lacking or entirely absent, further complicating risk management efforts in large-scale construction projects [24].

2.2 ML in Construction

This chapter is an overview of how ML models are being perceived in construction, the challenges it might face in implementation, and how organizational culture and data maturity influence the adoption. This section also explores both the optimism surrounding ML and the practical limitations that currently hinder its adoption across the construction industry.

2.2.1 Applications and Limitations of Machine Learning in Construction mManagement

Limitation:

The construction industry has experienced a rapid increase in the amount of objective data generated and stored daily across various disciplines throughout a project< or facility's life cycle [25]. In this abundance of data presents an opportunity to extract valuable knowledge and develop effective solutions to the persistent issue of project delays. The use of advanced data analytics tools is proven to be essential due to the interconnected nature of construction related data.

Given this context, the potential of ML techniques and algorithms to analyze complex and diverse datasets holds significant promise for deriving meaningful insights that can enhance decision-making and project outcomes. However, the adaptation of ML and AI in the construction sector is still relatively new despite these benefits, the following section will be highlighting the limitations as well as the difficulties of integrating ML in construction.

Technological Readiness and Workforce Resistance
Implementing new technologies and innovative methods in the construction industry involves more than simply acquiring the latest computers or software [26]. As the industry moves deeper into the digital age, a critical question arises: even if construction companies are ready to adopt digital tools, are their employees equally prepared to make this transition?

According to the research done by Akinosho et al. (2020) construction employees are often reluctant to accept new technologies, especially when these require a steep learning curve. Many show less interest in advanced tools and tend to prefer more traditional, practical methods. Although companies can encourage these adaptations through targeted training programs, especially since digitalization has shown the ability to deliver projects faster, more cost-effectively and with improved efficiency.

Blackbox
One of the more prominent limitations of adopting AI and deep learning is the "black box" nature of these algorithms [26]. Deep learning models, especially neural networks, often produce predictions or recommendations without providing clear explanations behind these decisions. This lack of transparency is especially problematic in the construction industry, where decisions need to be justified and understood by all stakeholders. For instance, if a model suggests a reducing the amount of concrete used in a project, it must also be able to explain why this reduction is safe and effective. Many tools like LIME (Local interpretable Model-agnostic Explanations) and Interviewee F (Descriptive ML Explanations) have been developed to address these issues, but they are still in their developing stages and may not always provide complete explanations.

Data availability and quality
Another significant limitation of deep learning models is the reliance on large amounts of high-quality data to perform effectively [27]. This issue is even more eminent in the construction industry, which often struggles with data availability due its fragmented nature and the absence of standardized data collection practices. Regona et al. (2022) identified the scarcity of labeled data as a key factor contributing to the low accuracy of AI applications in construction [28]. This issue is further compounded by the lack of standardized data transformation techniques, which hinders the broader applicability of AI solutions.

While large infrastructure projects may generate substantial amounts of data, these datasets often suffer from imbalances, where certain labels are underrepresented compared to others. Such imbalance can create significant challenges for AI model training, leading to biased predictions and reduced generalizability [28]. Moreover, the process of collecting, labeling and standardizing data remains a major bottleneck, as it is both resource intensive and time consuming. This underscores the growing necessity for standardized protocols in data collection and transformation.

Low quality data, including errors and missing values, introduces additional bias into AL models [29]. Many deep learning models are not designed to handle such low quality data, which further compromises their reliability. Robust preprocessing and data cleaning techniques are therefore essential to ensure models are trained on accurate and representative datasets [30].

Data privacy and security
AI models rely on three core technical elements: data collection, data processing and data outcomes [31]. The data collected not only support model training but also serves as a range of management functions, including education and workforce training within the construction industry [32]. However, these datasets can raise significant privacy concerns. Confidential project information may be leaked, leading to fears among stakeholders regarding unauthorized use of private data.

The architecture, engineering and construction (AEC) industry relies on traditional data storage methods such as local or company-specific servers. These systems, however, are also more prone to data security risks. Concerns include the potential threats of data corruption during transmission and cybersecurity vulnerabilities, particularly as local devices or remote working setups may lack protection software against external threats. Not to mention, the industry requires engineers to synchronize data across multiple software, devices and users thus making them even more vulnerable to private data leakage.

Ethics Considerations
For the longest time, the construction industry has been resistant to adapting new technologies, largely due to its status as a well-established sector with an aging workforce. As the branch gradually begins to implement more AI systems and robots, concerns have been raised among workers about potential job displacement. There is a sense of paranoia among workers about being replaced by these technologies, as

robots are increasingly capable of performing tasks that are hazardous or inaccessible to humans.

In the survey done by Kim et al. 2021, it revealed that while many workers and managers acknowledge the benefits of AI and robots in construction, their views differ vastly [33]. Managers are generally more supportive of such innovations, viewing them as tools to boost productivity, minimize human error, and address persistent labor shortages. In contrast, on-site workers are more skeptical, especially regarding job loss and disruptions to established workflows. Many expressed a preference for robots that operate under human supervision rather than autonomous systems.

However, proponents argue that the rise of AI and automation does not necessarily reduce the number of jobs. Instead, it shifts the nature of available jobs, creating new roles that require new skills. As such, the focus should be on helping workers adapt though reskilling and retraining initiatives, ensuring that they remain active participants in the industry digital transformation [32].

Cost
Training an AI model is resource intensive and often requires considerable investments in both hardware and skilled personnel [26]. High-performance computing devices equipped with GPU processors are essential to reduce training times and handle computational loads efficiently. Simultaneously, companies must consider the financial implications of hiring skilled professionals with expertise in AI and ML.

2.2.2 Predictive Analytics in Construction Projects

Predictive analytics is a method rooted in the systematic analysis of data to develop forecasting models through computational techniques. It leverages statistical algorithms and data mining to anticipate future outcomes [34]. By analyzing both historical and real-time data, predictive analytics identifies patterns and trends to generate actionable insights to support informed decision-making. The rise of Building Information Modeling (BIM) in the construction industry has enhanced the potential of predictive analytics. As BIM adoption grows, the synergy between its data-rich models and predictive analytics allows the industry to proactively address challenges, reduce uncertainties, and drive efficiency across the project life-cycle.

ML has further advanced the potential of predictive analytics by offering powerful tools for extracting meaningful insights from complex and diverse datasets [25]. Unlike traditional rigid programming that depends heavily on assumptions about the data distribution, ML algorithms learn from implicit patterns within the data [35]. Through iterative learning and inductive reasoning, these models continuously refine their accuracy over time. This adaptability makes ML well suited to address the intricacies of the construction sector, a knowledge-intensive domain characterized by vast volumes of heterogeneous, interdependent data [25].

2.2.3 Comparative Studies of Predictive Models in Construction

Many studies have investigated various approaches to predictive modeling, ranging from traditional statistical methods to advanced ML algorithms and neural networks. These studies highlight both the potential benefits and inherent limitations when applying predictive analytics to construction projects.

One common approach is training ML models using historical project data. For example, Chakraborty et al. (2020) compared several ML techniques for predicting construction costs and demonstrated that these approaches provided better accuracy compared to traditional methods [36]. Similarly, Momade et al. (2022) employed AI tools to model labor costs in construction projects, underscoring AI's capability to capture complex patterns in cost estimation [37]. Nevertheless, these approaches heavily depend on extensive historical data for training, which poses practical challenges. Each construction project typically has unique characteristics in terms of scope, conditions, and execution specifics, making it difficult to find suitable historical data for comparable scenarios. Additionally, acquiring historical project data can often be restricted by legal considerations and privacy regulations, further limiting the availability and practical application of such predictive models.

As noted previously, the unique nature of individual construction projects significantly restricts the direct applicability of historical data to new scenarios. Even when past projects are similar, small variations in environmental factors, supply chain dynamics, workforce skills, management strategies, and unpredictable external events reduce the effectiveness of historical data in predictive modeling. To address these challenges, simulation-based approaches have become essential. For instance, Nguyen et al. (2013) illustrated how Monte Carlo simulations could generate a wide range of plausible project completion scenarios by varying critical inputs such as task durations and resource availability [38]. These mathematical simulations provide project managers with a broad perspective of potential project timelines. However, the accuracy of these simulated scenarios relies heavily on carefully defined probability distributions and realistic assumptions.

Furthermore, recent studies are exploring adaptive and reinforcement learning methods, which can continuously update predictions based on real-world project progress. Nguyen et al. (2022) investigated various ML approaches, including deep learning, to forecast preliminary factory construction costs, demonstrating that deep learning methods are particularly effective for handling complex datasets [39]. Similarly, Koc and Gurgun (2021) reviewed ML applications in construction safety research, highlighting the potential of these methods to predict and mitigate safety risks [40]. Such adaptive models aim to overcome the static limitations of traditional predictive methods, making them more suitable for the dynamic conditions experienced in actual construction projects.

Despite these promising advancements, deploying predictive ML and simulation-based models in practice continues to encounter significant hurdles. Among these are the fragmented data management practices prevalent in the construction industry and the limited accessibility of data due to privacy concerns. Successfully integrating predictive analytics into construction project management workflows remains challenging and represents a vital area for future research.

3
Theory

In this chapter, the theoretical concepts are presented and explained to serve as a foundation for the methodology of this study.

3.1 Machine Learning Theory

ML is a branch of AI that allows systems to recognize patterns, make predictions, or perform specific tasks by learning from data, rather than relying on explicit programming for every scenario. This flexibility makes ML particularly effective for addressing complex problems marked by uncertainty, variability, or dynamic data relationships. Arthur Samuel famously described ML as "the field of study that gives computers the ability to learn without being explicitly programmed" [41]. Before ML emerged, traditional programming depended on strictly defined frameworks, limiting programs to specific predefined actions. In contrast, ML algorithms generalize from data, enabling them to effectively manage situations they have not previously encountered [42].

ML incorporates various approaches, with supervised and unsupervised learning being the most prominent. Supervised learning, the primary focus of this study, involves training models using labeled data to predict outcomes or classify new information based on learned patterns. On the other hand, unsupervised learning works with unlabeled data to uncover hidden patterns or structures without predefined categories. Regardless of the method, ML models typically follow three fundamental stages: training, in which the model learns patterns from data; validation, where the model's accuracy is evaluated and improved; and inference, where the model applies its acquired patterns to new, unseen data. Internally, ML models leverage statistical techniques and optimization algorithms carefully selected to suit the specific problems they address [42].

In addition to ML, mathematical modeling represents another fundamental approach for tackling complex problems. It involves creating mathematical descriptions of real-world systems, using algorithms and statistical relationships to simulate their behavior under different conditions. A key advantage of mathematical modeling is the capability to run simulations, enabling analysis of system behavior across numerous hypothetical scenarios. This approach provides valuable insights into system dynamics and facilitates optimization by experimenting with variables and conditions in a simulated environment, free from real-world constraints [43].

3.1.1 Monte Carlo Simulation

Monte Carlo methods are numerical techniques that rely on randomness and statistical sampling to address mathematical problems or to simulate complex systems [44]. Initially inspired by observations of games of chance, these techniques were pioneered by researchers at Los Alamos during the 1940s, notably by John von Neumann and Stanislaw Ulam, who used them to tackle challenging nuclear physics problems.

Mathematically, many problems solved by Monte Carlo approaches can be described by integrals of the general form:

$$I = \int g(x)f(x)\,dx$$

Here, $f(x)$ represents a probability distribution (probability density function), satisfying $\int f(x)\,dx = 1$. Monte Carlo methods approximate such integrals by repeatedly generating random samples from the distribution $f(x)$ and computing the average value of the function $g(x)$ at these sample points. Formally, the Monte Carlo approximation of the integral is expressed as:

$$G \approx \frac{1}{N}\sum_{i=1}^{N} g(x_i),$$

where each x_i is independently drawn from the distribution $f(x)$. As the number of samples N increases, the estimated average becomes progressively closer to the true value of the integral due to the law of large numbers. Additionally, the uncertainty of the result measured as statistical error, can be quantified through the standard deviation of the sampled values. Importantly, this uncertainty diminishes as more samples are included [44].

To visualize this concept, consider estimating the area of a circular pond by randomly throwing pebbles onto a square plot of land that fully encloses it. By calculating the proportion of pebbles that fall within the pond, one can approximate the pond's area. This example demonstrates the core principle of Monte Carlo methods: using random sampling to address problems involving integrals or probabilities.

Monte Carlo methods are particularly advantageous when dealing with high dimensional problems, where conventional numerical methods can become computationally prohibitive. Because of their versatility, these methods have become important tools across numerous scientific fields, including physics, biology, chemistry, engineering, finance, and many others [44].

3.1.2 Neural Networks

Artificial Neural Networks (ANNs) are computational models inspired by how biological neural networks in the brain process information [45]. They are built from layers of interconnected processing units called neurons, which pass information along through weighted connections. These weights determine the strength of the connections and play a key role in how the network learns and updates its internal structure based on input data.

The foundational idea behind artificial neural networks dates back to 1943, when McCulloch and Pitts proposed a simplified mathematical model of a biological neuron. Now known as the **McCulloch-Pitts neuron**, this model treats neurons as binary units that compute a weighted sum of their inputs and activate only if this sum exceeds a certain threshold [45].

Mathematically, the state of a McCulloch-Pitts neuron at time step $t + 1$ is given by:

$$s_i(t+1) = \operatorname{sgn}\left(\sum_{j=1}^{N} w_{ij} s_j(t) - \theta_i\right) \tag{3.1}$$

where:

- w_{ij} is the weight of the connection from neuron j to neuron i,
- θ_i is the activation threshold of neuron i, and
- the signum function (sgn) outputs $+1$ if the result is positive (active), and -1 otherwise (inactive).

Although the McCulloch-Pitts model laid the groundwork, it oversimplifies how biological neurons behave. Real neurons do not just switch on and off, they respond in more continuous and nuanced ways. To reflect this, modern neural networks use **activation functions** that introduce non-linearity, allowing them to learn more complex patterns. Two of the most commonly used activation functions are the **Rectified Linear Unit (ReLU)** and the **hyperbolic tangent (tanh)**:

$$\text{ReLU:} \quad g(b) = \max(0, b) \tag{3.2}$$

$$\text{Hyperbolic tangent:} \quad g(b) = \tanh(b) \tag{3.3}$$

ReLU is especially popular in deep learning because it is computationally simple and helps address challenges such as vanishing gradients.

Neural networks also vary in how they update neuron states. There are two main strategies:

1. **Synchronous updating:** All neurons in a layer update their states at the same time using the inputs from the previous step.
2. **Asynchronous updating:** Neurons update one at a time, either in a fixed sequence or randomly. This method can sometimes lead to better convergence in certain types of models.

These core concepts form the basis of artificial neural networks and support their use in a wide variety of applications, from pattern recognition to complex decision-making tasks [45].

3.1.3 Multilayer Perceptrons (MLPs)

Multilayer Perceptrons (MLPs) are a class of artificial neural networks composed of multiple layers of neurons [45]. These layers are typically structured in a sequence from an input layer, through one or more hidden layers, to an output layer, as illustrated in Figure 3.1. Unlike single-layer perceptrons, which can only solve simple problems, MLPs significantly enhance computational capabilities, enabling them to handle more complex, nonlinearly separable problems.

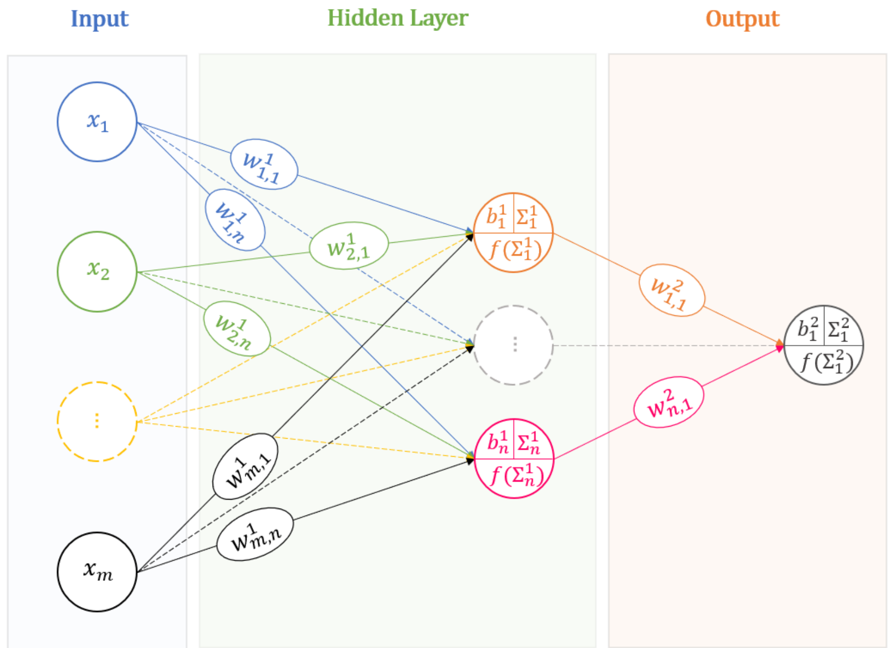

Figure 3.1: Structure of a Multilayer Perceptron (MLP) with input, hidden, and output layers.

A fundamental limitation of a single-layer perceptron is that it can only classify linearly separable data, where a straight line, plane, or hyperplane can perfecty separate different classes. Many real-world problems involve non-linearly separable patterns, MLPs address this limitation by incorporating hidden layers. The nonlinear transformations allow the network to learn complex dynamics that single-layer perceptrons cannot capture [45].

MLPs rely on differentiable and nonlinear activation functions, which enable learning through the backpropagation algorithm. This algorithm calculates the gradient of an error function and iteratively adjusts the network's weights to minimize classification errors or prediction deviations. Formally, an MLP operates as follows: inputs are fed into the input layer, then passed through successive hidden layers, where each neuron processes the input, applies a nonlinear activation function, and transmits its output to the next layer. Finally, the output layer computes the network's final predictions [45].

Each hidden neuron computes its output as:

$$V_j = g\left(\sum_k w_{jk} x_k - \theta_j\right) \tag{3.4}$$

where:

- w_{jk} represents the weight associated with the connection from input neuron x_k to hidden neuron j,
- θ_j is the threshold of neuron j.

Similarly, the output neurons compute their final outputs as:

$$O_i = g\left(\sum_j W_{ij} V_j - \Theta_i\right) \tag{3.5}$$

where:

- W_{ij} denotes the weight connecting hidden neuron j to output neuron i,
- Θ_i is the threshold for the output neuron.

By incorporating multiple layers and nonlinear transformations, MLPs significantly expand the scope of problems that neural networks can solve, making them a foundational architecture in deep learning and modern AI [45].

3.1.4 Embedding Layers

Embedding layers are a fundamental technique in ML that is used to convert categorical data, such as words, labels, or discrete categories, into numerical representations that can be effectively processed by a model [46]. Unlike traditional categorical encoding methods, embeddings capture relationships between categories, allowing models to leverage the underlying structures within the data.

A simple approach to representing categorical data numerically is to assign each category a unique identifier. For instance, encode the words *cat*, *dog*, and *apple* as the following:

- `"cat"` $\rightarrow 1$
- `"dog"` $\rightarrow 2$
- `"apple"` $\rightarrow 3$

However, this representation suffers from a key limitation: the assigned numbers do not capture any inherent relationships between categories. For example, while *cat* and *dog* are both animals and share semantic similarities, their numerical encoding does not reflect this relationship. The model treats them as completely independent entities, and does not recognize their conceptual connection [46].

Embedding layers solves this issue by representing each category as a multidimensional vector rather than a single arbitrary number. These vectors are learned in a way that preserves semantic relationships between categories. After training, words may be mapped to the following vector representations:

Word	Embedding (Vector)
"cat"	[0.8, 0.2]
"dog"	[0.9, 0.1]
"apple"	[0.1, 0.9]

Table 3.1: Example of word embeddings capturing semantic relationships.

In this representation, *cat* and *dog* have similar embedding values because they belong to the same semantic category (animals), whereas *apple* has a distinctly different representation, reflecting its classification as a fruit. This transformation enables ML models to recognize not just individual data points but also the relationships among them, making embeddings particularly powerful for tasks requiring pattern recognition and dynamic dependencies [46].

Mathematically, an embedding layer is defined as a learnable matrix E of size $V \times d$, where:

- V is the number of unique categorical items (e.g., words, labels).
- d is the embedding dimension, determining the amount of information stored in each vector.
- Each row in E corresponds to an embedding vector for a specific category.

Given an input category, the embedding layer retrieves the corresponding vector from this matrix, which is then used by the neural network to learn meaningful relationships and improve performance.

Embeddings are not predefined but are learned through training using one of two approaches:

1. **Pre-trained embeddings** – These embeddings are generated from large datasets using unsupervised learning techniques such as *Word2Vec*, *GloVe*, or *FastText*. They capture general semantic relationships and can be fine tuned for specific applications.
2. **Task-specific embeddings** – When training a model from scratch, the embedding layer initializes with random values and is gradually optimized using techniques such as *stochastic gradient descent (SGD)* or *ADAM*. During training, the model updates embeddings to minimize error, allowing similar categories to converge in the embedding space.

By replacing arbitrary numerical encodings with dense, structured vectors, embedding layers enhance the model's ability to process high-dimensional categorical data efficiently. This makes them an essential component of modern ML, with applications in natural language processing, recommendation systems, and structured data analysis [46].

3.1.5 Multi-Head Self-Attention in Transformer Models

Multi-head self-attention is a core component of transformer based architectures, enabling models to capture complex dependencies across input sequences [47]. Unlike recurrent or convolutional layers, self-attention allows models to process all elements simultaneously, making it particularly effective for tasks such as language translation, text summarization, and time-series analysis.

To illustrate this, consider the following sentence:

"The animal chased the ball because it was playful."

Humans understand that *it* refers to *the animal*, not *the ball*, but traditional models like recurrent neural networks (RNNs) struggle with such long range dependencies due to their sequential nature. Self-attention overcomes this by enabling each word to attend to all others in parallel, preserving contextual relationships [47].

Self-attention operates by computing attention scores between all elements in a sequence. Given input matrices:

- **Queries** (Q) – Elements seeking context.
- **Keys** (K) – Elements providing context.
- **Values** (V) – Data used for final representation.

The attention output is computed as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{3.6}$$

where QK^T measures similarity, softmax normalizes these values into attention scores, and $\frac{1}{\sqrt{d_k}}$ prevents large activations that could hinder learning.

3.1.5.1 Multi-Head Self-Attention

Single-head attention captures only one type of relationship at a time. To address this, *multi-head self-attention* extends the mechanism by running multiple attention computations in parallel, each learning distinct relationships.

Formally, it is computed as:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O \tag{3.7}$$

where each head is defined as:

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \tag{3.8}$$

Each head has unique weight matrices W_i^Q, W_i^K, W_i^V, enabling the model to focus on different aspects of the input. The outputs are concatenated and transformed using W^O, producing a final representation that captures diverse dependencies [47].

3.1.6 Loss Functions

In supervised ML, neural networks learn by adjusting their parameters to minimize errors in their predictions [45]. This process relies on two key components: loss functions, which quantify model performance, and optimization algorithms, which iteratively update parameters to improve accuracy.

A loss function, also referred to as a cost function or energy function, measures the discrepancy between a neural network's predictions and the true target values. The objective during training is to minimize this function, thereby enhancing the model's predictive accuracy [45].

For regression tasks, a widely used loss function is the mean squared error (MSE), defined as:

$$H = \frac{1}{2} \sum_{i,\mu} (t_i^{(\mu)} - O_i^{(\mu)})^2 \tag{3.9}$$

where:

- $O_i^{(\mu)}$ is the output of neuron i for input pattern μ,
- $t_i^{(\mu)}$ is the true target output, and
- the summation runs over all neurons and training patterns.

A lower loss value indicates better predictions, while a higher value suggests discrepancies between predictions and target values. Minimizing the loss function allows the network to learn meaningful representations of the data [45].

3.1.7 Optimization in Neural Networks

Optimization involves adjusting the network's parameters, such as weights and biases, to minimize the loss function. The fundamental optimization technique used in neural network training is gradient descent, an iterative method that updates parameters in the direction of the steepest decrease in loss.

The gradient descent update rule for a weight w_{mn} connecting neuron n to neuron m is given by:

$$w'_{mn} = w_{mn} - \eta \frac{\partial H}{\partial w_{mn}} \tag{3.10}$$

where:

- w_{mn} represents the connection weight,
- η is the learning rate, controlling the step size of updates, and
- $\frac{\partial H}{\partial w_{mn}}$ is the gradient of the loss function with respect to w_{mn}, indicating how the loss changes with small weight adjustments.

The choice of the learning rate η is crucial, if it is too small, convergence is slow and if it is too large, training may become unstable, causing the model to oscillate around or diverge from the optimal solution[45].

3.1.7.1 The ADAM Optimizer

A widely used optimization algorithm that improves upon gradient descent is Adaptive Moment Estimation (ADAM), introduced by Kingma and Ba (2014) [48]. ADAM combines the benefits of:

- **Momentum-based methods**, which accelerate convergence.
- **Adaptive learning rate methods**, which adjust step sizes for different parameters.

ADAM maintains two moving averages for each parameter:

3.1.7.1.1 First moment estimate (mean of past gradients):

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{3.11}$$

where g_t is the gradient of the loss function at time step t, and β_1 (typically 0.9) controls the decay of past gradients.

3.1.7.1.2 Second moment estimate (variance of past gradients):

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{3.12}$$

where β_2 (typically 0.999) determines the influence of past squared gradients.
Since both estimates start from zero, they are bias-corrected as:

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1 - \beta_2^t} \tag{3.13}$$

The final parameter update in ADAM is:

$$\theta_t = \theta_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{3.14}$$

where:
- η is the learning rate,
- ϵ (typically 10^{-8}) is a small value added for numerical stability.

[48]

3.1.8 Feature Engineering and Normalization

The quality and preparation of input data have notable affects on the performance of ML models. To improve a model's ability to learn patterns, two preparation techniques are essential, feature engineering and normalization. Feature engineering is the process of transforming raw data into meaningful features that capture relevant properties for a given prediction task [49]. Instead of directly using raw data, this technique creates more informative representations that improve the learning efficiency of ML algorithms.

Feature engineering includes several key approaches:
- **Feature transformation** – Modifying existing features to enhance their predictive power, such as applying polynomial expansions or logarithmic transformations.
- **Feature creation** – Generating new features by combining existing ones, identifying interactions between variables, or computing statistical aggregations (e.g., mean, sum, variance).
- **Feature selection** – Removing irrelevant or redundant features to improve model efficiency and reduce the risk of overfitting.

By selecting and constructing relevant features, models can extract more meaningful patterns from the data, leading to improved accuracy and generalization [49].

Normalization is a preprocessing step that scales numerical features to a consistent range, ensuring that all features contribute proportionally to the model's predictions [50]. Many ML algorithms are sensitive to differences in feature scales; without normalization, features with larger numerical ranges may dominate the learning process, potentially overshadowing smaller but equally important features.

Common normalization techniques include:

- **Min-Max Scaling** – Rescales features to a fixed range, typically between 0 and 1, using the formula:
$$x' = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \tag{3.15}$$
where x_{min} and x_{max} are the minimum and maximum values of the feature.
- **Z-Score Normalization (Standardization)** – Transforms data to have a mean of zero and a standard deviation of one:
$$x' = \frac{x - \mu}{\sigma} \tag{3.16}$$
where μ is the mean and σ is the standard deviation of the feature.

Normalization ensures that all features contribute equally to the learning process, resulting in more stable training, faster convergence, and improved model performance [50].

3.1.9 Model Validation Techniques in Neural Networks

Effective validation of ML models is essential for ensuring that a trained neural network generalizes well beyond the training data [45]. Without rigorous validation, a model may perform exceptionally well on training samples but fail to maintain accuracy on unseen data. To mitigate this risk, several validation methodologies are employed, including the train-validation split and K-fold cross-validation, both of which provide reliable assessments of model performance and generalization capabilities.

3.1.9.1 Train-Validation Split

A fundamental validation approach, commonly referred to as the train-validation split or holdout method, is widely used to prevent overfitting [45]. Overfitting occurs when a neural network memorizes patterns specific to the training data, including noise and random fluctuations, rather than identifying generalizable trends. This results in a model that performs well on the training set but poorly on new, unseen data.

To address this, the dataset is partitioned into two distinct subsets:

- **Training set** – Used to iteratively adjust the model's internal parameters, such as connection weights and biases, during the learning process.
- **Validation set** – A separate subset reserved for periodically evaluating model performance, ensuring that the learned representations generalize to independent data points.

Maintaining a strict separation between these subsets is crucial for obtaining unbiased performance estimates. The validation set provides feedback on how well the model generalizes, allowing for systematic hyperparameter tuning, including adjustments to the learning rate, regularization strength, and network architecture. By optimizing model performance based on validation results, the reliability and robustness of the model can be improved [45].

3.1.9.2 K-Fold Cross-Validation

One widely used method for robust model evaluation is K-fold cross-validation, which systematically partitions the dataset. In this approach, the dataset is divided into K equally sized subsets, or *folds*, and the model undergoes training and validation in multiple iterations: In each iteration, one fold is designated as the validation set, while the remaining $K-1$ folds constitute the training set. The model is trained on the training folds and evaluated on the validation fold. This process is repeated K times, ensuring that each fold is used exactly once for validation.

After all iterations, performance metrics such as accuracy or error rate are averaged across the K validation rounds. This method offers several advantages. Firstly, improved reliability and stability, averaging results across multiple validation rounds reduces variability and provides a more accurate estimate of the model's generalization capability. Secondly, each data point is used for both training and validation, maximizing the effective use of available data. This is beneficial for smaller datasets, where full use of the data is critical. Incorporating K-fold cross-validation reduces the risk of overfitting and ensures that the model remains effective when applied to unseen data [45].

3.1.9.3 Validation Metrics for Neural Networks

To evaluate the predictive performance of deep learning models, a variety of error metrics are employed [51]. These metrics offer insights into the model's accuracy, consistency, and reliability by quantifying the difference between predicted and actual values. Below are the theoretical foundation to each key metrics used in this project.

Mean Squared Error (MSE): Mean Squared Error measures the average of the squares of the prediction errors:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

MSE penalizes larger errors more than smaller ones due to the squaring term, making it sensitive to outliers. It is widely used in regression problems.[52].

Root Mean Squared Error (RMSE): RMSE is the square root of the MSE and has the same units as the target variable:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

RMSE provides a more interpretable error value for practitioners [51].

Mean Absolute Error (MAE): MAE computes the average absolute difference between predicted and actual values:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Unlike MSE, MAE treats all errors equally and is less sensitive to outliers. It is commonly used when interpretability and robustness to anomalies are prioritized [53].

Coefficient of Determination (R^2): The R^2 score indicates the proportion of variance in the dependent variable that is predictable from the independent variables:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

A value of $R^2 = 1$ indicates perfect prediction, while $R^2 = 0$ implies that the model performs no better than the mean of the data. It is widely used as a global measure of goodness-of-fit in regression models [52]. These metrics together provide a comprehensive framework for understanding the performance of regression-based models [51].

4
Hybrid Framework

The following chapter presents the technical methodology of this study. First, the developed hybrid framework is introduced, followed by a description of the technical components and the development of the program.

In this study a hybrid modeling framework was developed, integrating a mathematical simulation with a ML model to produce a predictive timeline for construction project management. The approach consists of two main components: a Monte Carlo simulation and a ML deep learning model, combining into a hybrid predictive model.

The Monte Carlo simulation served as the foundation of the model. It used project parameters, such as task durations and dependencies, to generate a range of possible project outcomes through stochastic sampling. Following this, an ML model complemented the predictions by learning from the simulated project outcomes and ranking them based on probability. Initially, it was trained on the Monte Carlo generated project timelines, later on when real-world project updates became available, the model was continuously optimized and fitted with actual progress data. Integrating the progress of real world project progress each week increased the model accuracy.

This hybrid framework combined the strengths of probabilistic simulation and ML pattern learning. While the Monte Carlo simulation generated a diverse range of potential timelines, the ML model processed these results to identify the most probable progress paths based on real-world project behavior. Together, these components created a forecasting framework that adapted to new information and improved over time.

4.1 Data Collection and Preprocessing

The initial phase of a construction project involves developing a project schedule using *PowerProject*, a widely used scheduling software. This schedule is structured as a Gantt chart, detailing all tasks required for project completion along with attributes such as task dependencies, durations, and assigned resources. Throughout the project's execution, the site manager continuously updates the PowerProject file to reflect real-time progress. Although the update frequency varies between projects, it is ideally conducted on a weekly basis to ensure that the schedule remains an accurate representation of on-site developments.

For this study, the final PowerProject file from the *Ingelkärr- Stenkullen* project was collected and used as validation data for the program. The file contained all updates recorded throughout the project's duration. The PowerProject file was systematically processed and key attributes associated with each task were extracted and exported to an Excel (`.xlsx`) file. The extracted attributes included:

- **Task Name**
- **Power Post**
- **Duration**
- **Start Date**
- **End Date**
- **Predecessors**
- **Successors**
- **Progress per week**

Before further analysis, the extracted data were preprocessed to ensure consistency and eliminate potential errors that could interfere with the computations. Several key issues were identified and addressed to structure the scheduled data appropriately for the hybrid model.

One primary preprocessing step involved removing *overtasks*, which were categorical rows serving as headers or grouping labels rather than actionable tasks. These entries were included in the original PowerProject file to organize related tasks under common categories. However, as they did not represent executable tasks, they could lead to misinterpretations and computational errors. Removing them ensured that only relevant task data was retained for analysis.

Another crucial issue involved inconsistencies in task dependencies. Some dependencies were either incorrectly specified or incomplete, resulting in missing or illogical task sequences. Given that accurate sequencing of tasks is essential for modeling project progress and predicting potential delays, these dependency errors were systematically corrected. The adjustments ensured that task relationships were properly structured and aligned with the actual construction workflow.

Several tasks in the data set lacked end dates and their progress never reached 100%. In many cases, these tasks had already been completed, but their status had not been properly updated in the PowerProject file. To address this the missing end dates were determined based on available project records and logical inferences drawn from surrounding tasks. This ensured that all completed tasks were accurately represented in the dataset, preventing potential gaps in the project timeline.

4.2 Hardware and Software Specifications

This section describes both the hardware and software required for the project. The hardware consisted of a cloud based GPU and CPU setup, while the software was built using various Python libraries.

4.2.1 Hardware

The hybrid modeling framework was implemented using high-performance computing (HPC) resources on the *Alvis* cluster, a GPU-accelerated computing infrastructure within the Chalmers Centre for Computational Science and Engineering (C3SE), Sweden. For the program both GPU and CPU resources were used to efficiently process large scale Monte Carlo simulations and train the ML model. To accelerate the computations *NVIDIA Tesla V100 GPUs* were utilized. The Monte Carlo simulations, matrix operations, and training of the deep learning models were done on the GPU. The parallel processing capabilities significantly improved computational speed and efficiency.

While GPUs handled computationally intensive tasks, CPU resources on the Alvis cluster were essential for data preprocessing, task scheduling, and dependency modeling. The CPU cores were utilized to construct the dependency structure, mapping the task dependencies and ensuring that project schedules adhered to logical constraints. Additionally, CPU based multi-threading was utilized.

4.2.2 Software and Libraries

The implementation was developed in Python, using a combination of GPU-accelerated libraries, graph processing frameworks, and ML tools. The primary Python libraries used in this project are outlined below:

- **CuPy** – Used for GPU-accelerated numerical computations, significant for the efficiency of matrix operations, statistical sampling, and vectorized Monte Carlo simulations.
- **Pandas & NumPy** – Applied for data handling, preprocessing, and statistical transformations, including time-series management and operations on large datasets containing project tasks, durations, and dependencies.
- **NetworkX** – Utilized for constructing the directed graph representing project task dependencies. This allowed for task sequence validation and detection of circular dependencies.
- **PyTorch** – Used to structure the ML model architecture, train the baseline model and the weekly weight optimizer.
- **Scikit-learn** – Employed for data preprocessing, feature scaling, statistical transformations, and model evaluation. Performance metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) were calculated to assess model accuracy.
- **Matplotlib** – Used for visualizing simulation outputs, including Monte Carlo distributions, project progress trends, and dependency graphs.

- **CuDF** – Used for GPU-accelerated DataFrame processing, providing Pandas like functionalities optimized for NVIDIA GPUs.
- **CuML (RAPIDS AI)** – Employed for GPU-accelerated ML preprocessing, such as feature scaling (`StandardScaler`).
- **SciPy** – Used for statistical modeling and probability distributions (e.g., `beta` distribution for Monte Carlo sampling).
- **Seaborn** – Utilized for enhanced data visualization, particularly for model validation results and error distributions.
- **Joblib** – Used for parallel processing and model persistence, enabling efficient execution of computations.
- **TQDM** – Implemented for progress bars to track execution time during simulations and model training.

4.3 Data Pipeline

The data pipeline developed for this study was a structured, multistage process designed to integrate data ingestion, preprocessing, simulation, ML, and result visualization, see figure 4.1. It enabled continuous alignment between simulated forecasts and real-world project progress.

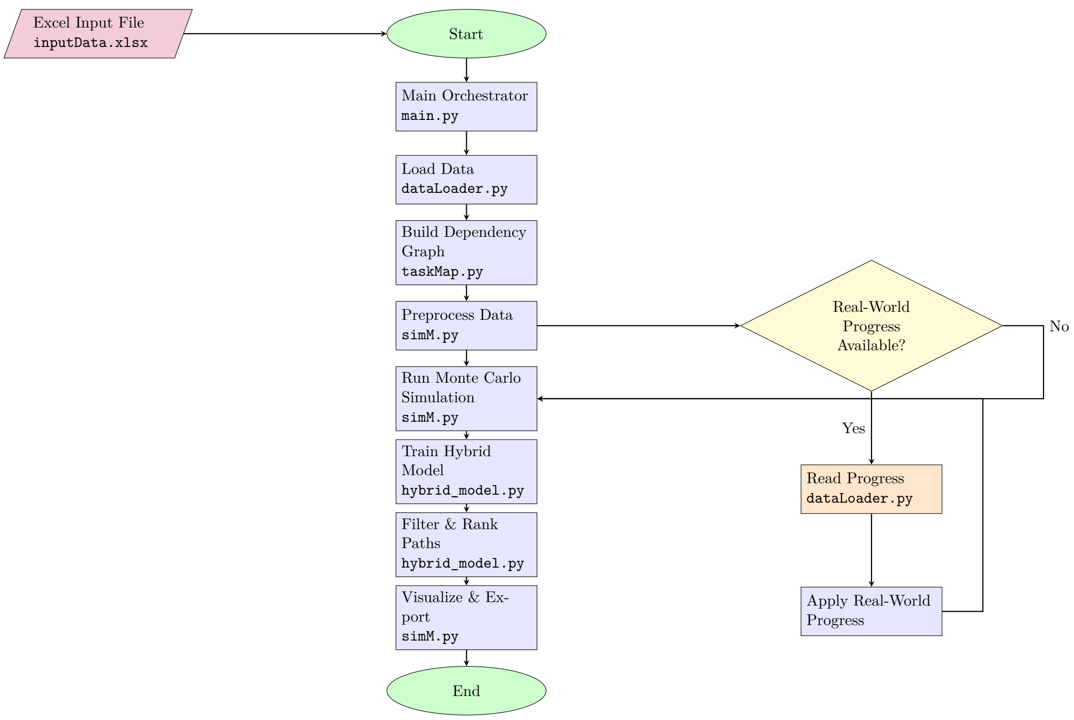

Figure 4.1: Data Pipeline Flowchart

The pipeline began with raw project data stored in an Excel file (`inputData.xlsx`). This file contained information about each project task, including task names, durations expressed in days, hours, or minutes, start and end dates, and weekly progress updates (e.g., “2023 v34”). The `dataLoader.py` module was responsible for importing this data into a `Pandas` DataFrame. During this process, column names were standardized, and a unique identifier was assigned to each task to maintain traceability throughout the pipeline.

After the data was loaded, the `taskMap.py` module constructed a task dependency graph using the `NetworkX` library. This directed graph modeled the relationships between tasks and was used to compute key features such as float days and the number of predecessors associated with each task. Simultaneously, the `simM.py` module performed additional feature engineering. Task durations were converted into a consistent unit (hours), and numerical features were scaled using GPU-accelerated preprocessing. These steps ensured the data was in a standardized and machine-readable format for simulation and modeling.

If a specific progress week was specified, the pipeline integrated real-world progress data to improve the simulation’s accuracy. The `dataLoader.py` module retrieved cumulative progress values from the Excel file and updated task durations and start dates accordingly. This adjustment allowed the simulation to reflect the actual status of the project, bridging the gap between planned and executed work.

Once the dataset was fully preprocessed and aligned with real-world progress, the `simM.py` module initiated a Monte Carlo simulation. The simulation strictly followed the task dependencies defined in the graph, ensuring that sequencing and concurrency constraints were respected. The simulation results were then passed to a hybrid ML model implemented in `hybrid_model.py`. Finally, the results were visualized using `Matplotlib`. All outputs, including processed data and visualizations, were exported in a structured format (e.g., `Parquet`) to support further analysis and reporting. The entire pipeline was managed by the `main.py` script, which coordinated each stage and ensured that the model remained responsive to updated project information throughout the construction life-cycle.

4.4 Monte Carlo Simulations

A construction project is made up of multiple interdependent tasks, each with specific attributes. Project progress is measured as the percentage of tasks completed; when every task is finished, the project reaches 100% completion. The mathematical modeling of a construction project begins with interpreting the project as a network of interdependent tasks. Each task is defined by its baseline duration, number of predecessors, and available float days. These attributes are extracted from the input file as mentioned above and preprocessed to build a functional representation of the project schedule.

The Monte Carlo method was applied to the mathematical model of the construction project, using random variations in task durations as input. A Beta distribution was selected as the probability distribution. For each independent simulation, every task in the project was assigned a random delay or acceleration. This variation was introduced by perturbing each task's original planned duration using the Beta distribution, controlled by user-defined parameters α and β. In practical terms, each task duration could become shorter or longer than initially planned, reflecting realistic uncertainties that affected project timelines.

Once these new task durations were simulated, they collectively defined a unique possible "path", project timeline outcome. The scheduling of tasks within this scenario relied on a *relative concurrency model*, which normalized the timeline based on the project's overall planned duration. Tasks were placed on this normalized timeline according to their logical order and dependencies.

If a task experienced a delay, the start of any dependent successor tasks was correspondingly adjusted. This delay propagation took into account "float days" built-in buffers allowing minor delays without immediately affecting subsequent tasks. However, if delays exceeded these float buffers, they cascaded further, pushing subsequent tasks later in the timeline. Through this mechanism, each simulation realistically captured how delays or improvements in individual tasks could ripple through the project schedule, influencing the overall completion timeline. The sampling bounds were controlled using two parameters: `variability_factor`, which scaled with the baseline duration, and `variability_hours`, an absolute adjustment range.

As an example, consider Task A with an initial duration of 10 hours. If the parameters are set as `variability_factor` = 0.2 and `variability_hours` = 32, the sampling range is computed as:

$$\text{Lower Bound} = 10 \times (1 - 0.2) = 8$$
$$\text{Upper Bound} = 10 + 32 = 42$$

Thus, the perturbed duration for Task A will be sampled from a Beta distribution scaled to the interval $[8, 42]$, where the shape of the distribution is controlled by the user-defined α and β parameters, see figure 4.2.

At the start of each simulation iteration, the model reconstructed the project timeline by enforcing all task dependencies and precedence constraints. If a predecessor finished earlier than expected, its dependent tasks could begin sooner, introducing realistic flexibility. This adjustment process was repeated until all tasks were aligned without conflicts, resulting in a logically consistent and feasible project schedule for the given set of sampled durations.

Example:
Consider a simple scenario with two tasks:
- **Task A**: Duration = 10 hours, Start = 0h, Finish = 10h
- **Task B**: Depends on Task A, Duration = 5 hours, Float = 2 hours

In the baseline schedule, Task B is planned to start 2 hours after Task A finishes at hour 12, but could legally start any time between hour 10 and 12 without causing delay to the overall project.

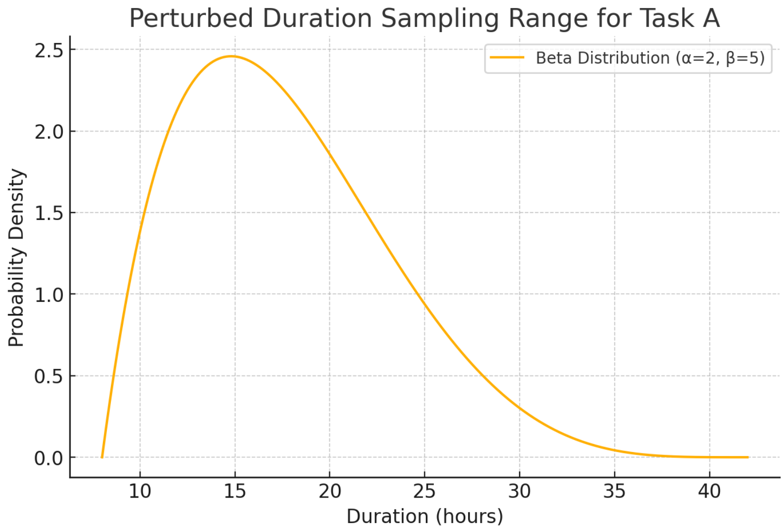

Figure 4.2: An example of a Beta distribution with parameters $\alpha = 2$ and $\beta = 5$, scaled to the task duration interval $[8, 42]$. The distribution is used to sample perturbed task durations in the Monte Carlo simulation framework.

Now, assume that in one simulation iteration, Task A is delayed by 3 hours (actual finish at 13h). Since the delay exceeds Task B's float (3h > 2h), Task B must also be delayed by 1 hour to start at hour 13 instead of 12.

Task	Baseline Start	Simulated Start	Float	Reason
Task A	0h	0h	–	No change
Task B	12h	13h	2h	Delayed due to predecessor delay (3h > float)

Table 4.1: Example of schedule adjustment based on task delay and float. Task B is delayed by 1 hour because the delay in Task A exceeds its float.

Each iteration of the simulation yielded two primary outputs: A *progress time-series* capturing cumulative project progress over time. A *task-level dataset* containing simulated durations, adjusted start and finish times, float values, and dependency information for each task.

When real-world data was available, tasks were partially updated to reflect actual progress, and durations were recalculated to represent only the remaining work. This simulation process was initiated from the `main.py` file and executed within the `simM.py` module.

4.5 Machine Learning Model

This model integrated task-specific simulation outputs and real-world progress data to predict and rank likely project completion paths, and was structured as illustrated in the UML-style code diagram in Figure 4.3.

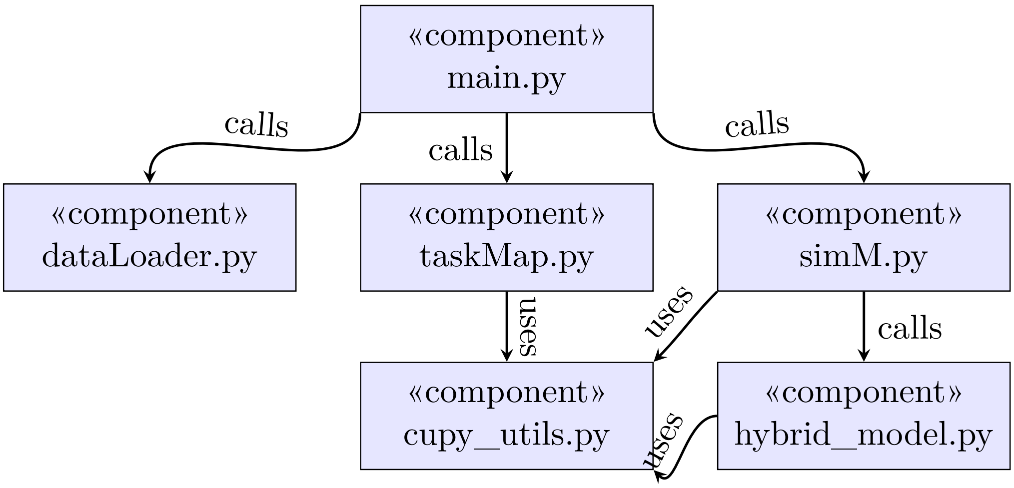

Figure 4.3: UML diagram for Project Files

4.5.1 Model Architecture

The ML component is based on a Multi-Layer Perceptron (MLP) augmented with a Multi-Head Self-Attention mechanism. The architecture consists of the following elements:

- **Embedding Layers**: Task identifiers were converted into vector embeddings, allowing the model to learn task specific representations.
- **Feature Embedding**: Input features such as simulated task durations, number of predecessors, and float days were concatenated with the task embeddings. This combined input was passed through a fully connected layer with ReLU activation and dropout for regularization.
- **Attention Layer**: A multi-head self-attention mechanism processed the embedded features within each simulation iteration. This allowed the model to dynamically capture dependencies and interactions between tasks.
- **Output Layers**: The output from the attention layer was fed through additional fully connected layers to predict task-level completion times.

4.5.2 Data Preparation

Each simulation iteration produced detailed task level data, including simulated durations, float days, and predecessor information. The features used in model training were limited to `unique_id`, `simulated_duration`, `predecessor`, and `float_days`. All features were standardized prior to training.

4.5.3 Training Procedure

Training was conducted using iteration aware batching: each batch consisted of all tasks from a single simulation iteration to preserve task interdependencies. This design allowed the attention mechanism to learn meaningful contextual patterns.

The dataset was split into training and validation sets based on distinct simulation iterations to ensure independence between subsets. Training was governed by an early stopping criterion triggered after 20 epochs without improvement in validation loss. The model was trained using the Huber loss function, optimized with the ADAMW optimizer. A learning rate scheduler dynamically adjusted the learning rate during training.

4.5.4 Model Updating and Path Ranking

After the model was initially trained on baseline simulation data, it was periodically updated using real-world progress inputs. These weekly updates were converted into feature representations consistent with those used during the initial training, allowing the model to incrementally adapt to the evolving conditions of the project.

Following each update, the model was used to evaluate newly simulated Monte Carlo project paths. For each path, the model predicted task completion times, which were then compared to the simulated values. A Mean Squared Error (MSE) score was computed for each path to measure the deviation between the model's predictions and the simulated outcomes. Based on these scores, all paths were ranked, and the highest-ranked (i.e., most realistic) paths were selected for visualization and further project management analysis.

4.5.5 Validation and Metrics

Model validation used a separate subset of Monte Carlo simulation data. Performance was assessed using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). Metrics were reported in both hours and days for practical interpretability. Visual validation included scatter plots comparing actual and predicted completion times, error distributions, and rank correlation plots to evaluate model reliability.

4.5.6 GPU Acceleration

A structured, three stage approach was used to transition from CPU-based processing to GPU-accelerated computation, with the goal of reducing execution time and improving scalability for large scale simulations and model training. In the initial stage, all computational tasks, including data handling, numerical simulations, and task dependency management, were executed using CPU-based Python libraries such as `Pandas` and `NumPy`. While this configuration ensured correctness, performance profiling revealed that Monte Carlo simulations suffered from long execution times. The main performance bottlenecks were associated with matrix operations and repeated numerical computations.

To address these limitations, the second stage introduced partial GPU utilization. Critical numerical operations, previously handled by `NumPy`, were migrated to their GPU-compatible `CuPy` equivalents. This included float day calculations and Monte Carlo sampling routines. Several preprocessing steps were also adapted for GPU execution.

The final stage involved a full integration of GPU acceleration by restructuring the entire computational pipeline. All major processes, including data preprocessing, simulation workflows, task scheduling, and ML model training, were implemented using `CuPy` and `PyTorch`, which are optimized for CUDA-enabled GPUs. This integration significantly reduced memory transfers between CPU and GPU, enabling more efficient performance.

4.6 Design and Visualization

To determine user preferences regarding data visualization, during the interviews the functionality and objectives of the software were initially presented and explained. Thereafter, interviewees were asked about the significance and desired characteristics of data visualization.

Interviewees were specifically asked to evaluate different visualization aspects, such as their preference between simplified outputs versus outputs that provide detailed information closer to the raw data. Furthermore, the managers provided concrete examples of visual tools currently utilized in their daily workflows, elaborating on strengths and shortcomings within these tools. To gain additional insights into their preferences, participants were shown examples of potential visualization output designed for the program. Their feedback on the example contributed valuable input for guiding the visualization development, ensuring alignment with actual user expectations and practical requirements.

After the final version of the program produced the output data in raw numerical form and matplotlib plot, this output was used as a blueprint for creating a mock-up visualization, based on the earlier input from the interviews. The mock-up was created using Canva's line diagram tool, aiming to reflect the users' preferences and expectations for visual clarity and usefulness.

5

Results

This thesis bridges the managerial and technical aspects of construction, producing an integrated outcome that reflects both viewpoints. This chapter is divided into two sections. First, the interview results highlight perspectives on current managerial practices and the various stakeholders' views on AI and predictive models.Second, the technical results from the predictive model demonstrate how data from the Ingelkärr–Stenkullen project could be utilized if properly managed.

5.1 Result of the Interviews

The following section presents the practical findings of the project, based on the interviews conducted with key stakeholders from NCC and Svenska Kraftnät. The interviews provided firsthand insights into current workflows, challenges faced during project execution, and industry perception of AI. These practical findings were essential for grounding the model's technical development in real-world needs and ensuring its relevance and usability in construction project management.

5.1.1 Interview with NCC

The interview with Interviewee E and Interviewee F provided valuable insights into NCC's approach to managing large-scale infrastructure projects, offering a deeper understanding of their strategies and decision-making processes. NCC manager, Interviewee E emphasized the importance of balancing the project management triangle: time, cost, and quality. Noting that real-world constraints inevitably demand constant trade-off, and to achieve high performance means finding the right balance between these three factors.

NCC Master Trainee Interviewee F emphasized the importance of thoroughly assessing a project's complexity and ensuring that NCC possesses the necessary expertise and resources before committing. Choosing projects that align with the company's strengths helps reduce risk and improves the chances of successful execution. Echoing this view, Interviewee E also underscored the need to evaluate environmental and geotechnical conditions early in the process, as they can pose significant challenges in infrastructure projects.

Managing project capacity requires effective leadership. According to Interviewee E, certain parts of a project may need to slow down to allow others to catch up, and knowing when and where to make these adjustments is crucial for maintaining overall efficiency. He also underscored the importance of managing the critical path, as critical activities can shift unexpectedly. Leadership must remain flexible and responsive to these changes in order to keep the project on track.

When it comes to reflection on completed projects, both of the interviewees acknowledged that the reflection on completed projects are often neglected as the construction teams have to quickly jump onto new projects due to the fast-paced nature of the branch. The interviewees emphasized the value of past project lessons, noting that properly collected data can be invaluable for improving future efficiency.

5.1.2 Interview with Svenska Kraftnät

From the project owner's perspective, accurately predicting the time frames and phases of an infrastructure project like Ingelkärr-Stenkullen is extremely difficult. The lengthy and unpredictable approval process is complicated by the dependencies on external stakeholders, such as government authorities, country administration and municipalities.

Project leader, Interviewee A expressed concern over the inconsistency in regulatory processing times. While some approvals might take months, others could extend beyond a year, making it even more troublesome to create reliable project schedules. For a project that spans 10 years, delays in securing necessary permits and concessions can prevent it from moving forward, leading to cost overruns and inefficiencies in resource allocation. Interviewee A underlined the need for more structured and efficient government process with greater accountability, implying that the current system is highly inconsistent and prone to unexpected delays.

During the interview, it was suggested that improvements in construction efficiency should be matched by faster government decision-making. However, Interviewee A disagreed with this comparison, explaining that the two processes operate on separate timelines and should not be linked. Ideally, all approvals and permits should be secured before the construction phase begins, but it is not the case as municipalities and agencies work independently. Therefore, even if contractors streamline their processes, government approvals are not necessarily expedited.

5.1.3 Interview with on-site leaders

Executing a project on the scale of Ingelkärr-Stenkullen presents significant challenges in scheduling and risk management. On-site leader Interviewee C noted that, while careful planning is essential, unforeseen complications such as terrain conditions, weather, and subcontractor coordination, often lead to unexpected delays. Initially planned for completion in January 2025, the Ingelkärr-Stenkullen project benefited from efficient planning and workflow optimization. This resulted in the timeline to be shortened by two months, with completion set for December 2024. However, delays still occurred at various stages, largely due to permitting issues and unexpected political resistance.

The team had originally planned to construct and transport materials using permitted municipal land, but local politicians ultimately opposed the agreement. As a result, the construction team was forced to relocate their equipment and reroute to a less-than-ideal path where the soil was softer and unstable. Consequently, the construction traffic completely destroyed the roads, leading to major disruptions for the local community. Traffic congestion increased, children were unable to attend kindergarten, postal deliveries were disrupted, and many parents were forced to stay home from work. Interviewee C described it as "total chaos," noting that this unforeseen setback was one of the primary reasons why costs escalated significantly during the earlier stages.

A crucial tool used in managing the project timeline was Power Project. On-site block leader, Interviewee D explained how this program enabled the team to visualize dependencies between tasks, update schedules dynamically, and assess the impact of delays in real-time. However, it is also worth mentioning that Power Project required manual inputs and decision-making, as unexpected disruptions such as weather conditions or regulatory delays could not be fully accounted for in automated scheduling models.

5.1.4 Task Visualization and Progress Tracking

Interviewee E and Interviewee F mentioned that NCC extensively uses whiteboards to visualize and track projects. This method allows them to write, draw, and organize key project elements in a visible and accessible way. The effectiveness of this approach was further validated by NCC on-site leaders Interviewee C and Interviewee D. In the Ingelkärr-Stenkullen project, the team had a whiteboard set up in a central location, making it easily accessible to all workers. Each pole was listed alongside its planned and actual progress, with a color-coded system indicating different completion levels. The visual tracking provided by the whiteboard proved invaluable when the project fell behind, as it enabled the team to immediately identify delayed areas and reallocate resources accordingly. Interviewee C highlighted that this method is easily understood by all workers, from project leaders to carpenters.

In both interviews, digital visualization emerged as a potential improvement to current workflows. Digital tools would not only enhance project tracking and forecasting but also enable better coordination with subcontractors by providing a clearer picture of expected completion times and potential setbacks. Interviewee E and Interviewee F viewed digital visualization tools positively, suggesting that integrating platforms like Power BI could help centralize project data and provide a more structured, accessible overview of progress.

In contrast, Interviewee C expressed concern that blue-collar workers might struggle with understanding and applying digital visualization, potentially limiting its impact on day-to-day operations.

5.1.5 NCC's Current Workflow

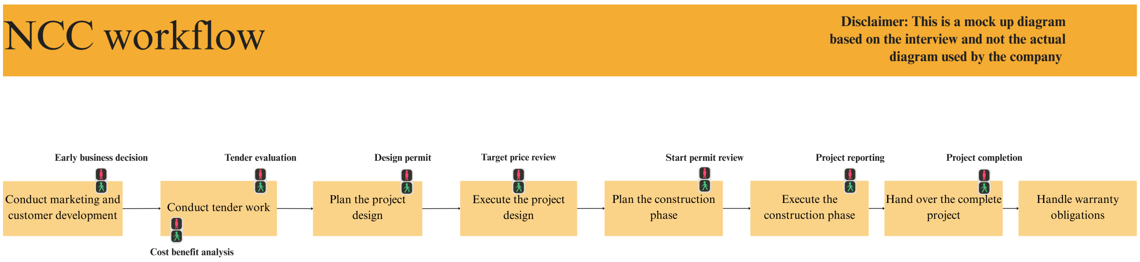

Figure 5.1: NCC workflow diagram comprising of eight-stages with traffic light checkpoints.

At the foundation of the company's workflow lies a methodical framework comprising eight stages. These stages systematically guide the project from the initial conception to completion, ensuring that no critical details are overlooked. The process begins with analyzing market trends and customer engagement. This phase is important as it allows the company to anticipate upcoming projects, sometimes years in advance and prepare their resources accordingly.

One of the defining elements of this method is the incorporation of the "traffic light" system, which acts as a decision checkpoint. After every major stage, approval is required before proceeding. This precautionary measure prevents costly mistakes and ensures that resources are allocated efficiently. For example, when bidding for a contract, a cost benefit analysis, "kalkylbeslutsprövning" is to be conducted. This helps determine whether pursuing a bid is financially viable, as some tenders can require months of work and cost millions in preparation.

The planning phase, which begins once the company secures a project, includes analysis of contract terms, risk factors, and resource requirements. Some projects are priced through detailed calculations, while others might involve a fixed percentage fee instead of an upfront bid. Slowly, the industry is shifting from a lowest price competition to a best quality approach, with experience and expertise play a bigger role than cost-cutting.

Execution is where complexity intensifies, particularly in mega construction projects which demand meticulous planning. Tasks are delegated, quality assurance systems are implemented, and environmental and safety protocols are enforced. Schedules must incorporate variables such as weather, regulatory compliance, and unforeseen delays. Monitoring project execution becomes vital with monthly or even weekly helping to track progress and adjust timeline accordingly. Regular reviews allow teams to track development, identify potential bottlenecks, and make necessary adjustments to maintain efficiency.

Another key component of successful project execution is risk management, as quality checks, material testing, and detailed documentation help minimize project mishaps and costly errors. A small mistake in construction can lead to massive financial losses, therefore, rigorous control methods are implemented to catch and resolve issues before they escalate.
By the time of the project completion, the focus shifts to final inspections and client handover. This is when the clients are introduced to the final product, while the project team compiles maintenance instructions and conducts final economic settlements.

5.1.6 Opinion on AI and Predictive Model

When developing the model, it is especially important to consider the perspectives of the stakeholders involved, as these can vary significantly depending on factors such as age and professional experience. While recognizing the potential benefits and convenience that an AI model can offer, Interviewee C maintains a cautious and grounded stance, raising critical questions about the limitations of what AI can and cannot interpret. Given that construction projects are heavily affected by unpredictable, real-world conditions such as terrain, political decisions, and weather, any ML model must be able to account for such variables. Interviewee C emphasizes that human expertise remains indispensable in decision-making process. For AI to be genuinely valuable in this context, it must not only provide insights but also integrate them with practical reasoning and situational awareness, capabilities that Interviewee C believes current tools still lack.

Interviewee C and Interviewee D share similar concerns, particularly regarding the model's inability to account for critical external factors such as weather conditions. At the same time, he acknowledged that digitalization is inevitable and emphasized the importance of adapting to new technologies. While older generations may find the transition challenging or uncomfortable, Interviewee D pointed out that younger professionals are well prepared to continue developing and integrating digital tools as the current workforce gradually retires.

Although Svenska Kraftnät has yet to adopt AI in their project planning processes, both Interviewee A and Interviewee B expressed a generally positive attitude toward the use of AI and predictive models. Interviewee A acknowledged that although such models may not resolve political challenges, they could still offer significant value by helping to identify inefficiencies and the underlying causes of delays. For him, the ideal scenario is one in which a project manager's intuition aligns with AI-generated insights, enabling decisions that are both intuitive and data-driven. This perspective reinforces the view that AI should serve as a complementary tool, not a replacement for human expertise.

Both Interviewee E and Interviewee F expressed clear interest and strong optimism in the potential of AI and ML to enhance project planning and execution. Interviewee E emphasized that an ML model could help identify critical and risk-prone tasks, enabling more effective resource allocation. He also noted that such a model would encourage teams to place greater value on data collection, which in turn supports future learning and continuous improvement. Beyond automation, Interviewee E highlighted the benefits of increased awareness, team discussions, and reflection through data-driven forecasting and feedback.

Interviewee F added that AI's main strength lies in its ability to make decisions based on historical data rather than subjective judgment, helping to reduce reliance on assumptions and improve consistency in project outcomes. Across all six interviewees, there was a shared preference for clear visual outputs and the ability to trace the data and logic behind AI-generated decisions. Trust in AI was closely tied to transparency and usability. Several interviewees also pointed out that AI is only as effective as the quality of the input data, highlighting that many construction firms still face challenges with structured and standardized data collection, a critical barrier to successful implementation.

5.2 Technical Insights

This section presents the technical results of the hybrid model with the plot and figures it outputs. The results are divided into three parts. The models baseline output with and without the ML models input. The model's progress over time, with real world progress updates included, to show the output development. Lastly, the results of the ML model validation.

5.2.0.1 Monte Carlo-Simulated Project Progress

Figure 5.2 illustrates the project progress simulated by the Monte Carlo simulation. The blue lines represent different possible project completion paths, each generated by randomly varying task durations while considering task dependencies. The green dashed line represents the initially planned project schedule, serving as a reference for comparison.

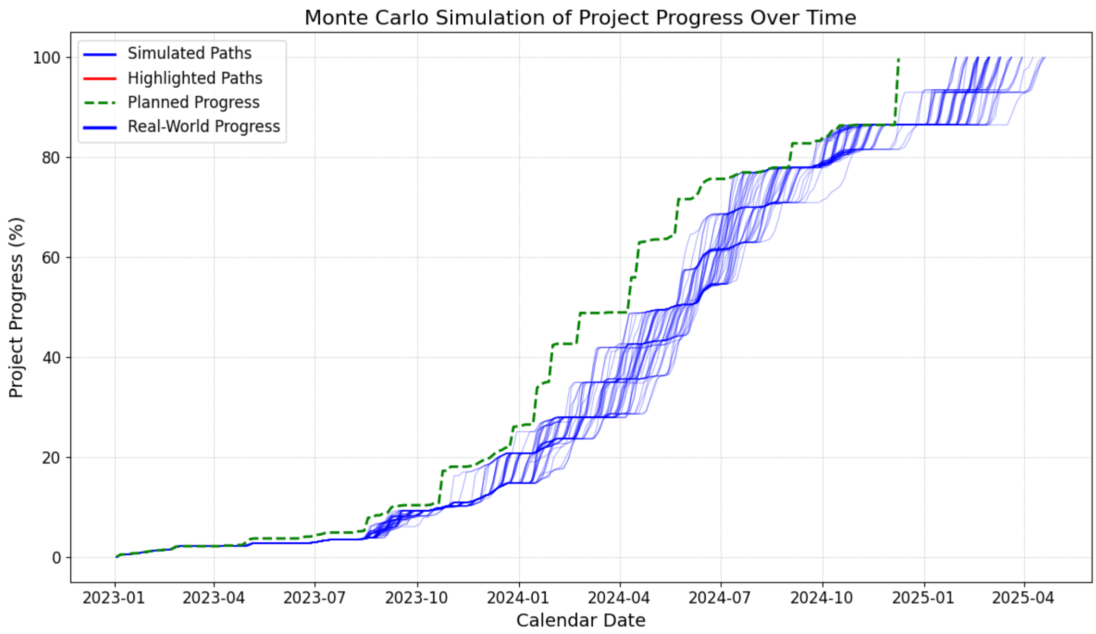

Figure 5.2: Monte Carlo simulation of project progress. Blue lines represent simulated project paths, and the green dashed line indicates the planned schedule. The x-axis shows time, and the y-axis shows project completion percentage.

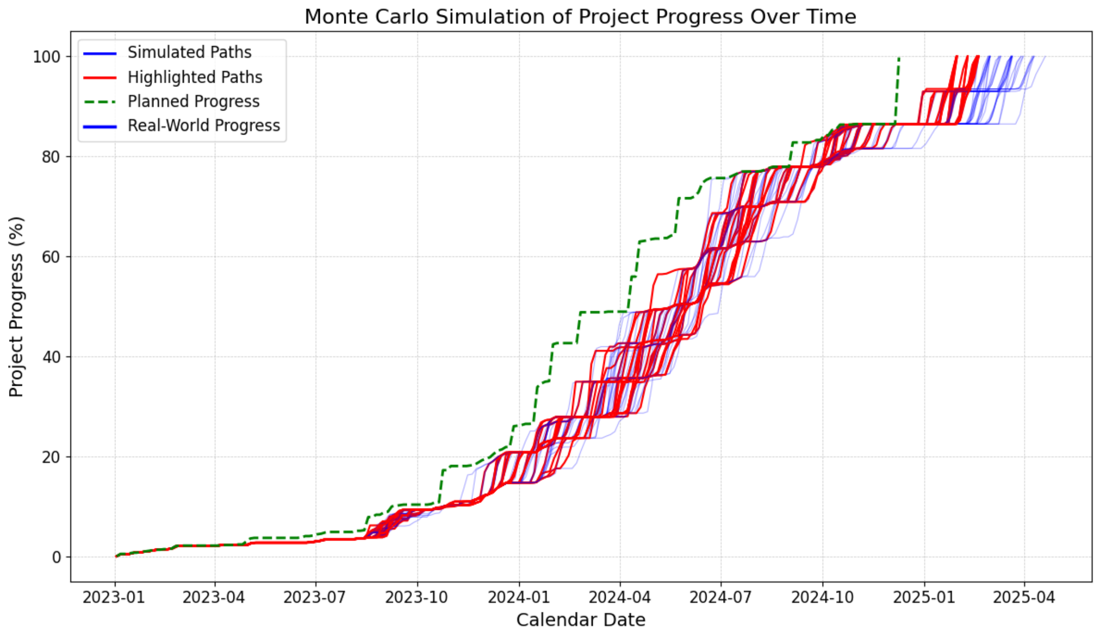

Figure 5.3: Monte Carlo simulation with ML predictions. Red lines represent the most probable project paths identified by the model. The x-axis shows time, and the y-axis shows project completion percentage.

5.2.0.2 Refined Predictions by the Machine Learning model

Figure 5.3 presents the predictions after applying the ML model. The red lines highlight the most likely project completion paths, as identified by the model based on past project data. Compared to Figure 5.2, these refined predictions narrow down the expected project completion dates, making the forecast more accurate.

5.2.1 Model Progress Over Time

This section examines how the model improves over time as more real-world project data becomes available. The ML model is optimized weekly to refine the models predictions based on newly recorded project updates. Figures 5.4, 5.5 and 5.6 present the evolution of the model's predictions from work Week 3 through Week 58. As the project progresses, the Monte Carlo simulation results become more focused, and the ML model adapts accordingly by narrowing the range of completion outcomes. The red lines in each figure indicate the most likely project completion paths at each stage.

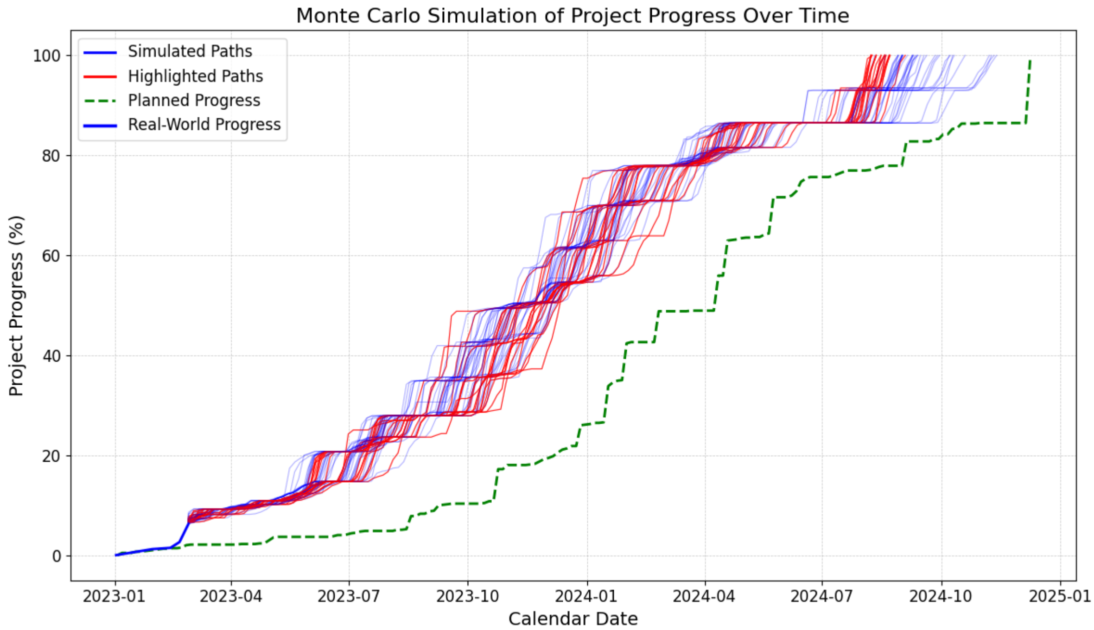

Figure 5.4: Model prediction and real-world progress update during Week 5. The red lines represent the most likely project completion paths.

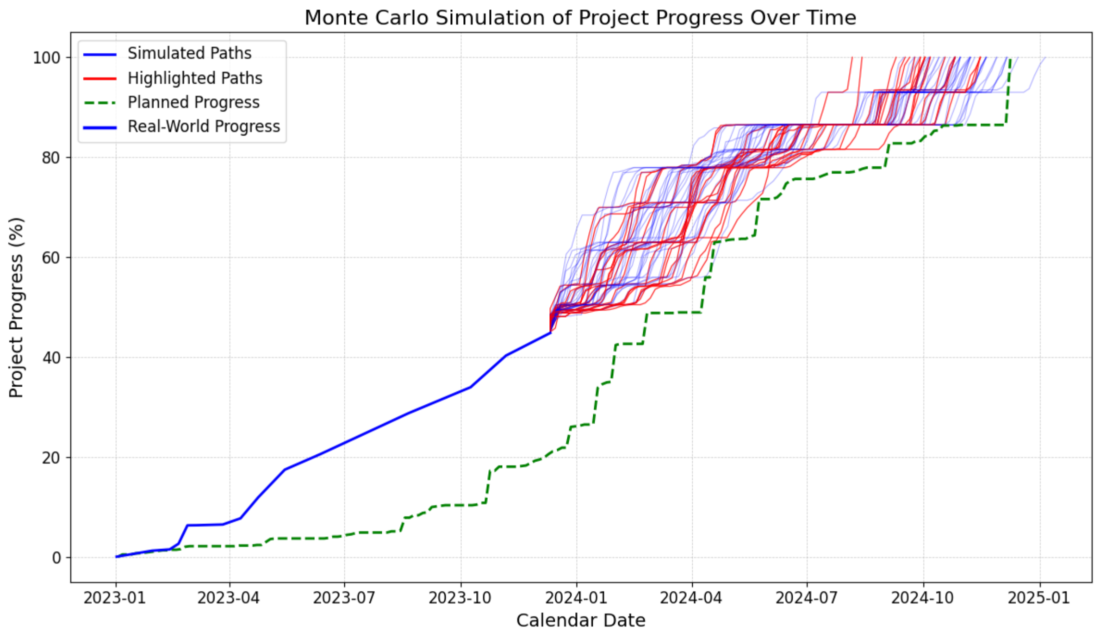

Figure 5.5: Model prediction and real-world progress update during Week 49.

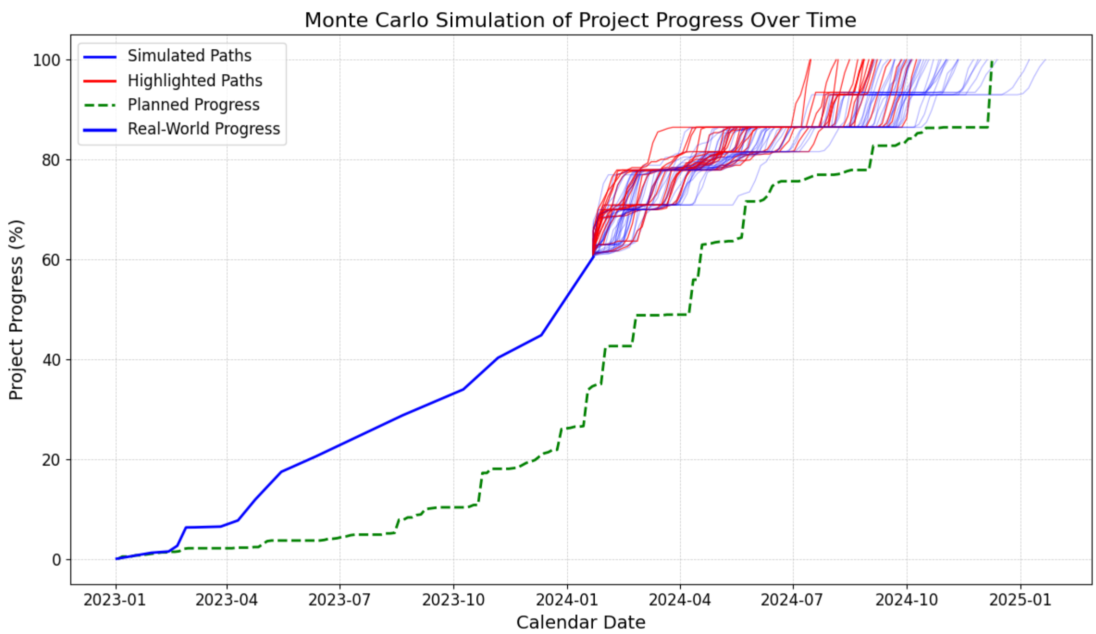

Figure 5.6: Model prediction and real-world progress update during Week 58.

These results demonstrate how the hybrid model becomes increasingly accurate as it incorporates new data from the project environment. Each weekly update yields better informed predictions and more reliable forecasts for managing the project schedule over time.

5.2.2 GPU Acceleration

To evaluate the impact of GPU acceleration, three versions of the simulation program were benchmarked using 100 Monte Carlo iterations:

- **CPU-only implementation:** 33 hours
- **Partially GPU-accelerated implementation:** 22 minutes
- **Fully GPU-accelerated implementation:** 5 minutes

The fully accelerated version achieved a speed up factor of approximately 396× compared to the CPU-only version. These results demonstrate the computational gains from parallelization and the use of GPU acceleration for large scale simulation runs.

5.2.3 Validation

In the sections below the results of the validation of the ML model is presented.

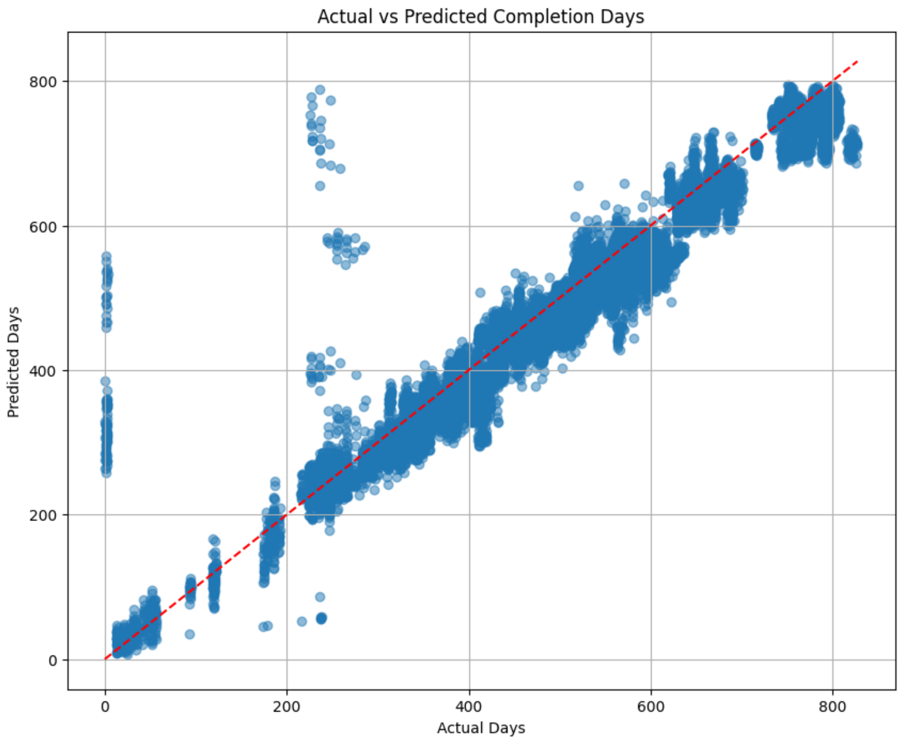

Figure 5.7: Actual versus predicted task completion times. The red dashed line represents perfect prediction alignment, with points close to the line indicating high model accuracy.

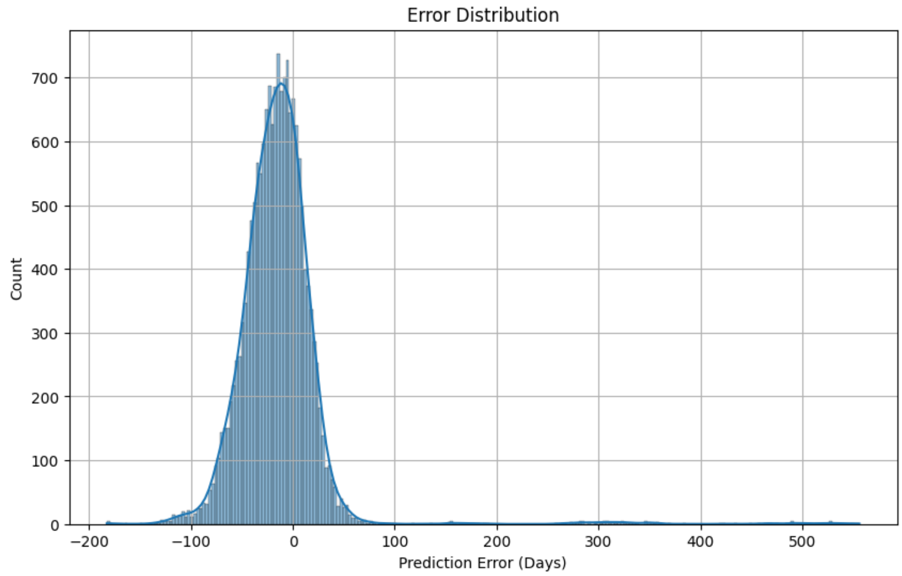

Figure 5.8: Distribution of prediction errors in days. The histogram shows how closely the model's forecasts aligned with actual task completion times.

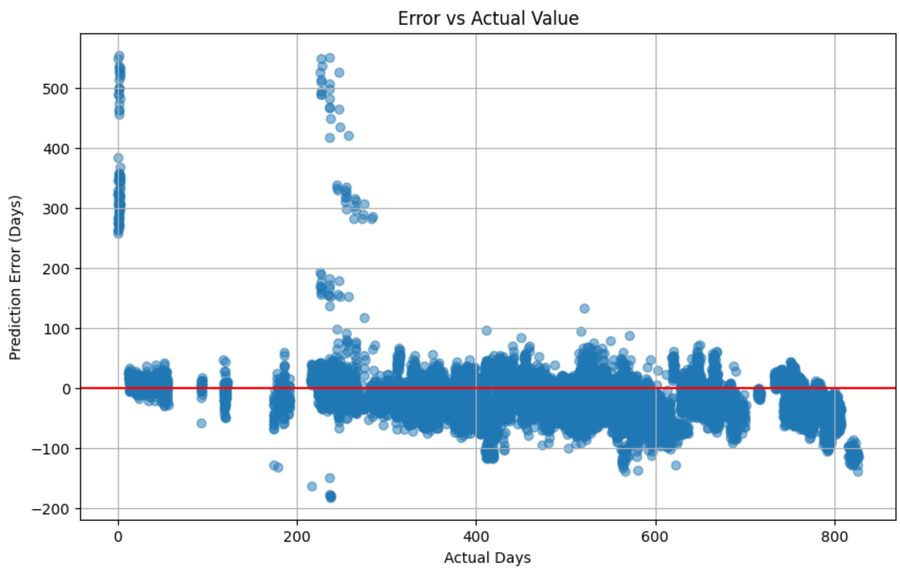

Figure 5.9: Prediction error plotted against actual completion time. The vertical spread indicates the error in days for each task, while the red line at zero represents perfect prediction accuracy.

Table 5.1: Comparison of Validation Metrics for the Two Runs

Metric	**Results**
MSE (Hours)	1 264 238.58
RMSE (Hours)	1 124.38
MAE (Hours)	682.98
R^2 (Hours)	0.9203
MSE (Days)	2 194.86
RMSE (Days)	46.85
MAE (Days)	28.46
R^2 (Days)	0.9203
Mean Percent Error (Days)	11.01%

5.3 Design Results

The design result can be seen in figure 5.10. Any non-essential data was removed to create a more minimalistic and clean appearance. Instead of showing all individual simulated paths, we chose to illustrate the range of possible outcomes as a transparent shaded area beneath the main curve. This shaded area represents the range of the most probable paths selected by the ML model.

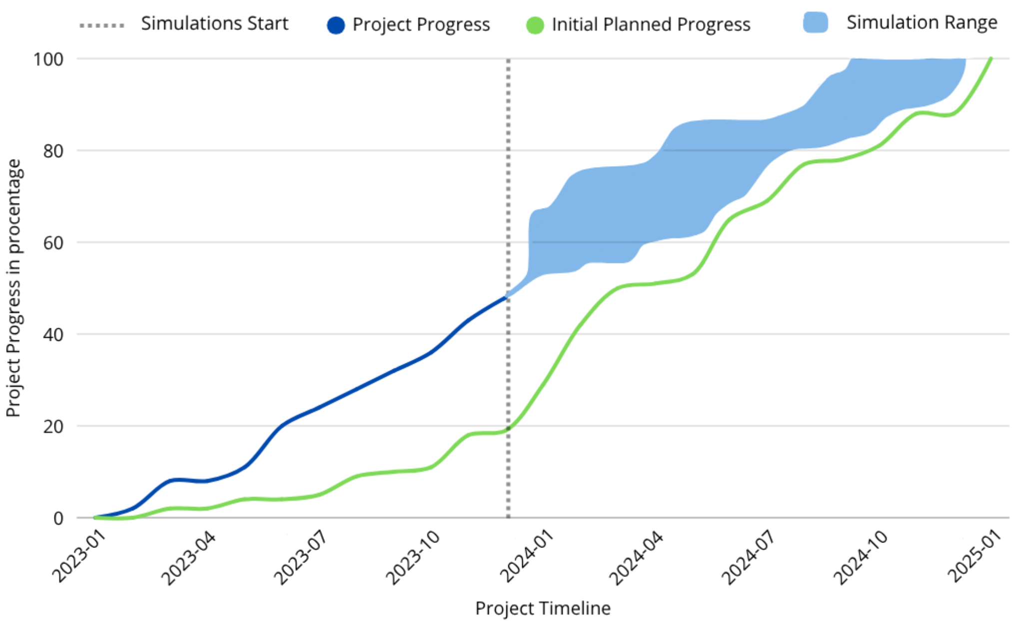

Figure 5.10: Final visualization after applying design adjustments. The chart compares actual project progress, planned schedule, and the simulation range, highlighting the most probable outcomes selected by the ML model.

6
Discussion

While AI and ML models in construction are grounded in a solid theoretical and technical foundation, the practical applicability in real world construction projects still remains a challenge. It is crucial to discuss the practical relevance and viability of the models, particularly within the context of the case study with NCC and expand on how the model can be applied, refined and scaled across the industry. The following sections will discuss the development of our ML model, the data challenges encountered during the development and the feedback from interviewees. Emphasis will be placed on how the model would integrate with existing workflow, its potential to support decision-making and the importance of clear result visualization to encourage adoption.

6.1 Key Aspects of Project's Development and Evaluation

In this section, the interpretation of results covers both the practical and technical outcomes of the project. On the practical side, the interviews and literature review confirmed that while traditional project management methods remain dominant, there is a clear interest and recognized need for more data-driven decision-making tools.

From the technical perspective, the developed hybrid model demonstrated the ability to generate realistic project outcomes by combining Monte Carlo simulations with machine learning. However, the model's performance remains dependent on the quality and structure of input data, reinforcing the importance of systematic and standardized data collection practices. The following sections will discuss key aspects of the project's development and evaluation.

6.1.1 Data Management

A significant portion of our project was dedicated to data management, largely due to the absence of an existing data pipeline. As a result, the data handling process had to be built from the ground up. This began with engaging project managers and on-site personnel to understand what data was available, how it was structured, and which parts would be relevant for the forecasting model. Interpreting and selecting useful features required considerable effort, since there were no established references available for building a hybrid framework for this type of project data. Understanding the meaning and context of the dataset was essential before we could determine which variables would contribute meaningfully to the simulation and ML model.

Once relevant features were identified, we transformed the data into a consistent and usable format. As this manual work was time-consuming, we developed an partly automated data pipeline to handle preprocessing and updates efficiently. This pipeline ensured that the data could be repeatedly used for Monte Carlo simulations and neural network training without manual intervention. This was important to establish a method that could be reused in future projects and datasets. The pipeline was developed with generalizability in mind.

To ensure the outputs of the Monte Carlo simulations were realistic, a trial-and-error process was performed on a sample dataset of 100 tasks. This step was crucial, as it would have been impossible to verify the correctness of the simulations on a larger dataset without first confirming their behavior on a smaller scale. However, the biggest improvement came after implementing standardized data structures, particularly for the ML model, which showed a significant increase in accuracy and performance once the data was properly scaled. It was observed that the ML model performed better when real-world updates were frequent. Since the validation data had inconsistent intervals, ranging from one to four weeks, we believe the prediction accuracy was lower than what might have been achieved with more consistent updates.

As there were no previous studies identified that used a similar hybrid framework, we lacked direct references for the exact pipeline approach. However, the interviews revealed that exporting project data from Power Project into Excel was a commonly used method in the managers' analytical workflows. This insight confirmed the approach we should take for exporting the data. A limitation of this method was the substantial amount of manual work required throughout the early stages. This slowed the workflow and occasionally disrupted the pace of development and experimentation.

In conclusion, this experience demonstrated that effective and continuous data management in construction projects is critical. When handled properly, data becomes easier to work with, leading to more frequent and more valuable insights that project managers can use to make better decisions. Since developing the data pipeline and managing the data took approximately half of the project's total time, having an existing, functional pipeline in place would have significantly reduced the project's duration.

6.1.2 Hybrid Model Efficiency

From the start of the study, the primary goal was to develop a predictive framework broadly applicable across many construction projects. Reviewing existing literature revealed two main methodologies used in applying ML to construction management: training ML models on historical project datasets or employing highly detailed networks (e.g Bayesian Networks) at an individual worker level.

Previous attempts, such as training models using historical project data, demonstrated practical limitations. Such approaches needed access to large databases of comparable old projects, which is uncommon in the construction industry due to project uniqueness and varying documentation standards. Furthermore, obtaining permissions to historical data often poses significant bureaucratic and practical challenges. These constraints severely limit the generalizability and practical application of such models across different projects.

Alternatively, methods involving detailed networks based on individual worker data offered very granular predictions. Despite their high theoretical accuracy, methods that rely on detailed daily data introduce numerous variables related to human factors, such as individual productivity, mood, or health, which change frequently and unpredictably. These daily variations cause significant fluctuations in the data, making it difficult for ML models to identify long-term trends or the "Big picture". While ML excels at recognizing broader patterns and overall project progress, it is practically impossible for it to accurately predict daily human behavior changes due to their randomness. Furthermore, continuously tracking every minor detail at construction sites is impractical and inefficient for off-site managers. Therefore, these managers typically benefit more from forecasting methods that provide a clear, strategic overview rather than highly detailed, short-term predictions.

Given these practical limitations, the approach was centered on designing a framework that balances predictive accuracy with broad applicability. The resulting hybrid framework, a method that does not rely on historical datasets or detailed individual, level data. This approach addresses the challenges of data availability and the unpredictability of human behavior. While still offering a lightweight, robust overview of the project outcomes. The design makes the framework practical to implement and flexible enough to fit different project settings, achieving the goal we determined at the start of the research.

6.1.3 Monte Carlo Simulation Outcomes

The use of Monte Carlo simulations to generate multiple potential construction timelines proved highly effective. Once task dependencies and task specific features were correctly defined, the simulations successfully identified the most probable project paths. This method produced a range of technically feasible scenarios, offering valuable insights into potential project outcomes.

For project managers, these predictive capabilities are especially useful. By visualizing a spectrum of possible futures, they can make informed decisions proactively. For example, if simulations indicate a risk of delays, corrective measures can be taken early. Conversely, if the project appears ahead of schedule, adjustments to resource allocation and budget planning can be made to avoid inefficiencies.

The simulations' dynamic nature further increases their value, as they can be continuously updated with new project data. This adaptability ensures that decision-making remains grounded in current conditions. An additional advantage is the use of a relative time framework, which normalizes all task timings based on the overall project duration. This allowed simulations to be independent of specific calendar dates, making it easier to compare different scenarios, evaluate progress, and re-align timelines when real world data is introduced.

However, one of the limitations observed during implementation was the model's sensitivity to parameter variations. While the customizable nature of the simulation is ideal for incorporating expert knowledge and managerial intuition, it can also act as a double-edged sword, small changes in input parameters sometimes led to significant shifts in simulation outcomes. Striking the right balance between flexibility and stability proved to be a necessary challenge.

A technical difficulty during development involved synchronizing the simulations with actual project progress. Ensuring that new simulation runs began precisely where real-world data ended required careful alignment. Despite its complexity, this step was essential, as it improved the tool's ability to reflect ongoing project realities.

Compared to traditional deterministic scheduling, this probabilistic approach offers greater flexibility and awareness of uncertainty. It enables project managers to not only anticipate deviations from the plan but also to understand the full range of potential progress paths. By using the simulations they are able to get an overview of the mathematically possible outcomes.

6.1.4 Machine Learning Model Refinements

The ML model we developed showed strong performance, achieving a low error rate and successfully identifying the most probable project paths. This capability adds substantial value, complementing the Monte Carlo simulations by offering insights into which of the simulated outcomes are most realistic based on actual project progress. This enhanced the usefulness of our overall framework and provided critical support for project management decisions.

Developing this ML model involved several challenges, particularly balancing the selection of task specific attributes. We needed sufficient detail for the model to learn meaningful patterns without introducing unnecessary complexity or noise. Through an iterative trial-and-error process, we ultimately settled on using simulated durations, float days, predecessor counts, and unique task identifiers. With these features, the initial model achieved an R^2 value of 0.52, numerically, this reflects how closely the predicted values follow the actual variation in task outcomes. This R^2 value showed that the model successfully captured some underlying trends in the data.

To further enhance model performance, we deepened the neural network architecture by adding embedding layers and multi-head attention mechanisms. These additions allowed the network to more effectively capture sequencing and relationships within the data, significantly improving model performance to an R^2 of 0.79. Additional refinement involved experimenting with various learning-rate strategies. Ultimately, a simple fixed learning rate combined with a learning rate scheduler proved most effective, further increasing performance to an R^2 value of 0.92, indicating a very strong match between predicted and actual task completion times, and demonstrating that the model could reliably capture the full complexity of task dynamics.

However, refining the model was hindered by the infrequent updates of real-world progress data. More frequent weekly data updates would have allowed for continual refinement and potentially even higher accuracy. Given additional time, further architectural adjustments and more consistent data updates could lead to improved predictive performance.

6.1.5 Validation of Machine Learning Model Performance

To objectively evaluate and validate the performance of our machine learning model, we performed an extensive analysis using unseen data from later project stages. The validation results, summarized in Table 5.1, show that our model achieved robust predictive performance, with an R^2 score of 0.9203, both when measured in hours and days. This indicates that about 92% of the variability in actual project timelines was accurately predicted by the model.

When the ML model is evaluated, it predicts task completion times for unseen simulation runs. For each task, we compare the predicted finish date with the simulated actual date and calculate the difference. The model achieved a MAE of 28.5 days (Table 5.1), on average the model is about 28 days off per task. This error is measured per task, and is relatively small when compared to the average task duration of approximately 470 days. It also falls well within the expected variation generated by the Monte Carlo simulations, which typically span several months per task. The root mean square error (RMSE), which gives greater weight to larger errors, was about 46.85 days, indicating that while most predictions were close, a few tasks had significantly higher discrepancies, particularly those with very short actual durations.

In Figure 5.7, a small number of extreme prediction errors can be observed, particularly for tasks with actual durations near zero or around 200 days. In these cases, the model predicted durations of several hundred days, resulting in large discrepancies. These outliers had a disproportionate effect on error metrics sensitive to large deviations, such as the root mean squared error (RMSE), which were significantly higher than the mean absolute error (MAE). Despite these extreme cases, the majority of predictions remained close to the actual values, indicating that the model captured overall task duration patterns.

Visual representations, shown in Figures 5.7, 5.8, and 5.9, further support these numerical findings. These figures clearly demonstrate a strong alignment between predicted and actual project completion times. Additionally, prediction errors are normally distributed around zero, confirming that the model does not suffer from systematic biases or significant outliers, further bolstering its reliability. These validation metric outcomes showed us that the deep learning model was reliable enough and that with more time to develop the model we could get even more accurate predictions from the model.

6.1.6 Model Performance Over Time

The performance of the ML model improved as the project progressed, due to the incorporation of incremental real-world progress data. Initially, the model's predictions reflected the broader uncertainty from the start of the project. However, with each new data update, the model became progressively more accurate and stable in its forecasting capabilities. Consequently, consistent and frequent data updates are essential for maintaining high predictive accuracy and providing valuable insights throughout the life-cycle of a project.

6.2 Strengths and Contributions

If future users are unable to recognize the benefits that a model like this can offer, then its development would serve little to no purpose. Therefore, this section will focus on highlighting the model's key strengths and the practical value it can bring to project management. In addition, the reasoning behind the final visualization choices will be discussed, emphasizing how user feedback and practical considerations shaped the presentation of results.

6.2.1 Organizational and Cultural Barrier to AI Implementation

Throughout the study, several challenges relating to organizational and managerial resistance to implement AI and ML models were identified. While these models have a lot of potential and are generally seen as beneficial, the actual adaptation is hindered by a range of technical and cultural factors. The most pertinent obstacle is the availability of data, particularly data from finished projects. Older construction project data can be fragmented, missing or stored incorrectly. In the case of NCC, Interviewee E mentioned that there is little to no reflection on past projects, which means the quality and structure of historical data cannot be guaranteed, making it unreliable for training AI, especially when aiming to identify long term trends or bench mark.

Another significant hindrance is the hesitancy and concern among companies regarding data privacy and the risk of information leakage. The construction industry often handles sensitive data related to contracts, finances, personnel, and, in some cases, even politically sensitive matters. It is therefore understandable that organizations are cautious about sharing data, particularly with external platforms or systems.

Our developed model processes real project data, including task names, durations, and progress metrics which could, in theory, reveal internal project structures or performance patterns. However, no financial data is used in the model, and measures are in place to protect data confidentiality. Task identifiers can be anonymized prior to training, and all model files and logs are stored locally or within secure environments.

Furthermore, the framework adheres to a privacy-by-design approach, offering optional controls for removing or obfuscating identifiable information before data is stored or shared. File formats such as `".pth"` and `".pkl"` are only used within trusted environments, and no data is transmitted to any external servers. In this way, the program enables powerful forecasting and simulation capabilities without compromising data security or confidentiality.

Finally, the ageing workforce presents a cultural barrier, as many experienced project managers and site personnel have long-established routines and are often less inclined to alter their workflows. As block manager, Interviewee D pointed out, there is frequently a generational gap when it comes to digitalization where older individuals may feel overwhelmed or even excluded by the introduction of ML systems. However, construction, as a major industry, can no longer afford to lag behind in adopting new technologies, especially as other sectors are rapidly advancing with the help of AI and ML models.

Rather than resisting the shift or relying on large-scale turnover of older staff, successful implementation must involve both technical readiness and a strong organizational commitment to change management and education. Efforts must be made to bridge the digital divide through training and support. In parallel, developers must prioritize user-friendly design, ensuring that tools are intuitive and accessible, thereby encouraging broader adoption and smoother integration into existing workflows.

6.2.2 Computational Performance

At the start of the development, the model was built and tested using a relatively small dataset of about 100 tasks. This made it easier to verify that everything worked correctly without facing heavy computational demands, as we were able to try small changes in the simulation part of the program. This gave us the possibility to verify that the simulations followed the dependencies correctly. However, when we tested the program with the validation dataset we realized the run time was not practical. With a approximately 33 hour run time, we had to find a way to make the program faster.

As mentioned in section 4.5.6 to speed up the program run time we chose to use GPU-acceleration. This approach suited us best as the framework was built on calculating several different iterations of similar calculations, which meant running them concurrently would solve the issue. The first steps toward GPU acceleration, however, only delivered modest improvements. This was mainly due to high overhead costs from transferring data between the CPU and GPU and because the GPU was only lightly utilized (about 15%). It quickly became clear that simply shifting parts of the code to the GPU would not be enough. We needed to fundamentally restructure the program, moving from a sequential, CPU-focused design to a modular, parallelized structure that could fully take advantage of GPU capabilities, specifically using CuPy.

After fully integrating GPU support, we saw major performance improvements. Ultimately, runtime for 100 iterations dropped to between 5 and 10 minutes a speed up of nearly 400 times compared to the original CPU-only version. This dramatic improvement was largely possible because Monte Carlo simulations and related calculations are highly parallelizable by nature.

Beyond just the speed-up, the final GPU-accelerated model was designed to be modular and adaptable. It can be applied to other construction projects or even entirely different fields with similar computational needs. Tests showed that the program scales well, with runtime increasing almost linearly as the number of tasks or simulations grows. Although current GPU memory use stayed moderate, future extensions, such as handling even larger datasets or applying multi-GPU setups, could further enhance performance.

From a practical standpoint, these computational improvements make the tool much more usable. Project managers can now quickly test different scenarios and adjust parameters without long waiting times, making it far more attractive for real-world use. Faster runtimes also lower the barrier for new users, helping advanced forecasting tools such as this become part of standard project management practice.

6.2.3 Model Integration into NCC's Workflow

As mentioned earlier, our model is built to help predict how a project might develop based on real data. It works as both a visual and analytical tool, giving managers a clearer view of different ways the project could unfold under various conditions.

Take the execution phase as an example, when coordination between multiple teams and subcontractors becomes more challenging. At that stage, the model can generate several possible timelines based on current progress and past trends. If a delay happens in one task, the model shows a range of realistic outcomes depending on how the situation plays out.

By continuously updating its predictions with real-time project data, the model adds an extra layer of foresight to NCC's existing planning process, which typically revolves around set schedules and monthly reviews. It does not replace managers' expertise but supports it by highlighting potential risks or changes before they become problems. In that way, the model helps teams think ahead and explore "what-if" scenarios, while keeping all final decisions firmly in the hands of the people running the project.

6.2.4 Data Visualization

The feedback collected from user interviews made it clear that future users strongly preferred simplicity in the visualization of data. Users emphasized the importance of clear and easily understandable visuals, not only for themselves but also for other stakeholders or workers they might share the outputs with. Therefore, our primary focus when designing the visualization was to find a good balance between providing meaningful information and presenting it as simply as possible.

The initial raw plots generated with Matplotlib tended to appear overly complex and intimidating. Therefore the result was a minimalistic graph with essential labels and suitable colors. By taking this approach, the final visualization became easier to interpret and effectively conveyed the relevant information without overwhelming the users.

Due to time constraints, we opted to create a mock-up version of the visualization using Canva to demonstrate the results of the visualization research and to propose a potential user-friendly interface. However, future developments could explore various approaches for transforming raw output data into dynamic, user-friendly interfaces. Such interfaces should ideally be both intuitive to use and easily customizable, potentially utilizing tools such as Power BI or Tableau.

6.3 Understanding the Role and Realistic Expectation of AI

When discussing the integration of AI into construction management, it is crucial to recognize that AI is not and will not be the solution to all challenges the industry faces. While learning models can offer valuable support by providing mathematically derived outcomes, they should be viewed as tools that complement, rather than replace human intuition and expertise. In many cases, AI can reinforce a manager's gut feeling but it can as easily produce an outcome that contradicts that intuition. This contrast should not be seen as a failure of any parties, but rather an opportunity to reflect critically and explore alternative perspectives in the decision-making process. Many of the interviewees also agreed that this is the ideal outcome of implementing AI in the construction industry.

The high expectations placed on AI, while encouraging in terms of innovation and forward thinking, reveal a gap between enthusiasm and practical understanding. The belief that AI can deliver instant, transformative change is not only unrealistic but also counterproductive. When expectations are misaligned with what AI can feasibly deliver in the short term, the result is often overconfidence, followed by disappointment when those expectations are not met. This risk is particularly prominent when early implementations are rolled out without sufficient consideration for model limitations or data constraints.

It is important to stress that AI models are only as good as the data they are trained on. Without high quality, structured, and relevant data, even the most advanced algorithms will produce weak or misleading predictions. In conclusion, AI should be framed not as a silver bullet, but as a decision support tool, capable of enhancing project planning and forecasting but only when integrated with expertise, realistic expectations and a solid foundation of data.

7
Conclusion

Numerous studies explore the integration of ML in the construction industry, and this thesis contributes to the growing body of work at the intersection of AI and project management. Through an in-depth study of NCC's workflow and project practices, it becomes evident that although digital tools are in use, the full potential of data remains untapped primarily due to the fragmented nature of construction data and the industry's traditionally slow pace in adopting new technologies.

To address these challenges, a ML model is developed using data collected from the Ingelkärr–Stenkullen project. The model is designed to automate data processing, forecast project progress, and identify potential delays. Initial testing shows promising results, indicating its potential to support more efficient and proactive project management. One of the key advantages of the model is its ability to continuously learn and adapt as new data becomes available, allowing it to improve its predictive accuracy over time. Furthermore, the model complements managers' subjective judgments by providing data-driven insights and enabling earlier identification of risks.

While the results were promising, the model's performance is highly dependent on the quality of and consistency of input data. This limitation of constrained the accuracy of some predictions. To support the adoption of data-driven tools in construction, it requires big investment in structured data from companies and ensure that project data is consistently formatted.

Beyond technical development, this thesis also provides practical insight from a managerial perspective, recognizing that the effectiveness of a model significantly depends on the adoption of the end user. Interviews and workflow analyses revealed several key conclusions: project managers require intuitive interfaces to comfortably interact with predictive tools, trustworthiness of predictions greatly influences their adoption, and data transparency enhances managers confidence in model outcome.

By balancing the technical innovation and practical usability, the thesis demonstrates how ML can be and should be integrated into existing workflow in a way that supports, rather than disrupts current project management routines. Ultimately, the findings highlight the importance of combining technological development with a deep understanding of end-users to ensure that digital solutions deliver meaningful value to the construction industry.

7.1 Addressing the Research Questions

In this section, we aimed to provide clear and concise answers to the research questions, drawing from our interview findings and the development of the machine learning model.

- *How can AI and ML be implemented effectively and practically into construction management workflows?*
  Based on insights from our gap analysis, we found that the most effective and practical way to implement AI and ML in construction management is through a hybrid approach that combines strong technical capabilities with user-focused design. Our forecasting model integrates Monte Carlo simulations with a neural network, enabling it to generate a wide range of possible project outcomes while continuously learning from weekly progress updates. This setup allows the model to deliver accurate and adaptive forecasts throughout the project. Most importantly, we developed the tool in close collaboration with project managers and engineers at NCC to ensure it responded to real operational needs.

  The user interface and visualizations were kept simple, transparent, and minimalistic to promote understanding and build trust among end-users. The model also integrates smoothly with existing tools like Excel and PowerProject, help minimize disruption to current workflows. On the technical side, we used modular code structures and GPU acceleration to significantly reduce runtime, making the tool efficient enough for weekly use in live projects. However, it is important to recognized that successful implementation depends not just on technical performance, but on organizational readiness. Barriers such as limited digital skills among some professionals and concerns about data privacy need to be addressed through training, clear communication of benefits, and the adoption of privacy-conscious design principles.

- *In what ways can predictive models contribute to data-driven decision-making, and to what extent does data management affect their performance?*
  In general, predictive models play a crucial role in supporting data-driven decision-making, particularly in construction projects where they provide timely and objective insights to improve planning and risk management. In our work, we developed a model capable of forecasting task delays and identifying high-risk paths based on real project data. This allows managers to anticipate potential issues, optimize resource allocation, and maintain better control over project execution. Unlike traditional tools that rely heavily on manual input and offer limited adaptability, our model continuously refines its predictions as new data becomes available.

  However, the performance of predictive models like ours depends heavily on several factors, most notably the quality and structure of the input data. We observed that the model's accuracy and overall effectiveness would improved significantly if the data was well-organized, regularly updated and standardized. Systematic data management played a critical role in enabling the model to detect realistic paths and delay trends. In addition, we had also implemented automated preprocessing pipelines and clear formatting guidelines, which enhance scalability and reduced risk of human error. It is important to highlight that fragmented data practices, inconsistent documentation, and the lack of shared industry standards posed significant challenges. Therefore, it is recommend to establish robust data management practices as a foundational requirement for the successful deployment of predictive tools in construction management.

- *How do construction professionals perceive the use of AI and predictive models in their daily workflows?*
  Construction professional showed a mix of enthusiasm and caution toward the use of AI and predictive models. While many younger professionals tended to express a more positive outlook, experienced practitioners like Interviewee C emphasized that AI cannot replace human judgment. They viewed AI as a complementary tool, one that can support managerial decisions and prompt reflection, especially when its outputs challenge intuitive assumptions.

  Interviewee E and Interviewee F shared a strong belief in AI's potential to enhance project planning by identifying critical paths and resource risks, promoting more consistent data collection as well as fostering better team alignment. However, the literature review revealed that adoption of AI in construction is still hindered by challenges related to transparency, data privacy and security. These issues are further complicated by fragmented data collection practices and a lack of standardized structures across projects, limiting the full integration AI into daily workflows.

7.2 Future Improvements

Given the broad scope of challenges that this software program addresses, there remains significant potential for future enhancements, each aimed at improving decision-making for project managers. Initially, two immediate steps stand out clearly. First, developing a user-friendly interface would significantly streamline the program's adoption, allowing project managers to effortlessly navigate and utilize the system. Second, the implementation of an automated data cleaning and structuring module would greatly enhance usability. Such a module would precede the existing data preprocessing steps, automatically transforming correctly formatted project files from tools like PowerProject into program-compatible data. This approach would minimize manual intervention and facilitate quicker onboarding of new users.

In terms of core program improvements, several highly impactful development can be pursued. One particular method identified through interviews with project managers is the integration of the CPM. Implementing CPM would not only help managers quickly pinpoint the most critical tasks but also illustrate clearly within the Monte Carlo simulations how changes in critical paths could impact overall project timelines. Such a feature would provide managers with actionable insights directly linked to project success. Additionally, by extracting CPM-related metrics from Monte Carlo outputs and integrating these as new features into the ML model, the predictions could become significantly more reliable and informative regarding critical task paths.

Another area for enhancement is the inclusion of resource allocation, workforce management, and budget balancing within the program's analytical framework. Developing multiple operational modes, one similar to the current setup and another enriched with these additional factors, could substantially enhance the practical value provided to project managers. This expanded mode would allow for scenario analysis, where managers could experiment with varying resource distributions, workforce levels, and budget scenarios. Consequently, decisions would be grounded not only in past experience but also informed by tailored, data-driven predictions.

Moreover, integration of external factors like seasonal variations and weather conditions, would further enhance the accuracy and relevance of predictions. Interviews indicated that project timelines are heavily influenced by weather. While the current model captures such variations implicitly through patterns in data, explicitly incorporating weather data as dedicated input features could significantly improve the accuracy and transparency of predictions. Notably, all interviewed managers regarded transparency as more critical than achieving flawless predictive performance. By explicitly including and presenting factors influencing predictions, the program can clearly communicate the rationale behind its outputs, thus directly addressing this managerial priority.

Lastly, an additional recommendation for future work involves the development of diagnostic functionalities that extend beyond mere predictive capabilities. Such functionalities would identify primary sources of delay or disruption based on the simulations and provide managers with targeted recommendations or proactive alerts as real-world data becomes available. During model development, it became clear that further improvements could also be achieved through more nuanced adjustments in model architecture or learning strategies. Although such advanced modeling techniques were beyond the current scope of this study, they represent valuable directions for future research.

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A

Appendix A

Include additional materials, such as interview questions or technical details.

A.0.1 Transkription av intervju med Interviewee E och Interviewee F

Datum: 2024-10-11
Intervjuperson(er): Interviewee E och Interviewee F
Intervjuare: Mohammed Rauf, Ha Vu
Transkriptionen startades och alla deltagare samtyckte till inspelning
Denna intervju började med Interviewee E och Interviewee F beskriver företagets process för projekt med focus på planering och genomförande av produktion. Frågor om visualisering och maskininlärning och deras förväntningar på en ML-modell.

Frågor:
- Vilka är de viktigaste faktorerna att ta hänsyn till innan man påbörjar planeringen av ett projekt?
- Vilka faktorer påverkar den totala kapaciteten i ett byggprojekt, och hur kan dessa variera beroende på projektets omfattning?
- Hur ser du på inlärningskurvan i byggprojekt? Vilka faktorer gör att aktiviteter kan utföras snabbare med ackumulerad erfarenhet?
- Hur tror du att maskininlärning modell prediktering kan bidra till att öka kapaciteten och förbättra projektets effektivitet?
- Hur påverkar tidspress och deadlines kapaciteten i ett projekt, och hur balanserar du mellan kvalitet och hastighet när kapaciteten behöver ökas?
- Hur identifierar ni i dagsläget om kapaciteten kommer att bli ett hinder i ett projekt, och vilka åtgärder vidtar ni för att hantera det?
- Har ni genomfört ett projekt där ni blev klara före deadline? Vad tror du var orsakerna till att ni lyckades med detta?

Interviewee E och Interviewee F började med att förklara NCC workflow:
Våra kärnprocesser är indelade i åtta steg. De kallas ofta för huvudprocesser, och man följer dem från vänster till höger, längst till vänster befinner man sig tidigt i processen. Det är där vi bevakar marknaden och bearbetar kunder, försöker påverka dem att handla upp på ett visst sätt. Fokus för exjobbet ligger på att planera och genomföra produktion, vilket kommer senare i kedjan.

Den tidiga fasen, det vi kallar genomföra marknadskundbearbetning, handlar om att ha koll på vad som är på väg. Att till exempel veta att om tre år kommer det ett miljardprojekt i Trollhättan, då måste vi börja förbereda oss redan nu, kanske anställa på plats och fundera på hur vi ska ta oss an det projektet. Det handlar också om att påverka kunderna i hur de väljer att handla upp projekten.
De här trafikljussymbolerna representerar det vi kallar för beslutspunkter. Det innebär att vi måste redovisa för högre chefer att vi har uppfyllt vissa kriterier innan vi får gå vidare till nästa skede i processen.

I ett stort projekt, redan i ett tidigt skede, måste vi till exempel kunna visa att vi har en tydlig lösning på problemet innan vi får gå vidare till fasen genomför anbudsarbete. Den fasen inleds när vi får en förfrågan, till exempel från Trafikverket eller Svenska kraftnät, och vi går igenom vad som efterfrågas.
Då kommer nästa beslutspunkt, symboliserad med ett nytt "trafikljus", som vi kallar för kalkylbeslutsprövning. Där tar vi ställning till om vi faktiskt ska gå vidare och lämna in ett anbud eller inte. Ett anbud kan vara väldigt kostsamt att ta fram. I vissa fall kan det innebära att tio personer arbetar med det i upp till ett år, och det kan kosta flera miljoner kronor. Därför vill vi inte lägga ner tid och resurser i onödan, bara de anbud vi verkligen tror på ska vi gå vidare med.
Om man får "grönt ljus" vid kalkylbeslutsprövningen får man gå vidare och lämna sitt anbud. Beroende på projektets omfattning kan arbetet med ett anbud ta allt från tre veckor till ett helt år, så det varierar mycket.

När vi går in i fasen genomföra anbudsarbete arbetar vi oss återigen från vänster till höger i processen. Det kan låta enkelt, men det innebär flera komplexa steg. Det börjar med att vi går igenom själva anbudsförfrågan. Det handlar ofta om juridiska aspekter och att förstå vilka krav som ställs. I vissa fall kan det till exempel finnas väldigt höga vitesbelopp, vilket kan göra att vi känner: "Nej, det här är inte rätt projekt för oss." Vi behöver också planera själva anbudsarbetet och genomföra en kalkylprövning. Därefter startar vi upp arbetet med anbudet. I vissa fall innebär det att vi kalkylerar hela projektet, till exempel: "Det här kommer att kosta 20 miljoner."
Men det är inte alltid vi behöver lämna ett pris. Vissa anbud handlar mer om att lämna in CV:n och beskriva hur vi arbetar, vi kanske inte ens lämnar ett fast pris, utan bara ett föreslaget arvode. Det kan till exempel låta: "Vi kan genomföra det här arbetet. Vi har rätt kompetens och tillgängliga resurser, och vi gör det för 11 % i arvode." Det här sättet att lämna anbud har blivit ganska vanligt. Fokus ligger då inte på lägsta pris, utan snarare på högsta kvalitet. Man kan förstås gå ännu djupare in i detaljer. Ta till exempel delen som heter sammanställ underlag – där ingår mycket riskanalys. Ser vi att underlagen är otydliga eller att vissa kontraktskrav känns osäkra, gör vi en riskanalys för att bedöma hur mycket pengar vi bör ta höjd för. Vi överväger också om det finns möjlighet att reservera oss mot vissa risker.

Nästa trafikljus i processen kallas anbudsprövning, och det ser man också i huvudprocesskartan. Det handlar om att få ett "grönt ljus" alltså att vi får tillåtelse att lämna in ett anbud.Beslutet tas av en behörig chef, och vem det är beror på hur stort projektet är. Är det ett mycket stort jobb är det vår VD som fattar beslutet. Är det ett mindre uppdrag, så tas beslutet av en lokal chef.

Nästa steg i processen är planera projektering, men det är endast aktuellt om det handlar om en totalentreprenad. Många av våra anläggningsprojekt är dock utförandeentreprenader, vilket innebär att det är beställaren, alltså kunden som ansvarar för projekteringen. Men vi ser att det blir allt vanligare med totalentreprenader, eller design and build, som det också kallas. Personligen tycker jag de är roligast, eftersom vi då själva får ansvara för projekteringen och ta fram handlingarna.I de fallen går vi igenom två steg: planera projektering och genomför projektering. Dessa två steg hoppar vi alltså över helt vid utförandeentreprenader, eftersom vi då inte ansvarar för projekteringen.

Nu kommer vi in på de två stegen planera produktion och genomföra produktion. Det är de som är mest aktuella i vårt fall, alltså i det här exjobbet. När vi har fått jobbet är det dags att börja planera produktionen och säkerställa att allt är redo för att starta. Men innan vi faktiskt får sätta igång behöver vi genomföra en starttillståndsprövning. Det är ännu ett exempel på våra "trafikljus" i processen: om det är rött får vi inte starta internt, om det är grönt är vi redo att köra vidare. Att planera produktionen innebär att fördela ansvar, vem gör vad samt planera för kvalitetsarbete, miljöarbete, arbetsmiljö och inköp. Det handlar också om att planera tider och ekonomi. Det här steget är kärnan i exjobbet: Vad var egentligen planerat från början, innan uppstarten? Här kan man gå in i väldigt stor detalj och se exakt vad som ska göras i varje skede. Det handlar bland annat om att upprätta en produktionstidplan och hur gör man det?

Vi gör hela planeringen: vi bygger tidplaner med länkar, resurser och säkerställer att allt är på plats. När det är klart gör vi en starttillståndsprövning. Om det får grönt ljus, då kör vi igång produktionen.
Under genomföra produktion ligger stort fokus på att följa upp, styra, planera och säkerställa att allt fungerar. Vi bevakar att arbetet sköts som det ska. Vi har ofta månadsvisa avstämningar där vi följer upp tidplanen och ser om vi ligger rätt till.
Ekonomin är förstås också en viktig del. Om vi har kommit halvvägs i projektet, så ska vi också ha använt ungefär hälften av budgeten, inte mer än så.
Samtidigt arbetar vi mycket med kvalitet, vi gör kontroller, mäter exempelvis betongkvalitet. Ibland blir det fel, och då vill man minimera konsekvenserna. Det kan handla om felaktig betongkvalitet eller fel mängd armering. I värsta fall måste man riva upp och göra om och det är ju bara tråkigt och kostsamt. Därför är det viktigt att kvalitetssäkringen följer med genom hela projektet.

Det kommer vi också att se när vi besöker projektet Stenkullen–Ingelkärr. Där används mycket visuell planering, med whiteboardtavlor där man exempelvis markerar varje stolpe: "Har vi gjort kvalitetskontroll på den här?" Allt dokumenteras.
Det här är kärnan i vår produktion, att vi styr våra projekt: ekonomi, kvalitet, tidplaner. Allt för att kunna leverera en bra produkt till våra kunder.
Efter produktionsfasen kommer uppföljning. Varje kvartal gör vi en projektrap-

portering. Vi går igenom prognoser och bedömer hur projektet ligger till, håller vi tidsplanen? Budgeten? Hur ser arbetsmiljön och kvalitetsarbetet ut? En behörig chef ger ett godkännande: "Ni har kontroll på läget, ni får fortsätta."
Det är sällan ett projekt stoppas däremot kan man behöva sätta in extra resurser om något halkar efter.

När vi närmar oss projektets slut sker överlämningen. Overlamningsfasen handlar om att introducera kunden, den som ska förvalta anläggningen eller elledningen. Man lämnar över drift- och underhållsinstruktioner, genomför slutbesiktning och sammanställer en form av manual: "Så här sköter ni det om något händer." Det görs också en sista ekonomisk reglering, och projektet avslutas. Samtidigt samlar vi in lärdomar: höll vi kapaciteterna? Vilka leverantörer fungerade bra? Vilka samarbeten fungerade mindre bra?
Här tror jag att vi har stor förbättringspotential. För att bli datainformerade måste vi bli bättre på att samla in information. Om det inte görs ordentligt riskerar all erfarenhet att gå förlorad. De som arbetar i produktionen vill gärna snabbt vidare till nästa uppdrag när ett projekt är klart, och då är det lätt att man tappar just det här avslutet, att fånga upp och reflektera. Men det är en superviktig del för att stänga informationsloopen. Även efter projektets slut finns ansvar kvar. Ett projekt kan pågå i två till tre år, men därefter har vi fortfarande garantitid – ibland upp till fem år. Det ingår i våra åtaganden att genomföra uppföljande besiktningar efter tre och fem år för att säkerställa att allt fungerar som det ska.
Vi arbetar mycket med visuell målstyrning och använder många visuella verktyg. Det är mycket whiteboard, vi skriver ut, ritar, följer upp. Men det vore väldigt bra att få in allt detta digitalt, till exempel i Power BI, så att det samlas på ett ställe.

Frågor och svar:
Vilka är de viktigaste faktorerna för att ta hänsyn till innan man påbörjar planeringen av ett projekt?
Interviewee E:
Det finns en klassisk projektledningstriangel att förhålla sig till: kvalitet, tid och ekonomi. Det är våra ramar, det är de tre faktorerna vi alltid måste balansera.
Om vi till exempel skulle bygga ett höghus med obegränsad budget och obegränsad tid, då skulle vi kunna bygga något med extremt hög kvalitet med material som guld och titan om vi ville. Men i verkligheten har vi ett ganska kort tidsspann och en begränsad budget. Då måste vi förhålla oss till just de tre aspekterna: tid, pengar och kvalitet och hitta en så bra avvägning som möjligt. Vi kan bygga väldigt billigt, med till exempel pappväggar, men då blir kvaliteten därefter. Så det handlar hela tiden om att göra avvägningar mellan de tre delarna: kvalitet, tid och ekonomi.

Interviewee F:
Något som också är viktigt att ta hänsyn till är komplexiteten i det som ska byggas och storleken på projektet. Är det något liknande vi har gjort tidigare? Har vi personer med erfarenhet av liknande typer av projekt? Sådana faktorer är viktiga att väga in för att minska riskerna. Det handlar om att välja projekt där vi har rätt förutsättningar och kompetens, projekt som vi tror passar oss och där vi har goda

chanser att lyckas. Resurser spelar också en stor roll.

Interviewee E:
Något som särskiljer oss som arbetar inom infrastruktur, jämfört med de som jobbar med husbyggnation, är att miljön och de geotekniska förhållandena spelar en avgörande roll, särskilt i elledningsprojekt eller andra stora, långa projekt.
En väldigt viktig faktor är alltså: Hur ser miljön ut? Är det kvicklera, berg, sand? Hur ser marken ut över sträckningen? Det påverkar komplexiteten i projektet i hög grad och måste alltid tas med i bedömningen.

Vilka faktorer påverkar den totala kapaciteten i ett byggprojekt och hur kan detta variera beroende på projektets omfattning?
Interviewee E:
När man tittar på den totala kapaciteten i ett projekt skulle jag säga att det i grunden handlar om ledarskap. Ett större projekt består av många olika discipliner, någon ansvarar för markarbetet, någon för betongarbetet, en annan för montering av stolpar och så vidare. Ibland måste en disciplin hållas tillbaka tillfälligt för att en annan ska hinna komma ikapp, och det bästa för projektet som helhet kan då vara att sänka tempot i en del av arbetet.
Ett konkret exempel: Här på bygget har vi gjort planteringen och allt runt omkring huset, men det fick vi göra ganska långsamt och dessutom ganska dyrt, eftersom våra kollegor behövde ha ställningar och kranar på plats. Då var deras arbete det viktigaste just då. Jag skulle säga att för att nå den totala kapaciteten krävs ett ledarskap som förstår när och var man behöver bromsa och att de olika disciplinerna har förståelse för varandra.

Är det det man menar med critical path? Att man växla mellan vad som är kritiskt just nu?
Interviewee E:
Ja, precis. Det stämmer helt. Det kan vara fyra aktiviteter som pågår samtidigt, men det är bara en av dem som ligger på den kritiska linjen (critical path). Då är det den aktiviteten som är prio ett. De andra kan i vissa fall till och med behöva lämna arbetsplatsen och komma tillbaka om en månad eller ta ett annat jobb under tiden eftersom ytan måste vara tillgänglig för den kritiska aktiviteten.
Det är inte alltid man vet vilken aktivitet som ligger på den kritiska linjen. Den kan variera från dag till dag, vilket gör det hela väldigt komplext. I tidplanen kanske det ser ut som att ”här är den kritiska linjen”, men om någon blir sjuk kan det plötsligt förändras. Då blir en annan aktivitet kritisk. Att ha koll på detta, att ha ett ledarskap som kan hantera förändringar och sätta in rätt åtgärder i rätt tid. Det är avgörande för att nå bra kapacitet i projektet.

Hur ser du på inlärningskurvan i projektet? Om vi ni skapa ett nytt program, hur tror du arbetsledare eller chef kommer att lära sig? Hur implementera vi det i projektet?
Interviewee E:
Det finns många studier som visar att inlärningskurvan förbättras när man upprepar

samma moment. Ju fler gånger man gör något, desto snabbare och effektivare blir man. En viktig faktor är erfarenhetsåterföring och hur vi sparar data. Det är avgörande för att bygga upp en ackumulerad kunskap. Vi var inne på det tidigare, att vi är ganska dåliga på projektavslut. Men vi är också dåliga på att lära oss under själva projektets gång av det som faktiskt händer.

Interviewee F:
Jag tror att en viktig aspekt i det här är tid. När man väljer att introducera en ny metod eller ett nytt arbetssätt måste man också avsätta tid, både för att lära sig och för att återkoppla. Det handlar inte bara om att lära sig själva verktyget eller processen, utan också om att reflektera över det man precis gjort. Gärna i grupp, genom diskussioner och gemensam utvärdering. Tyvärr är tid ofta en bristvara i projekt, och det är där det lätt kan falla bort, tror jag. Det är viktigt att komma ihåg att det behövs tid både i inlärningsfasen och efteråt, för att man verkligen ska ta till sig nya arbetssätt.

Interviewee E:
Kommunikation är också en viktig del, särskilt att lyssna och låta alla komma till tals. Det kan vara en grävmaskinist eller någon annan yrkesarbetare som har en riktigt bra idé om hur något kan göras snabbare. Då krävs det ett ledarskap som är lyhört och kan säga: "Okej, jag hör vad du säger, kanske kan vi göra på det här sättet istället." Det handlar om att anpassa sig efter de man har i laget och utnyttja styrkan i det team man spelar med.

Hur tror ni att en maskininlärningsmodell i projekteringen kan bidra till att öka kapaciteten? På vilket sätt tror ni att det skulle kunna hjälpa?
Interviewee E:
Jag tror att en maskininlärningsmodell kan bidra genom att ge alla en gemensam bild av vilka aktiviteter som faktiskt är viktigast i ett projekt. Den kan hjälpa till att identifiera vilka förhållanden som styr sluttiden. Jag tror inte att själva maskininlärningen i sig kommer vara någon slags knapp man trycker på, och sen är tidplanen klar. Snarare kan den fungera som ett diskussionsunderlag.
Traditionella Gantt-scheman kan upplevas som ganska tråkiga, men om man kopplar mer data till dem så kan man enklare se vad som är viktigt. Modellen kan också hjälpa till att identifiera inte bara vilka moment som ligger på den kritiska linjen, utan också vilka som är mest riskfyllda. Det kan vara ett värdefullt verktyg för att samla och analysera data.
Jag tror också att en sådan modell kan skapa en medvetenhet om varför vi faktiskt måste arbeta mer datadrivet. Det kan bli ett sätt att förstå vikten av att samla in och använda data, inte bara för det aktuella projektet utan även för framtida projekt.
Vi har länge sagt att vi ska bli mer datainformerade, men många har inte riktigt förstått varför. Det handlar om att kunna dra nytta av tidigare erfarenheter, och på så sätt öka kapaciteten över tid. Jag tror att den största effekten av maskininlärningen blir just bättre erfarenhetsåterföring och lärande mellan projekt

Interviewee F:
Det handlar om att inte bara göra det jag tror är bäst, utan att faktiskt utgå från det som har fungerat bäst historiskt. Det är egentligen samma princip som inom forskning man ska basera sina beslut på resultat och beprövad erfarenhet. På samma sätt borde vi i projekt jobba utifrån vad som har fungerat tidigare, snarare än att bara gå på magkänsla eller antaganden.

Interviewee E:
Det sämsta som kan hända är att vi fortsätter göra en viss typ av projekt, till exempel vatten- och avloppsprojekt, där alla projekt under 20 miljoner kronors värde faktiskt går med förlust. Om vi aldrig samlar in den datan så lär vi oss heller aldrig något. Då ser vi inte att vi kanske borde sluta ta den typen av jobb, eller åtminstone göra dem på ett annat sätt.
Det här är ett exempel på hur maskininlärning eller prediktion kan hjälpa oss att lära känna vår egen organisation bättre. Det blir ett sätt att identifiera mönster och fatta smartare beslut framåt.

Hur påverkar tidspress och deadlines kapaciteten i ett projekt, och hur balanserar du mellan kvalitet och hastighet när kapaciteten behöver ökas?
Interviewee F:
Som jag upplever det så kan tidspress och deadlines öka kapaciteten, men bara upp till en viss gräns. När trycket blir för stort och man inte längre hinner med, då kan det vända snabbt. Kapaciteten faller och det kan bli som ett korthus som rasar. Jag tror att tidspress kan vara något positivt, men bara om det sker inom en kontrollerad och hanterbar ram.

Interviewee E:
Återigen kommer vi tillbaka till projektledningens klassiska triangel: kvalitet, tid och ekonomi. Visst är det ofta fokus på tid, att vi måste framåt och lösa saker snabbt, men det kostar pengar och det kan även påverka kvaliteten. Om man vill behålla en hög kvalitet samtidigt som det ska gå väldigt snabbt, då blir det väldigt dyrt. Då kanske man behöver dubbla organisationer, dubbla bodar, extra resurser och så vidare.
Det här projektet som vi har byggt under två år, det går att bygga på tre månader, men det skulle kosta fruktansvärt mycket pengar. Rent personligt upplever jag också att om tidspressen blir för hög och går över en viss gräns, så kan det till slut bli för mycket. Både för individen och för organisationen. Det kan börja falla. Jag tror också att planering spelar en väldigt stor roll inom den här triangeln. Ju mer man kan planera i förväg, desto effektivare, billigare och säkrare kan man arbeta. Men om man inte har tid att planera ordentligt, då kastas man rakt in i produktionen, och då kan det skena iväg i kostnader.

Hur hanterar ni i dagsläget om kapacitet kommer att bli ett hinder i projekt och vilka åtgärder tar ni för att undvika det då?
Interviewee E:
I alla våra projekt har vi en mastertidplan. Den bryts ner till veckoplanering, där

vi tydligt definierar vad som ska göras varje vecka. Varje vecka hålls ett veckomöte där hela projektorganisationen samlas. Det gäller både maskinister, tjänstemän och övriga yrkeskategorier, både från produktions- och tjänstemannasidan. På mötet går man igenom var vi befinner oss, vad som var planerat till den här veckan, och vad vi faktiskt har hunnit med.
Om vi inte nått hela vägen försöker vi identifiera vad som har påverkat och vad som gjort att vi halkat efter.Alla projekt arbetar inte lika aktivt med detta, men vi har en tydlig struktur för våra veckomöten där vi går igenom aktiviteter, utförande och framdrift. Det är just där man ska kunna identifiera om vi håller den kapacitet vi har planerat för, eller om vi behöver justera något.

Interviewee F:
Vi har ett väldigt tydligt exempel just nu, som ni kommer att få se om ni besöker Korsvägen. Det är en så kallad flexstation. Där har vi en planering som innebär att vi ska gjuta varannan torsdag. Inför varje gjutning finns ett antal moment som måste vara klara.
Om vi inte når dit i tid börjar vi direkt fundera på varför. Det kan bero på att vi har mycket sjukfrånvaro, att det saknas formar, verktyg, material eller något annat.Men genom att ha veckovisa eller till och med dagliga avstämningar kan vi fånga upp problemen tidigt. Då hinner vi ofta komplettera det som saknas innan vi missar en deadline.Annars riskerar man att stå där och inse först samma dag att det inte går att genomföra och då är det för sent.

Interviewee E:
Alla projekt är inte där än, men vi jobbar aktivt med att bryta ner det som finns i kalkylen till konkreta mål och nyckeltal. Det kan till exempel handla om att räkna ut hur många kubikmeter schakt vi ska göra per dag, hur många meter ledning som ska läggas per dag, eller hur många lastbilar med jord som ska köras bort från platsen.
Det här är sådant som våra arbetsledare följer upp dagligen för att säkerställa att vi håller den kapacitet som är planerad. Det ideala är att kunna bryta ner kalkylen till tydliga nyckeltal, så att man hela tiden har kontroll på utfallet i förhållande till planen.

Sista fråga: Har ni genomfört ett projekt där ni blev klar före deadline, som t.ex nu: Ingelkärr- Stenkulle med svenska kraftnät. Vad tror du är orsakerna till att ni lyckades med detta?
Interviewee E:
Vi har genomfört många projekt som blivit klara i tid, eller till och med tidigare. Men byggbranschen i stort är ju ofta mer känd för det motsatta. Stora och komplexa projekt är svåra att planera, och det finns många studier som visar hur svårt det är att förutse alla risker. Västlänken är ett typexempel på det.
Jag skulle säga att en viktig orsak till att vissa projekt lyckas bättre är att man får till ett bra samarbete med kunden. Det handlar om att inte jobba mot varandra, utan att alla drar åt samma håll. Ett exempel är vårt projekt med Svenska kraftnät. Där hade vi en öppen ekonomi, vilket innebär att kunden kunde se exakt vilka

kostnader vi hade och vilka fakturor som låg bakom. På det lade vi ett visst påslag. Det är en stor skillnad från klassiska entreprenader, där det ofta är stängda böcker och stängd ekonomi. I den typen av upplägg finns det en risk att varje part bara gör det som är bäst för sig själv. Men om man istället utformar samarbetet så att alla parter gör det som är bäst för projektet, och att det samtidigt blir mest lönsamt för alla inblandade, då ökar sannolikheten att man klarar deadline eller till och med blir klar i förtid.
När samarbetet fungerar och alla fokuserar på produktionen, då går det framåt. Men så fort det blir konflikter mellan parter, då hinner man inte längre fokusera på att driva arbetet effektivt.I många stora projekt är det just kontraktsformen och graden av samarbetsvilja som avgör hur det går.

Interviewee F:
Jag har själv aldrig varit med och genomfört ett projekt hela vägen till slutet. Men jag kan tänka mig att om man har underskattat kapaciteten, alltså om det faktiskt gått snabbare än man trott, då kan det bero på att man varit lite för snäll i tidplanen. Interviewee C kommer säkert att berätta mer om det, men det finns till exempel en kritisk aktivitet i projektet som har att göra med lindragning. Där har teamet arbetat väldigt bra och verkligen klarat av den kapacitet som krävdes. Det visar att rätt insatser på rätt plats kan göra stor skillnad.

A.0.2 Transkription av intervju med Interviewee C och Interviewee D från NCC

Datum: 2024-11-21
Intervjuperson(er): Interviewee C, Interviewee D
Intervjuare: Mohammed Rauf, Ha Vu
Transkriptionen startades och alla deltagare samtyckte till inspelning
Introduktion till projektet:
Syftet med projektet är att kombinera teknisk kompetens och maskininlärning inom byggbranschen för att kunna utveckla en prediktiv modell baserat på Monte Carlo simulering och linjär regression. Modellen syftar på att ge överblick och underlag för beslutsfattande.Prediktiva grafer presenteras för att ge intervjupersonerna en bild av hur resultaten från en maskininlärningsmodell skulle kunna se ut.
Interviewee C och Karlsson arbetar som platschef respektive blockchef på NCC för elledningsprojektet Ingelkärr–Stenkullen. De inledde med att berätta om sina roller, arbetsuppgifter och projektet i stort. Vi intervjuade Interviewee C och Interviewee D separat för att få deras individuella perspektiv.

Frågor och ämne:
Projektledning och Planering:
- Vilka är de största utmaningar du står inför när du kan hantera byggprojekt och dess planering?
- Varför har just detta projekt varit så bra på att hålla deadline?
- Hur resonerar du kring prioriteringar som tid, kostnad och kvalitet?
- Hur ser du på inlärningskurvan i byggprojekt? Vilka faktorer gör att aktiviteter kan utföras snabbare när teamet får mer erfarenhet i slutet av ett projekt?

Verktyg och programvaror:
- Vilka software verktyg använder ni idag som hjälper med planeringen och resursallokering? (Finns det några specifika program som ni använder bortsett från PowerProject)

Prediktiva modeller och digitala verktyg:
- Om detta verktyg implementeras, hur skulle det passa in i dina nuvarande beslutsprocesser?
- Vilka bekymmer har du om ett sådant verktyg?
- Vilken typ av prediktering eller insikter skulle du vilja få från en sådan prediktiv modell?
- Vilka fördelar tror du en predikeringsmodell kan bidra till i en konstruktion projekt?
- Hur ska resultatet på bästa sätt presenteras för att vara enkel för er att implementera i planeringsprocessen?
- Vad skulle du säga är viktigast? Hur modellen fungerar eller endast fokusera på resultatet?

Intervju med Interviewee C:

Vilka är de största utmaningarna du står inför när du hantera byggpro-

jekt och dess planering?
- Då utgår vi alltid från våra kalkyler. Vi gör en kalkyl som vi sedan exporterar till PowerProject. Utmaningen är väl att få ett bra flyt i arbetet, kan man säga. Det kräver ganska mycket arbete att sitta och bestämma hur framdriften ska gå och att vi inte gör två saker samtidigt med samma maskin på olika ställen. Det är mycket sånt jag sitter med i början, att få ihop allt så att det funkar praktiskt.
- Du får ju datan från PowerProject och du kan ha med maskinkoder och alltihop. Men vi använder även andra program utöver PowerProject för att ta fram kalkylen. Excel använder vi mycket. Just i det här projektet upptäckte vi, när vi hade byggt kanske 20–25 % av byggnaden, att vi redan hade förbrukat 50–60 - Det är PowerProject, elanalys, Excel, kartor, var vi befinner oss, väder- Alltså det är mycket som ska vägas in. Ofta gör man så att man kallar det workshop eller brainstorm eller något liknande, där man sitter och frågar: ”Varför hade vi tio bilar till den här grävmaskinen? Var det för många? Eller för få?”
- Det är svårt att sätta ord på, men med erfarenhet får man en känsla ganska tidigt. Man känner det i magen: ’Nej, det här kommer inte funka.’ Man behöver inte ens titta på något, magkänslan säger allt.

Varför har just detta projekt varit så bra på att hålla deadline?
- Det är ett samverkansprojekt där vi har nyttjat vår erfarenhet, beställarens erfarenhet och våra underentreprenörers erfarenhet för att få till ett så optimalt upplägg som möjligt. Redan när vi byggde byggvägarna passade vi på att samtidigt anlägga kranuppställningsplatserna som behövdes för att resa stolparna, så vi behövde bara vara där en gång.
- Konventionellt sett, vilket jag har lärt mig nu, så brukar man först schakta, sedan gjuta fundamenten, och därefter bygga kranuppställningsplatsen. Men i det här projektet valde vi att bygga en gemensam uppställningsyta, en så kallad APD-yta som fungerade både för bodar, för betongbilar och som plats för en mobilkran.
- Jag tror det är en viktig anledning till att det har gått bra. Vi har också haft regelbundna avstämningar varje vecka där vi går igenom: Hur långt hade vi tänkt komma den här veckan? Varför gjorde vi mer än planerat? Varför gjorde vi mindre? Det har gett oss kontroll och möjlighet att justera direkt.

Var vädret någon slags indiktator?
- Ja, det var det. Vädret var absolut en indikator. Anledningen till att vi tappade pengar på byggvägarna var att vi från början hade planerat att bygga på kommunens mark, där vi fått ett löfte om ett frivilligt avtal. Tjänstemännen var redo att skriva på, men politikerna hade en annan agenda, så vi blev tvungna att flytta våra maskiner därifrån.
- Den första platsen hade bra markförhållanden för årstiden, det var en av de bästa platserna att bygga på just då. Men vi fick istället flytta till ett område där vi hade ett annat frivilligt avtal, men som egentligen hade de sämsta markförhållandena för den årstiden.
- Vi hann inte förstärka samfällighetsvägen innan vi började köra där, och det resulterade i att vägen blev sönderkörd. Det blev trafikstockningar, barn kunde inte ta sig till skolan, posten kunde inte levereras, och föräldrar fick stanna hemma från

jobbet. Det blev total kaos. Och det var en stor anledning till att kostnaderna drog iväg.
- Vi gjorde ganska kraftiga insatser här på kontoret. Jag och projektchefen satt och diskuterade: Hur gör vi? Vi hade tio bilar per grävmaskin, vilket jag från början tyckte var lite för mycket, men vi hade 30 bilar som snurrade på samma grusväg, som var kanske fyra meter bred.
- Det var inte optimalt. Arbetsledaren och projektchefen menade att tio bilar gick att hantera, men problemet var att det kom in för mycket grus på för kort tid. Man hann inte bygga vägen ordentligt den blev för tjock, för bred och det innebar att materialkostnaderna drog iväg, och även lastbilstiderna.
- Vi höll tiden för grävmaskinerna, men eftersom vi körde så mycket mer material, blev det ohållbart. Då sa vi: 'Nu får vi sätta oss ner och tänka om.' Vi gick ner till sju bilar per grävmaskin, vilket gjorde att grävmaskinerna kunde hantera materialet mycket bättre. Vi kom längre på varje lass man kan säga att vi fick bättre utdelning per byggmeter väg.
- I början låg kalkylpengen på faktor 2 under de första 25 procenten av arbetet. Därefter lyckades vi faktiskt få ner det till faktor 1, alltså inom budget i stora delar. Men tappet vi hade i början gjorde att vi till slut landade på en faktor på 4,15.
- Vi var snabba med att reagera. Vi såg tidigt att det här inte skulle hålla. Det var inte som att vi gjorde en avstämning och märkte att vi låg 10 eller 20 procent över materialkostnaden, nej, det visade sig att vi hade kommit 25 procent av vägen men redan gjort av med 60 procent av pengarna. Då insåg vi att det inte skulle vända, det skulle bara fortsätta att skena.
- Det handlade om produktionsstyrning, att tänka på ett annat sätt. Arbetsledarna byggde byggvägarna med målet att de aldrig skulle behöva repareras. Men i min kalkyl och budget fanns det med att vi skulle behöva reparera vissa byggvägar här och där. Så det var lite olika sätt att tänka.

Hur resonerar du kring prioritering som tid, kostnader och kvalitet?
- Tid är pengar, det har det alltid varit. Tar det längre tid, så blir det också dyrare. Vi ska bygga det som beställaren efterfrågar, inte något som är "bättre" men som vi ändå inte får betalt för.
- Tid och kostnad går ju hand i hand genom hela livet, så är det bara. När det kommer till kvalitet... Jag vill ju kunna se tillbaka på mitt jobb om 15 år och fortfarande känna mig stolt över det.
- Jag kan inte riktigt sätta en exakt prioritet på tid, kostnad och kvalitet, det är inte så enkelt som att säga "1, 2, 3". Men om jag ändå ska försöka, så är tid och pengar nästan samma sak, de får dela första plats, och kvalitet kommer som 1.5.
- Samtidigt kan det vara så att just kvaliteten gör att det tar lite längre tid och kostar lite mer. Men det är också det som gör att du får ett godkänt slutbesked. Så... ja, jag vet inte exakt. Det är alltid en balans.

Hur ser du på inlärningskurvan i byggprojekt? Vilka faktorer för att aktiviteterna kan utföras snabbare när teamet får mer erfarenhet i slutet av projektet?
- Det vi brukar kalla inarbetning, det är ju en naturlig del. Den kurvan är oftast

brantare när det handlar om moment som vi inte har gjort tidigare.
- Vad ska jag säga mer... Det finns ju alltid någon form av inarbetning. Man hamnar kanske i ett nytt team, och det tar ett tag innan alla lär känna varandra, innan alla hittar sin roll.
- Det är svårt att sätta en exakt procentsats på hur mycket tid man kan kapa genom inarbetning, eller exakt hur det ska göras. Men visst, man kanske kan kapa 10 %, 20 % av tiden? Jag vet inte riktigt. Det beror på många faktorer.
- Vi pratar nog inte om veckor av inarbetning. Vi pratar snarare om en månad eller två. Det beror naturligtvis på individen. Vissa hittar varandra direkt och fungerar ihop utan att man ens behöver diskutera det, medan andra behöver lite mer styrning.
- Men om man ska kunna se en tydlig effekt av inarbetningen, så skulle jag nog säga att det tar en till två månader.

Om man hade implementerat detta verktyg, hur skulle det passa in i er beslutprocess?
- Jag försöker bara fundera på vad jag ska säga för att inte låta alltför negativ. Hela det här, med de skuggade delarna i diagrammen, det sker ju här uppe konstant [*pekar på huvudet*]. Jag vet inte om jag personligen behöver se det i ett diagram.
- Men jag tror ändå att det är bra. Jag tror att det är jättebra, faktiskt. Det gäller verkligen att man får in rätt data för att få ett meningsfullt utfall.
- Vi har ju jobbat med visualiseringar tidigare. Tyvärr har vi slaktat hela det rummet nu. Vi hade whiteboardtavlor där vi följde upp betongen. Först gick det bra, men sen hade vi en period där det inte flöt på. Det tunga arbetet gick inte som planerat, vi gjöt inte det vi hade kommit överens om.
- Då satte vi upp en whiteboard med stolpnummer, planerad gjutning, och faktiskt utfall. 0 %, 50 %, 100 %, det satt mitt i korridoren, så oavsett om du var snickare, armerare eller platschef så såg du det direkt. 100 % skrevs i grönt, 0 % i rött, jag minns inte exakt vad vi hade för 50 %, men det blev väldigt tydligt. Principen är densamma som med graferna. För mig var whiteboarden mycket tydligare. Jag tror mycket på visualisering, absolut. Så ja, jag tror att de här graferna är tydliga men inte för en markarbetare, armerare eller snickare. Men jag skulle absolut kunna använda dem om det inte kräver för mycket jobb eller tid.
- Jag tror det finns en tydlig generationsskillnad. För mig känns det mer naturligt att gå till beställaren och säga att något inte känns rätt, snarare än att visa en graf. Men för den yngre generationen är databaserade beslut mer accepterade, och jag tror att sådana verktyg kommer bli allt mer normala i branschen framöver.

Vissa företag har grundkurser för de anställda för att lära dem nya program. Hur gör ni på NCC?
- Vi har kurser för allt. Vi har gått flera PowerProject kurser och kommit upp till en viss nivå, men sen blir det svårt att hitta lärare som kanta oss vidare. Problemet är också att man går på en kurs, känner sig redo men sen kanske man inte använder vertyget förran ett år senare i ett nytt projekt och då har man glömt det mesta.

Intervju med Interviewee D:

Vilka är det största utmaningar ni står för när ni hanterar ett byggprojekt och dess planering?
- Det varierar väldigt mycket skulle jag säga. Men det viktigaste är nog att få allt att klaffa, att saker görs i rätt ordning. Sen kan man aldrig helt veta vad som finns i marken när man börjar gräva till exampel.

Finns det några program som ni använder nu för att utföra dessa aktiviteter?
- Jag använder BluBeam och andra program. Det är ju ett program som SVK har där man kan bland annat möta och se tomt- eller fastighetsgränser som underlättar mitt arbete.

Varför har ni varit så bra på att hålla deadlines för detta projekt?
- Det har mycket att göra med alla som varit involverade i projektet. Alla har haft en vilja att driva arbetet framåt, varit samarbetsvilliga, och ingen fråga har känts dum eller fördomsfull.
- Ibland kan man tveka och tänka: ”Vågar jag verkligen ställa den här frågan?” Men här har det aldrig varit ett problem. Man har kunnat ställa så kallade ”dumma frågor” utan att någon reagerat negativt, tvärtom, man har fått hjälp hela tiden.
- Vi har också jobbat väldigt tätt tillsammans. Det har inte varit så mycket mejlande fram och tillbaka man har kunnat gå direkt till någon, ställa sin fråga och få ett svar direkt.

Hur resonerar du kring prioriteringar som tid, kostnad och kvalitet?
- Jag vill ju få allt att hålla samma nivå, skulle jag säga. Man försöker hålla en jämn standard genom hela projektet.
- Om vi tar byggvägarna som ett exempel, där byggde vi först nästan för bra. Men sen hade vi ett möte, och vi lyckades sänka kostnaden rejält, utan att tumma på kvaliteten.
- Standarden var ändå densamma, även om vi gjorde det mer kostnadseffektivt. Så det handlar om att hålla balansen att göra ett bra jobb, men samtidigt ha kontroll på kostnaderna.

Hur ser du på inlärningskurvan i byggprojekt, vilka faktorer gör så att aktiviteterna kan utföras snabbare när teamet får mer erfarenhet i slutet av projekt?
- Tidplanen är verkligen ett nyttigt verktyg. Där ser man direkt om något börjar luta åt fel håll. Man får mycket information om hur arbetet går, även om jag också kan gå ut och se med egna ögon att det inte går som det ska. Men tidplanen ger en helhetsbild av hela kedjan, inte bara mina specifika arbetsuppgifter. Man ser hur allt hänger ihop.
- Det går snabbare efter någon månad in i projekt. Byggvägarna är ett bra exempel. Vi har lärt oss enormt mycket där både hur man kan hålla nere kostnaderna och samtidigt behålla samma standard. Jag har i alla fall lärt mig mycket.

- Till exempel att man faktiskt kan bygga en väg rakt över en mosse, istället för att gå runt den. Med hjälp av virke kan man skapa en stabil grund, och det har sparat både tid och resurser.

Baserat på det du såg, grafen från ML modellen, hur skulle du kunna se att något sådant implementeras i er beslutsprocess under projektets gång?
- Det här är ju fortfarande ganska nytt, men precis som med allt annat, ju mer tid man får arbeta med det, desto bättre blir programmet, skulle jag tro.
- Om systemet kunde ta hänsyn till faktorer som vädret och årstider, så tror jag att det också skulle kunna identifiera faktorerna bakom förseningar snabbare.
- Det här är framtiden, så tror jag att det också skulle kunna identifiera faktorerna bakom förseningar snabbare.

Du såg graferna som vi visade, har du någon recommendation på hur man presenterar resultatet? Vad är det viktigaste egentligen? Att ni ser prognosen eller hur modellen tänker?
- Det ni visade är bra. Jag tror verkligen att ju mer ni får arbeta med programmet, desto bättre kommer det att bli.
- Just nu var det ganska luddigt för oss som aldrig har sett det tidigare men jag tror att om man får jobba lite mer med det och ni behåller samma struktur, så blir det mycket lättare.
- Det viktigaste är att förstå hur programmet ”tänker”, skulle jag säga. Så att det inte arbetar i en helt annan riktning än vi själva gör. Annars blir det lätt väldigt förvirrande.

Hur brukar teamet anpassa sig efter ny teknologin?
- Det beror mycket på vem det är, skulle jag säga. Jag själv är väldigt intresserad av sånt här och har ganska snabb inlärningsförmåga.
- Men sen finns det ju äldre personer som knappt vet hur man sätter på en telefon, för dem tar det längre tid. Samtidigt är den generationen på väg ut ur arbetslivet, många går i pension nu.
- Det kommer in yngre förmågor, och samhället idag är ju byggt på datorer. Så jag tror att det här kommer bli lättare med tiden.

A.0.3 Transkription av intervju med Svenska Kraftnät

Datum: 2024-12-13
Intervjuperson(er): Interviewee A och Interviewee B
Intervjuare: Mohammed Rauf, Ha Vu
Transkriptionen startades och alla deltagare samtyckte till inspelning
Introduktion till projektet:
Syftet med projektet är att kombinera teknisk kompetens och maskininlärning inom byggbranschen för att kunna utveckla en prediktiv modell baserat på Monte Carlo simulering och linjär regression. Modellen syftar på att ge överblick och underlag för beslutsfattande.Prediktiva grafer presenteras för att ge intervjupersonerna en bild av hur resultaten från en maskininlärningsmodell skulle kunna se ut.
Interviewee A och Interviewee B introducera sig själva och deras roller i Svenska Kraftnät.
Frågor:
• Har ni använt AI-verktyg i era projekt tidigare, eller har ni funderat på att använda det?
• När ni påbörjar ett nytt projekt, vilka risker eller utmaningar stöter ni oftast på?
• Hur brukar ni, som kund, agera när det uppstår oväntade förseningar i projekt?
• Vilka typer av data eller rapporter är mest användbara för er när ni ska fatta beslut under projektets gång?
• Hur tycker ni att projektets framsteg bäst kan visualiseras?
• Om ni fick se ett resultat från en projektledare som genererats med hjälp av AI, hur skulle ni känna kring att lita på det?
• Vad tror ni skulle krävas för att öka ert förtroende för AI-genererade resultat?

Frågor och svar:

Har ni från Svenska Kraftnät använt AI i projekt? Om inte, vilket program använder ni och vilka utmaningar uppstår i planering?

- Nej, det skulle jag säga att vi inte har gjort, inte inom projektverksamheten. Jag vet att det har funnits ett projekt inom underhåll där man använt AI drönare för att upptäcka felmönster på våra stolpar, men inte i någon form av planeringssyfte. Inte vad jag vet, i alla fall.
- Vi brukar använda Microsoft Project och rita upp en plan.
- Våran utmaning är ju egentligen att vi har långa projekt, traditionellt mellan 10 och 14 år vilket för det oerhört svårt att uppskatta tidsåtgången för olika delmoment. Vi har dessutom många boroende till externa intressenter som myndigheter, länsstyrelser och kommuner. Istället för att söka bygglove, vi söker något som heter koncession. Dessa myndigheter, om jag kan uttrycker mig så- lite slumpmässig svarstider. Det är väldig svårt att veta om det ta tre månader, sex månader eller ett år innan vi får besked, vilket gör det svårt att planera.
- Så det är där våra största utmaningar ligger. Vi arbetar inte med produktionsplanering på det sätt som man gör inom NCC. Vår planering är inte heller lika repetitiv det handlar inte om att exempelvis bygga 57 stolpar, som i Ingelkärr Stenkullen, utan tidplaneringen sker på en helt annan nivå.

När det kommer till förseningar, finns det något ni önskar som skulle kunna förbättra processen vid förseningar?
- Det viktigaste vore att länsstyrelsen och kommunen håller sina löften, att de svarar i tid och när de har sagt att de ska. Den stora utmaningen är att det är väldigt svårt att förutse hur lång tid tillståndsprocessen tar. Det är egentligen inte kopplat till entreprenörens tidplan, utan deras del är bara en period i det hela.

Får ni detaljerad uppdatering från NCC eller mer övergrippande information och tror ni det vore värdefullt med modellet som visar vad som går bra eller dåligt i projektet?
- Vi får en ganska deljerad tidsplan med vad som ska göras, sen brukar vi ha en kortare, mer deljerad produktionstidplan som kanske sträcker sig över en månad som visar alla aktiviter. Det är oftas en PDF fil som vi har.
- Det skulle vara jättevärdefullt för oss att veta exakt vad som orsakar förseningar eller ineffektivitet, så vi kan göra ändringar och förbättra processen. Svenska kraftnäts stora utmaning är att vi ska genomföra väldigt mycket på väldigt kort tid. Så om vi kan få information om vad det är som gör att saker drar ut på tiden, eller vad som gör arbetet ineffektivt, så kan vi faktiskt påverka det göra justeringar som förenklar och förbättrar processen.
- Det är förstås svårt att säga exakt vilken detaljeringsnivå som behövs. Men allt som hjälper oss att fatta bättre beslut eller göra ändringar som gör att saker går snabbare och blir mer effektiva, det är otroligt positivt.

Skulle ni kunna lita på ett AI-genererat resultat från en projektledare?
- Jo, det skulle vi nog kunna ha användning av, om man bara får se logiken och förklaringarna bakom resultaten. Det tror jag. Det är i alla fall min känsla. Jag vet inte om du har något att tillägga, Interviewee B?
- **Interviewee B:** Nej, jag är också lite omodern för att vara ung. Jag har inte heller använt ChatGPT eller AI så mycket.
- Men jag tänker lite som du var inne på: så länge man har koll på vad inputen är, och man upplever den som trovärdig och vet vad AI:n är tränad på. Då tror jag att man kan ha förtroende för den.
- I början är det nog lite osäkert, eftersom modellen måste övas upp på olika projekt. Men det är definitivt framtiden, jag tror man kan få väldigt stor nytta av det.

Det här är väldigt intressant. Vi ställde samma fråga till platschefen i ett annat projekt. Han hade 35 års erfarenhet. Han försökte se det positivt, men landade ändå i att han litade mest på sin magkänsla. Och jag håller med, det är fullt förståeligt. Men när man ska förklara något för en kund, eller i ett möte med andra intressenter, kan det ibland vara enklare att visa sin magkänsla genom en graf, snarare än att säga "jag känner det på mig". Så därför vill jag ställa samma fråga till er: Vad är viktigast för er? En enkel graf som visar nuläget och vad som väntar, eller en tydlig förklaring till hur programmet har resonerat och räknat fram resultatet?

- Jag tror att man i första hand vill ha en enkel bild, något som ger en överblick. Till exempel: om det har gått långsamt, vad är det då som har tagit tid?
- Om man kan få en tydlig sammanställning som ger en översikt, så tror jag att det är väldigt värdefullt. Samtidigt vet jag att det kommer att väcka frågor och då behöver man också en mer förklarande bild eller underlag. Något som visar: ”Vi har tagit in den här datan, bearbetat den, och kommit fram till de här slutsatserna.”
- Så för att det ska vara lätt att använda i praktiken behöver man en bra översiktsbild. Men för att folk ska kunna lita på det, måste man också förstå logiken bakom.
- Man vill ju att det ska komma ut något konkret, som: ”Om du gör så här istället, så skulle du kunna öka tempot.” Det hade varit perfekt att kunna se tydligt: ”Det är de här momenten som gör att det tar längre tid, eller att det drar ut på en vecka extra.”
- Det tror jag är jättebra att få fram i en bild, och sen kunna underbygga den med ytterligare information som vilken data som använts och hur den har bearbetats. Så jag skulle säga att det behövs lite av båda delarna.
- Det optimala vore ju att de två sakerna: magkänslan och datan kunde komplettera varandra. Så att när Interviewee C säger ”Jag har en känsla av att det här inte stämmer”, så kan han också säga: ”Och det stöds dessutom av det här underlaget.”
- Det är dit man vill komma att använda visualiseringar och data som ett stöd och komplement i sådana diskussioner. Det tror jag skulle vara väldigt värdefullt.

Hur brukar ni, kunderna anpassa sig till nya verktyg och teknologier? Om till exempel NCC skulle börja använda AI, hur skulle ni förhålla er till det?
- Som myndighet är vi generellt ganska långsamma när det gäller förändring, skulle jag säga. Vi är inte lika benägna att ta in ny teknik eller nya idéer.
- Ofta är det privata aktörer som driver utvecklingen framåt, med fokus på produktionstänk och effektivitet, eftersom det ofta kan kopplas direkt till ekonomi. Det betyder inte att ekonomi är oviktigt för oss som myndighet men det har inte samma fokus eller status. För oss handlar det mer om att allt ska gå rätt till, vara tryggt och leda till rätt kvalitet. Det är vår grundläggande utgångspunkt.
- Däremot står vi nu inför vissa utmaningar. Vi ska göra mycket på kort tid, och vi behöver hitta sätt att bli mer effektiva. Jag tror att om man kan visa på konkreta tidsbesparingar med hjälp av AI-genererad dataplanering, så skulle vi absolut kunna ta till oss det. Eller, jag hoppas det i alla fall.
- Traditionellt sett har vi dock inte varit lika snabba på förändring som andra aktörer i branschen.
- **Interviewee B**: Vi har också mer interna krav på att vissa specifika programvaror måste användas, till exempel för rapportering. Men när det gäller verktyg i själva projektet så finns det ofta inga fasta krav.
- Nej, oftast inte. Om en entreprenör använder ett verktyg som effektiviserar arbetet, så står det dem oftast fritt att använda det, beroende på hur kontrakten är utformade.
- När det gäller att bygga en elledning sker det ofta genom konkurrensutsatt upphandling, där priset är en mycket viktig parameter.
- Om entreprenören har interna verktyg som skapar effektivitet, är det en konkur-

rensfördel och inget vi lägger oss i. Däremot är det värdefullt för oss att få information och återkoppling kring vad det faktiskt är som tar tid i projekten.

Jag tror att vi nästan har kommit till den sista frågan. Jag tänker på visualiseringen ni såg tidigare (graferna). Frågan är: Hur lätt är den att förstå? Jag skulle nog inte säga att det är helt lätt direkt
- Det är ju inte helt lätt att greppa vad det är man presenterar här, skulle jag säga.Jag tänker att syftet med visualiseringen är att man ska kunna se skillnaden mellan det som var planerat och det faktiska utfallet. Och då måste det nog vara något i den här stilen, tänker jag.
I bilden att det här är det som är planerat. Vi önskar att vi hade kunnat presentera det på ett enklare sätt, men vi har inte kommit på något bättre. Vi tänker att era ögon kanske ser något som vi själva inte ser, att ni kanske kan komma på ett tydligare sätt att visa det.
- **Interviewee B**: Något jag fick lära mig redan i skolan var att en graf alltid ska kunna stå för sig själv. Det innebär att axlarna ska ha tydliga rubriker som förklarar vad de visar, och att själva diagrammet ska ha en rubrik som tydligt beskriver vad man tittar på.
- På så sätt kan man lyfta ut grafen ur sitt sammanhang och ändå förstå den direkt, utan att behöva kompletterande förklaringar.
- Nu är det visserligen visuellt snyggare utan rubriker, men en så enkel sak som en tydlig titel gör stor skillnad för att förstå vad som presenteras.