Master's thesis

NTNU
Norwegian University of Science and Technology

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Integrating System Dynamics Modelling and Machine Learning to Improve Safety in Construction Projects

Master's thesis in Engineering and ICT
Supervisor: Antoine Rauzy
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ABSTRACT

This master's thesis is part of the DiSCo research project, which aims to investigate the potential for developing a machine learning (ML) tool to improve accident risk in the construction industry. The objective of this master thesis is to address the research question of integrating system dynamics modeling and ML to enhance the assessment of construction projects, with a primary focus on reducing accident occurrences. While another thesis focuses on the planning phase, this thesis specifically models the construction phase of building projects. The adopted methodology aims to gain a better understanding of industrial accidents in construction projects by creating a metaphor model and exploring variable dynamics. The model is intended to serve as a learning laboratory and communication tool for stakeholders.

The simulation model generates a specified number of projects and an output indicating the number of accidents that occurred during each project based on various indicators that affect the safety performance in projects. The projects are simulated to encompass both fatal accidents and serious accidents, as these two categories exhibit notable disparities in their frequency of occurrence. The model's potential and reliability are further assessed by conducting experiments that involve exploring the model's functions and datasets generated by the model. Moreover, several ML algorithms are utilized to explore the applicability of ML in accident prediction for construction projects. The algorithms employed in this study consist of Support Vector Machine (SVM), XGBoost, AdaBoost, Random Forest (RF), and Decision Trees. These algorithms are applied to datasets collected from the planning phase, along with the corresponding accident records during the construction phase of the projects.

The findings from the experiments demonstrate that the model can simulate projects that closely resemble reality to a certain extent. The study reveals the complexity of accidents and the challenges associated with predicting them, par-

ticularly in the case of fatal accidents. These incidents are influenced by a multitude of factors, including various events, conditional probabilities, and inherent randomness. However, based on the outcomes of applying ML to the dataset encompassing serious accidents, it is evident that the models possess the ability to predict a significant amount of projects with accidents. This observation underscores the potential of this technology in enhancing the safety standards within construction projects.

In terms of future work, the developed model would benefit from validation using real-world data and conducting validation tests to ensure its accuracy. Furthermore, the assumptions made during the construction of the model should be validated by domain experts to enhance its reliability and effectiveness. Collaborating with industry experts is also crucial to incorporate varying accident rates for each activity during a project, improving the model's precision in predicting accidents. Furthermore, exploring the inclusion of accident types in the model could provide insights into patterns and severity, leading to targeted safety measures and reduced overall accident incidence. However, careful consideration is needed to balance model complexity and accuracy. Continuous refinement, validation, and collaboration with experts are key to enhancing the model's predictive capabilities and promoting effective accident prevention in construction projects.

Overall, the study explores the use of digital solutions to address challenges in the construction industry. The findings showcase the model's potential as a proof-of-concept for leveraging modeling and ML techniques to enhance safety in the construction industry. It has the capacity to initiate discussions among project managers and foster a deeper understanding of the complexities inherent in construction projects.

SAMMENDRAG

Denne masteroppgaven er en del av forskningsprosjektet DiSCo, som har som mål å undersøke potensialet for å utvikle et verktøy basert på maskinlæring (ML) for å forbedre risikohåndtering av ulykker i bygge bransjen. Målet med denne masteroppgaven er å undersøke metoder for integrering av systemdynamikk-modellering og ML for å forbedre håndtering av ulykker i bygg og anleggs prosjekter. I denne oppgaven er hovedfokuset å modellere byggefasen av bygningsprosjekter, mens en annen oppgave tar for seg planleggingsfasen. Den anvendte metodikken har som mål å oppnå bedre forståelse av industrielle ulykker i byggeprosjekter ved å skape en metaforisk modell og undersøke dynamikken blant ulike variable. Modellen er ment å fungere som et kommunikasjonsverktøy for interessenter.

Simuleringsmodellen genererer et bestemt antall prosjekter og et antall ulykker som har oppstått i løpet av hvert prosjekt basert på ulike indikatorer som påvirker sikkerheten i prosjektene. Prosjektene blir simulert for å omfatte både dødelige og alvorlige ulykker, ettersom disse to kategoriene viser betydelige forskjeller i forekomsten deres. Deretter, blir modellens potensial og pålitelighet evaluert gjennom utførelse av eksperimenter som innebærer å utforske modellens funksjoner og de datasettene den genererer. Videre benyttes flere ML-algoritmer for å utforske bruken av ML i forhold til å forutsi ulykker i byggeprosjekter. Algoritmene som er brukt i denne studien inkluderer Support Vector Machine (SVM), XGBoost, AdaBoost, Random Forest (RF) og Decision Trees. Disse algoritmene blir anvendt på datasett innhentet fra planleggingsfasen, sammen med tilhørende ulykkesregistreringer som oppstår under byggefasen av prosjektene.

Resultatene fra eksperimentene viser at modellen i noen grad kan simulere prosjekter som ligner virkeligheten. Studien avdekker kompleksiteten ved ulykker og utfordringene med å forutsi dem, spesielt når det gjelder dødelige ulykker. Disse hendelsene påvirkes av en rekke faktorer, inkludert ulike hendelser, betingede sannsynligheter og tilfeldigheter. I henhold til resultatene av å anvende ML på

datasettet som omfatter alvorlige ulykker, er det imidlertid åpenbart at modellene har evnen til å forutsi en betydelig mengde prosjekter med ulykker. Denne observasjonen understreker potensialet denne teknologien har for å forbedre sikkerhetsstandardene innenfor byggeprosjekter.

Når det gjelder fremtidig arbeid, vil den utviklede modellen dra nytte av validering med virkelige data og gjennomføring av valideringstester for å sikre nøyaktighet. Videre bør antakelsene som er gjort under konstruksjonen av modellen valideres av fagpersoner innen feltet for å øke påliteligheten og effektiviteten av modellen. Samarbeid med eksperter innenfor bygge bransjen er også avgjørende for å inkorporere varierende ulykkes rater for hver aktivitet i et prosjekt og forbedre modellens presisjon i å forutsi ulykker. Å undersøke inkludering av ulike ulykkes typer i modellen vil også kunne gi innsikt i mønstre ved ulykker og alvorlighetsgrad, og bidra til målrettede sikkerhetstiltak og redusert ulykkes frekvens. Imidlertid er det viktig å nøye vurdere avveiningen mellom modellens kompleksitet og nøyaktighet. Kontinuerlig forbedring, validering og samarbeid med eksperter er nøkkelen til å styrke modellens prediktive evner og fremme effektiv ulykkesforebygging i byggeprosjekter.

Samlet sett undersøker studien bruken av digitale løsninger for å takle utfordringene i bygge bransjen. Resultatene demonstrerer modellens potensial som et konseptbevis for å utnytte modellerings- og maskinlæringsteknikker for å forbedre sikkerheten i bygge bransjen. Den har evnen til å initiere diskusjoner blant prosjektledere og fremme dypere forståelse av kompleksitetene som ligger i byggeprosjekter.

PREFACE

This master's thesis finalizes my studies at the MSc program in Engineering and ICT at NTNU with a chosen main profile within Machine Technology. The report is written during the spring semester of 2023 under the Department of Mechanical and Industrial Engineering, and builds on findings from the specialization project carried out in the previous semester.

First of all, I would like to give a major thanks to my supervisor Professor Antoine Rauzy for the valuable and excellent guidance throughout the whole process, as well as for the numerous insightful discussions related to the project. I would also like to thank Professor Nils Olsson for valuable input on the project, and the rest of the DiSCo project for participating in feedback and discussions about the work conducted during this thesis. Additionally, I would like to acknowledge the excellent collaboration with Ingrid Borkenhagen and Jenni Sveen Olsen throughout this project. Finally, I am grateful to my family and fellow students for continuous motivational support throughout the semester.

Josefine E. Stiff Aamlid

Trondheim, 11.06.2023

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ABBREVIATIONS

List of all abbreviations in alphabetic order:

- **AdaBoost** Adaptive Boosting
- **AI** Artificial Intelligence
- **ConAc** Construction Accident Causation
- **CSV** Comma-Separated Value
- **DiSCo** Digital predictions of Safety Construction
- **HSE** Health, Safety and Environment
- **NAV** Norwegian Labour and Welfare Administration
- **NLIA** Norwegian Labour Inspection Authority
- **NTNU** Norwegian University of Science and Technology
- **ML** Machine Learning
- **PERT** Program Evaluation and Review Technique
- **RF** Random Forrest
- **SD** System Dynamics
- **SSB** Statistics Norway
- **SVM** Support Vector Machine
- **VS Code** Visual Studio Code
- **XGBoost** Extreme Gradient Boosting

CHAPTER

ONE

INTRODUCTION

This master's thesis is a continuation of a specialization project completed in the fall of 2022, and as such, some sections of the theoretical background have been taken from it. The project of this thesis is conducted in collaboration with another master thesis titled "Combining System Dynamics and Machine Learning for Predicting Safety Performance in Construction Projects" authored by Ingrid Borkenhagen and Jenni Sveen Olsen [1]. Thus, there are numerous similarities between the two theses, as they both share results from the same model. However, the two theses have different focuses on the developed model. This thesis is centered around the construction phase of a project, whereas the other thesis primarily focuses on the planning phase.

1.1 Motivation

The construction industry is one of the most hazardous industries, accounting for 3.6 deaths per 100,000 workers in 2019, compared to 1.1 deaths per 100,000 workers in other sectors [2]. In addition to these fatalities, there are many near-misses and accidents with lower severity that can result in significant costs for both companies and society as a whole. Previous literature suggests that increased focus on digitization in various industries can be a tool to reduce the risk of accidents. Nonetheless, the utilization of digitization in the construction industry is not without its challenges, with the scarcity of accident-related data emerging as a notable obstacle. Therefore, it is interesting to study the implementation of system dynamics modeling in the construction industry, specifically for simulating accident data, and further explore the integration of machine learning techniques to enhance safety predictions. This leads to the research question of this master thesis: How can a proof-of-concept approach that integrates system dynamics modelling and machine learning be utilized to generate and assess construction projects, with the aim of improving safety predictions?

The Research Project DiSCo

This master's thesis is associated with the DiSCo research project, which has been initiated by NTNU in collaboration with industry partners to address the safety challenges of the construction industry. Led by the Department of Industrial Economics and Technology Management at NTNU, the project commenced in December 2021 and is scheduled to conclude in December 2025. Its primary objective is to enhance knowledge and methods for utilizing artificial intelligence in the early stages of construction projects, to predict future safety levels during production and provide better decision-making support to reduce the number of accidents in the industry [3]. The project aims to identify the critical factors in the early project phases that can impact the control of danger sources in the production phase, as well as the relevant data that can be leveraged to forecast future danger sources [3]. Not only safety data but also project-related data will be considered for this purpose, and incorporated into models and machine learning techniques [3]. The DiSCo project is expected to contribute to the development of safe and secure working environments, thus promoting sustainability in the construction industry [3].

1.2 Project Description

In this project, a simulation model of construction projects is developed using the system dynamics modeling approach. The model is being built using a combination of empirical data, such as accident statistics in the construction industry, and knowledge that is obtained from literature on causal factors of accidents. The model consists of a set of interrelated variables and equations that represent the different factors that affect the likelihood of accidents in a construction project, such as quality of equipment, and weather conditions during the work. The model is used to simulate construction projects and analyze the impact of these factors on the likelihood of accidents. The simulation is used to generate data based on initial conditions and input variables. This is done by running the simulation and recording the output data, which is further used as synthetic data for investigations through machine learning algorithms. These algorithms are employed to predict the safety performance of the projects. Ultimately, the aim of the project is to create a proof-of-concept model of a construction project that can help improve the safety in the construction industry.

1.3 Thesis Structure

The organization of the remaining chapters in this thesis is as follows: In the upcoming chapter, the relevant theory that underlies the developed model is explained. Chapter 3 then delves into the methods employed for model development, providing a detailed account of the code implementation and the software employed. The chapter also provides a comprehensive description of the conducted validation tests of the simulation model and how the ML model is employed. Subsequently, in chapter 4, the results from the validation tests and ML algorithm's performances are presented, along with a concise discussion. This chapter also includes a section dedicated to discussing future research opportunities for the model. Finally, chapter 5 serves as a comprehensive summary of the work conducted throughout the thesis, encapsulating the key findings and contributions.

CHAPTER

TWO

BACKGROUND THEORY

This theory aims to provide an understanding of the concepts underlying the work of the thesis. It presents a detailed analysis of the construction industry, focusing on the risk profile and accidents, as well as an examination of the different phases of a project and their interrelationships. The theory further utilizes the principles of system dynamics as a foundation for constructing a simulation model, which enables the exploration of industry behavior under various scenarios. Additionally, the application of artificial intelligence in construction projects is presented, along with an introduction to machine learning techniques. Furthermore, the theory explores the potential interactions between system dynamics and machine learning, highlighting how their combinations can enhance the benefits derived. By utilizing these theories, this project aims to contribute to a better understanding of the construction industry and how digitization can be utilized as a valuable tool for improving safety in this sector.

2.1 The Construction Industry

The working methods in the construction industry are characterized by being project-based [4], where each project is unique with its own goals, timelines, and resources. Construction projects are often characterized by the involvement of many different actors who perform their specified tasks in different parts of the project, such as architectures, engineers and project managers [5]. There are many small businesses in the industry and the need for labor fluctuates with economic cycles, making them reliant on flexible access to labor [5]. The industry is also characterized by complexity, extensive use of subcontractors, and bidding competitions. These structural characteristics make it particularly challenging to carry out good occupational health and safety work [5]. Thus, accident investigations in the construction industry are influenced by unique project characteristics such as varying company sizes, construction site dimensions, resource availability, and the expertise and experience of managers and workers [6]. It is a complex and hazardous industry that involves a wide range of activities, including design, planning, construction, and maintenance.

2.1.1 Risk Profile in the Construction Industry

The construction industry has been highly susceptible to work-related accidents [7]. The industry has historically had the highest number of work-related fatalities per year and is the fourth industry with the highest frequency of work-related fatalities (number of work-related fatalities per employed person) in the period 2012-2017 [7]. Figure 2.1.1 presents a compilation of all work-related fatalities for the period 2012-2021 in connection with construction projects [2]. In 2018, there were 2670 non-fatal work-related injuries and only four work-related fatalities in the construction industry. This is the lowest number of work-related fatalities in ten years, but in the period 2019-2021 the statistics show a negative trend with 8 and 9 work-related fatalities in connection with construction projects [2].

In 2021, there were 2978 reported cases of injury in the construction industry [2]. This is an increase of approximately 500 from the previous year, and the highest number recorded in the statistics dating back to 2014. Additionally, the risk of injury per 1000 employees showed a significant increase. In 2021, there were 11 reported cases of injury per 1000 employees. This is the highest since 2016 and an increase from 9.3 in 2020 [2]. Additionally, the Norwegian Labour Inspection Authority (NLIA) highlights underreporting of accidents with serious injuries to both the authorities and work-related injuries reported to the Norwegian Labour and Welfare Administration (NAV) [2]. This suggests that the actual number of work-related accidents may be higher than what is presented in official statistics on work-related injuries and fatalities. Thus, the statistics are not entirely complete but can still be used as an indicator of safety in the industry [7].

2.1.2 Influencing Factors on Accidents

Further insight into accidents and safety can be gained by focusing on factors such as work systems, project management, and higher management, as well as framework conditions. A simplified model of Rasmussen's socio-technical system is visualized in Figure 2.1.2. His aim of the model was to demonstrate how levels, disciplines, and factors, both external and internal, can influence and control

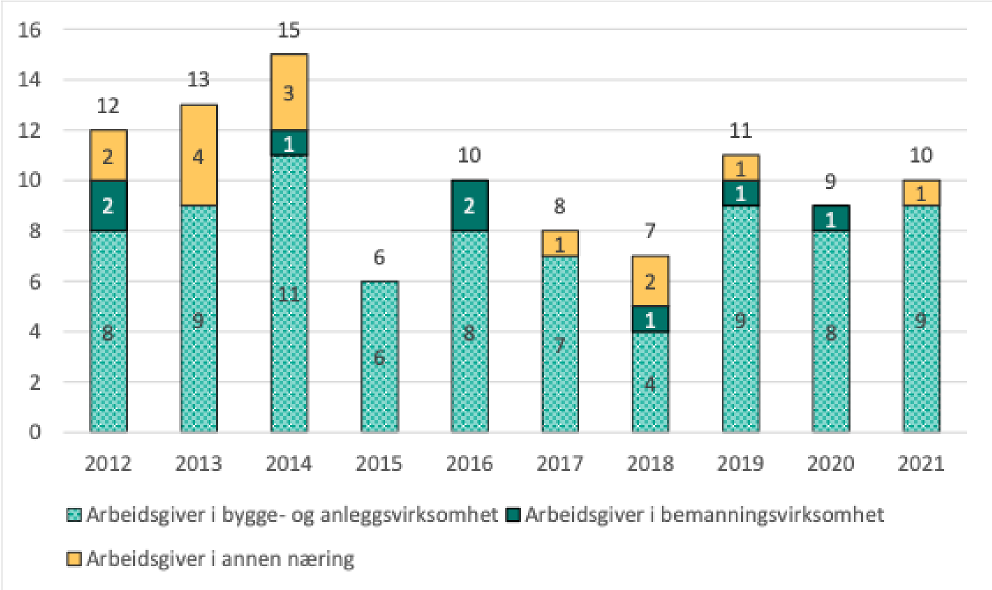


Figure 2.1.1: The number of work-related fatalities in the construction industry where the deceased person's employer is registered in the construction sector (green dots), as well as work-related fatalities in connection with construction projects where the deceased person's employer is a staffing agency (green) or another industry (yellow).

Source: [2]

or trigger accidents in a work process [8]. This model is developed using systems thinking, and one of the conclusions of this system is that accidents are not caused by one single factor such as unsafe behavior, but rather system failures. Accidents can be viewed as complex processes involving the entire socio-technical system, and thus traditional event-chain models cannot describe this process sufficiently [9]. This view can also be supported by Perrow [10], which states that accidents often result from a combination of factors, making it challenging to identify a single root cause. Although individual failures within an accident may seem trivial, their significance arises when they interact with other factors [10]. It is the interplay and interaction of these multiple failures that ultimately leads to the occurrence of the accident.

The model in Figure 2.1.2 also illustrates the arrangement of stakeholders according to their distance from hazardous processes. Farthest away from the hazards are the government that can gain control over the processes through regulations in the law and politics. The company's job is then to implement these laws and regulations in company-specific policies. Within the company, these policies affect the management's decisions and plans for projects to control hazardous processes. Closest to the hazards are the workers which are directly involved in the work pro-

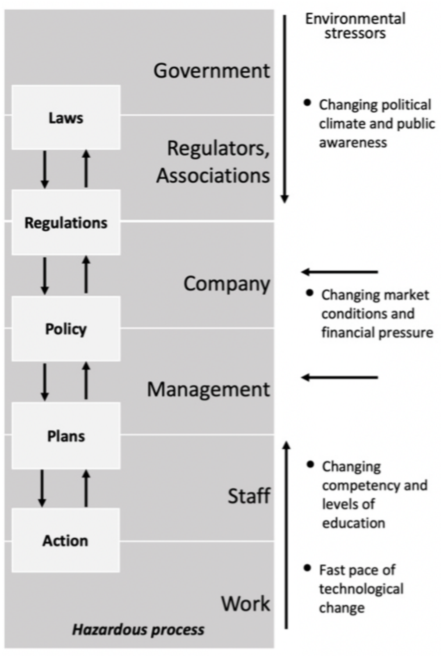


Figure 2.1.2: Simplified model of Rasmussen's socio-technical system.

Source: [8]

cess and can affect hazardous processes with their own actions [8]. This emphasizes that clients in the construction industry are influenced by actors above them and are in position to influence actors on a lower level, such as operators, contractors, and sub-contractors. This model illustrates the importance of a broader approach across disciplines, including feedback loops running upwards in the hierarchy to ensure that the higher levels are aware of lower levels' safety performance in order to modify control mechanisms [8].

How accident risks are managed also depends on the company's structural conditions. For instance, the size of a company can influence communication patterns as well as the need for advanced safety management systems or resources for personnel and safety solutions [8]. Also, when fatal construction accidents occur they usually just result in improvements within a project in a company, rather than the whole industry [8]. Therefore, the number of small companies in this industry is indicated to be a challenge to the overall development of safety in this industry. There is a need for common attitudes, norms, and values which today are too varied from company to company. Attitudes toward safety and understanding the risks of working are described as challenging in the construction industry [8], which influence how much safety is emphasized in a project.

In a study conducted by Haslam et al. [11], the focus is on comprehending the underlying factors contributing to construction accidents. The author cites previous research on the subject, including focus group studies and an analysis of 100 individual construction accidents. Based on this research, the author proposes a model, that acknowledges the dynamic and interconnected nature of socio-technical systems in construction operations [11]. The model proposes that accidents stem from a combination of managerial, design, and cultural factors within the workplace, emphasizing the need to address these underlying influences in order to enhance construction safety.

Building upon this research, Winge, Albrechtsen and Mostue [12] further investigate construction accidents, aiming to contribute to the limited research on the causes of accidents in the construction industry. Their study focuses on identifying common causal factors and exploring the relationships among them. This research uses the Construction Accident Causation (ConAC) framework to investigate 176 relatively severe construction accidents that happened during 2015 in Norway [12]. The ConAC framework involves three levels of factors: immediate factors, shaping factors and originating factors [12]. The immediate factors are influenced by the shaping factors and the shaping factors are influenced by the originating factors. The immediate factors include the workers' action and the shaping factors represent immediate supervision. They are both divided into worker/team, workplace, and material/equipment factors [12]. Originating factors are factors deriving from the management [12]. Figure 2.1.3 illustrates the relative strength of connections among the different factors.

In their analysis of contributing factors to accidents, Winge, Albrechtsen and Mostue [12] found that actions and behavior, operative management, and risk management were the most frequent and important factors. In 90 % of the accidents studied, worker and team factors were identified, while 55 % were attributed to site factors, 56 % to material and equipment factors and 66 % to originating factors [12]. This study defines worker and work team factors as including worker actions, capabilities, communication, attitudes, knowledge, health, and immediate supervision. Site factors include local hazards, work environment, housekeeping, work scheduling, and site constraints. Materials/equipment factors cover condition, usability and availability of materials or equipment. The originating factor includes permanent works design, project management, construction process, safety culture, and risk management [12].

Winge, Albrechtsen and Mostue [12] states that the findings of their study are consistent with many other studies. This can be demonstrated in Table 2.1.1,

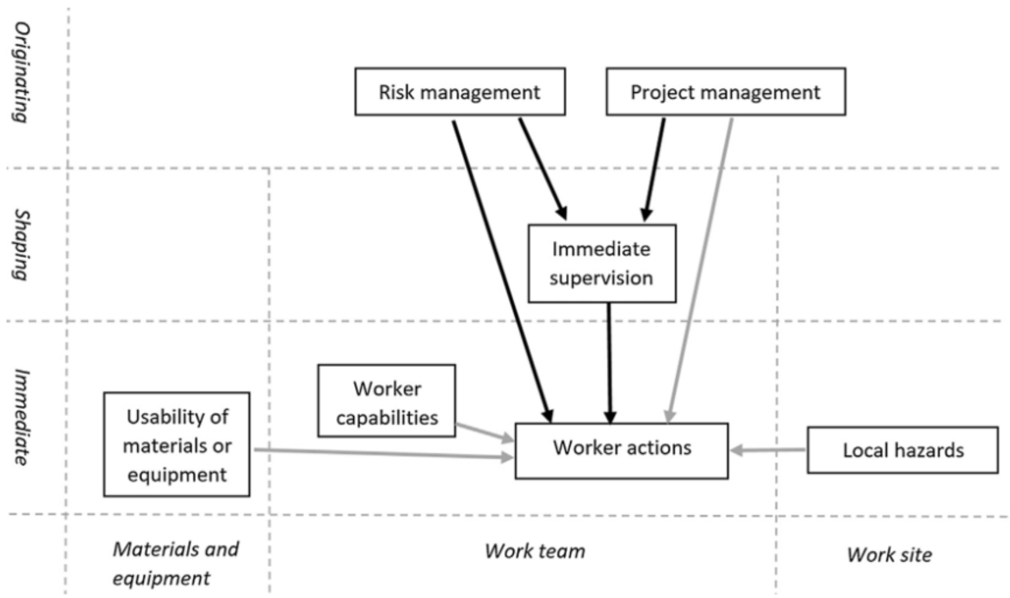


Figure 2.1.3: Factors consistently connected to poor worker actions (coverage > 0.3) and poor immediate supervision, and connections between these factors. Black arrows indicate strong connections (coverage > 0.5).

Source: [12]

which presents a comparison between the results obtained in their study and those of the study conducted by Haslam et al. [11]. According to the findings reported in Haslam et al. [11], worker/team factors account for 70% of the cases, equipment factors for 56%, originating factors for 84%, and site factors for 49%. Thus, it can be implied that human error is a leading cause of accidents. Potentially indicating that workers' actions are influenced by other safety-related factors such as knowledge and skill levels and the availability of liable materials and equipment [12].

Factors	«Causal Factors and Connections in Construction Accidents» [12]	«Contributing Factors in Construction Accidents» [11]
Worker/Team	90 %	70 %
Equipment	56 %	56 %
Originating	66 %	84 %
Site	55 %	49 %

Table 2.1.1: Results from studies by Winge et al. [12] and Haslam et al. [11].

2.1.3 Phases of a Construction Project

Studies and investigations show that accidents in the construction industry often stem from the early phases of a project. This highlights the importance of closely examining the various phases, such as planning and design, initial site preparation, excavation, and final completion, to identify potential hazards and risks of accident. Construction work is typically structured around projects that have a limited duration, and the conditions at the construction site and the activities being performed change throughout the course of the project [13]. Research from other countries has shown that value-based collaboration leads to better construction and lower costs [14]. As a result, almost all actors today use a standardized division of project phases and roles in a construction process [14]. However, the problem is that these frameworks are different and create communication problems on the construction site. Therefore, Bygg21 has developed a common framework and language for construction processes in Norway called "Neste Steg" (Next Step) [14]. This framework describes the construction process over time, in eight steps from start to completion. It aims to highlight the necessary information and decisions needed in each phase, and describes transitions and information delivery between actors in the value chain [14].

Figure 2.1.4 represents a modified version of the eight phases presented in "Neste Steg" [14]. In this modified version, the framework has been simplified to focus on the phases most relevant to the production or construction phase of the project. The first phase, "Pre-construction planning", includes the strategic definition, concept development, and processing chosen concept phases. The second phase, "Engineering and design", includes the detailed engineering phase. The third phase, "Production", focuses on the construction phase of the project. This is the phase where the physical construction work takes place, and depending on the type of project it includes activities such as site preparation, foundation work, framing, electrical and mechanical installations, and finishing work. The fourth phase, "Handover", includes the activities necessary to transfer the completed project to the client. The final phase, "Liquidation", includes the activities required to close out the project.

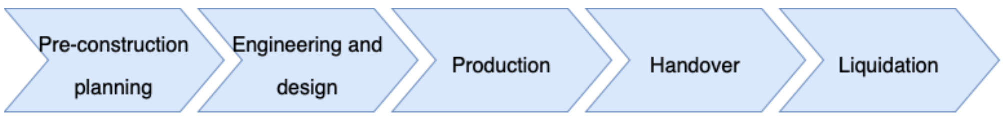


Figure 2.1.4: Construction project phases.
Inspired by: [14]

The production phase is considered to be the critical stage, as it is during this period that accidents and incidents are most likely to occur. Factors such as working at heights, operating heavy machinery, exposure to hazardous substances, and working in confined spaces are just a few examples of the potential hazards that workers face during this phase. However, early phases of a project can have a significant impact on subsequent phases, whereby decisions made during the initial stages can impact safety during construction. Therefore, it is crucial to consider all stakeholders involved in the project, not just during the construction phase, but also in the earlier stages [6]. Effective management of the pre-construction phase is consequently crucial to ensure that the necessary safety measures and protocols are in place to minimize the risk of accidents and incidents.

Production Phase

This thesis' emphasis is placed on the production phase of a construction project, which is the phase where accidents actually occur. In this phase, the plans developed in the previous phases are executed. The process shifts from the turbulent ideation phase to a more structured and linear process driven by specific activities. A project is made up of a variety of temporary activities that are assigned specific resource allocations and defined targets, all of which must be completed within a limited timeframe in order to achieve successful project completion [15]. Looking closer on the different activities during this phase can be done by using the Program Evaluation and Review Technique (PERT) diagram, which is a useful tool for modeling and planning construction projects [16]. The PERT diagram is a graphical representation of a project's critical path, which shows the sequence of activities that must be completed on time in order to meet the project's overall deadline. Figure 2.1.5 illustrates a PERT diagram displaying the sequential activities involved in building a house. In the context of constructing a building, a PERT diagram can help project managers identify dependencies between different activities, estimate the time required for each activity, and develop a schedule that accounts for delays and uncertainties. By breaking down the project into smaller, more manageable tasks and visualizing the relationships between those tasks, the PERT diagram can facilitate the creation of a simulation. This involves modeling the different tasks and their dependencies in the project to simulate various scenarios and assess the outcomes.

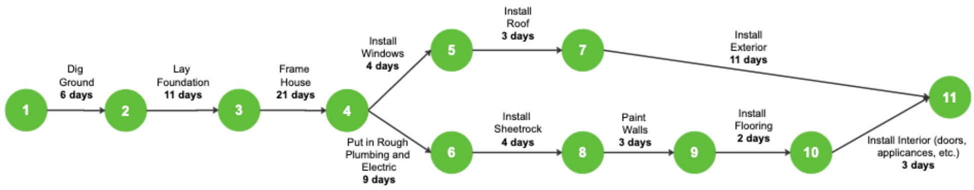


Figure 2.1.5: PERT diagram of building a house.

Source: [17]

2.2 System Dynamics

System dynamics (SD) is a methodology and computer simulation modelling technique used to understand and analyze complex issues and problems [18]. Accordingly, the purpose of SD is to help people understand complex and dynamic systems in the world. This can then make people enhance their abilities to make better decisions in complex systems. In the context of the construction industry, SD can provide significant value by enabling the capture of all project phases and their associated indicators. By applying SD principles, it is possible to develop models that address specific problems and simplify the understanding of complex systems, such as the high number of accidents that occur in construction projects. These models can be a valuable tool for construction professionals, as they can help to identify areas where improvements can be made and lead to better decision-making. It can make it easier to understand the complexity of a construction project.

SD includes tools and methods for analyzing and understanding dynamic and complex systems [19]. According to Sterman [19], successful implementation of SD involves several key principles. First and foremost, a model should be developed to address a specific problem, and should be simplified rather than attempting to capture every detail of the system. To improve performance, the model should have a clear purpose and focus on the desired results. Additionally, SD should be integrated into the project from the beginning, and used in conjunction with other tools and methods. By considering these factors, the model is more likely to be effective and achieve its intended goals [19]. The main concepts within SD models are feedback loops, stocks and flows, delays and goals.

2.2.1 Feedback loops

To understand complex systems, one of the first steps is to identify and analyze the interactions among its components, known as feedback in the field of system dynamics [19]. Feedback is a directed interaction between two components that can be either positive (increase in one leads to increase in the other) or negative (increase in one leads to decrease in the other). The dynamics of a system arise from feedback loops, which can be either positive (reinforcing) or negative (balancing).

Figure 2.2.1 illustrates a feedback loop in the context of safety in construction projects, underlining the importance of integrating safety programs for workers. The loop represents a balancing feedback loop that impacts the safety knowledge of workers involved in a project. With the initiation of more safety programs, the workers' safety knowledge increases, thereby reducing the lack of knowledge among workers. As a result, the need for implementing additional safety programs decreases, closing the balancing loop.

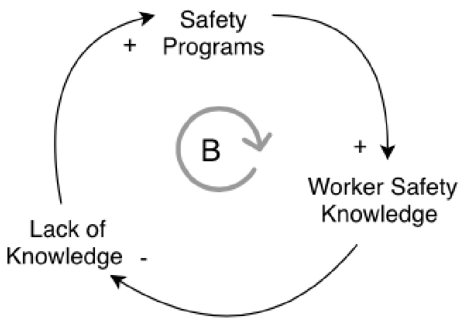


Figure 2.2.1: Feedback loop.

2.2.2 Stocks and flows

Another key concept in SD for understanding the behavior of complex systems is the distinction between stocks and flows. Stocks represent the state of the system and provide information that is used to make decisions and take action [19]. Flows, on the other hand, represent the completion of activities. The stocks are altered by inflows and outflows and by accumulating the difference between the inflow and outflow of a process, delay is created [19]. When the inflow exceeds the outflow, the stock will increase and vice versa.

The stock and flow diagram presented in Figure 2.2.2 illustrates the dynamics of work load in a project management context. The stock, referred to as work load, represents the amount of work to be completed within a given project. This stock is influenced by two key flows: the inflow, represented by the rework rate, and the outflow, represented by the completion rate. The rework rate signifies the rate at which additional work is added to the existing work load due to errors or suboptimal execution of work. When the rework rate increases, the stock of work load also increases, as more tasks are added to the project. Conversely, the completion rate reflects the rate at which work is completed and removed from the work load. A higher completion rate indicates a faster rate of task completion, resulting in a decrease in the work load stock. Thus, the completion rate acts as an outflow, reducing the overall work load. The interrelation between the rework rate, completion rate, and work load in this stock and flow diagram highlights how changes in these factors impact the overall workload and project progress. Understanding and effectively managing these factors is crucial for minimizing the work load and ensuring timely project completion.

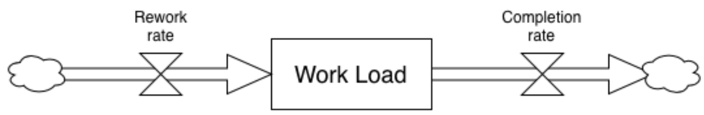


Figure 2.2.2: Stock and flow.

2.2.3 Delays

Delays are an integral concept in the field of SD, which play a crucial role in shaping the behavior of complex systems. A delay is when an action between two components in a system is much slower than the rest of the system, and it therefore creates fluctuations in the systems [20]. For example, when touching a hot stove there will be an immediate feedback of pain. However in complex systems, there can be substantial delays between the cause and effect, which can make it challenging to understand and identify the causal relationships. For example, changing the water temperature of a tap will not immediately change the temperature, but there will be some kind of delay before the water is the desired temperature [20]. Delays can be observed in the introduction of new policies, concepts, or technology into the construction process, where it takes time to adjust the working processes and change the culture and behavior. The effect of such changes may not be immediately visible, and the delay in the system's response can lead to misunderstandings and misinterpretation of the system's behavior.

In order to provide a comprehensive understanding of the previously presented system in Figure 2.2.1, the feedback loop is further elaborated upon by introducing the concept of delay. The extended feedback loop, illustrated in Figure 2.2.3, incorporates the inherent time delays within the system. As previously discussed, the implementation of additional safety programs in the project impacts the safety knowledge of workers. However, it is important to acknowledge that an effective transition to increased knowledge requires a certain amount of time for workers to encounter these programs and incorporate new information. By incorporating the delay within the feedback loop, a more dynamic and realistic representation emerges, capturing the effects of safety programs on workers in a temporal context.

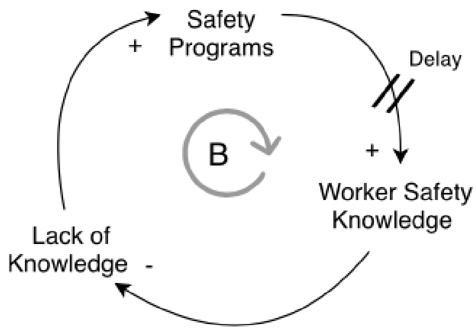


Figure 2.2.3: Delay in system.

2.2.4 Goals

According to Sterman [19], all negative feedback loops aim to achieve a specific goal, which represents the desired state of the system. These loops function by comparing the actual state of the system to the desired goal. Figure 2.2.4 illustrates the previously discussed balancing system, now also incorporating goals. The goal of this system is associated with enhancing the worker safety knowledge to the desired amount of knowledge, which is decided by the management. Thus, the loop operates on the premise that as the level of knowledge among workers is lower, there is a corresponding initiation of additional safety programs with the intention of remedying the knowledge deficiency. As the system reaches its goals of the desired safety knowledge, the implementation of safety programs will cease.

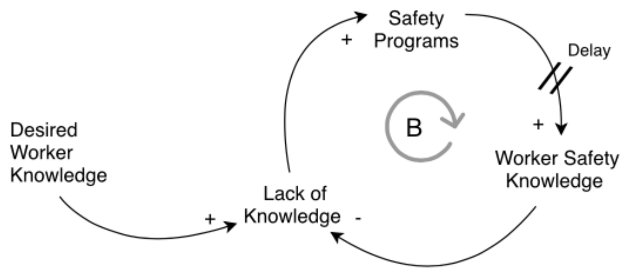


Figure 2.2.4: Goal in system.

2.2.5 Simulation Models

Simulation models are widely used in various industries to replicate real-world scenarios and test various strategies and decisions in a controlled environment. In the field of SD, the modeling process typically involves creating a mathematical representation of the system under investigation. This model is constructed using a set of equations that represent the relationships between various variables. The modeling process is situated within the ongoing activities of the individuals within the system, as stated by Sterman [19]. It is an integral part of the broader process of learning and action that is continually taking place within organizations.

According to Sterman [19], the modeling process must involve a constant iteration between experimentation and learning in both the virtual and real worlds for it to be effective. Hence, it is crucial for the modeler to engage with the real-world dynamics throughout the virtual modeling process, repeatedly running the model until its output accurately reflects the actual system condition. The strategies, structures, and decision rules that are employed in the real world should be represented and tested in the virtual model. This feedback can lead to the development of new strategies, structures, and decision rules in the real world. The process described by Sterman [19] is illustrated in Figure 2.2.5. After developing the model, it can be used to simulate the system's behavior over time, exploring different scenarios or interventions' potential impacts. The simulation results can inform decision-making and provide a better understanding of the system's complex dynamics.

Monte Carlo Simulation

Monte Carlo simulation is a computational technique that works by generating random samples of a system or process to approximate its behavior. It allows for

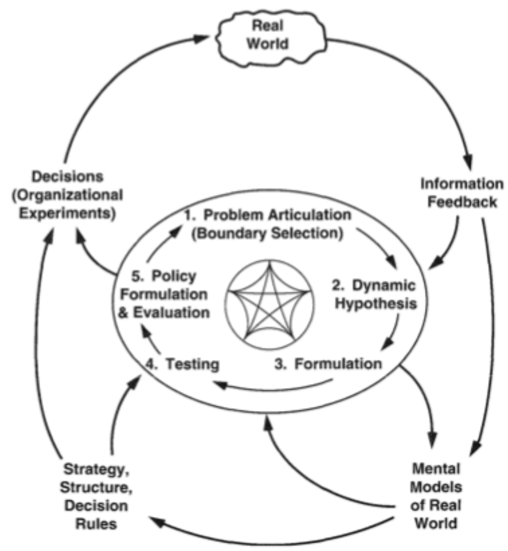


Figure 2.2.5: Modelling process.

Source: [19]

the generation of dynamic confidence intervals for the trajectories of the variables in a model [19]. It utilizes an estimated range of values and probability distribution [19], such as uniform or normal distribution, to generate a set of outcomes for variables that possess inherent uncertainty. By repeatedly recalculating results using varying sets of random numbers within the defined probability distribution, a model of possible results is constructed. This process can be repeated numerous times, often thousands, in a typical Monte Carlo experiment, to generate a vast number of probable outcomes [21]. This statistical distribution provides information about the behavior of the system or process under different conditions and can be used to estimate the probability of various outcomes.

Monte Carlo simulation is particularly useful when dealing with complex systems that are difficult to analyze analytically. By generating a large number of random samples, Monte Carlo simulation can capture the nonlinear relationships between inputs and outputs, as well as interactions between variables. One of the strengths of Monte Carlo simulation is its flexibility. The technique can be used with a wide range of mathematical models and probability distributions, making it applicable to a variety of problems in different fields. Monte Carlo simulation can also be used for optimization and decision-making by simulating the performance of a system under different scenarios and identifying the best course of action.

In the context of construction, Monte Carlo simulation can provide valuable insights in decision-making. For example, let's consider a construction project where various uncertainties exist, such as material costs, labor availability, and weather conditions. By incorporating these uncertain factors into a Monte Carlo simulation, it is possible to generate a large number of project outcomes based on different combinations of inputs. This allows for the possibility of producing thousands of different project scenarios and visualizing the distribution of possible outcomes. With this information, stakeholders can make informed decisions, assess the likelihood of meeting project deadlines, and look at accidents happening in projects. Monte Carlo simulation empowers construction professionals to better understand the inherent uncertainties in projects and make choices to enhance project success.

2.3 Literature Review: System Dynamics in Construction Projects

SD is a methodology that has been applied to various fields to better understand complex systems and their behaviors over time. In recent years, there has been an increasing interest in applying SD to the construction industry to identify and address the underlying causes of challenges in the industry. This literature review aims to provide an overview of the existing literature on SD, and how it has been used in the construction industry, particularly in addressing the problem of accidents. Furthermore, the literature review aims to identify gaps in the existing literature that can be addressed in the present study.

System Thinking and Modeling

One particularly interesting source for system thinking and modeling is the book «Business Dynamics: Systems Thinking and Modeling for a Complex World» [19]. The book provides an introduction to system dynamics for analyzing policy and strategy, with a focus on business and public policy applications [19], which is essential to understanding the complexities of the construction industry and the impact of safety factors. It is written by John D. Sterman, a Professor of Management at the Massachusetts Institute of Technology (MIT) and a leading expert in the field of system dynamics. The book provides an introduction to the principles of systems thinking and how it can be applied to complex business problems. It covers a range of topics, including feedback loops, stocks and flows, behavioral modeling, and the use of simulation to test and evaluate alternative policies and strategies [19]. One of the key ideas in the book is that businesses and other organizations are complex systems that are affected by feedback loops and nonlinear dynamics [19]. These dynamics can make it difficult to predict the outcomes of interventions, and can lead to unexpected results. By understanding these dynamics and using systems thinking and modeling techniques, it is possible to make more informed decisions. Overall, this book is an essential resource for understanding how to use system dynamics and modelling to improve decision-making in complex environments.

System Dynamics Models for Safety in Construction

Furthermore, several articles investigate the development of a system dynamics model for safety in the construction industry. The studies conducted in the articles that is reviewed in this section provide a deeper understanding of the impact of safety factors on construction projects and help in identifying ways to develop models more accurately.

In the article titled «A System Dynamics Model for Construction Safety Behavior» [22], the authors develop a system that consists of two subsystems; the production and the safety system. The developed model enables the simulation of the trade-off between these subsystems, allowing for an analysis of their dynamic relationship. According to the authors, efforts and time the management spend on production and safety are limited resources and therefore an increase on one side may be followed by a decrease on the other. The production system affects the safety subsystem through the management's variations in their commitment to production and safety [22]. The safety subsystem consists of both management and individual conditions on safety, where the management conditions influence the individual conditions. The effect of co-workers' behavior on each worker is also taken into consideration through cellular automata integrated in the system dynamics model.

Moreover, the complex nature of the developed model [22] makes it difficult to comprehend as a starting point for further research. However, it is essential to note that the model offers valuable insights into the complex interplay between production and safety in the construction industry. It serves as a valuable tool for making informed decisions regarding resource allocation and balancing trade-offs between production and safety. Nonetheless, it is imperative to calibrate and validate the model using real-world data, as the study acknowledges that no such data were available during the research. Additionally, the weight of individual conditions on labor's overall safe behavior remains unknown, which the researchers address by distributing the weights equally. Despite these limitations, the model can provide significant contributions to the construction industry by revealing the complexity of the system and identifying critical factors affecting safety and production.

In the study conducted in the article titled «Modeling the Effects of Production Pressure on Safety Performance in Construction Projects using System Dynamics» [23], Mohammadi and Tavakolan develop a model that simulates an incident rate based on the level of production pressure. The study employs the Ground Theory Method (GTM) to create a causal loop diagram that illustrates the relationship between the incident rate and other variables such as labor hour, actual and planned progress, safety climate, rework, and safety training. The importance of considering the complex nature of construction incidents and the interactive effects of production pressure on safety performance in order to improve the construction industry is highlighted through this study [23]. However, the study is limited by the fact that some of the variables, such as incidents, are self-reported, which may affect the accuracy of the data. Despite these limitations, the study provides valuable insights on the complex nature of construction incidents and the interactive effects of production pressure on safety performance. These insights can be useful in developing a simulation model that captures the entire story of a construction project.

The article «Toward an Understanding of the Impact of Production Pressure on Safety Performance in Construction Operations» [24] also explores the impact of production pressure on safety performance in construction operations. It emphasizes the importance of considering the effects of production pressure when developing safety strategies for construction projects. The study develops a causal loop diagram to identify the relationship between schedule quality performances and safety-related factors and conducts a case study to investigate the relationship between accident occurrence and schedule delays and rework on a construction site. The data collected from the site is used to build a system dynamics model, which is then validated through inequality statistics analysis [24]. The results of the case study suggest that schedule delays and rework are critical factors affecting accident occurrence on construction sites.

However, the study is limited by its data collection methods. The reliability of the survey questionnaires' scales has not been thoroughly measured and evaluated, and the questions on the survey forms were developed by the construction company [24]. Additionally, workers' perceptions of safety may have been underestimated in data collection. Despite these limitations, the article provides valuable insights into the process of conducting a system dynamics analysis and constructing a precise model for understanding the complex nature of construction incidents and the interactive effects of production pressure on safety performance.

Table 2.3.1 provides a summary of the key findings, strengths, and limitations of the articles discussed. Although the articles that are reviewed discuss the use of system dynamics to address safety issues, there is still a need for more research in this area. Safety is a major concern in the construction industry, and more attention should be given to developing models that can effectively identify and manage safety risks. The majority of the reviewed literature has considered specific indicators, such as schedule pressure, when utilizing system dynamics modeling. However, there remains a significant gap in the literature with regards to the development of comprehensive models that incorporate all relevant factors. The construction of such a model would enable the creation of projects that more closely reflect real-world scenarios. Thus, there is a need to expand the current body of research and incorporate a broader range of factors into system dynamics models to improve their effectiveness in simulating and analyzing construction projects. By doing so, a model will be developed that has the capability to comprehensively represent the entire narrative of a construction project.

Article	**Main Findings**	**Strengths and Limitations**
"A System Dynamics Model for Construction Safety Behavior" [22]	The model allows simulation of the trade-off between production and safety subsystems, highlighting their dynamic relationship. Management's commitment to production and safety affects the safety subsystem. Coworkers' behavior is considered through cellular automata.	Strengths: Offers valuable insights into the interplay between production and safety. Useful for resource allocation decisions. Limitations: Complex and may be difficult to comprehend as a starting point. Calibration and validation using real-world data are needed. Weight distribution of individual conditions on safe behavior is unknown.
"Modeling the Effects of Production Pressure on Safety Performance in Construction Projects using System Dynamics" [23]	The model simulates incident rates based on production pressure. Ground Theory Method used to create a causal loop diagram. Importance of considering complex nature and interactive effects of production pressure on safety performance is highlighted.	Strengths: Provides insights into construction incidents and effects of production pressure on safety. Useful for developing a comprehensive simulation model. Limitations: Some variables are self-reported, affecting data accuracy.
"Toward an Understanding of the Impact of Production Pressure on Safety Performance in Construction Operations" [24]	The study emphasizes the impact of production pressure on safety performance. Causal loop diagram identifies relationships between schedule quality performances and safety-related factors. Schedule delays and rework are critical factors affecting accidents.	Strengths: Examines the relationship between production pressure and safety performance. Conducts case study and builds a system dynamics model. Limitations: Reliability of survey questionnaires' scales not thoroughly evaluated. Workers' perceptions of safety may have been underestimated.

Table 2.3.1: Summary of findings in literature review.

2.4 AI in Construction Projects

Artificial Intelligence (AI) is a broad concept that can be defined as a system or structure capable of performing tasks in complex environments without constant user guidance [25]. It is widely believed that AI has the potential to increase productivity across the entire construction project life-cycle chain, leading to improved sustainability in environmental, economic, and social factors [25]. Thus, it is believed that AI has the potential to significantly impact how the construction industry approaches policies on health and safety [25], particularly in relation to the large scale of fatalities that have occurred in this industry. By leveraging the power of AI, it may be possible to identify and mitigate potential hazards more effectively, and to develop and implement proactive measures to enhance safety and reduce risk. As a result, the application of AI in construction may ultimately contribute to the development of a safer and more sustainable industry.

In the context of construction, AI systems can be grouped into four categories: machine learning techniques, knowledge-based techniques, evolutionary algorithm and hybrid systems [25]. Machine learning algorithms are capable of learning from data to improve their performance, while knowledge-based systems replicate the problem-solving skills of humans to address complex issues [25]. Evolutionary algorithms are based on biological evolution and incorporate natural selection and genetic algorithms [25]. Hybrid systems, on the other hand, combine two or more AI approaches to leverage the strengths of each and mitigate the limitations of individual approaches [25].

2.4.1 Machine Learning

Machine learning (ML) is a subset of artificial intelligence, as shown in Figure 2.4.1, that have been recognized to be an effective predictive tool [26]. The field of ML is concerned with the development of algorithms that enable computers to learn from data and improve their performance in recognizing complex patterns and making intelligent decisions. Unlike traditional programming, which involves explicit instructions for a computer to follow, machine learning algorithms allows computers to learn how to perform specific tasks without the need for explicit programming [27]. Through training on a dataset, a machine learning model can generalize its learned patterns and predict outputs for new input data beyond the examples observed in the dataset. The potential of machine learning to enable computers to learn from data and make predictions has significant implications for a range of applications, including those in the construction industry. By analyzing large volumes of historical safety data and identifying risk factors and patterns associated with accidents, machine learning techniques can contribute to the prediction of safety incidents. This can significantly transform safety management practices by implementing preventive measures and safety interventions, and thus mitigate risks on construction sites.

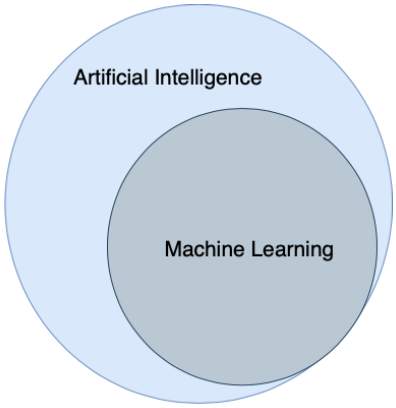


Figure 2.4.1: Connection between artificial intelligence and machine learning.

The aim of automatically learning a model to describe patterns in given data [28] involves utilizing mathematical and statistical techniques to identify patterns within the data, and subsequently use them for making predictions or decisions. ML algorithms characteristically fall into one of two learning types: supervised or unsupervised learning, each with its unique approach and set of applications [29].

Supervised Learning: This approach involves a setting where the learner receives labeled data, and the task is to learn a model that can predict the labels for new, unseen data [29]. Supervised learning systems can also be divided into two primary categories, namely regression and classification [27]. Regression involves predicting a continuous numerical value based on input data [27]. On the other hand, classification predicts a discrete output, indicating which category or class the input belongs to, which can either be binary or multi-class classification [27].

Unsupervised Learning: This learning method deals with unlabeled data, meaning data that has no predefined categories or labels. The goal of unsupervised learning is to identify patterns or structures in the data without any prior knowledge of the labels [29]. Unlike supervised learning, unsupervised learning does not rely on identifying a specific measurement variable. Instead, it uses algorithms to search for patterns and structures across all variables in the data [30]. Since there is no human expert labeling the data, there are no pre-defined categories for the model to follow during training [30].

Steps during machine learning model construction: The initial step involves the identification of relevant datasets and their preparation for analysis [30]. The dataset is then split into a test set and a training set. The training set data is preprocessed to normalize the data and the most relevant features from the preprocessed data are identified. Subsequently, an appropriate ML algorithm is chosen, serving as the basis for constructing an analytical model. The model is trained using the training set, where the algorithm is not employed for making future predictions, but solely for the purpose of learning [30]. Following the training phase, the model undergoes testing using a separate test set and is adjusted if necessary. During this testing phase, the target variable values are temporarily hidden from the model to evaluate its classification performance based on the patterns and structures it learned from the training set [30]. Lastly, various model evaluation techniques are applied to estimate the performance of the model on unseen future data [30]. Figure 2.4.2 presents a visual overview of the process involved in constructing a machine learning model. With the completion of these stages, the machine learning model is fully constructed and prepared to perform automated analysis on new data [30].

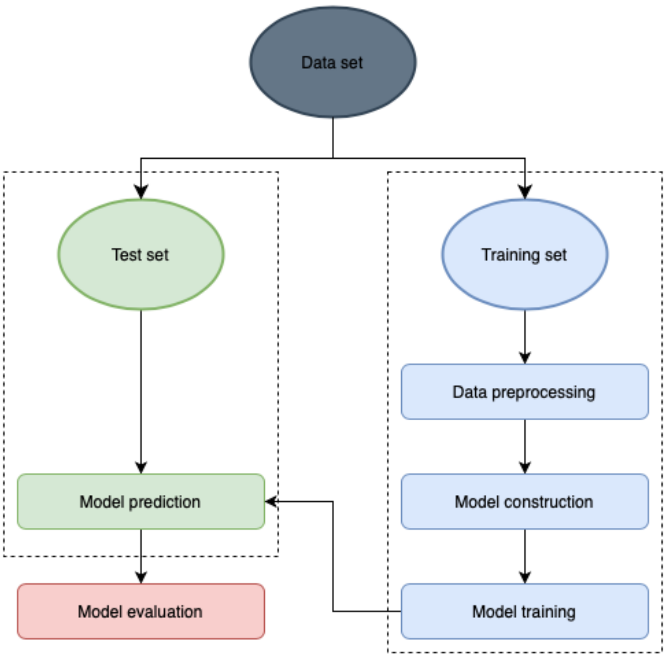


Figure 2.4.2: Flow chart machine learning model construction.
Inspired by: [31]

Model Selection

According to Bang [25], most construction projects that utilize ML employ supervised learning. Because of its fit for addressing the challenges and complexities encountered in such projects it is a natural choice. The selection of suitable supervised learning approaches depends on factors such as the desired model performance, execution speed, and target definition. These algorithms differ in their underlying structures for organizing input data and exploring the hypothesis space [32]. Some of the frequently employed methods found in the literature search relevant to construction projects is described in the following:

Support Vector Machine (SVM) represents the training data as spatial points and constructs a model of N-dimensional boundaries, where N represents the number of features in the data. These boundaries are utilized to classify new input labels by measuring their distances in the spatial space [33]. The objective is to select the hyperplane that maximizes the distance between points of different target values in order to minimize generalization loss [33]. SVM is particularly effective in handling high-dimensional data, which refers to data with a large number of features or variables [34]. Due to its ability to handle complex, high-dimensional data, SVM is an ideal choice for the present study.

XGBoost is a gradient boosting algorithm for supervised learning [35]. Due to its simplicity and demonstrated high performance, it is widely favored among researchers and commonly used as one of the most popular tree models [36]. Its capability to handle high-dimensional data without restrictions on the size of the dataset [35] makes it a suitable choice for predicting accidents in construction projects. The large number of indicators and features in such datasets make them complex and difficult to analyze using traditional algorithms. However, XGBoost's ability to handle high-dimensional data enables it to efficiently process and analyze the large dataset, thus improving the accuracy of the accident prediction.

AdaBoost, short for Adaptive Boosting, is another popular algorithm used for classification tasks. It combines multiple weak classifiers to create a strong classifier, thus improving the overall accuracy of the model. A weak classifier is a simple model that performs only slightly better than random guessing, such as a decision tree with limited depth [37]. AdaBoost works by training multiple instances of the same weak classifier on different subsets of the data, and then combines their predictions to make a final prediction [37]. This approach is particularly effective when dealing with complex datasets with multiple features, making it a suitable choice for predicting accidents in construction projects where there are numerous indicators that could affect the outcome.

Decision Trees is a practical and widely used approach for inductive learning.

It is a method for approximating discrete-valued target functions, in which the learned function is represented by a decision tree [32]. Decision trees are graphical representations that systematically map all possible solutions based on an initial question. They take the form of structured graphs with branches and nodes. Nodes in the tree represent different features of the data, while the branches connect the features' values. At each level of the tree, a condition is posed regarding a specific feature. The outcome of this condition determines the path taken through the corresponding branch, leading to the next level or feature. The leaf nodes, found at the final level of the tree, provide the ultimate predictions or decisions [32]. Decision trees also have certain limitations, such as overfitting to the training data, which may lead to a loss of generalization ability, and favoring overrepresented classes, resulting in a biased outcome [26].

Random Forest (RF) is a type of classification algorithm that involves the use of multiple decision trees [38]. This algorithm implements bagging and feature randomness during the construction of each individual tree to create an uncorrelated forest of trees. The prediction of the random forest is based on the combined prediction of the individual trees, which is expected to be more accurate than the prediction of any single tree [38]. As compared to decision tree, it is more robust in terms of diversity [26]. RF can handle missing data, noisy data, and other complex features, making it a suitable algorithm for this study.

Model Evaluation

When evaluating a machine learning algorithm, examining its predicted results is crucial. This can be accomplished by utilizing a confusion matrix, which serves as a tabular representation of the algorithm's performance within each class of a classification problem. The confusion matrix provides a visual depiction of the four possible outcomes of class prediction: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN), offering valuable insights for calculating performance measures that can effectively assess the algorithm's effectiveness. In Figure 2.4.3 such a matrix is presented for a binary problem, where the predicted classes are arranged horizontally in rows and the actual classes are arranged vertically in columns. In a binary task with *yes* or *no* as the target values, the goal is to predict yes when the true target class is yes and vice versa for no. Consequently, the model achieves correct predictions in the form of TP and TN. Conversely, incorrect predictions occur when the model predicts a class value that contradicts the true class value, resulting in FP and FN. An ideal learning algorithm would produce a confusion matrix with entries solely along the main diagonal, indicating that all predictions are TP and TN, i.e. accurately predicted [39].

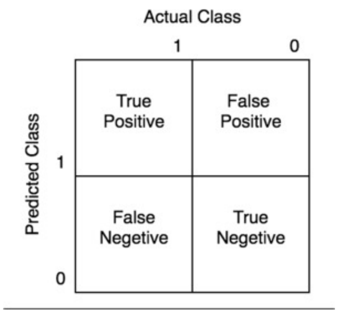


Figure 2.4.3: Confusion matrix.

Source: [40]

These four cases can now be used to introduce several commonly used measures for understanding and explaining classification performance [39]. One such measure is accuracy, which is the percentage of correctly predicted cases out of all cases in the dataset (Equation 2.1). While accuracy is a useful measure, it may not provide a complete picture of the algorithm's performance, particularly in the case of an imbalanced dataset. Its limitations include its inability to consider the type of prediction errors being made and the distribution of the classes [26].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{2.1}$$

Precision (Equation 2.2), on the other hand, measures the fraction of TP predictions among all positive predictions. It is a useful measure when the goal is to minimize FP. Recall (Equation 2.3) measures the fraction of TP predictions among all actual positive cases. Since it takes FN into account, it is a useful measure when the goal is to minimize FN. In the context of construction projects, the implication of overlooking an accident (FN) is much more serious than incorrect prediction of an accident. Thus, the recall value is a suitable measure for this case.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2.2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2.3}$$

The F1 score is a measure that combines precision and recall, giving equal weight to both measures, as indicated in Equation 2.4. It is a useful measure when the algorithm needs to balance between precision and recall, such as in cases where both FP and FN need to be minimized. These measures provide a straightforward interpretation, and as a result, researchers commonly apply them as performance measures [26]. By using a combination of these measures, the effectiveness of a machine learning algorithm can be fully assessed and optimized for the specific task at hand.

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{2.4}$$

2.4.2 Machine Learning in Construction

Decision-making under uncertainty is a challenge faced by numerous industries, including construction [41]. The severity of the consequences of making the wrong decisions is particularly significant in cases where human lives are at risk. Accident prevention is a critical concern in construction sites to avoid significant loss of life and property damage. Individuals involved in the earlier stages of construction, such as designers, face a higher risk of overlooking potential hazards and miscalculating risks [41]. By utilizing ML, it is possible to derive general rules from vast quantities of data belonging to complex spaces, which can provide empirical knowledge for safety-related decision-making under uncertainty [41]. This approach has the potential to enhance decision-making and ultimately save lives. ML algorithms can be trained to predict accidents by analyzing various factors such as the type of equipment used, the number of workers on-site, weather conditions, and past accident records. By identifying patterns and risk factors, ML models can provide insights that can help prevent accidents and improve safety in construction projects. The benefits of implementing these models is that when the ML model is trained to find patterns, it is an automatic process.

Poh et al. [26] conducted a literature study on the use of machine learning algorithms in construction projects, and found out that the most commonly applied algorithms in safety-related applications were classification algorithms. Specifically, they identified five classification algorithms that were frequently used in this area: neural networks, decision trees, random forest, stochastic gradient tree boosting, and support vector machine. This suggests that these algorithms are effective in addressing safety issues in construction projects and may be useful for safety-related research in this field. Poh et al. [26] also refers to a study which uncover the characteristics of fatal injuries in the Taiwan construction industry by mining association rules from 309 accident reports of fatal injuries. This study identified that the two most significant factors associated with fatal injuries were "worker's age & time of day for civil projects" and "worker's salary & day of week for building projects." This suggest that a lot of data surrounding accidents are needed for a ML algorithm to work properly with the prediction of fatal accidents.

However, using ML to predict accidents in the construction industry poses several challenges due to varying data quality, lack of standardization, and significant variation in the use of IT tools. Variable quality in reporting is a challenge in collecting HSE-data. It is likely that there are significant under-reporting and uncertainties surrounding what should be reported, along with a lack of standardized reporting tools [42]. A high number of reported incidents does not necessarily indicate poor safety performance in the project at hand compared to other projects; on the contrary, it may suggest that the project in question has a strong culture of reporting and registering unwanted incidents [42]. This creates room for subjective assessments and makes the data very difficult to compare and utilize, especially in applications like ML. Subjective assessments introduce subjectivity and bias into the data, making it challenging to establish objective criteria for analysis and comparison. As a result, the data may lack consistency and reliability, hindering the accurate training and performance of ML algorithms. The difficulty in comparing and using such data in ML models arises from the need for standardized, objective, and reliable data inputs to ensure the effectiveness and accuracy of the predictive capabilities of ML algorithms.

2.5 Combining Simulation Modeling and Machine Learning

Integrating ML techniques with simulation modeling can help overcome the challenges associated with using ML in construction projects, while also leveraging its strengths. The main difference between simulation modeling and ML is that within simulation the model is often known while in ML the model is initially unknown [43]. In simulation models the inputs are random variables that through a set of known calculations in the model create outputs. The objective is to determine a spectrum of results through the process of randomly selecting input variables and iteratively computing the corresponding outputs. In ML the model is trained based on datasets of inputs and outputs, making it capable of learning how to predict outputs based on input values.

Another key difference between simulation modeling and ML is the nature of the output. In simulation modeling, the outputs are generated from a set of deterministic calculations based on the input variables, so the results are directly related to the inputs and the underlying model [43]. In contrast, ML models can generate outputs that are not explicitly related to the input variables, but are based on patterns learned from the training data [43]. This means that ML models can uncover complex relationships between input and output variables that might not be obvious or even known beforehand.

However, the combination of simulation modeling and ML can offer several advantages. Simulation models can provide an additional source of data that is rich in knowledge and beyond typically available data [28]. The outputs generated by simulation models can serve as training data for ML models, especially in cases where real-world data is limited or difficult to obtain [28]. As presented earlier, this is the case with accident data within the construction industry and it therefore exists a need to explore the usage of combining machine learning with simulated data. Furthermore, simulation models can produce clean labeled synthetic data, which is highly desirable in the development of ML algorithms. Additionally, outputs generated by simulation models can be executed virtually, saving time and resources compared to real-world testing.

The utilization of simulation models as training data for ML algorithms offers the potential for enhanced insights and increased flexibility in the approach. ML can help identify patterns and correlations in the simulation data that may be difficult to discern manually, leading to more accurate modelling. Moreover, ML can identify important variables and relationships in the simulation data, providing better insights into the underlying mechanisms and guiding further research on simulation model. Overall, using simulation models as a source of training data can serve as a proof-of-concept for the efficiency of ML models in solving complex problems as for an instance predicting accidents in construction projects. It can also improve the accuracy, speed, and flexibility of simulations, leading to more efficient decision-making.

CHAPTER

THREE

METHODS

When developing a model of a complex system, two primary objectives are typically considered. The first objective involves creating a model that closely emulates reality. This process requires careful calibration of the model to match real-life events and scenarios. However, achieving this objective is complex and advanced, and requires a deep understanding of both the underlying technology and the reality being modeled. Given the current level of knowledge and lack of input from collaboration partners, the chosen approach is to pursue the second objective, which involves using the model as a metaphor. Rather than attempting to replicate reality, the aim is to devise a metaphor or narrative that can enable individuals to comprehend the importance of the issue at hand. This approach requires the model to convey a message with a story, bringing the issue to the forefront of people's minds. The primary goal of this project is to educate and encourage individuals to think more deeply about the issue, leveraging the model as a tool to promote discussion and debate.

Thus, this study aims to develop a proof-of-concept modeling and simulation tool, that can serve as a learning laboratory that provides a virtual environment for exploring multiple scenarios, and capturing the potential behaviors of the actual system. This way it is possible to analyze the construction process and identify areas for improvement in a virtual setting. The focus of this research is on the construction phase of the project, with the planning phase being addressed in another thesis. The simulation model is designed to simulate the construction activities, evaluate the efficiency and effectiveness of the process, and assess the impact of changes to the number of accidents happening during a project. Assumptions are made in the construction phase simulation model, with outputs from the planning phase serving as inputs. The potential of machine learning algorithms to accurately predict accidents is investigated using the simulation model developed in this study. The configuration of the project is illustrated in Figure 3.0.1. This chapter provides a detailed account of the methods used in developing the simulation model including the code implementation, assumptions made during the development, and the experimenting with the model. Additionally, the methods used to assess the accuracy of machine learning algorithms in predicting accidents are described.

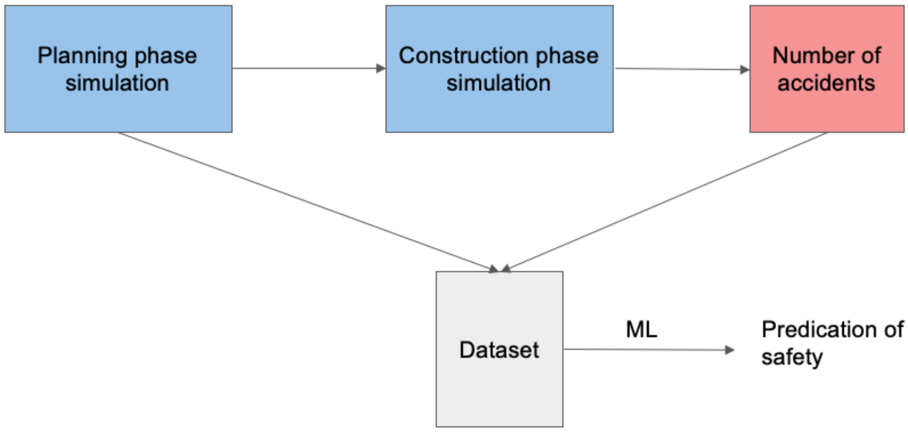


Figure 3.0.1: The configuration of the project.

3.1 Software and Programming Language

The implementation of the proposed methodology presented in this chapter were carried out using Visual Studio Code (VS Code) as the primary development environment, with Python as the programming language. VS Code is a source-code editor redefined and optimized for building and debugging modern web and cloud applications [44]. Its minimalistic design ensures a smooth coding experience while minimizing resource consumption, making it well-suited for working on simulation models that involve complex computations and data processing. It also offers excellent support for the Python programming language, which was chosen due to its ease of use and strong online community support. In addition, Python comes with several frameworks and libraries that support scientific calculations and data analysis. The most important ones for this project includes Pandas for data manipulation and analysis, Numpy for efficient numerical computations, and scikit-learn for ML functionalities. Moreover, VS Code seamlessly integrates with version control systems such as Git, which is utilized as a collaboration tool throughout the project. This integration enables efficient teamwork, allowing for easy tracking of code changes, version management, and collaboration among the development of the planning phase and building phase of the model.

3.2 Code Implementation of the Models

The code accompanying this study showcases the implementation of a system dynamics model in Python, utilizing various imported modules such as sys, random, NumPy and CSV to support its functionalities. The code also consists of several implemented modules, each serving a specific purpose. The first module is the *Indicator* class, which represents project indicators and their values. It provides methods to retrieve and manipulate indicator information such as name, initial value, and current value. The second module is the *Task* class, which represents project tasks and their associated actions. It allows for task information retrieval and modification, as well as task execution within a project context. The third module is the *Project* class, which serves as the main container for managing a project. It includes functionality for creating and accessing indicators and tasks, executing project tasks, and performing calculations based on indicator values. Additionally, it provides methods for importing indicator values from a file, conducting Monte Carlo simulations, and generating an output file reporting the project's indicators. Overall, this modular design, which is illustrated in Figure 3.2.1, promotes code organization, reusability, and flexibility in the simulation. The code of the simulation model accompanies a total of approximately 825 lines, encompassing the modules and functions responsible for updating indicators during the simulation execution.

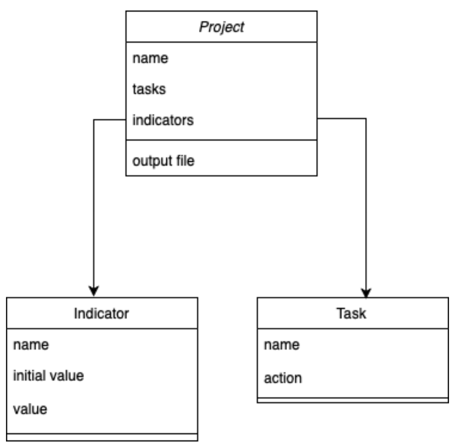


Figure 3.2.1: The main classes of the simulator.

Furthermore, the Python code implements a machine learning model that facilitates the classification of data based on the provided features. It imports modules including Pandas, NumPy, and various classifiers and metrics from the sklearn package. The code performs data preprocessing, merging data from separate CSV files into a unified dataframe, and splitting the data into training and test sets. The classifiers employed in this study include Support Vector Machines (SVM), XGBoost, AdaBoost, Random Forest, and Decision Trees. The confusion matrices for each classifier are visualized using the Matplotlib library. Additionally, accuracy, precision, recall, and F1 score metrics are calculated and reported for each classifier. The code accompanying the machine learning model encompasses approximately 200 lines. A more thorough explanation of the implementation of both the simulation model and the machine learning model are further explained in this chapter.

3.3 Simulation Model

The simulation model utilizes a breakdown of the project into distinct phases and deliveries, making it easier to comprehend and incorporate all relevant factors. Each phase and deliverable is represented through individual performance models with specific inputs and outputs, thus resulting in a comprehensive simulation model. It is important to include both the planning and building phase of the project as prior studies show that accidents occurring at construction sites have inseparable relationships with upstream phases [45]. The planning phase of a construction project, as discussed in the work by Borkenhagen and Olsen [1], is characterized by a performance model encompassing inputs such as the project scope and timelines. The outputs of this phase consist of indicators such as a detailed project schedule and the quality of the plans. To simulate different projects, random values are assigned to the planning inputs. Subsequently, all the indicators utilized during the planning phase are generated and stored in a CSV file.

Similarly, the construction phase is represented by a performance model that includes inputs such as the quality of construction equipment, project size, and schedule plans that are derived from the generated CSV file from the model of the planning phase. The model of the construction phase then generates a CSV file with outputs such as the project progress during each activity, and number of accidents that have occurred. Thus, the connection between the two phases is established through the utilization of outputs from the planning phase as inputs for the building phase, as illustrated in Figure 3.3.1. Additionally, the construction model incorporates certain external factors as inputs, such as weather conditions. By using these performance models to simulate the project phases and deliveries, potential problems and inefficiencies can be identified. The use of simulation modeling can greatly enhance the construction project planning and management process, by leading to the management picking up on warning signs early in projects, which could result in less accidents.

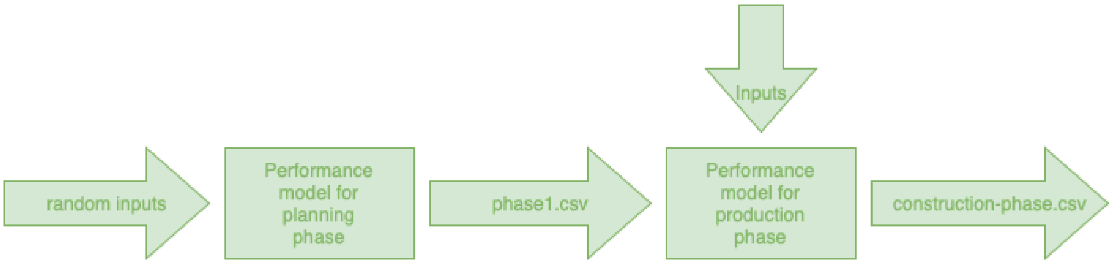


Figure 3.3.1: The set up of the simulation model.

3.3.1 Operation Phase of the Model

To avoid making the model too complex, it is developed from a specific project of constructing a building. This makes it easier to make assumptions to the modelling and look at the specific tasks of the building process. The different tasks, implemented in the model, are investigated through the use of PERT diagram, as well as the risks for each task. The building phase includes a series of activities that are necessary for completing the project, illustrated in Figure 3.3.2. For each activity to begin, the preceding activity needs to be finished and give an output to the beginning activity. Some of the activities can initially start independently of each other, such as electrical, plumbing and roof. However, since this will not affect the output of the model it is simplified so that the implemented model is completely sequential.

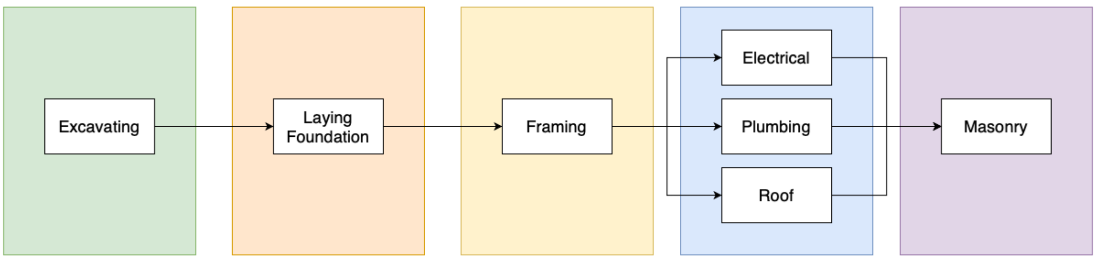


Figure 3.3.2: Activities in construction phase.

While the construction of a building may involve a multitude of different activities, these can be simplified into a few key categories. Excavation and laying the foundation are typically the first steps in the building process, as the foundation is crucial for supporting the weight of the structure. Thus, the developed model starts with these two activities. The next activity is framing, which includes the column structure, wall and frame works. Roof (ceilings and tiles) works, comes next, and provides the skeleton of the house. Electrical and plumbing installations, including sanitary works, are essential components that need to be planned and installed carefully. Finally, masonry work, such as plaster, floor works, and installation works, can be considered complementary to the other activities. While there may be additional activities involved in constructing a building, simplifying them into these categories can help provide a more straightforward understanding of the construction process. Each of these activities requires careful planning and coordination to ensure that they are completed safely, efficiently, and to the required standards.

Influencing Diagrams

To create a highly accurate simulation model that can generate data for a machine learning algorithm, it is crucial to consider various factors and their interactions. By acknowledging and modeling the interactions between these contributing factors, the simulation model can provide a more comprehensive understanding of accident dynamics. Specifically, it is important to identify the indicators that influence the number of accidents in a project and determine the magnitude of their impact. The production phase of the model encompasses the range of activities previously described, each associated with its own set of indicators that ultimately affect the likelihood of accidents. These indicators include plan quality, worker competence, safety knowledge, environmental harshness, equipment liability, phase duration, schedule pressure, and expected accident rate. While many of these factors originate in the planning phase, there are others, such as environmental harshness, that are external to the planning process and challenging to predict.

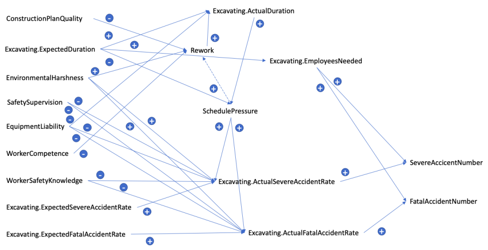
To visualize and comprehend the relationships between these factors, influencing diagrams are constructed for each phase, as depicted in Figure 3.3.3. For a more comprehensive evaluation of the influences, the diagrams are also included in the appendix (see Appendix A), where they are presented in a larger format, facilitating a clearer understanding of their content. As reflected in the diagrams, most of the phases incorporate the same influences on accidents. Nevertheless, it is noteworthy that plumbing and electrical work remain unaffected by environmental harshness, as these tasks are performed indoors. In these diagrams, a positive influence of one factor on another is indicated by an arrow with a plus sign, while a negative influence is represented by a minus sign. These influencing diagrams serve as the foundation for developing the simulation model, enabling a more accurate representation of real-world accidents and their underlying dynamics.

3.3.2 Indicators in the Operation Model

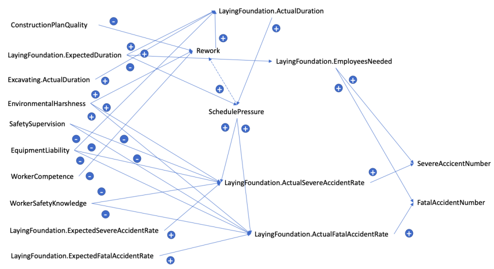
The indicators in the operation model comprise several factors, including plan quality, project size, equipment liability, worker competence, safety supervision and safety knowledge, which are derived from the planning phase. The precision and comprehensiveness of the project plan are reflected in the plan quality indicator. Equipment liability assesses the reliability and availability of project equipment. Worker competence and safety knowledge reflect the knowledge and expertise of the project workforce. Safety supervision is an indicator of the level of supervision on the construction site. The value of these factors is determined using a 10-point scale, where 1 represents the minimum presence of these factors in the project, and 10 represents the maximum presence. These values are obtained from the planning phase of the simulation model.

In addition to these factors, external aspects which occurs during the construction phase are also considered, such as environmental harshness and expected accident rate. Environmental harshness takes into account external factors like weather and terrain that can impact project operations and is measured on a scale of 1-10. During the simulation of projects in the construction phase, this indicator is randomly assigned a value within its range. Expected accident rate reflects the likelihood of safety incidents in the project, and historical data from comparable projects are used to determine it. To gain a more comprehensive understanding of the accident likelihood, the system also includes expected and actual activity duration, number of employees needed during the various activities, rework, and schedule pressure. Rework is measured as the percentage of additional time required to resolve issues, based on key performance indicators such as plan quality, equipment liability, and worker competence, and is calculated during each activity. Schedule pressure measures the pressure on the project workers to accomplish tasks according to a fixed timeline and is also measured on a scale of 1-10.

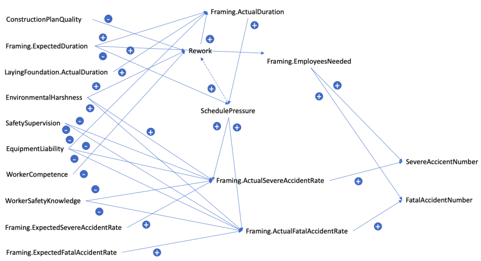
To calculate the actual accident rate, the system considers various indicators such as equipment liability, environmental harshness, safety knowledge, schedule pressure, worker competence, and expected accident rate. Each of the influencing factors, except expected accident rate, have different weights depending on how



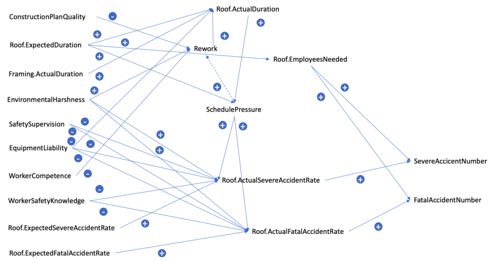
((a)) Excavating



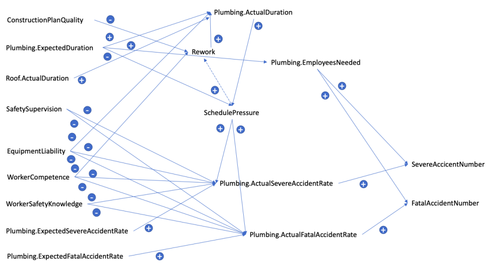
((b)) Laying Foundation



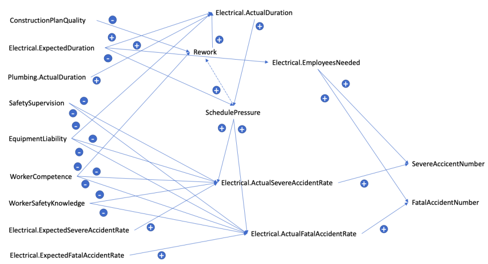
((c)) Framing



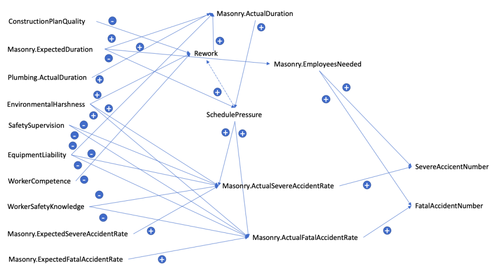
((d)) Roof



((e)) Plumbing



((f)) Electrical



((g)) Masonry

Figure 3.3.3: Influencing diagrams for phases of construction model.

large the influence from the indicator is. This allows the system to accurately predict the likelihood of accidents and adjust its indicators accordingly. Finally, the system estimates the number of accidents that occur during a project based on the actual accident rate and number of employees in the project. Accidents are classified into severe and fatal categories, reflecting their distinct frequencies and varying accident rates. NLIA also classifies their accident statistics into distinct categories based on accident types, defining severe accidents as incidents that lead to an absence of more than three days. By differentiating between these accident types, a more nuanced understanding of their occurrences and impact can be gained. In conclusion, considering these indicators collectively, the system offers a comprehensive analysis of the accident probability during the construction phase of a project.

Table 3.3.1 provides an overview of the stocks in the system, along with the unit and domain of each stock. The table includes a total of sixteen stocks, with the first nine representing outputs from the planning phase and the remaining seven representing stocks derived during the construction phase. It serves as a reference point for understanding the different components that make up the system. The simulation model representing the planning phase generates outputs that are saved in a CSV file, where the nine indicators serve as inputs for the construction model. To account for the influences previously described, several functions are developed and applied to modify the stocks. These are presented in Table 3.3.2, which illustrates the flows within the system. It highlights the various actions that occur within the system, showcasing how the stocks interact between each other. By interacting with each other, the stocks get updated values which are stored in an additional CSV file. This approach enables a systematic analysis of how different factors influence the occurrence of accidents during the construction phase of the project.

Together, Table 3.3.1 and Table 3.3.2 provide a comprehensive understanding of both the individual components (stocks) and the interactions and movements (flows) within the system. They contribute to gaining insights into the overall functioning and behavior of the system as a whole.

Stocks	Units	Domain
planQuality	[1,10]	
projectSize	[1,10]	
safetyKnowledge	[1,10]	
workerCompetence	[1,10]	
schedulePressure	[1,10]	
projectDuration	Integer	Days
actualDuration	Integer	Days
safetySupervision	[1,10]	
equipmentLiability	[1,10]	
numberOfEmployees	Integer	Employees
environmentalHarshness	[1,10]	
rework	Float	% of total duration
severeAccidentRate	Float	Accidents per employees
fatalAccidentRate	Float	Accidents per employees
numberOfSevereAccidents	Integer	Accidents
numberOfFatalAccidents	Integer	Accidents

Table 3.3.1: Stocks in the system.

Flows	Influencing Stocks
calculateSchedulePressure()	projectDuration, actualDuration
calculateRework()	planQuality, schedulePressure, environmentalHarshness, workerCompetence
calculateActualDuration()	equipmentLiability, workerCompetence, rework
calculateSevereAccidentRate()	equipmentLiability, environmentalHarshness, safetyKnowledge, schedulePressure, workerCompetence, safetySupervision
calculateFatalAccidentRate()	equipmentLiability, environmentalHarshness, safetyKnowledge, schedulePressure, workerCompetence, safetySupervision
calculateNumberOfEmployees()	projectDuration
numberOfSevereAccidents()	numberOfEmployees, actualSevereAccidentRate
numberOfFatalAccidents()	numberOfEmployees, actualFatalAccidentRate

Table 3.3.2: Flows in the system.

3.3.3 Assumptions

In the process of developing the simulation model, various assumptions must be made. The primary purpose of making these assumptions is to simplify the actual scenario being modeled, which in turn increases the efficiency and reduces the complexity of the model. However, it is important to acknowledge that the accuracy of the assumptions made during model development significantly impacts the validity of the model's results. As such, documenting the assumptions and methodologies used during model development is essential to ensure that the results can be easily replicated and investigated.

In order to ensure the validity and relevance of the simulated accident data, the assumptions employed in the simulation are grounded in rational inferences derived from an analysis of construction industry theory and practices. The model's assumptions and outcomes are primarily aligned to practical construction scenarios, placing emphasis on real-world applicability rather than solely relying on regulatory compliance. As there is limited theoretical evidence regarding the influence of several factors on the indicators, the assumptions are primarily formulated based on logical deductions drawn from research on relevant theories within the construction industry. While the model does provide a certain level of realism in terms of construction projects, it cannot be considered entirely accurate without the input of expert knowledge. In this model, the assumptions are mostly made according to the impacts the previously presented flows have on certain stocks in the system. The following subsection presents all the assumptions considered in the model.

Schedule Pressure

In the model it is assumed that the schedule pressure of a construction project is dependent on the level of delay in the project. If the project is delayed 13% or more, the schedule pressure in this model will be a value from 6 to 10, with higher delay leading to higher pressure. If the project is delayed between 10% and 13%, the schedule pressure will be between 2 and 5, and less than 10% delay will give a schedule pressure of 1.

Rework

The amount of rework in a construction project is influenced by the quality of the plan, worker competence, and schedule pressure. These factors have equal influence on the amount of rework. Additionally, there is some randomness in the amount of rework in each project, reflecting the inherent unpredictability and variability of construction activities. The rework is expressed as a percentage of the expected duration that requires revision.

Actual Duration

The actual duration of a construction project is dependent on worker competence, rework, and equipment liability. If either the equipment liability or worker competence is 5 or above, the base duration will be varied around or slightly above or below the expected duration. Otherwise, the base duration will be varied over the expected duration. The impact of rework is calculated as a percentage of the expected duration and then added to the expected duration. Given the assumption that projects rarely deviate significantly below their planned time schedule, it is assumed that the actual duration will always be at least 95% of the expected duration. Furthermore, if the equipment is highly reliable (rated 9 or 10 on the liability scale), it is anticipated that the actual duration of the project will be shorter than initially estimated, based on the assumptions described earlier. This expectation is rooted in the belief that improved equipment reliability leads to enhanced work efficiency.

Accident Rate

The accident rate of a construction project has an expected value based on the industry standards and historical data. However, the accident rate for a specific project can be increased or decreased beyond the expected rate depending on the values of the impacting factors. The model assumes that each of the factors has a distinct fixed weight assigned to it that corresponds to its impact on the likelihood of accidents occurring. Although the specific indicators that have the most impact may vary based on the context and characteristics of the construction project, these weights are assigned based on logical assumptions drawn from studies of accidents in the industry.

As presented in the Theory Background chapter, Winge, Albrechtsen and Mostue [12] suggest that a majority of accidents are caused by worker-related factors. As a result, the weights of safety knowledge and competence are assigned the highest value of 0.3. Originating factors are also identified as a key driver of accidents [12], and assuming that schedule pressure and safety supervision stem from this, they are given a slightly lower weight of 0.2. Site and equipment factors make up the lowest contribution of around 55% of accidents [12]. Therefore, the weights of environmental harshness and equipment liability are set to 0.1. Also, it is assumed that indicators with extreme values will have a greater impact on the frequency of accidents. Therefore, when the indicators exhibit these values, the accident rate is expected to increase by a factor of 2 or decrease by a factor of 0.9. The expected accident rate is thus adjusted based on the indicator's value and their weight.

Number of Employees

In the planning phase, only the total estimated time for the entire construction phase is provided. As a result, each phase is allocated a percentage of this total time during the construction phase. The assumed time estimates for each activity in the constructed construction projects in this model are as follows: excavation (10%), foundation (10%), framing (30%), electrical (5%), plumbing (5%), roof (20%), and masonry (20%). Based on the duration of a phase, the required workforce during the project is calculated. It is also assumed that the workforce needed for each phase varies depending on the phase's complexity, for example more employees are needed for excavation that electrical work. Thus, the number of employees required are randomly generated within a range which is based on the phase. Since all projects generated by this model involve the construction of a building, it is reasonable to assume that the number of workers required can be determined by the project duration. The duration of a project is influenced by its size and complexity during the planning phase, providing a better indication of the overall scope of work. It should be noted that the time estimates and number of employees in this model are based on simple assumptions and not empirical data.

Accidents

After incorporating the influencing factors for each indicator during a specific phase, the corresponding expected number of accidents occurring within that phase is calculated. This calculation takes into account both the accident rate and the number of employees present during the phase. The accident rate is defined as the number of accidents per employee count. By utilizing a Poisson distribution, the model estimates the actual number of accidents during the phase based on these factors.

3.3.4 Data Foundation for Accident Rate

The accident rates in the model rely primarily on data obtained from the NLIA report from 2022 [2]. Official statistics on work-related accidents in Norway are compiled by Statistics Norway (SSB) [2], and these are based on employers reporting occupational injuries/occupational diseases to NAV as per the National Insurance Act § 13-14 [2]. The construction industry reported 2978 work-related injuries to NAV in 2021. Approximately half of these injuries were expected to result in more than three days of absence from work, which is the definition of "serious injuries" [2].

Although serious injuries should always be reported to NLIA, it is worth noting that NAV has registered 3.8 times more serious injuries than the number of work-related accidents with serious injuries that have been officially reported to NLIA [2]. SSB's statistics on non-fatal work-related injuries are also incomplete because not all work-related injuries are reported to NAV [2]. This indicates that there is a notable discrepancy in the reporting of accidents with serious injuries to NLIA and to NAV, which creates uncertainty around the available data on this topic. Regarding work-related fatalities, NLIA maintains a register that is assumed to be fairly comprehensive and serves as the basis for official statistics on work-related deaths [2].

As data foundation for the accident rate in the simulation model both the rate of serious injuries and the rate for fatal injuries have been considered. The rate for serious injuries is found by dividing the total number of accidents that happened during 2021 in half, since it is expected that half of the total number of injuries is serious injuries. This number is then dividing by the total number of employees in the construction industry. To calculate the rate of serious injuries, the total number of accidents that occurred during 2021 is divided by two, assuming that half of the total number of injuries are serious, and then this is divided by the total number of employees in the construction industry. The Norwegian construction industry currently employs nearly 240,000 people who are residents of Norway [2]. In addition, there are approximately 22,000 people on short-term stays in Norway [2]. By incorporating the relevant data from Norwegian accident statistics, the resulting equation 3.1 can be used to determine an accident rate of 5.68 injuries per 1000 employees.

$$AccidentRate = \frac{2978/2}{262000} = 0.00568 \tag{3.1}$$

The rate of work-related deaths per 100,000 employees has fluctuated between

4.7 (in 2014) and 1.6 (in 2018) during the period between 2012 and 2021. In 2021, there were 3.5 work-related deaths per 100,000 employees [2]. This rate remained consistent with the previous five years, except for 2018 when there was an unusually low number of registered work-related deaths [2]. Therefore, the fatal accident rate used for this simulation model is 3.5 accidents per 100 000 employees.

3.4 Experimenting with Model

Given the absence of real data for calibration, the need for sensitivity testing and extreme condition testing of the model is required to validate it. Sensitivity testing is used to assess the sensitivity of the model output to changes in the input, while extreme condition testing is used to test if the model provides reasonable results when exposed to extreme conditions. Thus, the sensitivity tests are conducted with experiments that assess the extent to which the results are influenced by individual indicators as well as different weighting schemes applied to them. This experimentation includes formulation of different hypothesis and assumptions, which are tested within the simulation environment. Extreme condition tests are conducted with experiments to validate that the model produces reasonable values despite very poor or very high input values. Heatmaps are also utilized to analyze the relationships among indicators in the model.

This approach may not provide the same level of accuracy as models calibrated with real data, but it can still be an effective way to test and refine theories, gain insights, and make informed decisions. By experimenting with different scenarios and inputs, a better understanding of how the system works can be gained, also potential issues or opportunities can be identified, and strategies to address them can be developed. Ultimately, the success of the simulation model experiments depends on the quality of the hypotheses and assumptions made, as well as the accuracy and comprehensiveness of the model itself.

3.4.1 Adjusting Functions in Operation Model

Adjusting functions in the operation model by tuning the impact of various parameters allows for the testing of different hypotheses and the demonstration of how seemingly unimportant factors can actually have a significant impact on the model. This approach can be particularly valuable in an industry where there are often beliefs and assumptions without concrete proof. As in the construction industry where there is a widely held belief that project management has an influence on the number of accidents, but this has not been definitively proven. By using the simulation model to adjust the impact of project management and other variables, it becomes possible to gain a better understanding of the factors that contribute to accidents in construction projects and to identify strategies to mitigate them.

The function that ultimately affects the number of accidents happening in a project is the function that calculates the accident rate, which is based on several factors that could potentially impact the accident rate. By adjusting the weights of the different factors, it is possible to demonstrate how different hypotheses affect the model and to show that factors that are not usually considered to be important may in fact have a significant impact on the accident rate.

The first hypothesis that is tested is the original assumptions that safety knowledge and competence have the greatest (0.3) impact on the accident rate. Safety supervision and schedule pressure have less but also great impact (0.2), while equipment liability and environmental harshness have the least (0.1). Also, for extreme values of the indicators, the accident rate will respectively increase or decrease by 2 or 0.9 since large/small values have a greater impact on the frequency of accidents.

In addition, another hypothesis where each indicator is assigned different weights based on its perceived impact on the accident rate is tested. This hypothesis assumes that environmental harshness, equipment liability and safety knowledge have the same and the largest impact (0.3) on the accident rate, since these are reflected as key drivers of accidents on construction sites in some studies [46]. On the other hand, schedule pressure and safety supervision are assumed to have a slightly less impact (0.2) and competence has the least impact (0.1). The simulation model is used to test the validity of this hypothesis and to determine how variations in these weights can affect the overall accident rate. Analyzing the outcomes from the experiment enables the identification of how alterations in the impact affect the model's results.

How the model responds to equal weights, implying that no single indicator significantly influences the accident rate, is also tested. The first hypothesis built on this assumption suggests that each indicator's weight are uniformly set to a small value of 0.1. Additionally, the impact of varying the weight values equally is investigated by assigning a high impact weight of 0.9 for all indicators and a medium impact weight of 0.5.

Another hypothesis is also tested to explore the relationship between extreme values of the indicators and the accident rate. Specifically, the hypothesis is that when some of the indicators reach very good or very bad values, the accident rate will increase or decrease even more than expected based on the assigned weights. To test this hypothesis, the extreme values of each indicator are changed to increase by 1.5 and decrease by 0.7, respectively. This is to investigate how the model's results will be affected by the fact that very bad values of indicators affect the accident rate less, while very good values of indicators affect the accident rate more. This hypothesis is tested combined with the first and second hypothesis.

All these seven hypotheses are tested on both serious accidents and fatal accidents, as they represent two distinct levels of severity in construction accidents. To determine the percentage of projects that involve accidents, a statistical analysis is performed on a simulation comprising 1000 projects for each severity level. In order to ensure consistency across projects, the environmental harshness indicator is assigned a constant value of five for all project phases that incorporate it. Meanwhile, the remaining values are derived from simulated projects during the planning phase, thereby remaining constant throughout the experiments. This approach enables us to assess the impact of some of the indicators on accident occurrence, while also accounting for the potential interactions between different indicators.

3.4.2 Best and Worst Case Scenarios

To evaluate the effectiveness of the model, an additional experiment is conducted by Borkenhagen and Olsen [1], in which various scenarios is inputted into the system to analyze their statistical outcomes. The purpose of this experiment is to determine the impact of different indicators on the incidence of accidents in projects. First, the optimal, sub-optimal, and least optimal cases of the indicators are inputted into the operational model, with each test using projects of the same moderate length. Then, further tests are conducted with each indicator having sub-optimal values, and only the project duration is varied between the shortest possible duration of 91.25 days, 500 days, and the longest possible duration of 912.5 days.

After running these tests on 10,000 projects, the resulting average number of accidents per project is calculated. To reduce the uncertainty of the indicators' impact on accident incidence, it is essential to test the model on a large number of projects. Testing on a single project can create more uncertainty, whereas running the tests on 10,000 projects can establish a more linear relationship between the indicators. Testing on multiple projects can provide a more accurate evaluation of the model's effectiveness and its ability to accurately simulate accidents in construction projects. Since the inputs are predetermined, the planning model is not utilized in this particular instance. The goal of these experiments is to assess the model's performance under different scenarios and to determine its suitability for predicting accidents in construction projects.

3.4.3 Heatmaps

In collaboration with Borkenhagen and Olsen [1], experiments have been conducted using heatmaps to investigate the correlation between different indicators. Heatmaps are a powerful visualization tool that enables easy visualization of the strength and direction of relationships between two variables. This study utilizes heatmaps to identify pairs of indicators with a strong positive or negative correlation. This facilitates the determination of indicators that have the most significant impact on the risk of accidents in the construction projects simulated by the model. Furthermore, insights into how different indicators interact and affect each other can be gained, which can help in evaluating the accuracy of the model by comparing it with real-world scenarios to see if the relationships are consistent with observed trends and patterns.

3.5 Machine Learning Model

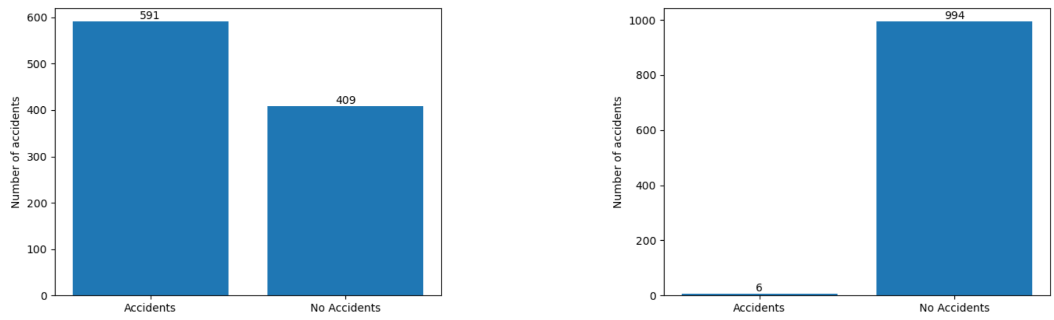
The ML model implemented in this study is developed in collaboration with Borkenhagen and Olsen [1]. The model utilizes ML algorithms to predict the probability of accidents in construction projects. Particularly, binary classification algorithms are applied on 1000 simulated projects. The algorithms are tested on projects that include serious as well as fatal accidents. Binary classification algorithms are utilized for this purpose, as it is a suitable choice when there are two possible outcomes or classes for a given task. In the case of predicting accidents occurring in a construction project, there are typically only a few instances of accidents in each construction project. Therefore, a binary classification algorithm allows for the classification of a project as either an accident has occurred or an accident has not occurred.

The implementation of a binary classification algorithm involves several steps including data preparation, feature selection, selecting a classification algorithm, training the model, evaluating its performance, fine-tuning the model, and finally making predictions. During the data preparation stage, the dataset is partitioned into training and testing sets with a ratio of respectively 0.75/0.25. For projects involving serious accidents, the training set is composed of nearly balanced positive and negative examples. However, for projects that involve fatal accidents, it is not feasible to balance the training set due to the rarity of such instances in the dataset. The datset used in this study is further elaborated in Section 3.5.1.

The next step is selecting appropriate classification algorithms, which are implemented using the Scikit-learn library in Python. During these evaluations, the algorithms SVM, XGBoost, AdaBoost, RF, and Decision Trees are applied to the model, as they are considered appropriate choices for this domain. These algorithms are well-suited for predicting the classification of projects with or without accidents due to their ability to handle complex data patterns, and provide interpretable results that can aid in identifying the factors contributing to accidents. An elaborate description of all of these algorithms is given in Section 2.4.1. The chosen algorithms are trained using the training data and tested on the testing data. Finally, performance measures such as accuracy, precision, recall, and F1 score are calculated and reported for each algorithm, along with the confusion matrices depicting the algorithm's predictions. These results serve as the foundation for evaluating the effectiveness of applying ML on the simulated projects.

3.5.1 Dataset

The dataset employed in this ML model is obtained from the output data of the simulation model during the planning phase and the corresponding number of accidents observed in the building phase model. It consists of 1000 simulated projects. Figure 3.5.1 presents the distribution of projects categorized as having accidents and those without accidents for both the serious accidents dataset and the fatal accidents dataset. Figure 3.1(a) demonstrates a relatively balanced distribution of data, whereas the dataset depicted in Figure 3.1(b) exhibits a significant imbalance. The planning phase output includes 53 indicators, which encompass both the primary indicators utilized during the building phase (e.g., expected duration, equipment liability, and safety supervision) and other indicators not directly linked to the building phase. However, these indicators are interlinked with other metrics that influence the indicators utilized in the building phase. For further clarification on the planning phase and its corresponding indicators, reference can be made to the master thesis written by Borkenhagen and Olsen [1].



((a)) Dataset serious accidents ((b)) Dataset fatal accidents

Figure 3.5.1: Distribution of projects with and without accidents in the datasets.

3.5.2 Overview of model development

Figure 3.5.2 summarizes the steps outlined in this section for the application of ML classifiers on the dataset described in Section 3.5.1.

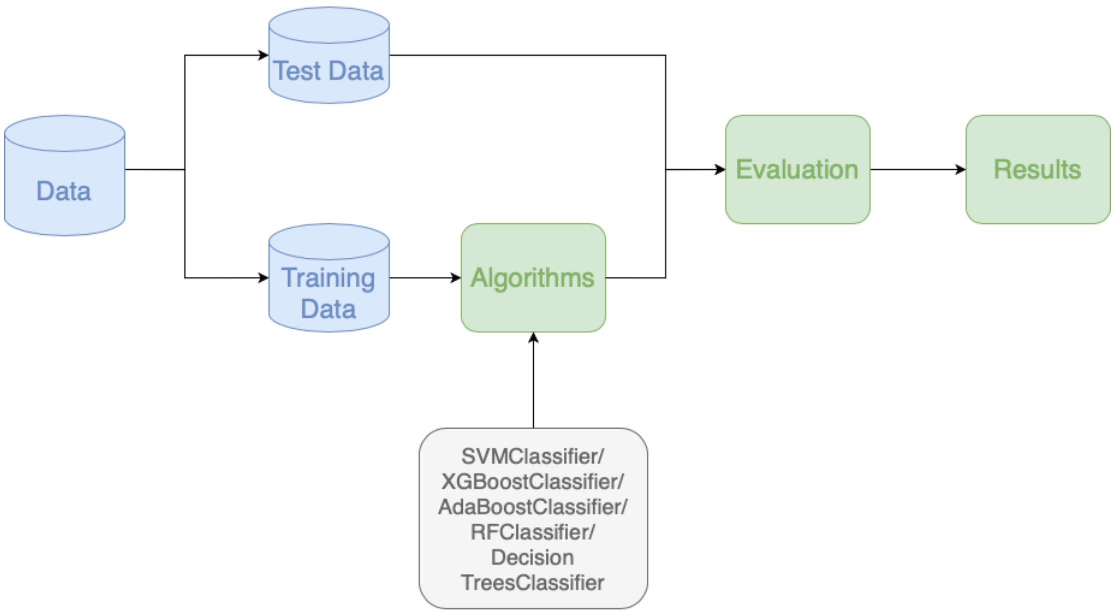


Figure 3.5.2: Work flow of the ML model.

CHAPTER

FOUR

RESULTS & DISCUSSION

In the following chapter, the results obtained from two different approaches, namely experimenting with the simulation model and applying ML algorithms, is presented and discussed. Firstly, the insights gained from experimentation with the simulation model are discussed. Then, the results obtained from the ML algorithms implemented are presented. These results are analyzed and discussed in the context of their potential for predicting and preventing accidents in construction projects. By utilizing these two approaches, a comprehensive analysis of the performance and potential of the model in terms of its predictive power and practical application in the construction industry is aimed to be provided. Additionally, further work on the model is discussed, based on the insights gained from the results and discussions.

4.1 Experiment 1: Adjusting Functions

The seven different hypothesis tested in the first experiments involving the adjustment of functions in the model and their results are presented in Table 4.1.1. Looking first at the results from testing the hypotheses on serious accidents in projects, it shows that the results varies slightly between the lowest value being 52.9 % of projects involving accidents and the highest value being 78.6 % of projects involving accidents. The first five hypotheses use the same functions for extreme values of the indicators affecting the accident rate, and can thus be closely compared. The empirical findings from hypothesis 3, 4 and 5 demonstrate a negative correlation between the weight of indicators and the occurrence of accidents in projects. This is a logical outcome since it indicates that the model is effectively capturing the fact that accidents tend to occur less frequently when indicators have a weaker influence. Hypothesis 2 suggests that the weights from the first hypothesis should be changed so that both equipment liability and environmental harshness have more impact and competence has less impact on the accident rate, which also results in more projects with accidents. However, hypothesis 6 and 7 suggest that the impact of extremely low values affects the accident rate less and for extremely good values affects it more, i.e. the accident rate increase by less and decrease by more. This gives, not surprisingly, a lower number of projects with accidents. However, an examination of the results of projects with fatal accidents reveals their rarity, as they range from only 0.2 % to 1.4 % of projects experiencing accidents.

4.1.1 Discussion of Results

The experimental results presented in Table 4.1.1 offer several insights into the effectiveness of adjusting the functions affecting the accident rate in construction projects. However, it is important to note that further investigation is needed to determine which of the models mimics reality the most.

While the findings from hypotheses 3, 4, and 5 demonstrate a logical outcome by indicating a negative correlation between the weight of indicators and the occurrence of accidents in projects, hypothesis 2 suggests that changing the weights of indicators can result in more projects with serious accidents. This indicates the importance of carefully considering the weight of different indicators when designing the model, as even small adjustments can lead to significant changes in the accident frequency. However, the results indicate that these adjustments have minimal impact on the occurrence of fatal accidents. In fact, there is a decrease in fatalities observed in hypothesis 2 compared to hypothesis 1, despite the increase in serious accidents from hypotheses 1 to hypotheses 2. This could be attributed to the small number of fatalities occurring, which also introduces a certain level of randomness to their incidence.

Hypotheses 6 and 7 demonstrate a lower accident rate compared to their respective counterparts (hypotheses 1 and 2), suggesting that adjusting the model to better align with reality may involve modifying the impact of extreme values. However, determining the most accurate model for reflecting accident frequency in projects requires the involvement of domain experts who possess the necessary expertise.

It is important to identify which indicators have a significant impact on the accident rate, so that managers can prioritize their efforts and resources to effectively reduce the number of accidents. Since these results are based on a model and not real-world data it is important to consider further research to validate the findings. Overall, the experimental results provide a starting point for future research in this area and demonstrate the potential of adjusting the functions in this model to improve the model's accuracy in simulating projects with accidents.

Hypothesis	% of projects with serious accidents (accident rate = 5.68/1000 employees)	% of projects with fatal accidents (accident rate = 3.5/100 000 employees)
Hypothesis 1: Safety knowledge and competence have the greatest (0.3) impact on the accident rate. Safety supervision and schedule pressure have lesser but also great impact (0.2), while equipment liability and environmental harshness has the least (0.1). For extreme values of the indicators, the accident rate will vary by 0.9 or 2.	58.6 %	0.6 %
Hypothesis 2: Equipment liability, safety knowledge and environmental harshness have the greatest (0.3) impact on the accident rate. Safety supervision and schedule pressure have lesser but also great impact (0.2), while competence has the least (0.1). For extreme values of the indicators, the accident rate will vary by 0.9 or 2.	61.3 %	0.5 %
Hypothesis 3: Each indicator has the same small (0.1) amount of impact on the accident rate.	54.3%	0.5%
Hypothesis 4: Each indicator has a large (0.9) impact on the accident rate.	78.6 %	1.4 %
Hypothesis 5: Each indicator has the same medium (0.5) amount of impact.	70.9 %	0.6 %
Hypothesis 6: With weights in hypothesis 1 and for extreme values of the indicators, the accident rate will vary by 0.7 or 1.5.	52.9 %	0.4 %
Hypothesis 7: With weights in hypothesis 2 and for extreme values of the indicators, the accident rate will vary by 0.7 or 1.5.	55.4 %	0.2 %

Table 4.1.1: Results from adjusting functions.

4.2 Experiment 2: Best and Worst Case Model

These experiments aim to test the best and worst case scenarios of the model and the results are shown in Table 4.2.1 and 4.2.2. The first set of tests involve three different scenarios. In the first scenario, each indicator are set to its least optimal value, such as the quality of the plan set to 1 and the schedule pressure set to 10. The second scenario involves setting each indicator to a sub-optimal value of 5, while in the third scenario, all indicators are set to their best value, such as the quality of the plan set to 10 and the schedule pressure set to 1. To ensure consistency, all the tests are conducted with project size set to 5 and duration set to 500. As shown in Table 4.2.1, the results indicate that the number of accidents decreases as the indicator values improve.

In addition to these tests, three more experiments are conducted to examine the impact of duration variations on the number of accidents. In these tests, all indicator values are set to a sub-optimal value of 5, with only the duration varied. The results in Table 4.2.2 show a correlation between the duration of the project and the number of serious accidents, with longer projects experiencing more accidents. A similar trend can be seen for fatal accidents. However, for medium-long and long-duration tests 2 and 3, the number of fatal accidents remains the same.

Indicator	**Test 1**	**Test 2**	**Test 3**
projectSize	5	5	5
workerCompetence	1	5	10
projectDuration	500	500	500
planQuality	1	5	10
safetyKnowledge	1	5	10
safetySupervision	1	5	10
schedulePressure	10	5	1
equipmentLiability	1	5	10
numberOfSevereAccidents	1.338	0.934	0.664
numberOfFatalAccidents	0.005	0.004	0.002

Table 4.2.1: Results from best and worst models.

Indicator	**Test 1**	**Test 2**	**Test 3**
projectSize	5	5	5
workerCompetence	5	5	5
projectDuration	91.25	500	912.5
planQuality	5	5	5
safetyKnowledge	5	5	5
safetySupervision	5	5	5
schedulePressure	5	5	5
equipmentLiability	5	5	5
numberOfSevereAccidents	0.162	0.927	1.773
numberOfFatalAccidents	0.001	0.006	0.006

Table 4.2.2: Results from sub-optimal model with varying duration.

4.2.1 Discussion of Results

The results of the experiments provide insights into the impact of various indicators on the incidence of accidents in construction projects. The tests conducted with different indicator values and project durations indicate that projects with better indicator values have a lower incidence of accidents. This finding is consistent with real-world scenarios and highlights the potential of the model for predicting accidents in construction projects. Moreover, the model can be used as a metaphor to represent the complex and dynamic nature of construction projects, which involve tight schedules, and various risks and uncertainties.

However, the experiments also reveal some limitations and challenges in using the model for accident prediction and prevention. One of the limitations identified is that fatal accidents are rare events, which may require different risk assessment compared to non-fatal accidents. This suggests that the model may need to be refined to better predict rare but severe events. As a result of fatal accidents being rare events, the results from the experiment suggest that project duration may not have a significant impact on number of fatal accidents occurring. This is evidenced by the fact that projects with a duration of 500 and 912.5 both yielded similar average numbers of fatal accidents. However, the correlation between project duration and the occurrence of serious accidents suggests that duration is still a crucial factor to consider. Although, predicting accidents mostly based on the duration of the project is difficult in this model due to the random nature of fatal accidents when certain risk indicators are high.

Overall, the experiments provide a valuable contribution to the field of construction safety by demonstrating the potential of using the model and statistical analysis collected from the model to identify and mitigate accident risks. However, further research is needed to address the limitations and challenges of the model and to develop a more comprehensive model.

4.3 Heatmaps

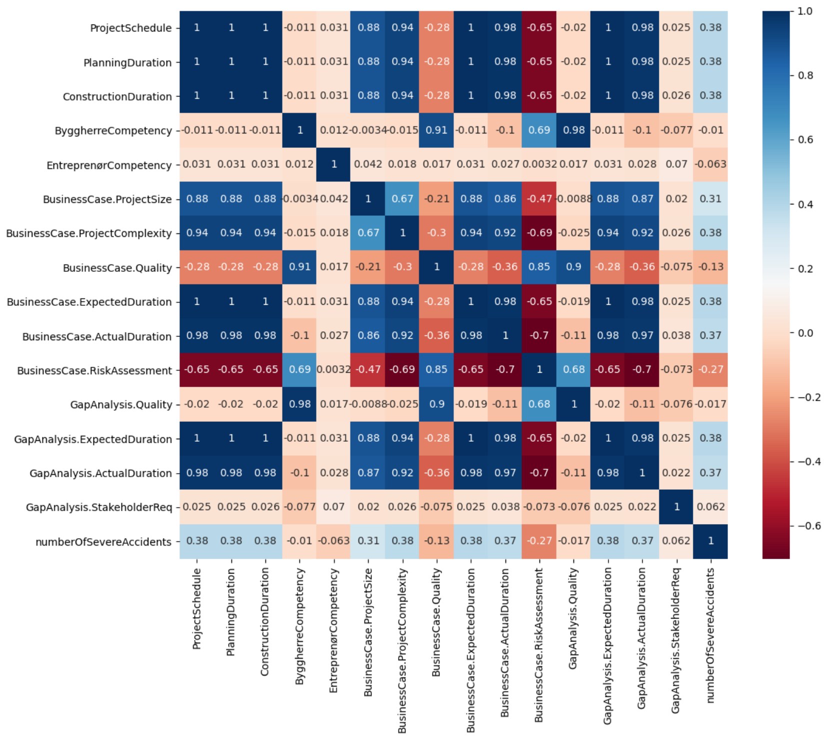
The use of four heatmaps allows for a clear representation of the correlations between indicators. The heatmaps, presented in Figure 4.3.1 and 4.3.2, are generated by analyzing the output of 1000 simulated construction projects in terms of the number of serious accidents. Each cell's color represents the strength and direction of the correlation between two indicators, with darker shades indicating stronger correlations. Positive correlations, where an increase in one variable corresponds to an increase in the other variable, are represented by cool colors like blue and green. Negative correlations, where an increase in one variable corresponds to a decrease in the other variable, are represented by warm colors like red and orange. From the first heatmap it can be seen that indicators like the construction duration has a positive correlation to the number of accidents happening in the project, which indicates the same as what was tested in the previous experiment.

Discussion of Results

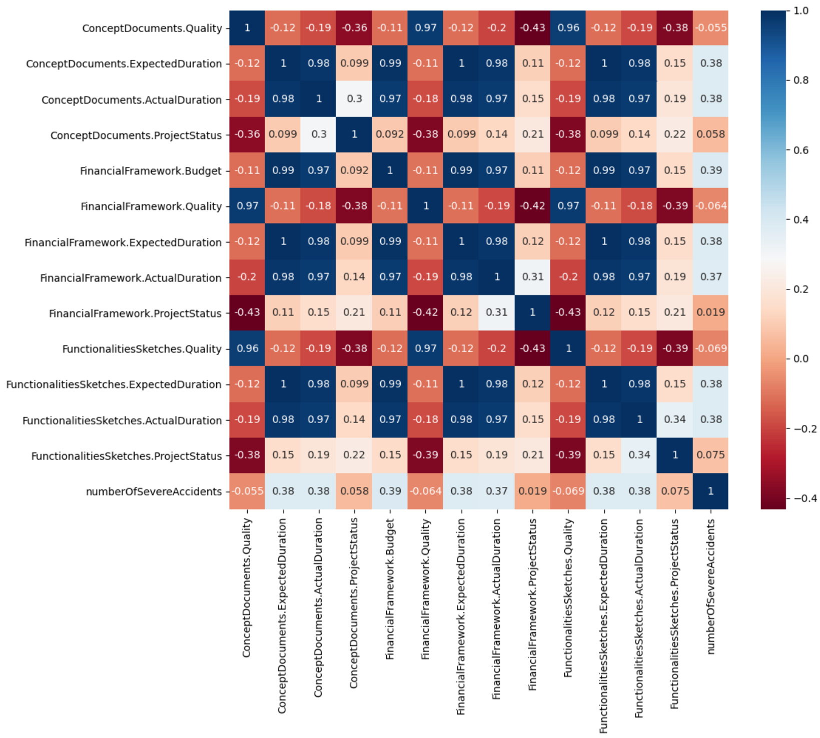
The final heatmap in the evaluation of the model provides valuable insights into the relationship between the indicators and the accident rate in the project. It serves as a means of comparing the model's outcomes with the results obtained from previous experiments. By focusing on indicators that directly influence the project's accident rate, the heatmap offers significant findings.

The results obtained from the heatmap align with the previous findings, further reinforcing their validity. The analysis reveals that indicators such as quality of plan, equipment liability, safety training, and safety supervision, when assigned high values, contribute to a decrease in the number of accidents. On the other hand, indicators like schedule pressure and duration, when assigned high values, lead to an increase in the number of accidents.

These observations highlight the interconnected nature of the indicators and reflect how they influence each other in real construction projects. The findings indicate that the model accurately captures these relationships, demonstrating its validity and ability to reflect the impact of various indicators on the occurrence of accidents.

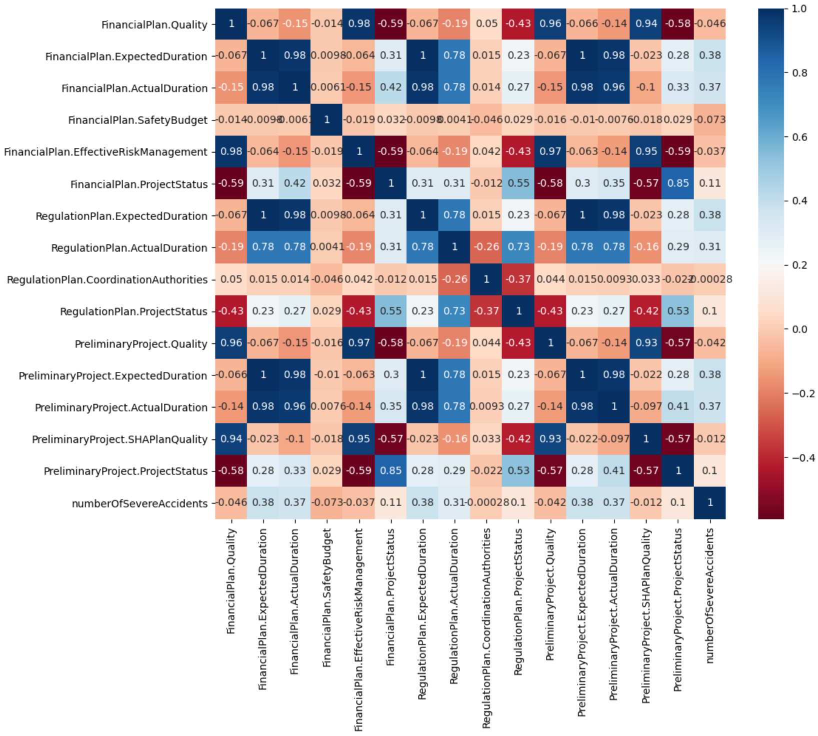


((a)) Heatmap 1

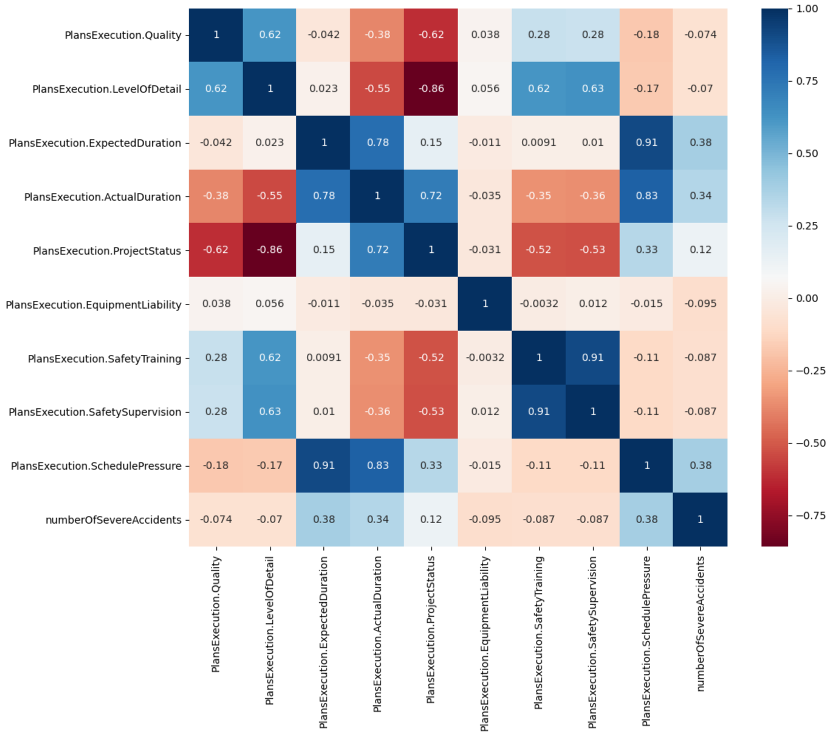


((b)) Heatmap 2

Figure 4.3.1: Heatmaps 1 & 2.



((a)) Heatmap 3



((b)) Heatmap 4

Figure 4.3.2: Heatmaps 3 & 4.

4.4 Machine Learning

The results of applying the five different ML algorithms on 1000 simulated construction projects with serious accidents are presented in Table 4.4.1, while the results for projects with fatal accidents are presented in Table 4.4.2. The confusion matrices for each of the algorithms are also illustrated in Figure 4.4.1 (serious accidents) and Figure 4.4.2 (fatal accidents).

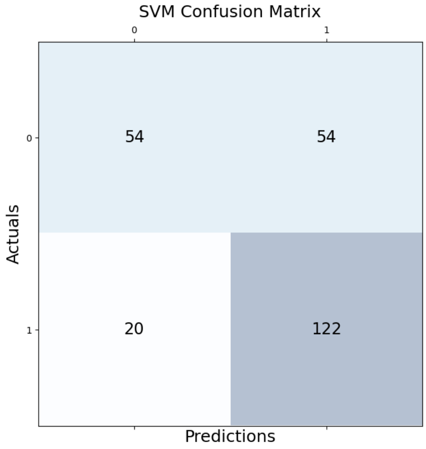
4.4.1 Serious accidents

When applying ML to the dataset comprising serious accidents, the algorithms are trained on an approximately balanced dataset, where 59 % of the projects are labeled as having accidents. These results, as shown in Table 4.4.1, indicate that the ML algorithms are moderately successful at predicting serious accidents in the simulated projects. The best-performing algorithm, SVM, has an accuracy of 0.704, meaning that it correctly predicts serious accidents in 70.4 % of the cases. The precision values range from 0.693 (SVM) to 0.627 (Decision Trees), indicating varying degrees of success among the algorithms in correctly identifying true positives. On the other hand, the recall values range from 0.859 (SVM) to 0.697 (Decision Trees), signifying more pronounced variations in the algorithms' ability to capture all actual positive instances. The F1 scores, which combine precision and recall, range from 0.767 (SVM) to 0.660 (XGBoost). Overall, the results suggest that while the algorithms are able to identify serious accidents to some extent, there is still room for improvement in their predictive power.

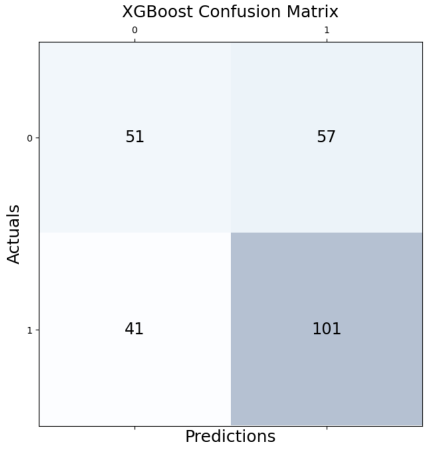
The confusion matrices presented in Figure 4.4.1 provide valuable insights into the performance of each algorithm. Notably, the SVM algorithm demonstrates a high level of success by correctly predicting 122 true positives while only misclassifying 20 actual positive cases. Similarly, the RF algorithm exhibits a strong predictive power, correctly predicting 116 cases while missing 26. The remaining three algorithms have an average of approximately 100 accurate positive predictions, but they tend to miss around 40 positive instances.

Discussion of Results

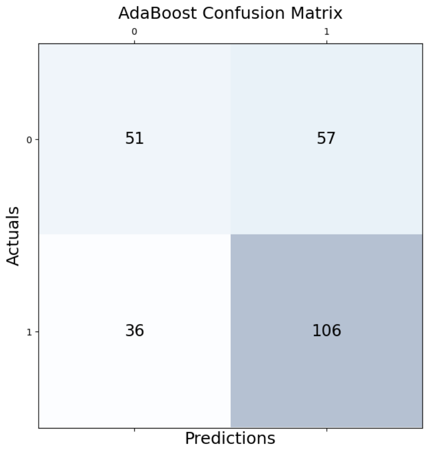
The results in Table 4.4.1 indicate that the performance of the ML algorithms in predicting serious accidents in the simulated projects is not perfect. However, the results do show that the algorithms are better than random chance, as the



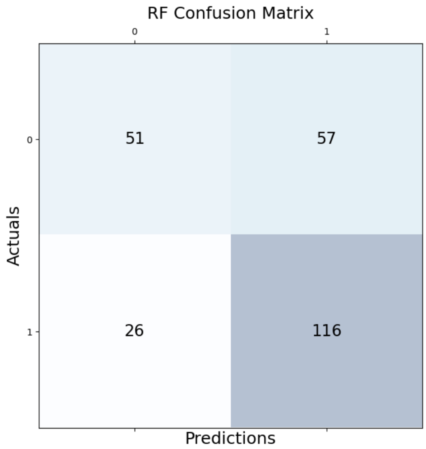
((a)) SVM



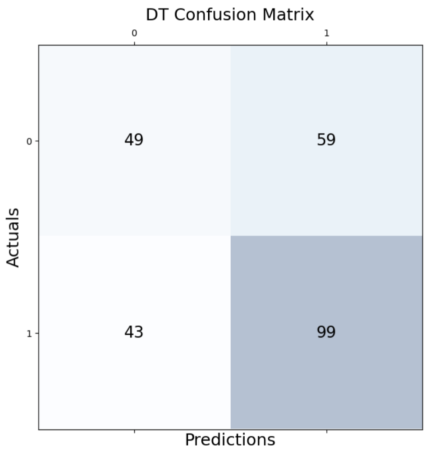
((b)) XGBoost



((c)) AdaBoost



((d)) Random Forrest



((e)) Decision Trees

Figure 4.4.1: Confusion matrices for serious accidents.

Algorithm	Accuracy	Precision	Recall	F1
SVM	0.704	0.693	0.859	0.767
XGBoost	0.608	0.639	0.711	0.673
AdaBoost	0.628	0.650	0.746	0.695
Random Forest	0.668	0.671	0.817	0.737
Decision Trees	0.592	0.627	0.697	0.660

Table 4.4.1: Performance measures for machine learning algorithms predicting serious accidents.

accuracy values are all above 50 %. It is important to highlight that certain algorithms, such as SVM, exhibit high recall values, indicating a substantial number of true positive predictions. In the case of SVM, the algorithm successfully predicts accidents in 85.9 % of the cases. These results are encouraging, as it is more critical for the model to raise alerts when there is a chance of an accident, rather than not raising them at all. Achieving a high recall value implies that the algorithm is effectively capturing a significant portion of the positive instances, enhancing its ability to identify potential accidents. However, some of the lower metrics may indicate that the features used in the model do not have a strong enough correlation with the target variable (in this case, serious accidents) to effectively capture all cases. As a result, the algorithms may be overly pessimistic in their predictions.

Regarding precision values, which range from 0.627 to 0.693, the models successfully identify a significant amount of true positives but also predict some false positives. However, considering the objective of raising alerts for potential serious accidents, a higher false positive rate can contribute to increased awareness and accident prevention efforts. Thus, the focus remains on the models' ability to identify true positives. In conclusion, the results demonstrate the potential of machine learning models to enhance safety in simulated projects, although further improvements are necessary to enhance their performance.

Figure 4.1(a) visualizes the distribution of predictions made by the SVM model, highlighting a significant proportion of true positives, indicating the model's ability to correctly identify projects with accidents. While there are also instances of false positives in the predictions, it is worth noting that these false positives are acceptable within the context of the model's objective. The focus is on maximizing the identification of true positives, even if it means accepting a certain number of false positives. This trade-off is necessary to ensure that the model captures as many potential accidents as possible. This consistent trend is observed across the other confusion matrices as well.

4.4.2 Fatal accidents

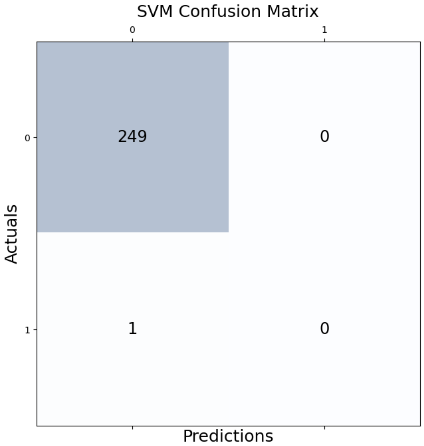
The results presented in Table 4.4.2 show the performance measures in predicting fatal accidents in the simulated projects. This shows a high accuracy of 99.6 % in all algorithms except decision trees, which have an accuracy of 98.4 %. However, all other metrics are set to zero. As seen in Figure 4.4.2, all algorithms fail to predict any true positives, resulting in both precision and recall being set to zero. As precision is the ratio of true positives to the sum of true positives and false positives, and recall is the ratio of true positives to the sum of true positives and false negatives, the absence of true positives leads to zero values for these metrics. Consequently, the F1 score, which is the harmonic mean of precision and recall, will also be zero. This signifies that the model is unable to correctly identify any positive instances, resulting in a complete lack of true positive predictions. Furthermore, Figure 4.4.2 reveals that all algorithms fail to correctly predict the only accident in the test data. Additionally, the decision tree algorithm incorrectly predicts three instances as positive, even though they are actually negative.

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1**
SVM	0.996	0	0	0
XGBoost	0.996	0	0	0
AdaBoost	0.996	0	0	0
Random Forest	0.996	0	0	0
Decision Trees	0.984	0	0	0

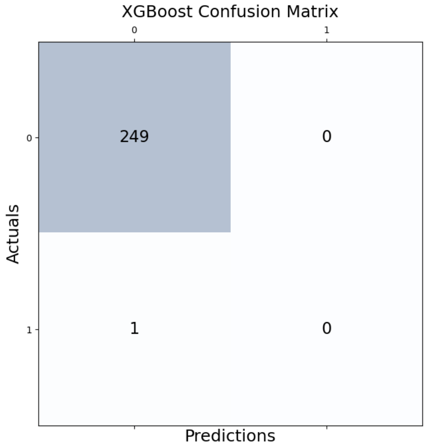
Table 4.4.2: Performance measures for machine learning algorithms predicting fatal accidents.

Discussion of Results

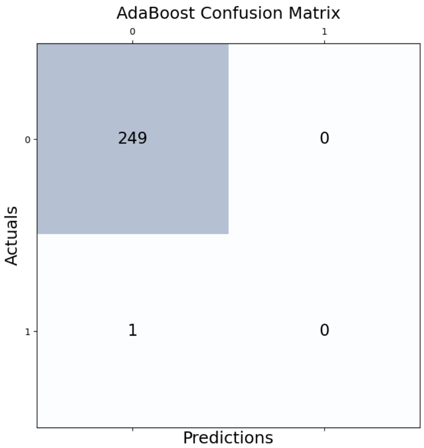
The high accuracy of the algorithms reflects the fact that the algorithms mostly choose not accident and since this is the majority of the projects it is usually correct. The other measures, which are all zero, are also due to the fact that only a small percentage of projects actually have a fatal accident, making it hard for the algorithm to correctly identify them. The recall value reflects that the algorithms are missing all the number of actual fatal accidents. Missing positive instances is considered a serious issue, as it may lead to potential accidents being overlooked or underestimated, and therefore this recall value is problematic for this case. These results therefore show that the algorithms are not effective in predicting fatal acci-



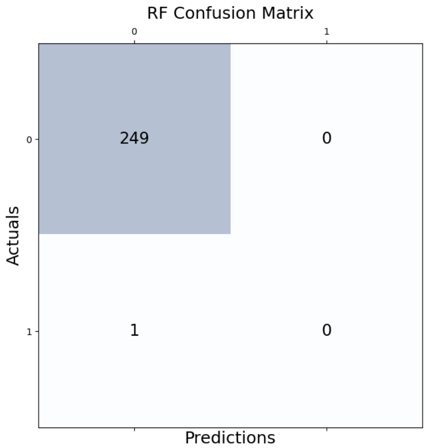
((a)) SVM



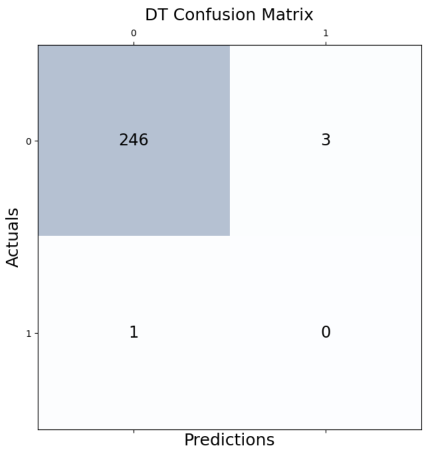
((b)) XGBoost



((c)) AdaBoost



((d)) Random Forrest



((e)) Decision Trees

Figure 4.4.2: Confusion matrices for fatal accidents.

dents due to their rarity and unpredictability. While a null value for these metrics may initially indicate poor model performance, it is necessary to identify the underlying causes, which could include the influence of the inherent randomness in fatal accidents and the need for more data surrounding these. Therefore, it can be concluded that the algorithms are not effective in predicting fatal accidents, and this may be due to the fact that there are several other factors around fatal accidents, and more information is needed to be able to predict such an accident accurately. There may also be a significant element of randomness involved in an fatal accident, making it hard to predict.

While statistical analyses can reveal certain conditional probabilities associated with fatal accidents, accurate prediction requires a more in-depth understanding of the construction phase and the specific circumstances surrounding fatal accidents. The complexity of accidents, with their multiple causative factors, adds to the difficulty in achieving precise predictions. The dataset for fatal accidents exhibits a significant class imbalance, also posing challenges for the algorithms to effectively identify patterns. Although techniques exist to balance the dataset to a greater extent, our understanding of these techniques remains relatively limited, and there may also be a significant element of randomness involved in a fatal accident. Consequently, it can be acknowledged that there is a need to consider alternative measures of safety performance that may be more appropriate. For instance, predicting the probability or rate of accidents, rather than the occurrence of a specific accident, could provide more meaningful insights. By focusing on these alternative metrics, the understanding of safety performance can be enhanced and more informed decisions regarding accident prevention strategies can be made.

4.5 Discussion of the Model

After analyzing the results obtained from both the simulation model experiments and ML algorithms, a comprehensive evaluation of the potential of the model can be conducted. This discussion explores the strengths and limitations of the model and provides recommendations for future improvements and applications.

The aim of this model is to serve as a metaphor for construction projects, wherein identifying indicators that raise alerts of potential accidents is crucial for preventing accidents from occurring. The model is developed based on such indicators, and the experiments conducted demonstrate that they can have a significant impact on accident rates. By using the model, individuals involved in construction projects can gain a better understanding of the importance of monitoring early warning signs and taking prompt action to mitigate potential risks.

The use of a simulation model as a metaphor for construction projects offers several advantages. Firstly, it can improve understanding by simplifying complex and abstract concepts and making them more concrete. This allows individuals to relate to the subject matter and remember it more easily. Secondly, using a model as a metaphor can enhance communication, especially to those who do not have a technical or specialized background in the topic. Thirdly, it can increase engagement by making the topic more interesting and accessible, leading to greater participation in discussions and action. Lastly, it allows for greater creativity in conveying the message and presenting the concept in innovative and interesting ways. Overall, using the model as a metaphor is a powerful tool for educating and inspiring individuals, making complex concepts more accessible and engaging, and promoting discussion and action.

Furthermore, it is evident that predicting fatal accidents in the construction industry proves to be particularly challenging due to their infrequent occurrence and the multitude of complex factors influencing their causation. The infrequency of fatal accidents makes it difficult for the machine learning algorithms to discern discernible patterns and develop accurate predictive models. Nevertheless, despite these challenges, the evaluation of the machine learning algorithms on serious accidents demonstrates their significant potential in predicting safety outcomes within construction projects. The results highlight the efficacy of employing machine learning techniques to enhance safety practices and mitigate potential hazards in the industry.

The prediction of fatal accidents often requires the consideration of multiple factors. For instance, a study referred to by Poh et al. [26] identified two significant factors associated with fatal injuries: the "worker's age and time of day for civil projects" and the "worker's salary and day of the week for building projects." This emphasizes the need to incorporate more comprehensive and detailed factors in the prediction of fatal accidents. While these factors can be helpful in predicting fatal accidents, incident type also plays a crucial role in determining accident severity. For instance, falling from a height incident type generally leads to more serious injuries as compared to being cut by an object. Additionally, relying solely on safety-related data may not be sufficient for effective prediction of construction accident occurrence and severity, as noted by Poh et al. [26]. Therefore, it would be important to consider additional factors, such as day of week and age of worker, when predicting fatal accidents in construction projects. Thus, comprehensive data on past fatal accidents in the industry should be used to enhance the model's construction phase. This would involve incorporating additional data that can help predict such accidents. While it may be possible to identify potential risks during the planning phase, predicting whether they will lead to a fatal accident remains difficult.

Nonetheless, the developed model shows great potential for assisting managers in the construction industry in identifying high-risk sites and taking proactive measures to prevent accidents. As demand on construction projects increases and experienced personnel become scarce, it becomes more challenging for managers to effectively allocate resources and address safety concerns. The model can help start a discussion among project managers about the complexity of projects and how to manage them effectively. By detecting bad indicators early on in a project, managers can take corrective actions to reduce the risk of accidents and improve overall project safety. However, it is important to note that the model still needs to be verified with real data to ensure its accuracy. Therefore, future work should focus on verifying the model with real data and exploring ways to enhance its capabilities to better address safety concerns in construction projects.

Ultimately, the experiments that is conducted in this study reveal three crucial factors to consider when predicting accidents in the construction industry: the inherent limitations of machine learning models, the presence of conditional probabilities associated with fatal accidents, and the need for comprehensive data on past accidents to enhance the accuracy of the model. The potential of the model lies in its ability to act as a proof-of-concept, demonstrating how alerts can be raised early on in a project. It is more beneficial for the model to generate false positives and alerts about potential accidents, than to not generate alerts at all. While predicting fatal accidents remains challenging, the use of data and statistical analysis can provide valuable insights that can help improve safety in the construction industry. By understanding the risks associated with each construction phase, individuals involved in construction projects can develop strategies to mitigate potential hazards and create a safer work environment for all involved. Thus, the findings of this study demonstrate the advantages of integrating system dynamics and machine learning in industries characterized by a substantial lack of available data.

4.5.1 Limitations

While the simulation model developed in this projects offers several advantages, it also has certain limitations that must be acknowledged. One such limitation is that the model only focuses on one type of construction project. This means that the model's applicability to other types of construction projects are limited, and its results should be interpreted with caution when applied to other types of projects. Additionally, the model has not been calibrated with real data on projects, which may affect its accuracy and reliability. While the model may provide valuable insights and predictions for the specific type of construction project it was designed for, its limitations should be taken into account when using it for decision-making purposes. Future research could explore ways to improve the model's calibration and expand its applicability to other types of construction projects.

Another limitation of this study is that most of the machine learning algorithms used do not provide clear explanations of how they arrived at their predictions. These algorithms are often referred to as "black boxes" because their internal workings are ambiguous and difficult for humans to comprehend. As a result, it may be challenging to understand the relationship between the input variables and the predictions made by the algorithm, which could limit the interpretability of the results.

4.6 Further Work

In terms of future work with the developed model, there are several areas that could be explored. Firstly, it is important to verify the model's accuracy with real-world data and consulting with experts. It should be noted that a significant amount of data around an accident is necessary to accurately predict it. Therefore, collecting sufficient data and performing validation tests on the model is an important next step. In the context of machine learning, it would be worthwhile to investigate whether incorporating data from the construction phase, in addition to the planning phase, could enhance the performance of the algorithms.

Another potential use of the model is the ability to input different accident rates for each activity during a project, which could provide a more accurate prediction of accidents. However, it is challenging to determine how the accident rate varies during a project without specialized knowledge and expertise in the field. In the current model, the accident rate is set to a constant value based on statistics from historical data, which may not reflect the reality of the situation. Therefore, to improve the accuracy of the model, there is a need for further collaboration with experts in the field to provide input and insights on how the accident rate varies throughout the project. With the help of experts, the model could be refined to provide more accurate predictions and assist in the identification of potential high-risk activities that require more attention in terms of safety measures.

Furthermore, it could be beneficial to consider incorporating various types of accidents into the model in order to capture the severity of accidents beyond the distinction between serious and fatal incidents. This could help to identify patterns in the types of accident that occur in specific project phases and locations. This information could be used to make targeted improvements in safety measures in those areas, potentially reducing the overall incidence of accidents. However, it is important to note that incorporating accident types into the model would increase its complexity. This would require additional data and potentially more sophisticated modeling techniques. Thus, careful consideration must be given to the trade-offs between model complexity and accuracy. Nonetheless, the potential benefits of incorporating accident types into the model suggest that it is an avenue worth exploring. Alternatively, considering the inherent randomness associated with accidents, it may be worth exploring alternative measures to assess safety in projects beyond solely relying on the occurrence of accidents. One potential approach could involve evaluating the probabilities of accidents happening within a project and using this rate as a measure of safety.

CHAPTER

FIVE

CONCLUSIONS

In conclusion, the research question regarding the application of a proof-of-concept approach that combines system dynamics modeling and machine learning to generate and evaluate construction projects, aiming to improve safety predictions, has been successfully addressed. Both system dynamics modeling and machine learning have been effectively implemented in this thesis, demonstrating the significant potential of their combined usage. The findings obtained from this integration highlight the promising outcomes that can be achieved, making a valuable contribution to the research regarding the utilization of digitization tools for enhancing safety in the construction industry. While the machine learning results from this model may not have achieved optimal performance, the model serves as a proof-of-concept and a metaphor for safety predictions in construction projects. It emphasizes the importance of early warning signs and proactive measures rather than relying on real-world scenarios or data.

The findings of this research highlight the significance of leveraging such models to address the challenges faced by senior managers in the construction industry. With the increasing demand for construction projects and the associated lack of resources and experienced personnel, it becomes crucial for senior managers to identify high-risk sites and take proactive measures to prevent accidents. The model that is presented in this thesis, which combines system dynamics and machine learning, serves as a valuable tool in initiating discussions among project managers about the complexities of construction projects and how to effectively manage them.

The investigation reveals the inherent complexity of accidents, resulting from the interplay of multiple factors. Accidents rarely have a single direct cause but instead arise from various underlying factors. This complexity poses challenges in establishing a straightforward cause-and-effect relationship for accurate accident prediction. However, understanding the multifactorial nature of accidents underscores the need for holistic approaches to accident prevention and mitigation strategies.

System dynamics proves to be a valuable tool for simulating projects when data availability is limited, while machine learning utilizes synthetic data derived from system dynamics to predict safety levels and test their capability. Although predicting fatal accidents poses challenges due to their relatively low occurrence, machine learning models demonstrate the ability to predict a significant proportion of projects with serious accidents. While alternative measures of safety performance, such as predicting probabilities or rates, may be more appropriate than predicting the specific type of accident, this research underscores the potential of machine learning to enhance safety levels in construction projects. The findings also showcase that it is possible to raise early warning signs of potential accidents, so that risks can be mitigated.

In summary, this thesis presents a simulation model based on system dynamics, incorporating accident data and multiple indicators affecting accidents. The model also incorporates machine learning, serving as a proof-of-concept for safety predictions in construction projects. While improvements are necessary, the model acts as a facilitator for discussions among project managers regarding project complexity and risk mitigation. The findings of the study demonstrate the advantages of integrating system dynamics and machine learning in an industry facing data scarcity. The combination of these approaches proves to be highly beneficial, enabling the simulation and analysis of projects even in the absence of extensive data. By leveraging system dynamics to generate synthetic data, machine learning models can be trained and deployed effectively, providing valuable insights and predictions for decision-making processes. Future work should focus on enhancing the model's performance and refining its capabilities to provide accurate safety predictions for construction projects.

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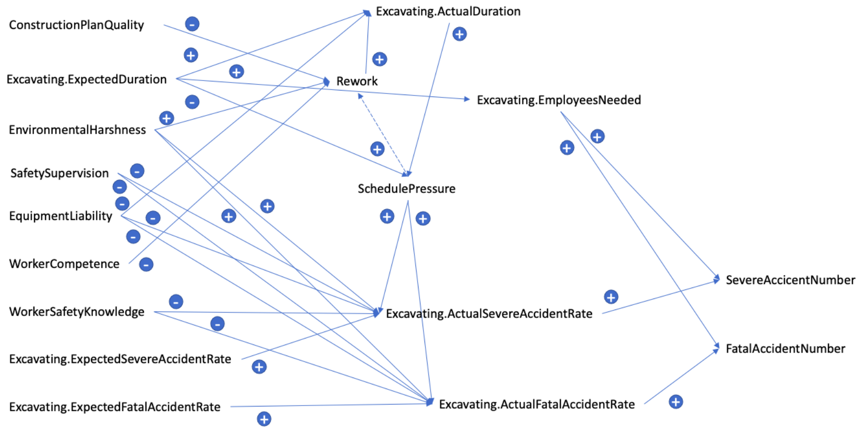
APPENDICES

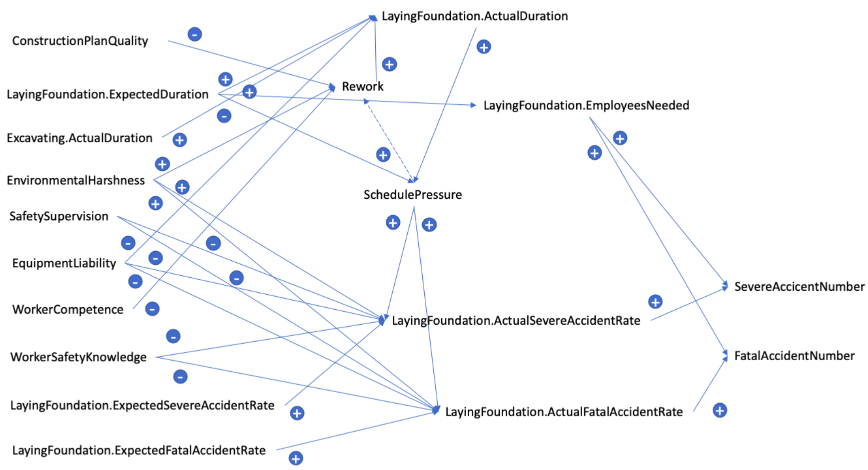
APPENDIX

A

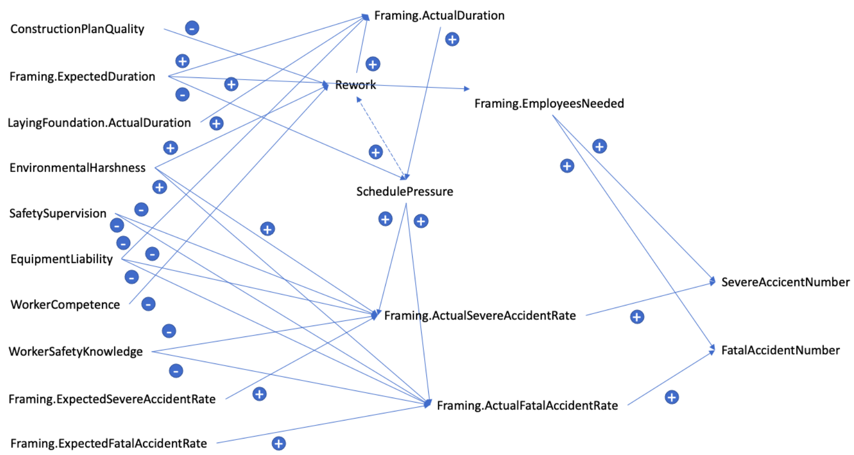
A - INFLUENCING DIAGRAMS



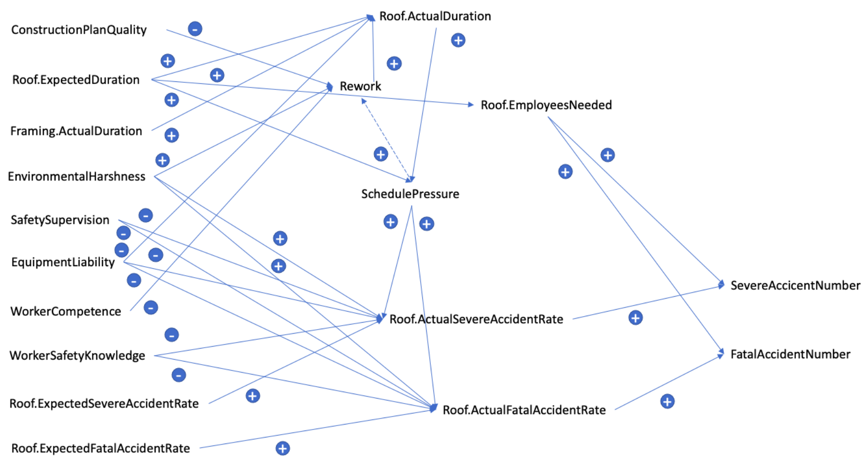
((a)) Excavating



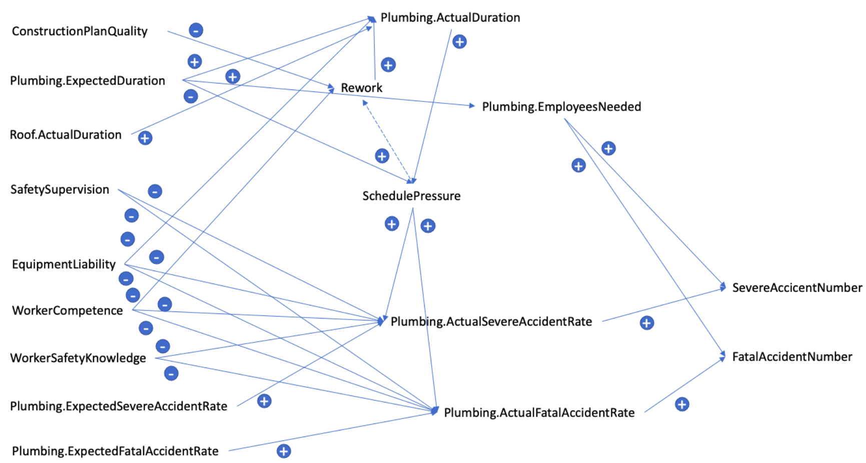
((a)) Laying Foundation



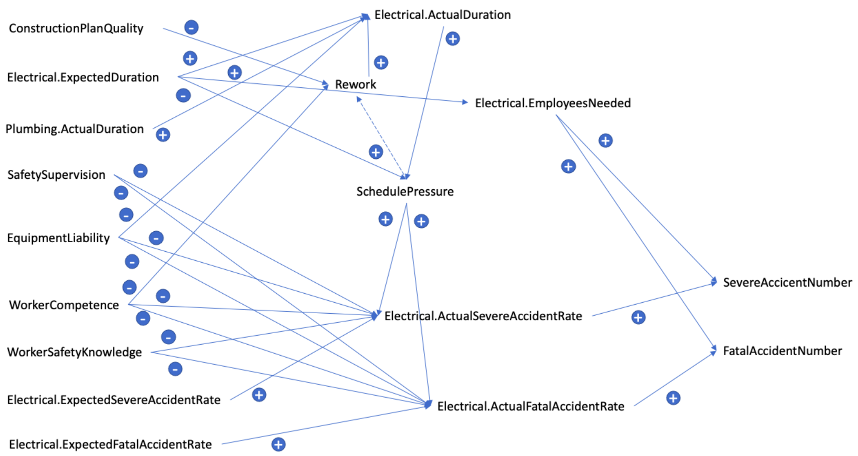
((a)) Framing



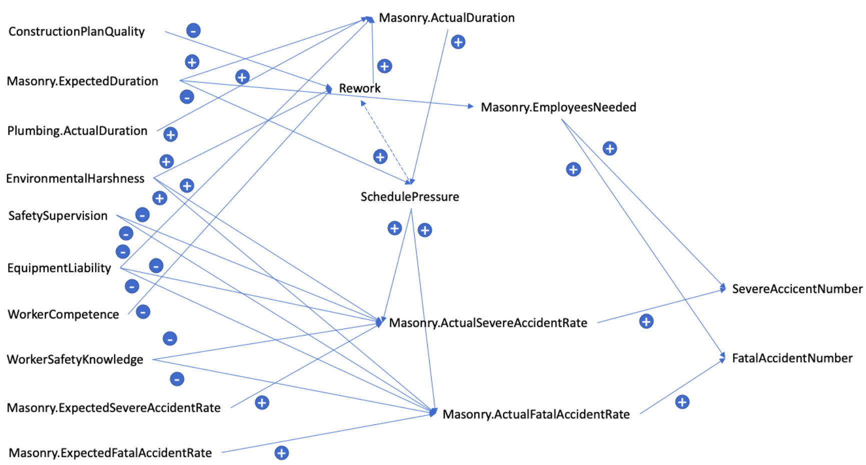
((a)) Roof



((a)) Plumbing



((a)) Electrical



((a)) Masonry

Figure A.0.7: Influencing diagrams for phases of construction model.

APPENDIX

B

B - MACHINE LEARNING

B.0.1 Dataset

Figure B.0.2 illustrates the structure of the datasets generated in CSV format, capturing both the planning phase and the building phase of the model. It is the dataset from the planning phase combined with the accidents occurring in the building phase output that are used as datasets in the ML model.

ProjectSchedule	PlanningDuration	ConstructionDuration	ByggherreCompetency	EntreprenørCompetency	BusinessCase.ExpectedProjectStartDate	BusinessCase.ExpectedProjectEndDate	BusinessCase.ProjectSize
456	228	228	9	2	01 16 2007	04 16 2008	4
912	456	456	8	9	01 07 2010	07 07 2012	6
1277	638	639	6	5	07 22 2007	01 19 2011	6
1277	638	639	1	4	10 01 2010	03 31 2014	6
1460	730	730	7	2	02 12 2005	02 11 2009	6
1460	730	730	2	6	03 22 2012	03 21 2016	8
1642	821	821	8	2	07 22 2019	01 19 2024	8
1460	730	730	1	4	01 10 2002	01 09 2006	8
638	319	319	2	3	07 14 2018	04 12 2020	6
456	228	228	6	3	01 30 2009	05 01 2010	4
1003	502	501	9	6	03 03 2006	11 30 2008	6
1095	548	547	8	9	06 11 2012	06 11 2015	6
1003	502	501	4	3	10 22 2007	07 21 2010	4
821	410	411	4	3	12 14 2021	03 14 2024	4
1277	638	639	6	7	07 09 2002	01 06 2006	7
1733	866	867	3	5	07 29 2019	04 26 2024	9
1186	593	593	2	9	08 07 2022	11 05 2025	6
1733	866	867	5	9	12 09 2021	09 07 2026	9
456	228	228	10	6	03 21 2015	06 19 2016	4
1003	502	501	6	8	03 08 2003	12 05 2005	6
1368	684	684	5	2	12 24 2005	09 22 2009	8
547	274	273	10	7	03 28 2010	09 26 2011	5
638	319	319	10	10	07 14 2004	04 13 2006	4
730	365	365	1	5	08 31 2017	08 31 2019	3
1368	684	684	8	2	10 29 2011	07 28 2015	8
638	319	319	5	2	09 22 2015	06 21 2017	3

((a)) Dataset generated by the planning phase of the simulation model

planQuality	projectSize	numberOfSevereAccidents	schedulePressure	projectTerminationDate	projectDuration	projectActualTerminationDate	safetySupervision
6.000000	4.000000	0.000000	1.000000	228.000000	228.000000	217.000000	3.000000
9.000000	6.000000	2.000000	1.000000	456.000000	456.000000	436.000000	5.000000
5.000000	6.000000	1.000000	1.000000	639.000000	639.000000	631.000000	6.000000
2.000000	6.000000	2.000000	1.000000	639.000000	639.000000	640.000000	6.000000
5.000000	6.000000	2.000000	1.000000	730.000000	730.000000	700.000000	6.000000
3.000000	8.000000	1.000000	1.000000	730.000000	730.000000	694.000000	6.000000
5.000000	8.000000	2.000000	1.000000	821.000000	821.000000	780.000000	4.000000
2.000000	8.000000	3.000000	1.000000	730.000000	730.000000	694.000000	3.000000
3.000000	6.000000	0.000000	1.000000	319.000000	319.000000	303.000000	4.000000
5.000000	4.000000	0.000000	1.000000	228.000000	228.000000	223.000000	2.000000
7.000000	6.000000	1.000000	1.000000	501.000000	501.000000	477.000000	6.000000
7.000000	6.000000	2.000000	1.000000	547.000000	547.000000	527.000000	9.000000
3.000000	4.000000	5.000000	1.000000	501.000000	501.000000	477.000000	4.000000
4.000000	4.000000	4.000000	6.000000	411.000000	411.000000	486.000000	6.000000
6.000000	7.000000	0.000000	1.000000	639.000000	639.000000	606.000000	6.000000
4.000000	9.000000	1.000000	1.000000	867.000000	867.000000	823.000000	6.000000
4.000000	6.000000	0.000000	1.000000	593.000000	593.000000	583.000000	5.000000
6.000000	9.000000	1.000000	1.000000	867.000000	867.000000	852.000000	9.000000

((a)) Dataset generated by the building phase of the simulation model

Figure B.0.2: Datasets generated by the simulation model.

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