Master Thesis

T. M. M. P. van Engelshoven

Intermediate Project Progress Tracking

A case study at an ETO Company

Technische Universiteit Delft

TU Delft

2021

Intermediate Project Progress Tracking

A case study at an ETO Company

by

T. M. M. P. van Engelshoven

Master Thesis

in partial fulfillment of the requirements for the degree of

Master of Science
in Mechanical Engineering

at the Department Maritime and Transport Technology of
Faculty Mechanical, Maritime and Materials Engineering of
Delft University of Technology

to be defended publicly on Friday March 19, 2021 at 10:00 AM.

Student number:	4283457	
MSc track:	Transport Engineering and Logistics	
Project duration:	March 2, 2020– March 19, 2021	
Report number:	2021.MME.8499	
Thesis committee:	Prof. dr. ir. R. Negenborn,	TU Delft, Committee Chair
	Dr. X. Jiang,	TU Delft, Supervisor
	Dr. V. Gentile,	Company Supervisor
	Dr. J. Vleugel	TU Delft, Committee member

This thesis is confidential and cannot be made public until March 19, 2026.

An electronic version of this thesis is available at `http://repository.tudelft.nl/`.

TU Delft

Summary

Delivering equipment in an Engineer-to-Order (ETO) environment starts with the design. The design phase plays a key role in a successful and timely completion of such a project. The increasing competition in the sector of customized large-scale equipment demands reduction of project lead times. As a result, the design phase becomes heavily intertwined with the other disciplines. Furthermore due to the complexity and often creative and iterative nature of engineering, the design phase usually spans over at least half of the entire project duration. Within this context, efficient and accurate project planning gains utmost importance.

The main goal of this research is to overcome this challenge, namely to develop a non-subjective method for progress tracking and prediction to support project planning in ETO environments. Focus is given to the engineering activities, as they are unanimously considered to drive progress and execution of these projects.

This research is done in cooperation with an ETO based company producing large scale equipment. It is assumed that a typical company adopting an ETO project based approach is similar to the collaborating company. So-called deliverables are the basis on which the projects within ETO companies are planned. These are physical blocks of the system which are to be eventually built. For each of such blocks, design activities are planned along with the procurement of the necessary materials and components, as well as with the production and testing activities. The current sub-division into so-called ”construction blocks” can be mainly related to the mechanical engineering activities and later on to the fabrication and assembly of the different parts. Within this sub-division however, emphasis is given to the physical parts of the system and therefore, to their mechanical design. Less space is given on the other hand, to the design tasks of the other engineering disciplines, i.e. electrical, hydraulical and controls systems, which focus on the functionalities of the equipment.

Currently to ensure timely delivery, a typical ETO company relies on planning on multiple levels. In particular, planning based on disciplines is extensively used in order to schedule engineering as well as production activities. The project schedule is structured such to reflect the sub-division of blocks and sections defined in the system design. For effective planning and replanning, regular planning meetings with the project team are needed to discuss the current and expected progress. This progress is reported to the planners directly from the discipline leads verbally, or in an overview document. As a result, the information provided by the schedules is highly dependent on the quality of the received input. This can be especially true for progress, which when reported is susceptible to the planning fallacy. Based on the input, planners make progress reports using the so-called S-curves.

In order to develop the current method, data from ongoing and completed projects were used. The data set was restricted to the case of mechanical engineering due to the great amount of available documentation. Within the present approach, mass of the designed equipment was used as a metrics for progress. In particular, the mass information linked with each released design (i.e. drawing) is herein compared to the total amount of mass to be designed. In this way, so-called mass curves can be obtained, which display the amount of mass designed over time. It was found that the mass curves best reflect the progress of the manufacturing design phase, which is an unique step in the overall design process.

Multiple methods of estimating the current progress of a project were found in a literature study. These methods however, did not meet the requirements set for this research. An integration of these methods resulted in the proposed method: Stochastic S-Curve Feature prediction (SSFP).

SSFP bases its estimation on the available data of the running project and a forecast based on previously completed projects. The forecast is obtained using a linear support vector regression analysis to find the relationship between the ongoing project and the estimated total mass of the equipment. Additionally a S-curve is fit to the available raw data of the ongoing project. With the curve fit and forecast, a weighted average of the progress curve is made. Additionally, using Monte Carlo Simulations, an associated uncertainty to the progress curve is found. In this way SSFP provides a current progress estimation with an uncertainty to indicate to planners how accurate the prediction is.

A simulated data set was used in the verification of the method. It was found that the tracking accuracy was marginally influenced by: the quantity of available documents, the magnitude of Gaussian noise in the data, and the size of the error of the forecast progress curve compared to actual progress. The most important result found in the case study was the error of progress tracking of the method: $0.6 \pm 4\%$. Translating the tracking error to the time domain, this error results in overestimating the progress no more than 2 weeks.

From these results, the tracking accuracy of SSFP can provide insights on the progress of a project for the planners. As no objective method for tracking engineering activities exists in the literature, this provides a good start to build on towards an objective project tracking method. This method additionally requires no prerequisite knowledge of all the individual activities, which is essential due to the flexible and iterative process of engineering. In this way, with accurate and robust progress tracking, the proposed method fulfills the objective on how a progress tracking method can be designed in an ETO environment.

Contents

Summary **i**

List of Terms **v**

List of Figures **vi**

List of Tables **viii**

1 Introduction **1**
1.1 Background 1
1.2 Research Objectives 3
1.2.1 Research Questions 3
1.3 Scope 3
1.4 Structure of the Report 4

2 ETO Company and Projects **5**
2.1 Typical ETO Based Company 5
2.1.1 Typical ETO Projects 5
2.1.2 Planning at an ETO Company 6
2.1.3 Current Progress Tracking 7
2.2 Available Data 8
2.2.1 Cabinet Curves 9
2.2.2 Design Mass Curves 9
2.2.3 Data Selection 11
2.3 Progress Tracking Requirements 11
2.4 Chapter Summary 12

3 Literature Review **13**
3.1 Pre-Processing Data 13
3.1.1 Progress vs Mass Curves 15
3.2 Progress Tracking Methods Review 16
3.2.1 Criteria for Methods 16
3.2.2 Progress Tracking Method Overview 16
3.2.3 Prediction Method Comparison 18
3.3 Mathematical Modeling Review 19
3.3.1 Criteria for Methods 19
3.3.2 Mathematical Modeling Method Overview 20
3.3.3 Mathematical Modeling Method Comparison 23
3.4 Error Quantification Review 24
3.4.1 Criteria for Methods 24
3.4.2 Error Quantification Method Overview. 25
3.4.3 Error Quantification Method Comparison 25
3.5 Chapter Summary 26

4 Development of Prediction Method **27**
4.1 Method Overview. 27
4.2 Feature Analysis 28
4.3 S-Curve Prediction 30
4.4 Monte Carlo Simulation 31
4.5 Chapter Summary 32

5 Performance Evaluation **33**
5.1 Model Verification. 33
5.1.1 Verification Criteria 33
5.1.2 Verification Tests 34
5.1.3 Verification Results 35
5.2 Model Validation 39
5.3 Chapter Summary 43

6 Conclusion and Discussion **44**
6.1 Discussion 46

Bibliography **47**

A Academic Paper **51**

List of Terms

Notation	Description	Page List
APM	Agile Project Management	2
EPC	Engineering, Procurement, and Construction	5
ETO	Engineer To Order	iii, vi, vii, 1–7, 9, 11, 16, 21, 23, 27, 39, 40, 43–45
EVM	Earned Value Management	vi, 2, 16–18, 26, 46
HDR	in-House Document Repository	11
LPP	Lean Project Planning	2
LPS	Last Planner System	2, 16
LR	Linear Regression	vi, 20–23
LRTM	Linear Regression Tree Model	vi, 22–24
MCMC	Markov Chain Monte Carlo	25
MLR	Multiple Linear Regression	20, 21
NN	Neural Network	vi, 18, 23, 24
PDCA	Plan-Do-Check-Act	2
PDF	Probability Density Function	24, 25, 31
RF	Random Forest	22, 23
RMSE	Root-Mean-Square Error	14, 31, 39, 45, 46
RTM	Regression Tree Model	21, 22
SSFP	Stochastic S-Curve Feature Prediction	vi, vii, 18, 19, 24, 26–28, 39–41, 43–46
StS-Curve	Stochastic S-Curve	vi, 16–19, 26, 46
SVR	Support Vector Regression	vi, 21, 22, 24, 26, 27, 29, 30, 32, 44
SWL	Safe Working Load	28, 29

List of Figures

1.1 Schematic of sequential planning vs concurrent planning. Adapted from [28] 1

2.1 Typical project execution sequence at an ETO company. 5
2.2 Sub-division of a simplified example piece of equipment into construction and functional blocks. 6
2.3 Screenshot of an example gantt chart and schedule [52] 7
2.4 Reported progress S-curve of a running project compared to an early and a late target planning. 8
2.5 Reported progress S-curve of a running project's design phase compared to an early and a late target planning. 8
2.6 Cabinet curve of a project at an ETO Company 9
2.7 Mass curve of a completed project 10

3.1 Sample of mass curves with a loglet lab model fit to the data. 14
3.2 Box and whisker plot comparing the error in duration to reach certain progress milestones for mass curves and reported progress curves. Error is calculated by subtracting the mass curve results from the reported progress curve results. 15
3.3 Box and whisker plots comparing features of modeling different mass or reported progress curves. 15
3.4 Example of EVM[12]. 17
3.5 Stochastic S-Curve (StS-Curve) estimation of an Earned Value Management (EVM) analysis of cost over time [3]. 17
3.6 Tree showing time estimation methods examined in this investigation subdivided into categories. 20
3.7 Graphical representation of the Support Vector Regression (SVR) method on a data set. 22
3.8 Graphical representation of a basic regression tree model. 22
3.9 Mathematical modeling of a set of data with Gaussian noise using Linear Regression (LR) (red) and Linear Regression Tree Model (LRTM) (blue). 23
3.10 Diagram of a Neural Network (NN) with three hidden layers, two inputs and one output [59]. 24

4.1 Block diagram of the proposed Stochastic S-Curve Feature Prediction (SSFP) method to develop. Where block 1a and 1b is explained in Section 3.1, 2 in Section 4.2, 3 & 4 in Section 4.3, and 5 in Section 4.4. 28
4.2 Diagram with the S-curve features labeled (L - total released "mass" or progress, k - progress at midpoint, x_0 - midpoint) 28
4.3 Scatter plots of the features of the mass curves compared to the overall weight of the equipment. 29
4.4 Midpoint of the S-curve based on SVR analysis - example. 30
4.5 Example of the output of the method of the same project with different amount of available documents. 32

5.1 Relationship between error on predicted progress at 75% and error on estimated S-curve features. 34
5.2 Test 4 - Gaussian Noise on data with *errorless* prediction: effect of increasing simulated points on prediction accuracy 35
5.3 Test 2 - Noiseless Data with *Error* in Predictions: Error on estimated progress over time 36
5.4 Predicted progress for noisy data: 50 data points (a) and 125 data points (b), and an errorless S-Curve prediction. 37

5.5 Plots of increasing amounts of simulated data points provided as the project progresses from the verification test: 'noise in data with an error in the prediction'. 38
5.6 Plots of increasing amounts of simulated data points provided as the project progresses from the verification test: 'random data with an errorless prediction'. 39
5.7 Error of the tracking accuracy versus the normalized time relative to project completion of the mass curves extracted from an ETO based company. 40
5.8 Found tracking error of 4% added (or subtracted) to an example S-curve from the SSFP method of case study project. 41
5.9 Average duration in time that overestimated progress tracking errors have on projects over the project progression. 41
5.10 Error of the prediction accuracy versus the time relative to project completion of the mass curves from the case study. 42
5.11 Output of the method in a case study test where only 5 documents are used to make a prediction. 42

List of Tables

2.1 Data range before and after filtering projects. 11

3.1 Different S-curve models and their equations. Where a and b are model variables which can be used to determine the inflection point and growth rate of the model. 13
3.2 DIfferent S-curve models and their RMSE fit to different data sets 14
3.3 Overview of the prediction methods and their different characteristics described in section 3.2.1. 19
3.4 Overview of the mathematical modeling methods and their different characteristics described in section 3.3.1. 24
3.5 Overview of the error propagation methods and their different characteristics described in section 3.4.1. 25

5.1 Tests (numbered) which will be performed to verify the method and its output. The numbers represent the subsection in which the verification will be discussed in section 5.1. . 35
5.2 Tracking and Prediction Accuracy Mean and standard deviation of the tests using controlled data explained and numbered further in table 5.1. All the tests in this example used 500 data points. The error is calculated by subtracting the output of the method from the actual progress or duration. 36
5.3 Tracking and Prediction Accuracy using simulated data with different amount of total possible documents. 36
5.4 Tracking and Prediction Accuracy using simulated data with different magnitudes noise. 37

6.1 Overview of the capabilities of available methods 46

1 Introduction

To tackle ever-growing and increasingly complicated projects, infrastructure grows and scales accordingly. To be able to install and implement this infrastructure, specialized equipment engineered for the task is necessary. This equipment can be ordered from many companies, where typically for heavy equipment production these companies take a so-called ETO approach [23]. This approach provides the customer with more flexibility regarding the design of the equipment but as everything is customized to their specifications they are faced with the total product lead times [40]. The delivery of highly customized heavy equipment faces two main challenges: the design needs to be highly flexible and the lead times need to be as short as possible [28, 29, 40]. For a successful execution of the ETO projects, effective and efficient project planning and control is necessary [19, 29, 31].

1.1. Background

Project planning and control is becoming a critical component of project management. As flexibility, customization, and fast delivery are becoming more important for ETO companies, concurrent planning is a typical practice due to the high level of customization [28]. In concurrent planning the engineering, procurement, and fabrication phases can overlap in the timeline(see Figure 1.1). The advantages of concurrent planning is an extended time to clarify the design with client and a reduced overall product lead time. This overlap in phases provides a challenge to provide the necessary information on-time to allow successive phases to function.

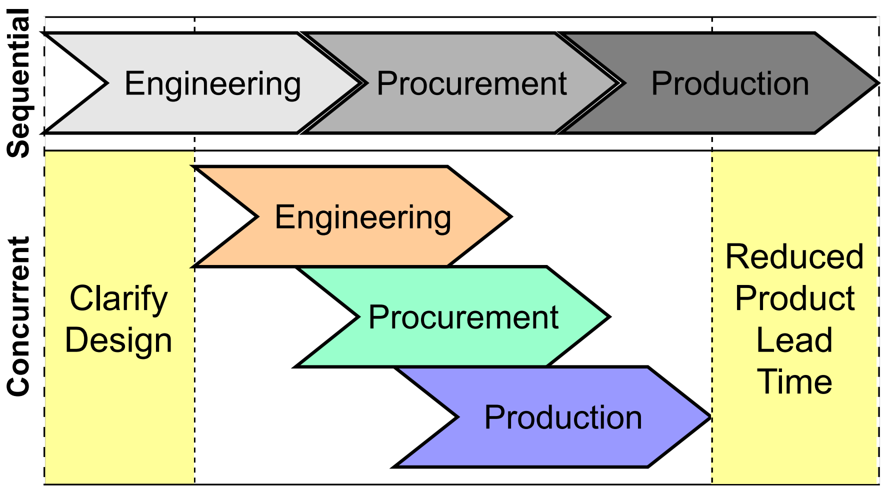


Figure 1.1: Schematic of sequential planning vs concurrent planning. Adapted from [28]

Prior to 2014, the available literature on ETO planning does not provide much data with respect to the planning of the product engineering phases [28]. Existing research in the field of Project Management literature does not propose any solutions to effective planning or progress tracking in Engineering [28]. In lean construction literature more attention has been given towards the design and production activities with the 'Lean' philosophy. Within this philosophy approaches Last Planner System (LPS), Plan-Do-Check-Act (PDCA), EVM, and Agile Project Management (APM) have been developed [23, 28, 31]. According to Jünge et al. [23], all the approaches have their respective limitations which can be solved by Lean Project Planning (LPP). LPP has nine important characteristics of effective project planning [30], which are explained and presented below:

1. *Flexibility*: Frequency of scheduling updates with actual data.
2. *High level of integration*: Efficient communication among project participants.
3. *Collaborative planning process*: Plans created through agreement between project manager and discipline leaders.
4. *Effective planning meetings*: Project updates are shared on a regular basis during meetings between the project participants.
5. *Good performance measurement system*: A system that informs all project participants regarding project status.
6. *Good progress-measurement tool*: To indicate real progress of the production process.
7. *Effective re-planning process*: Recovering the project plan after disturbances.
8. *Impact analyzing*: Awareness of inter-dependencies among project participants.
9. *Lessons Learned*: Improving based on what was learned from previous projects.

These characteristics are linked and highly inter-dependent, e.g. effective planning meetings cannot be achieved without collaborative planning and integration between the different parties. In the end it all revolves around flexibility, where flexibility in design also requires flexibility in planning [27]. Similarly effective re-planning requires good performance measurement system and good progress-measurement tools.

With progress tracking, a better overview can be had of the accuracy of planning with possibilities for adjustments in resource allocation or project control operations. Additionally it ensures for prompter planning adjustments from disturbances in the execution of the planning. Next to achieving a better overview, the flexibility in engineering also requires proactive and reactive scheduling to properly handle the uncertainties in the project [53]. The uncertainties in projects have multiple sources, from the iterative process of engineering, the uncertainty due to human influence, as well as input from the customer who also can request changes [27]. Tracking the progress of Engineering activities is essential to successful planning and control, as the activities precede all activities related to project delivery [40].

For ETO projects translating customer requirements means that every design is custom built and a unique product which will be delivered to the customer. The design phase is the most crucial for the project. In fact, engineering needs to elaborate the client's requests and drives the work of the other stakeholders, i.e. supply chain (through drawings and technical specifications) and ultimately production and commissioning. Typically in ETO environments, the design phase can take up to half the lead time [18, 35, 45].

While for some activities such measurement systems and tools already exist (e.g. counting products produced in bulk production, hour and cost tracking for standardized jobs), for other activities such as Engineering they are harder to implement. In fact, engineering activities in an ETO environment is inherently more difficult to track in that the activities are creative, complex, and often iterative [28, 42, 44]. In particular, the progress of engineering phases is usually tracked based on the release of drawings of the different parts of the equipment, which do not represent the design progress on a design. However, this might be in some cases difficult if the design of larger sub-systems or components is tackled at once [28].

When designing equipment, the construction and the functioning of the equipment are essential for delivery. Knowing the progress of each component of the equipment is therefor essential for planning and controlling the project. An additional challenge which is coupled to tracking the progress is how to subdivide the projects and what metrics can be used. This subdivision challenge is rooted in the fact that physical components are easy to subdivide, but functional components/aspects may span multiple physical components and therefor are hard to subdivide respectively. This challenge is made more difficult as released documents from engineers does not always represent the design progress and/or is limited to the subdivision.

1.2. Research Objectives

The objective of the present work is to develop a method for objective progress tracking on the design phase, which is the most crucial phase for ETO projects. This tracking is intended to support the planning of projects, in which progress tracking plays an essential role. The tracking is aimed to be an objective method to estimate the 'current' progress of the design phase. Currently the progress of the physical aspects is tracked through reported progress.

1.2.1. Research Questions

With the objective specified above, the following research question has been set up to answer in this investigation:

How can a method be designed to accurately and robustly estimate the progress of a project for Engineering activities in an ETO project based environment?

The above problem can be further outlined in the following research questions:

1. What is the current state of progress tracking in Engineering?
2. What kind of information and methods are currently available with respect to the tracking of progress of Engineering activities, and what is suitable for this application?
3. What is the best method to accurately and robustly track the progress of engineering activities?
4. How should such a progress tracking method be implemented within an ETO based environment?
5. To what extent does this method of estimating the progress of engineering activities improve the tracking and predicting of engineering activities?

1.3. Scope

This investigation is bounded in its breadth and has the following initial assumptions and limitations:

- **ETO Approach:** in cooperation with an ETO based company this investigation was done, so the method was designed towards this company assuming it is typical for ETO based companies.
- **Normal Operation:** it is assumed that this method is applicable in normal operational conditions e.g. no pandemics, economic crisis's, etc.
- **Available Data:** due to limited available data, this investigation was limited to a case study in a single discipline for a single type of product. As well it was assumed that the reported progress of the engineers was the actual progress and not biased, when comparing the proposed method to 'actual' progress.
- **Single equipment Type:** this investigation used only the available data for a single type of equipment delivered by the cooperating company, but all variations were included.
- **S-Shaped Progress:** it is assumed that the typical project progression is S-shaped with a gradual increase in the rate of project progress at the start and the inverse as it nears completion.

1.4. Structure of the Report

In this report the questions presented in Section 1.2 will be investigated and answered. This will be done with the following structure:

Chapter 2: This chapter will analyze the problem further, looking into ETO projects. In this section the company providing the data for a case study company will also be introduced. Next to this, in this section the available data will be explored. Lastly, in this chapter the requirements for the method will be defined which will be used for the rest of the design.

Chapter 3: This chapter will be a literature study of the existing methods and sub components of methods used to track the progress of engineering activities. These existing methods will be compared to each other considering the requirements of the method. From this chapter a suitable method will be proposed for project tracking.

Chapter 4: This chapter will apply the theory researched in chapter 3 by developing the method for progress prediction in Engineering within an ETO environment. Here the design and the theory behind the method will will be defined of the progress prediction method.

Chapter 5: This chapter will implement, validate, and verify the method results.

Chapter 6: This chapter will use the acquired results to make a conclusions about the research .This chapter will also discuss possible recommendations for future research.

2

ETO Company and Projects

This work has been conducted within a company which has adopted an ETO approach for large scale equipment. This company represents a typical case of engineering company active the sector with an ETO approach. This chapter gives an overview on the company, with respect to its projects and with emphasis on their planning. Furthermore, the main challenges of the ETO approach and of progress tracking within this approach and within the company will be discussed. The main goal of this analysis is to give a background to the present research, as well as to identify the main features of the progress tracking method which is object of the present research.

2.1. Typical ETO Based Company

In this investigation a typical ETO based company that delivers highly customized large-scale equipment to clients is considered. This company delivers their products to their client within an Engineering, Procurement, and Construction (EPC) contract. This means all the equipment is engineered to the client's specifications.

The company considered in this investigation has an international operation, design and production, spread over multiple continents. With the in-house engineering facilities, tracking the progress of the design is essential in the planning of future project activities and more generally, in the execution of the projects.

2.1.1. Typical ETO Projects

Once equipment is ordered, the design phase begins starting with the system design. Within the system design phase the system is sub-divided into smaller blocks and sections to account for construction and functional requirements, as well as contractual ones. For each of such blocks the design is further elaborated during the basic, detailed and manufacturing design phase. The input available from these phases is used for procurement, production and commissioning. The typical sequence of a project execution is shown in Figure 2.1. The typical sequence of equipment design at a company with an adopted ETO approach will be further discussed in the next paragraphs.

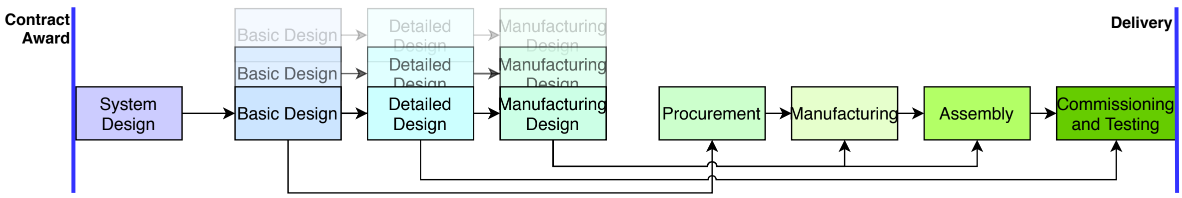


Figure 2.1: Typical project execution sequence at an ETO company.

The overview of the main construction blocks of the equipment is included in a drawing referred to as ”Construction poster”. This drawing as mentioned earlier, is released in the system design phase and it contains useful information also with respect to production lead times, delivery conditions of the equipment, as well as commissioning zones. A simplified schematic of a construction poster can be seen in Figure 2.2, where the undivided function blocks are also shown. These blocks are used to divide teams so that the equipment can be designed concurrently.

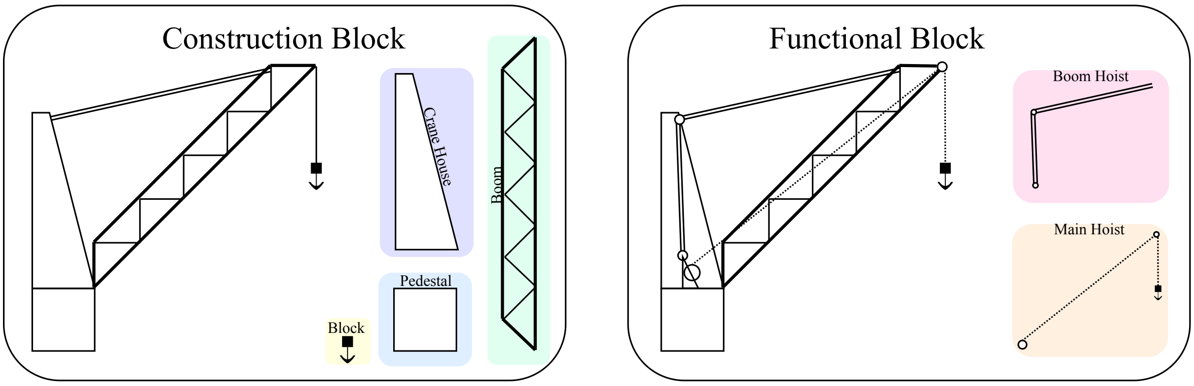


Figure 2.2: Sub-division of a simplified example piece of equipment into construction and functional blocks.

The construction block are physical blocks of the product. These blocks are defined in a construction poster, an overview drawing where the product is divided into blocks and assembly order of those blocks. Within these blocks the materials, parts, and assembly are designed considering the loads and interfaces with other blocks. To produce a design which can be manufactured, each block will individually go through the three design phases as shown in Figure 2.1. As these blocks are defined by physical components of the equipment, these can be tracked using drawings of the components throughout the complete design. Currently, the progress on the design of these so-called functional blocks is not monitored in the project schedules collaborating company. It is one of the present research objectives to include such blocks within the progress tracking scope.

The challenge with functional blocks is their interface with multiple construction blocks and disciplines. This large interface means the functional blocks are not explicitly subdivided in the construction poster, making it challenging to identify the boundaries of the block. The individual output documentation for the different disciplines also means that metrics to track the progress mismatch and are not one to one comparable.

2.1.2. Planning at an ETO Company

To ensure timely delivery, a typical ETO company relies on planning on multiple levels. In particular, discipline planning is extensively used in order to schedule engineering as well as production activities. The activities scheduled for the different disciplines within a project ultimately need to comply with the project schedule. The project schedule is structured such to reflect the sub-division in blocks and sections indicated in the construction poster as explained in Section 2.1.1. For each of these blocks, activities are scheduled accounting for the different interfaces between disciplines and phases, e.g. delivery of technical specifications from engineering for Supply Chain to initiate procurement of certain components. Progress and dates of all planned activities are regularly updated by the project planner. The scheduled activities are visualized by means of a so-called Gantt chart, as represented in the example gantt chart in Figure 2.3. Within this kind of overview the different activities are color coded based on the discipline and whenever needed, criticality. Moreover, this layout makes it easy to identify possible delays, bottlenecks and inconsistencies. For this purpose regular planning meetings with the project team to discuss progress of activities and possible upcoming challenges. Based on the update meetings and reported progress, replanning is done to ensure timely completion of the product.

This progress is reported to the planners directly from the discipline leads verbally or in an overview document showing the progress of the separate blocks of the project. The progress is also reported for individual documents in a document repository, but this progress is not actively tracked by planners as a planning is usually not made at a document level. Overall, the planning at an ETO company requires progress tracking which is dependent on the engineers and their capacity to predict their progress.

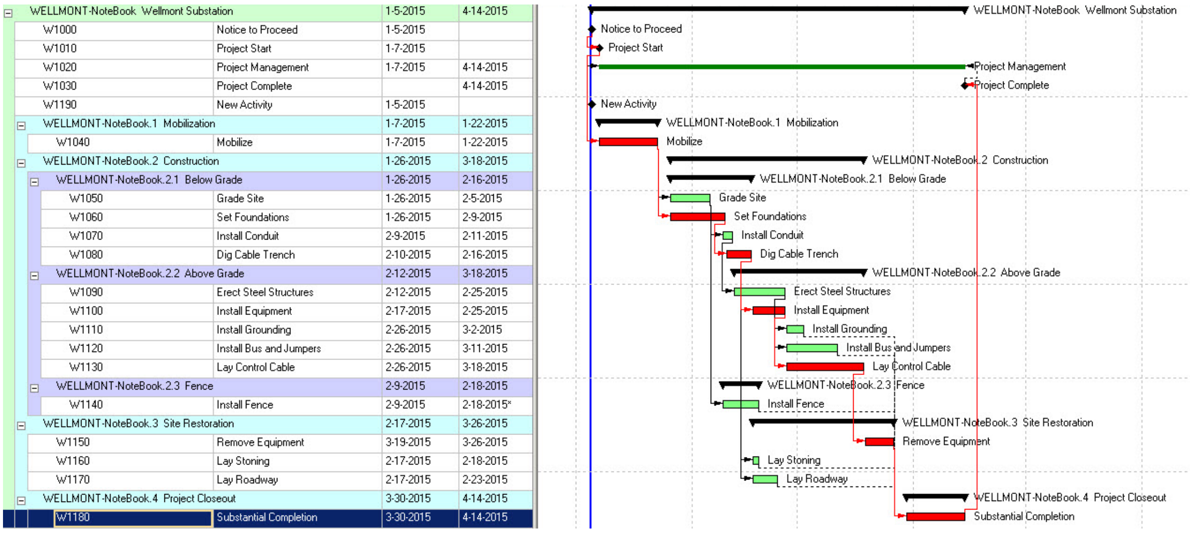


Figure 2.3: Screenshot of an example gantt chart and schedule [52]

As a result, the information provided by the schedules is highly dependent on the quality of the received input. This can be especially true for progress. While for some activities the progress merely results from lead time and start date, e.g. for procurement of components once they are ordered, for design activities this might be included in the planning as reported by the applicable discipline lead. Progress tracking influences planning and replanning of the project significantly. Currently, the reported progress is always dependent on estimates provided by discipline leads which can be experienced as conservative or optimistic. The latter is referred to in literature as the planning fallacy [9–11]. This phenomenon to describe how people are optimistic in predicting when they will complete a task.

2.1.3. Current Progress Tracking

Typically, progress is monitored by the planners based on the progress reports from the discipline leads involved in the different projects. Based on this input, planners make regular (usually monthly) progress reports to the project managers and to the client using the so-called S-curves. As such, they can be generated for the entire project, as can be seen in Figure 2.4, as well as for each discipline seperately as seen in Figure 2.5. Such curves are automatically calculated by planning software based on the progress of the different activities as a linear function of the percent or spent/remaining hours.

The planning of projects as stated in Section 2.1.2 is divided into activities which represent each phase, block, and discipline. Generally discipline leads provide progress updates in hours spent on their activities or in terms of the progress percentage. These values are then related to each other through simple linear extrapolation using the total budgeted hours.

The main pitfall of this representation of progress is inherently affected by the subjective evaluation of the involved discipline leads reporting their progress on their tasks. This is associated with issues, such as:

- **Self-reported progress:** The progress reported by the engineers of their own activities might result in optimistic estimations and simplifications where the progress may be rounded to the nearest percentage or other interval.
- **Budgeting errors:** The hours allocated for certain tasks could be wrongly estimated due to unexpected complexities of the project resulting in a wrong estimation of the progress.
- **Human influence:** The progress on all activities in a project might be affected by different kind of human factors, such as efficiency of working people, each stakeholder being involved in more than one project at a time, actions undertaken by the managers to prevent potential delays etc.

2.2. Available Data

To create a progress tracking method independent of the reporting of the engineers, data should be retrieved differently. The relevance of the design phase for project execution was outlined in the previous chapters. The design of the equipment involves different engineering disciplines, i.e. mechanical, electrical, hydraulic, and control systems engineering. In this investigation data from mechanical engineering will be considered due to the availability and the predominance of mechanical engineering within equipment design. Additionally a potential data source for electrical engineering will also be presented.

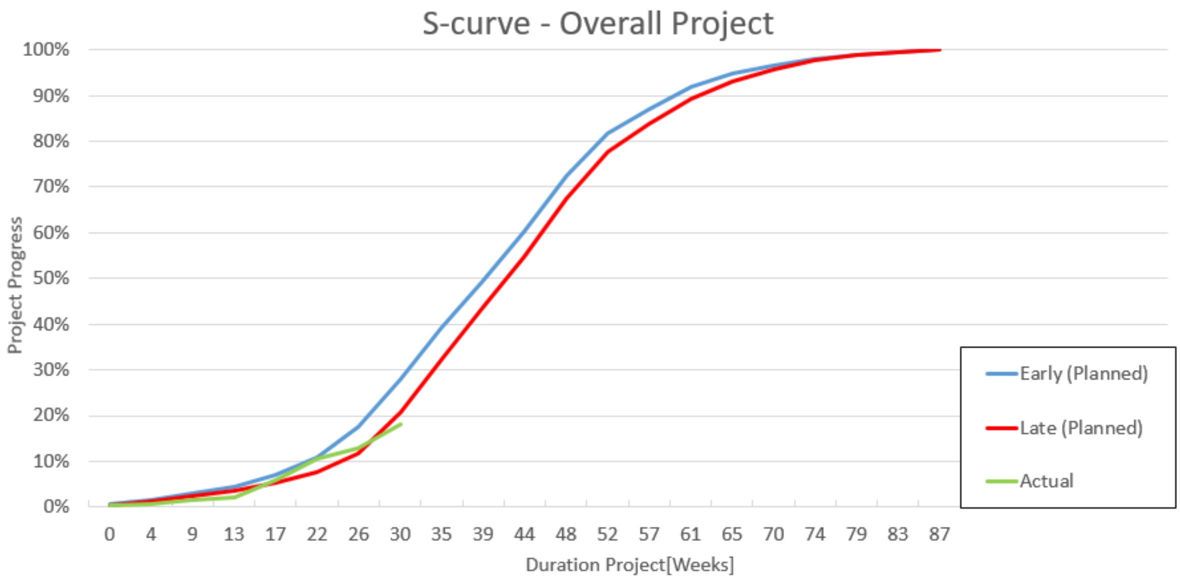


Figure 2.4: Reported progress S-curve of a running project compared to an early and a late target planning.

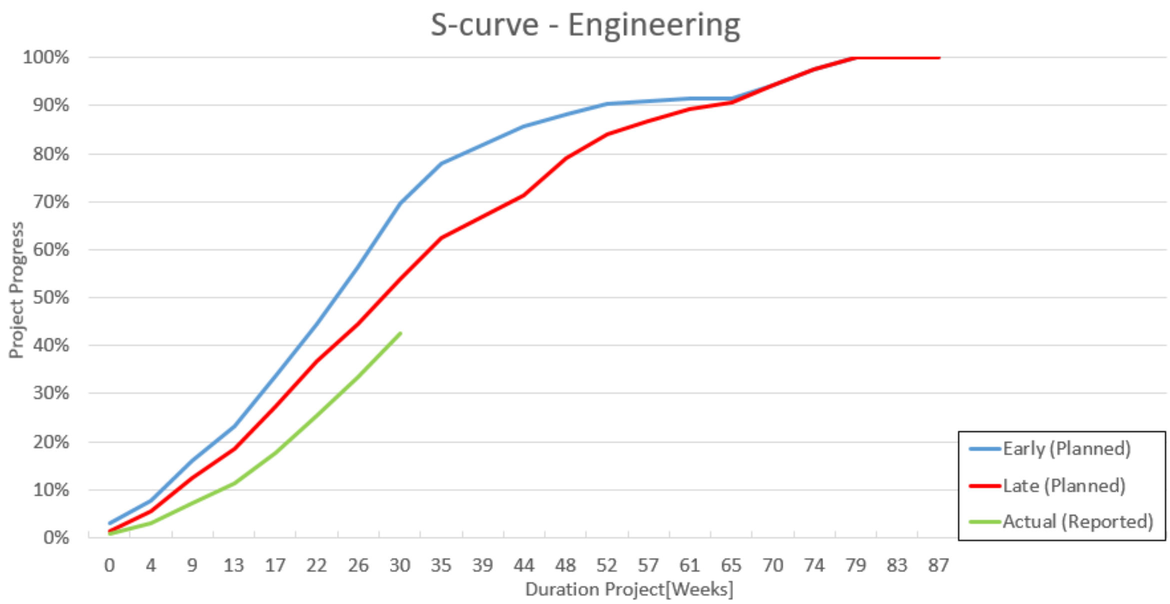


Figure 2.5: Reported progress S-curve of a running project's design phase compared to an early and a late target planning.

2.2.1. Cabinet Curves

When designing, electrical engineers create a whole network which spans multiple blocks. This network is based on many connections between cabinets, which potentially can be used to measure the progress. As the cabinets are linked to each other with wires, a curve can be generated by considering the release of the cabinet designs. A weight factor for the cabinets is the cross-sectional area of the metal within all the wires connected to them. Thicker wires usually adds complexity to the cabinet due to the need to handle the increased current. Not much data is available for the cabinet curves, but due to recent changes in the case study ETO company a cabinet curve for a single running project can be generated (see Figure 2.6). It can be seen that the curve does not take the shape of a S-curve in the current state, and so falls outside the scope of this research. Additionally, due to the lack of data, this method progress metric will not be extensively considered in the case study, but does show possibilities for using this as a progress tracking metric.

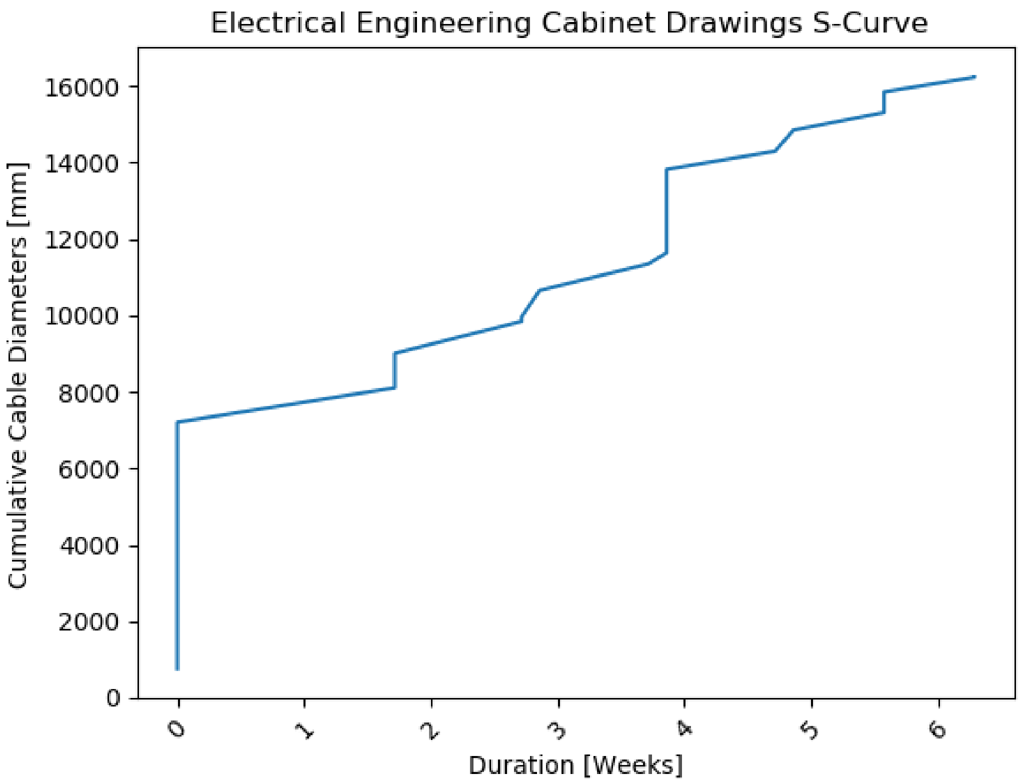


Figure 2.6: Cabinet curve of a project at an ETO Company

Cabinet curves can be interesting as the electrical network in large scale equipment is substantial. This network would contain many cabinets with their individual designs. This would mean that there would be many data points per project available to measure the progress. In the example in Figure 2.6, 1185 data points (releases and revisions) were available to track the progress. For that reason this type of curve would be interesting to consider further.

2.2.2. Design Mass Curves

It was found that each mechanical engineering document registered in the repository system is automatically linked to the correspondent (designed) block/part. This quantity was compared to the total mass of the equipment, which is usually predicted at the beginning of a project, to measure progress. This approach was applied to released documents only. This means that all in-progress (or working) documentation was excluded. In fact, based on the information collected in the company, it was found that the progress on the working documents tends to be updated sporadically in the repository and thus, it was concluded that accounting for working documents would have brought only a limited benefit to the accuracy of the method. An example of such a mass curve for can be seen in Figure 2.7. To extract information about the progress of the design phase of the project, some preliminary considerations were made.

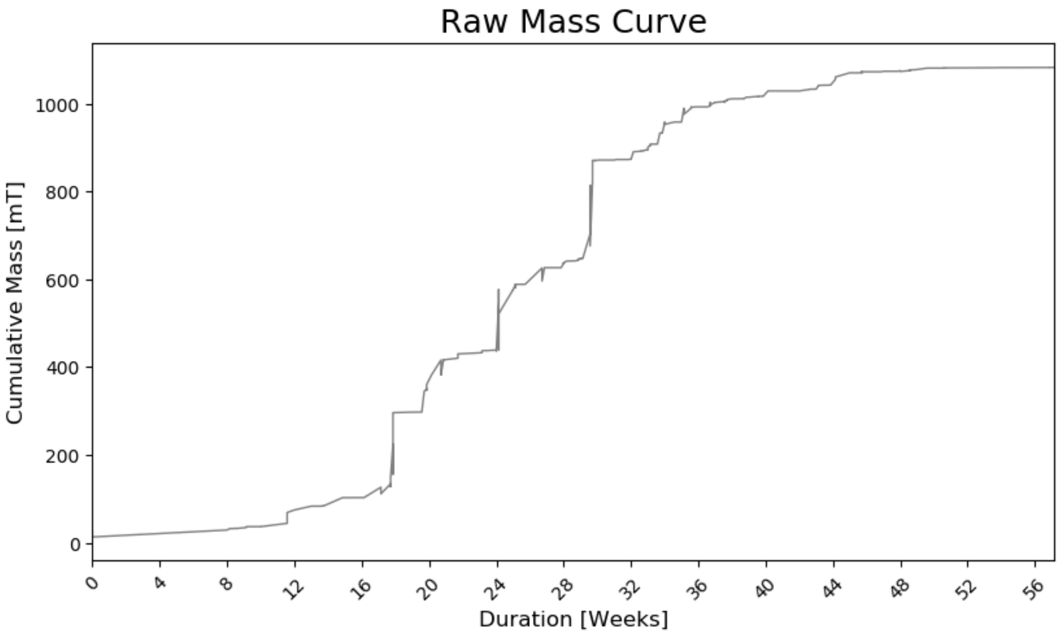


Figure 2.7: Mass curve of a completed project

Prior to generating a mass curve, the delta mass associated with each revision should be taken into account. Initially the mass difference between revisions of the same document. Once a document is released, it can still be changed and released again as a revision due to a design change, and this revision might cause a mass variation. The mass difference of a document is its relative mass compared to the revision preceding it, where if no revision precedes it then the relative mass is just the mass of the document. With the delta mass calculated, to create the mass curve as shown in Figure 2.7, the cumulative delta mass is plotted over time to see how the overall designed mass of a project changes.

Mass curves are a way to see how the project is progressing but they do have some limitations which should be considered when using them, such as:

- **Duplicate masses:** One component might often be associated to multiple documents with mass information. As a result, the mass of a certain component, might therefore be overestimated. This results in a cumulative mass curve where the mass of some components may be added counted more than once towards the cumulative sum of the mass.
- **Unique Project Cycles:** Projects are as mentioned, conceived in a ETO environment and as such, highly catered to customers' needs. As a consequence, although some typicalities can be identified in the way projects are run, there might also be a wide variety of scenarios when speaking about the actual execution of a project.
- **Copy projects:** Some designs are very similar or copies of other previously design products. For so-called "copy projects" old documents might be referenced and entirely replace the release of new documents. This might yield sudden increases in progress, i.e. designed mass. Projects may have limited to no new documents as they are complete copies of other projects, so the documents of previous projects may just be referenced. These are classified by all the documents being released within two weeks of the complete design.
- **Massless work:** Not all engineering work is related to physical components or has a mass. This progress will not be registered by the mass curves as the documents have no related mass to contribute to the mass curve. Engineering disciplines outside of mechanical engineering also design and deliver documents, but due to the nature of their work most work will be massless.

2.2.3. Data Selection

Amongst all different projects from the Case study ETO based company, data was taken from a selection of them based on the following criteria:

- **Project Type:** Projects related only to a certain category of equipment were included in the data set.
- **Missing curves:** Projects with missing mass data were excluded.
- **Copy Project:** As mentioned in Section 2.2.2, some projects involve documents copied from other projects. If a project is not engineered it will not be considered. Firstly, all copy-projects that were not engineered, i.e. those projects with no design documents released, were excluded entirely. Similarly, all projects which are largely or directly copied from other projects were manually excluded from the data set. Lastly any projects with less than 85 documents released on in-House Document Repository (HDR) will also be excluded. The value 85 represents 25% of the 341 total number of documents released for similar equipment types on HDR on average.

An overview of the selection using the criteria can be seen in Table 2.1.

Table 2.1: Data range before and after filtering projects [a].

	Type of Equipment									
Number of Projects	**Type 1**	**Type 2**	**Type 3**	**Type 4**	**Type 5**	**Type 6**	**Type 7**	**Type 8**	**Type 9**	**Total**
Before Filtering	33	107	21	1	34	1	1	4	3	**207**
Missing Data	13	41	13	0	20	1	0	3	3	**93**
Copy Projects	17	75	12	0	21	1	0	0	0	**78**
Remaining	**16**	**32**	**8**	**1**	**13**	**0**	**1**	**1**	**0**	72

[a]Both filters can apply to a single project.

Next to filtering the projects, documents within the projects were also filtered. In particular, all documents associated with a major portion of the total mass and not directly related to the equipment design were excluded from the data set, i.e. all those related to installation, commisisoning and testing, lift up, and, load out. Such a filtering was implemented by excluding all documents associated with 50% of the total equipment mass.

2.3. Progress Tracking Requirements

From the information gathered about the current state of progress tracking, requirements can be defined for the new time prediction method. These requirements have been defined based on what the current progress estimation method is lacking, what it should account for, and what it is expected to achieve. The requirements for the time prediction method are defined as follows:

- **Accurate Time Prediction**: the project duration estimated from the method should be as realistic as possible.
- **Uncertainty in Prediction**: The prediction method should provide information about the uncertainty of the predicted progress, as this facilitates rescheduling.
- **Ease of Use**: The tool must be easy to implement and frequent rescheduling must be possible. Therefor the method should use data, which is easily available and easy to update at least on a weekly base with maybe some more setup time for initialization at the start of the project.
- **Robust prediction method**: The method should be applicable to a variety of project, regardless of the function and design.
- **Limited Training Data:** Given the variety of the projects within ETO environments, as found in Section 2.2.3, there is a limited amount of projects available with usable data for this method, therefor the method should also be applicable to limited amount of data.

2.4. Chapter Summary

Currently to ensure timely delivery, a typical ETO company relies on planning on multiple levels. In particular, discipline planning is extensively used in order to schedule engineering as well as production activities. The project schedule is structured such to reflect the sub-division of blocks and sections defined in the system design. For effective planning and replanning regular planning meetings with the project team are needed to discuss the current and expected progress. This progress is reported to the planners directly from the discipline leads verbally or in an overview document. As a result, the information provided by the schedules is highly dependent on the quality of the received input. Based on the input, planners make progress reports using the so-called S-curves.

The available data for this research consists of reported progress curves from engineers and mass curves created from the mass related to released documents. When the cumulative sum of these documents are taken over time, they produce a curve similar to an S-curve. The cumulative mass also considers updated documents by only adding the difference in mass between revisions if a new revision is released. With the available data and the current state, the requirements for the progress tracking method are defined: accuracy, uncertainty quantification, ease of use, robustness, and limited train data.

3 Literature Review

Without dynamic and accurate planning of projects, completing them on time will be essential for good project execution. An accurate time prediction method is necessary to do this effectively. A literature review will be done on the possible techniques available for tracking project progress. Initially data processing will be explored to find how the data related to project progress. Afterwards existing time prediction methods are reviewed. From this further investigation is required in mathematical modeling and error propagation methods for sub components of a prediction method. The main goal of this analysis is to give an overview of available techniques and what is applicable for this investigation's requirements.

3.1. Pre-Processing Data

A model is required to represent the data to be able to track the progress. To model the progress of a project an S-curve is a commonly used standard to depict the cumulative progress of a project [14, 48]. At the start and end of a project progression slow with the most progress per time unit achieved in the middle [15, 24, 26]. The S-curve can be represented using different equations. The different equations of S-curves and important relationships in the models can be seen in Table 3.1. From these models, the most suitable one for the data and application will be selected.

Table 3.1: Different S-curve models and their equations. Where a and b are model variables which can be used to determine the inflection point and growth rate of the model.

Model Name	Equation	Variable Explanation
Loglet Lab Model [36]	$f(x) = \frac{L}{1+e^{-k(x-x_0)}}$	L - Maximum value k - Growth rate x_0 - Inflection point
Pearl Model[36]	$f(x) = \frac{L}{1+ae^{-bx}}$	L - Maximum value b - Inflection point
Gompertz Model[36]	$f(x) = Le^{-ae^{-bx}}$	L - Maximum value $\frac{ln(a)}{b}$ - Inflection point
Third Degree Polynomial [a] [14]	$y = ax^3 + bx^2 + (1-a-b)x$	$\frac{-b^2}{3a} + (1-a-b)$ - Growth Rate $\frac{-b}{3a}$ - Inflection point

[a]This is a continuous third degree polynomial, so to properly represent progress the polynomial only should be used until $f(x)$ is 100%

Comparing the models has been on the hand of the accuracy and the requirements set in Section 2.3. For example, the third degree polynomial model proposed by Chao and Chen [14] will not be considered as it requires to normalize the duration and progress of the project (from 0 to 1). This normalization creates a large challenge in the case of variation orders and/or project delays.

The least squares method was used to fit 18 mass curvres, and fit 44 reported project progress S-curves of the respective mass curves. The Root-Mean-Square Error (RMSE) was then calculated for each curve fit. The results in Table 3.2 show that the Gompertz model fits the mass curves and reported progress S-curve with the lowest error. However, the gompertz equation has more complex relationships between S-curve features and how they are represented. As the accuracy differs little between S-curve models, the Loglet Lab model will be chosen due to its ease of use to identify and determine relevant S-curve parameters in combination of its accuracy. From this analysis it is also clear that modeling the S-curve will always maintain an RMSE of 5%.

Table 3.2: DIfferent S-curve models and their RMSE fit to different data sets

		Average RMSE $\pm$Standard Deviation		
	Curve Type	**Loglet Lab Model**	**Pearl Model**	**Gompertz Model**
	Mass Curve	0.0612 ± 0.02	0.0612 ± 0.02	0.0622 ± 0.02
Reported Progress Curve	Complete Project	0.0300 ± 0.02	0.0300 ± 0.02	0.0229 ± 0.01
	Mechanical Engineering	0.0630 ± 0.06	0.0630 ± 0.06	0.0554 ± 0.06
	Shop Drawings	0.0305 ± 0.02	0.0305 ± 0.02	0.0265 ± 0.02
Overall Average		0.0450	0.0450	0.0408

With the Loglet Lab model chosen, a short analysis was done to compare how well the S-curves represent the mass curves. In Figure 3.1 it can be seen that the model follows the shape of the mass curves. It was found that, on average, the model has an average error of 0.02% and an average maximum error of 11.6%. This large difference between the average error and average maximum error indicates that the Loglet Lab model fits the mass curves well with only short peaks with large errors. These short peaks are due to some documents 'weighing' more than others where the mass curve can trail behind the progress temporarily before these documents are released, or the mass curve overestimates the progress shortly at the release of these heavy documents. With this analysis it shows that the Loglet Lab model can accurately represent mass curves.

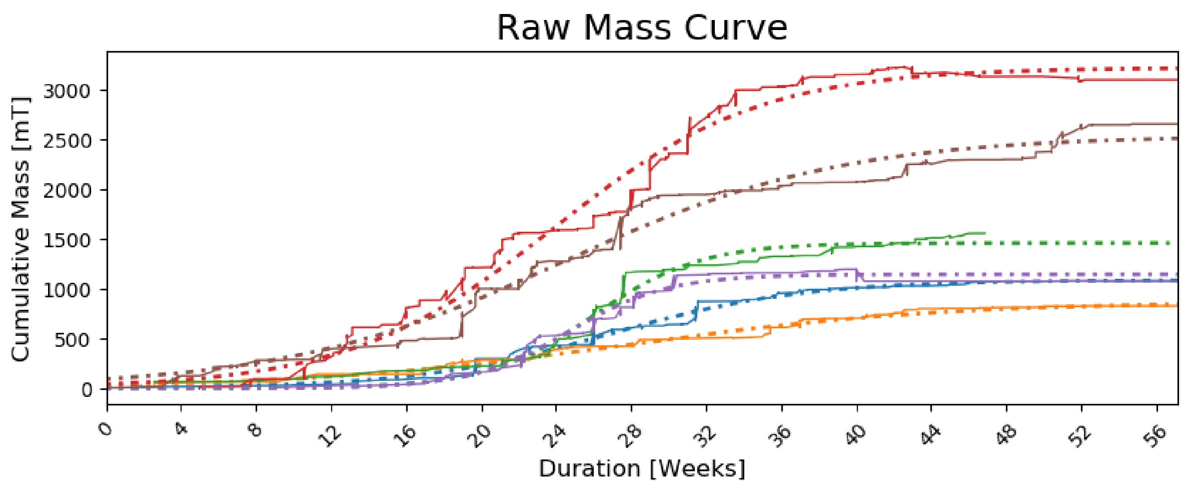


Figure 3.1: Sample of mass curves with a loglet lab model fit to the data.

3.1.1. Progress vs Mass Curves

Next to modeling accuracy, how well the modeled mass curves represent the progress of a project is also considered. It is assumed that the reported progress curves is the absolute progress of the project despite the uncertainties and errors described in Section 2.1.3. This assumption is made as the reported progress curves is the only progress data available.

The fitted mass curves are compared with the fitted reported progress curves. When this is done for all the projects, a box and whisker plot can be created comparing the error in duration to reach certain progress milestones(see Figure 3.2). It is clear that the mass curves are less representative of the complete project progress compared to the shop drawings phase. This is expected as shop drawings are produced for each part of the system and as such they regularly involve mass information. The mass curves best represent the progress of the shop drawings phase.

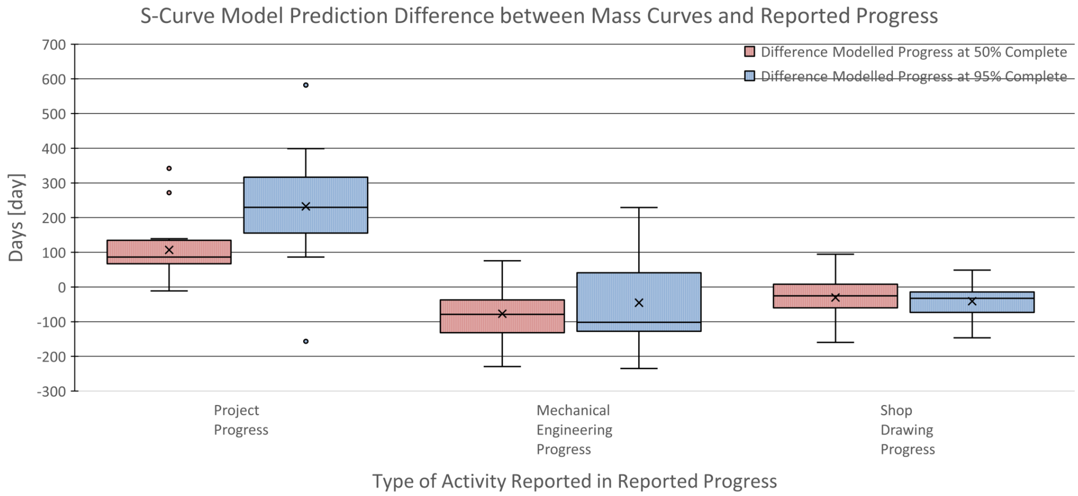
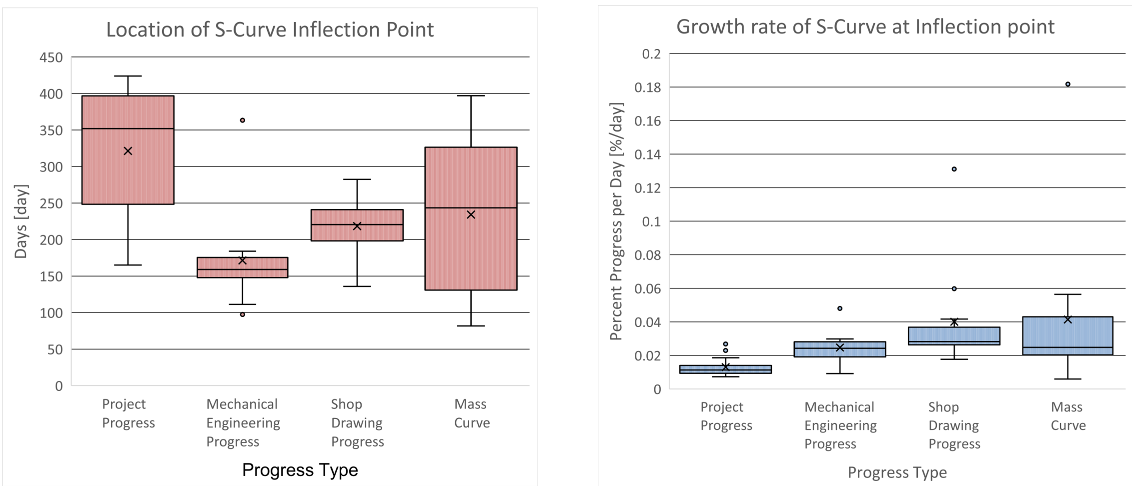


Figure 3.2: Box and whisker plot comparing the error in duration to reach certain progress milestones for mass curves and reported progress curves. Error is calculated by subtracting the mass curve results from the reported progress curve results.

The S-curve features of the mass curve and reported progress curves are also compared, see Figure 3.3. Mechanical engineering activities and shop drawing progress curves have the lowest interquartile ranges for their feature values. The mass curves have the largest spread of values for the inflection point and growth rate,howver the spread of error shown in Figure 3.2 is smallest. This implicates that it is likely that the inflection point and growth rate compensate to accurately represent the progress of the shop drawing phase.



(a) Box and whisker plots of the duration for the model to reach its inflection point of the different curves.

(b) Box and whisker plots of the growth rate of the model of different curves at the inflection point.

Figure 3.3: Box and whisker plots comparing features of modeling different mass or reported progress curves.

3.2. Progress Tracking Methods Review

Predicting the current progress of a large project in an ETO environment with concurrent planning is challenging with many uncertainties. Kjersem and Emblemsvåg have investigated this problem and found many literature sources discussing concurrent planning, but there are a limited amount that proposed solutions to the actual planning, scheduling and controlling of the activities [27, 28]. Many base their solutions off of LPS, where a hierarchy of plannings at different levels of detail are used to plan and schedule tasks. This does not consider what was recommended by Kjersem et al. [30], where progress-measurement was essential for good planning, scheduling, and control.

3.2.1. Criteria for Methods

When looking at different methods to predict the current progress of a project, they will be compared considering characteristics based off of the requirements defined in Section 2.3:

- **Progress Prediction Accuracy:** As the prediction of the progress and/or remaining time is essential for planning, the accuracy of the prediction method should be considered.
- **Uncertainty propagation method:** With an estimation of the current progress and a forecast of the remaining time, how the propagation of uncertainties in the method and data is handled is essential.
- **Flexible Progress Measurement:** This method should be able to be implemented for multiple projects or aspects. The more flexible the method is, the more input data types that could be used for the method.
- **Interpretability:** As a requirement for the progress tracking method is ease of use, the method's results should also be easy to interpret.

3.2.2. Progress Tracking Method Overview

In this section an overview of the available progress tracking/prediction methods will be made considering the characteristics mentioned previously. The advantages and disadvantages unique to the method will also be investigated. From this overview, a comparison of the methods in Section 3.2.3 will be possible to be able to choose the best method for the intended application in this investigation.

Earned Value Management

EVM is a method of project control for planning and scheduling which considers the costs of the project over time. Within this method the costs and earned value is tracked over time, as visualized in Figure 3.4. The most common cost metrics are measured with the monetary cost or the man hour cost. This cost is compared to the earned value, which is the (estimated) value created by the progress of the project. When the costs and earned value is tracked over time, the trends form into a similar shape as a S-curve discussed in Section 3.1. Comparing these two metrics a project's cost and schedule variance can be determined to be able to implement control actions if necessary.

EVM is considered the basis of project planning, scheduling, and control. The strength of this method is in that it is flexible in its implementation and the results are easy to interpret. The earned value is a predefined monetary value related to activities required for a successful project completion, which makes any activity easy to relate to the costs in a project. With this method, the curves created by the costs and earned value over time create a plot which is easy to interpret what the current state is of the project (e.g. over budget, delayed, etc.). This method does not make any predictions about the progress or remaining time of the project, so no comments can be made about its accuracy or error propagation. As no estimation or prediction is made on the project progress, this method is deterministic in its evaluation of the progress of a project. This method is can be used as a basis on to build a progress prediction method.

Stochastic S-Curve Estimation

StS-Curve estimation is a prediction method based on the concepts of EVM. This method removes the deterministic nature of EVM curves by enveloping the S-curve with a range of possible outcomes, as shown in Figure 3.5 [3]. The envelope is created by initially looking at the possible variability of costs and duration with activities. With the variability in activities defined, a Monte Carlo simulation is performed to see how the variability in activities influences the S-curve. Combining all the simulated S-curves an envelope is created around the scheduled or actual curve, with a distribution to represent the time and cost at desired increments [3, 4]. These distributions show the variability of the predictions, providing planners with a metric to see the accuracy of the prediction as well.

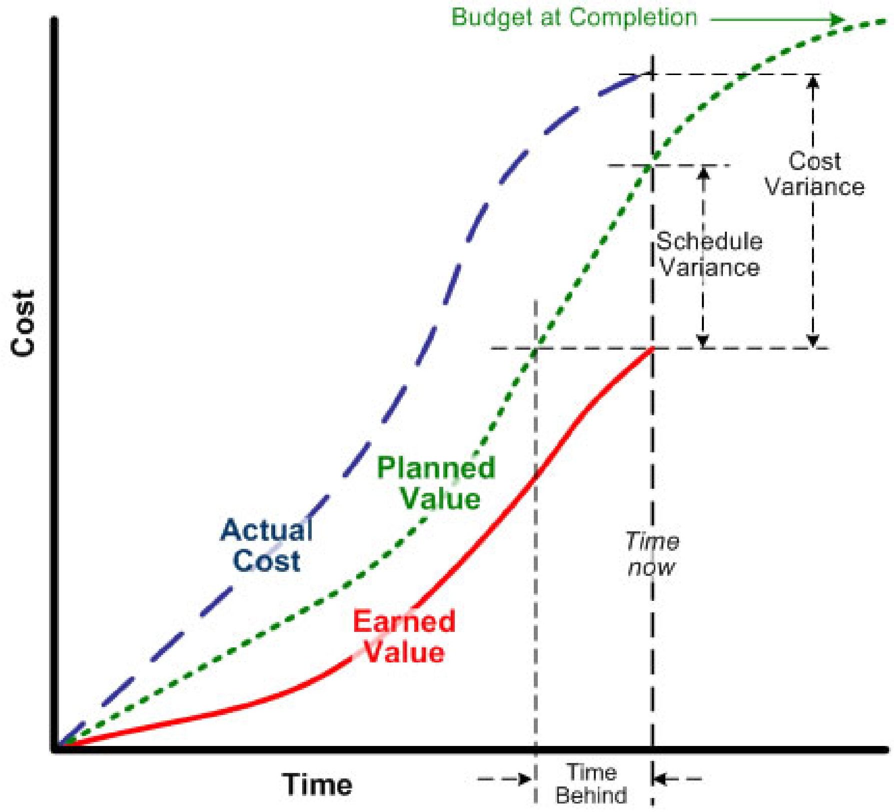


Figure 3.4: Example figure of EVM [12].

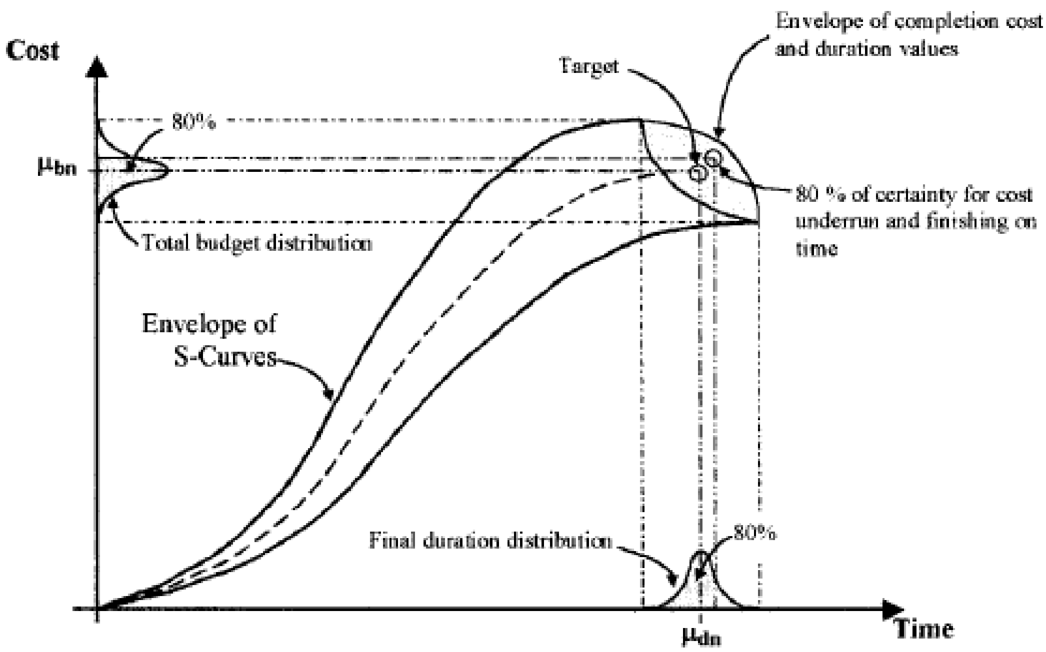


Figure 3.5: StS-Curve estimation of an EVM analysis of cost over time [3].

With StS-Curve estimation method using EVM as a basis of its prediction method, it inherits some of its advantages but builds further on some pitfalls. The interpretability is still very good with this method, but it does require a better understanding of the tool as it now shows a stochastic solution instead of a deterministic solution. Next to this, the flexibility of this method is lower as a Monte Carlo simulation is run using the variability present in each activity related to the project, it requires more preparation to implement as this information must be gathered. The progress prediction accuracy of StS-Curve estimation is dependent on the knowledge about activities within the project. If the estimates about the activity variability is accurate, then the accuracy of the whole model increases as well [3]. This model not only relies on the accuracy of activity estimates, but also needs to know the relationship between the activities for the Monte Carlo simulation to be run [3, 4]. By using the variability of activities in conjunction with Monte Carlo simulation to provide the user with distribution of the estimated progress, uncertainty propagation in StS-Curve estimation is good as well. Therefor, StS-Curve estimation is a good solution, with the largest challenge it faces is acquire all the information about activities and their relationships with each other.

Geometric Feature Prediction

Geometric feature prediction uses key features of a project to predict the geometric features of the S-curve of a project [14]. This method, proposed by Chao and Chen [14] gathers features about the project through questionnaires, looking into contract amount, duration, type of work, location, simplicity, and team competence. With this set of features a NN model is created to predict the point of inflection and slope of at inflection point of the S-curve. With these two parameters defined, a S-curve can be created which provides an approximate estimate for early planning and forecasting [14]. In this way geometric feature prediction used historical information of previous projects to provide an estimate of the progress of projects.

With the simplification of a project to only a few key features, this method has some advantages over the StS-Curve estimation method. Considering the interpretability, this method produces an S-curve of the project progress based on a prediction of the location of the inflection point and slope at that point, which are two variables which are easy to understand. How this prediction is made through a NN model does make the method of gathering this result less interpretable however, as discussed in Section 3.3.2, which in the end makes the overall method hard to interpret on how it came to the solution it presents. This method is also flexible in its implementation, as it requires only knowledge of a few key features of the project to make the prediction of the progress curve, meaning it can be applied to many progress measurement metrics. The accuracy of the prediction is lower due to the simplification made by reducing the project to only a few key features. This simplification has resulted in Chao and Chen [14] recommending this model as a method for approximate progress progression for initial plannings and budgeting, but not as a replacement for planning itself. Next to this, this method is used to predict the project planning not considering the current progression of the project, meaning it cannot predict the current project progress or remaining time. As this method also only provides a determinant S-curve solution, it does not have any uncertainty propagation within the method. Therefor, geometric feature prediction as a complete method will not be an ideal solution to the problem, but the simplifications and some steps within this method could be of interest for this investigation.

3.2.3. Prediction Method Comparison

With a limited selection of prediction methods, the most suitable 'available' method needs to combine multiple methods. In Table 3.3 an overview is given of the prediction methods characteristics, as well as a combination of methods (StS-Curve Feature Prediction). StS-Curve estimation makes a prediction and propagates the error to provide the error in the prediction. This method uses the 'current' state of a project as a basis to predict the progress and remaining duration of a project. The interpretability is high of this method uses EVM metrics, which is also very interpretable. The flexibility of StS-Curve estimation is low as knowledge of each activity needs to be known before a prediction can be made. An available option to counter the low flexibility is to combine geometric feature prediction with StS-Curve estimation.

Combining geometric feature prediction (method 3) with StS-Curve Estimation (method 2) would result in SSFP method. In this combined method the flexibility of geometric feature prediction would be inherited as it simplifies the project S-curves into features. The mathematical modeling method to predict these features can be chosen independently, dependent on the application. A further overview

Table 3.3: Overview of the prediction methods and their different characteristics described in section 3.2.1.

#	Method	Prediction Accuracy	Error Propagation	Flexibility	Interpretability
1	Earned Value Management	-	-	High	High
2	Stochastic S-Curve Estimation	Medium	High	Low	High
3	Geometric Feature Prediction	Low	-	High	Low
4	Stochastic S-Curve Feature Prediction (SSFP)	Low	High	High	High

of the mathematical modeling methods is presented in the next section. As this method simplifies the prediction model, the accuracy will be lower than a more extensive StS-Curve estimation. Lastly error propagation will be implemented similarly to StS-Curve estimation, using the predicted progress from historical data in combination with the current progress. The method of error quantification will be further explored in Section 3.4. With these two progress points a weighted average can create an uncertainty distribution. Combining StS-Curve estimation and geometric feature prediction would deliver a method which exceeds the currently available progress prediction methods in light of the before mentioned characteristics.

3.3. Mathematical Modeling Review

From the previous section a method has been presented, SSFP, which could be applied to predict the progress of projects. To successfully implement SSFP a mathematical model is required. In this section an overview of mathematical models is presented to find the model to best suit the requirements.

3.3.1. Criteria for Methods

Similarly to the review of prediction methods, the mathematical modeling methods review is also based on pre-defined characteristics. The characteristics of the algorithms can be split into two sets; characteristics which are required for the method and characteristics which will be used to compare the methods. Below are the characteristics required for the methods to be considered and the assumptions they are based on:

- **Explicit:** With predicting the progress of engineering, the method should be able to use the information provided to make the prediction.
- **Continuous Output:** The progress of the activities is a continuous spectrum, therefor the output of the method also has to be continuous.
- **Continuous Input:** The data about engineering activities is continuous, therefor a continuous input is required for the model to work effectively.

With the required characteristics explained, the characteristics used to compare the methods are listed below:

- **Variance of method:** As every project can be considered to be unique with high human involvement, the variance of the method will influence its sensitivity towards the stochastic nature of the data. With a low variance, the method will not model the noise in the data, but the intended trends to predict the project progress. A method with a high variance has more probability to overfit the data.
- **Bias of Method:** As this method should reflect reality, it should be able to model the trends in the system and not miss trends due to assumptions inherent in the method. This is linked to variance, where a method with low bias has high variance and vice versa, therefor a balance must be found in these two methods.
- **Required amount of Training data:** Different methods require different amount of training data to successfully predict the progress. To ensure that the method can work in this situation, it is necessary to consider the required amount of training data.

- **Interpretability:** From the input data a prediction is made, the more interpretable the data is the easier it is to understand how the prediction is made.

3.3.2. Mathematical Modeling Method Overview

In this section the different S-curve feature estimation methods will be described and analyzed. This will be done by considering the characteristics of the method and how it works. Afterwards, the application of the methods in different industries will be explored. Lastly the advantages and disadvantages unique to the modeling method will be investigated. With this overview, a comparison of the methods in Section 3.3.3 will be possible to be able to chose the most suitable method for the problem being tackled in this investigation. The methods considered can be classified into the following categories:

- Neural Networks,
- Regression Algorithms,
- Regression Tree Algorithms.

Within the categories different methods exist, with an overview of these methods provided in Figure 3.6

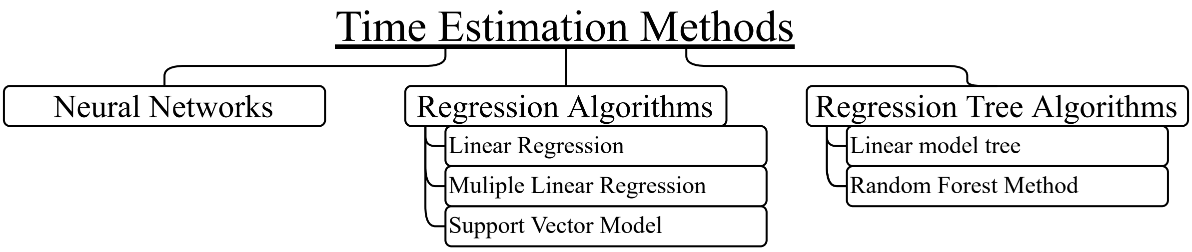


Figure 3.6: Tree showing time estimation methods examined in this investigation subdivided into categories.

Regression Algorithms

The regression algorithms considered are also called machine learning algorithms. Machine learning according to Shalev-Shwartz and Ben-David [51] is the automated detection of meaningful patterns in data. Machine learning is a coverall term for many different types of algorithms which can be used to find pattern in data. These techniques can be used to classify data or predicting continuous responses. All algorithms which do not fulfill the required characteristics listed in Section 3.3.1 will not be considered in this investigation. Additionally, only supervised algorithms will be considered which are designed to learn the function which relates the input to the output [51] as we know what the desired output is. Lastly, to filter techniques further, only techniques will be considered which have literature relating it to similar applications compared to this investigation. With these requirements the machine learning algorithms in this investigation have been found.

Linear Regression and Multiple Linear Regression

LR is a method to create predictive models with data which is assumed to have a linear relationship. This method seeks to find a linear function which describes the quantitative input data such that the sum of mean squared error is minimized [34]. This linear relationship can be expressed as shown in equation 3.1, where 'Y' is the output, 'x' is the input, and 'α' & 'β' are constants [16].

$$Y = \alpha + \beta x \tag{3.1}$$

Linear regression can also be expanded to consider the relationship between multiple variables. Such an approach can be described as Multiple Linear Regression (MLR), where the linear relationship is shown in equation 3.2 [16]. The challenge faced to LR and MLR is determining the constants 'α' & 'β', which can be done in multiple ways which all builds upon the method of least squares.

$$Y_i = \alpha + \beta x_i + U_i \quad \text{for} \quad i = 1, 2, \ldots, n \tag{3.2}$$

Some of the characteristics of LR and MLR are defined by how 'α' and 'β' are determined in the relationships. A basis to determine the constants is through the method of least squares. Through this method, the constants are determined such that the distance between 'Y' and the regression line '$\alpha + \beta x$' is minimized, formally presented in equation 3.3 [16].

$$S(\alpha, \beta) = min(\sum_{i=1}^{n} (y_i - \alpha - \beta x_i)^2) \tag{3.3}$$

This approach to finding the constants does make a couple assumptions in the data, namely that the error's are normally distributed, not auto correlated, and have a constant variance and that there is no linear dependence between input variables [41]. Using the least square method the focus lies on model bias, some of the assumptions mentioned earlier can be avoided by focusing on the model variance using the ridge and lasso regressions [51]. These two methods do not change the characteristics listed in Section 3.3.1 of the LR method however.

LR and MLR are widely applied methods in forecasting data in different problems. This has been applied and researched in shipbuilding [22], construction [6], flow-shop manufacturing [21, 47], and semiconductor manufacturing [34], all industries comparable with the ETO environment being considered. These techniques have the advantage that it is widely used and finds relationships between multiple inputs and the output. This has the counter argument that this technique can find relationships between independent variables, so to ensure an accurate prediction the relevant and important inputs are required [13, 22]. When compared to other machine learning prediction methods, it has come out as the most inaccurate method [21, 34, 47] but does exceed the prediction capabilities of some analytical methods [21]. Due to the linearization of the relationships between in the input and output, LR and MLR could simplify the data analysis and make it easier to interpret. The linear assumption within the methods does result in a high bias which could result in modeling inaccurate trends. If the underlying assumptions in LR and MLR apply to the data to be analysed, these could be applicable methods to the problem at hand.

Support Vector Regression

SVR is a method of finding a relationship within data by enveloping the trend with upper and lower limits [17]. This envelope around the data represents a tube which can be used to make predictions, where the future outcomes will most likely fall within the tube [17]. This approach is visualized in Figure 3.7, where the it is clear to see how the SVR method determines a tube made of support vectors, with an offset 'ϵ', around the function, '$f(x)$', which describe the relationship. SVR bases it predictions on the ϵ-insensitive loss function, where values within the 'tube' are not penalized [39] and are penalized with 'ξ' or 'ξ^*' when they are outside the 'tube'. This method can be used for linear and non-linear functions of quantitative data [39]. This method can be used to find relationships between input data and from the relationships make predictions about future events.

SVR is new small sample learning method which simplifies regression problems [60]. This method has been (partially) explored in manufacturing [54], semiconductor manufacturing [34], construction [57, 60], and project control [57] settings. In these studies SVR has proved to provide accurate forecasts even with small training data sets [25, 46]. A strength with using this method for prediction is that it is less sensitive to noise and stochastic nature of the input data, as the data points within the support vectors does not influence the prediction. As the support vector tube can be adjusted in width, depending on the sample data the variance and bias can both be low, just not simultaneously. Lastly, the predictions from support vectors can easily be interpreted as the method can easily be visualized to show the basis of the prediction. For these reasons SVR is an applicable method for prediction.

Regression Tree Model

Regression Tree Model (RTM) is a method of predicting outcomes by dividing the input data into smaller groups and where then simple regression techniques could be applied to the subdivisions [37]. A representation of how a basic regression tree works is shown in Figure 3.8. In this figure every node with a question mark indicates a decision node which then continues to either the next decision node or a prediction. Basic regression trees are usually poor predictors and unstable as small fluctuation in the input data or too many branches can heavily influence the result (high variance) [37]. To consider regression trees for this investigation, boosted regressions trees will be considered, which implement other machine learning techniques to improve the performance of the regression tree.

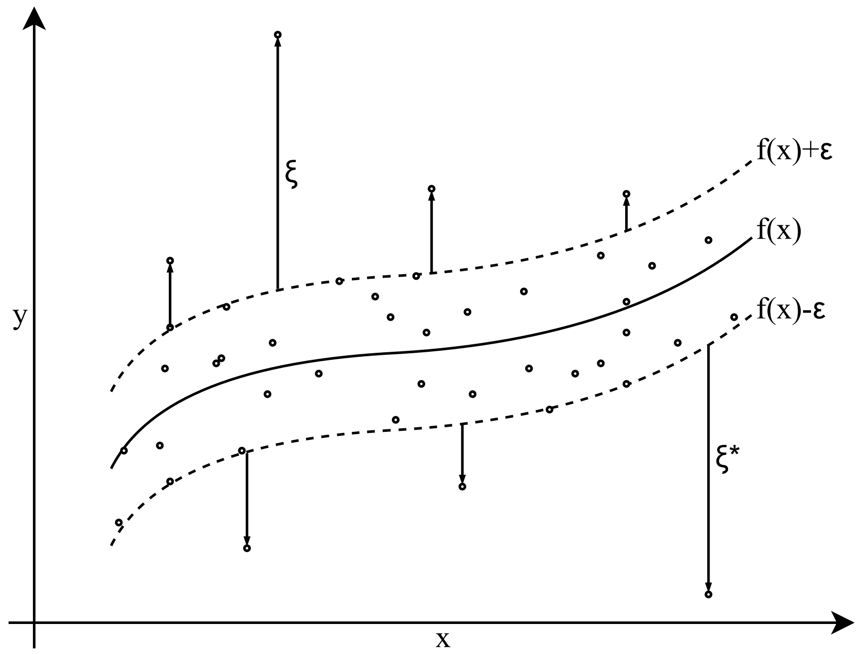


Figure 3.7: Graphical representation of the SVR method on a data set.

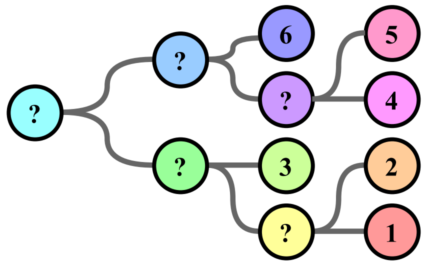


Figure 3.8: Graphical representation of a basic regression tree model.

LRTM

With the limitation of LR, a combination can be made using RTM to create a LRTM. With this method, a non-linear model is split into piece-wise linear estimation [49]. An example of this method is shown in Figure 3.9, where it is clear to see that the model split into multiple linear segments represents the data more accurately than a single LR over the whole data. This method is a common approach for complex regression problems [49]. This method allows for LR to be applied to non-linear problems. Additionally if the LRTM is pruned sufficiently, the LR of the segments will be less prone to noise and uncertainty within the input data [38]. Even though this has not been applied to similar applications, it is still an applicable solution for the problem within this investigation.

Random Forests Method

Another approach to using RTM is by using the Random Forest (RF) method. This uses the basic decision tree and bagging as a basis for its prediction [7, 8, 33]. Bagging ('**B**ootstrap **Ag**gregat**ing**' [7]) is forming multiple trees with the same training data resampled using the bootstrapping method, where after the results of these trees is aggregated and averaged to give a prediction of the result [7, 33]. Where RF differs from Bagging is that in Bagging techniques the individual trees have many similarities due to having the same predictors in their dataset [33]. In RF the trees are generated using the bootstrapped resampled dataset, but at each branch a random predictor is selected to branch off of further, reducing the correlation between trees [8]. In this way the variance of regression trees is reduced and an applicable solution for this investigation.

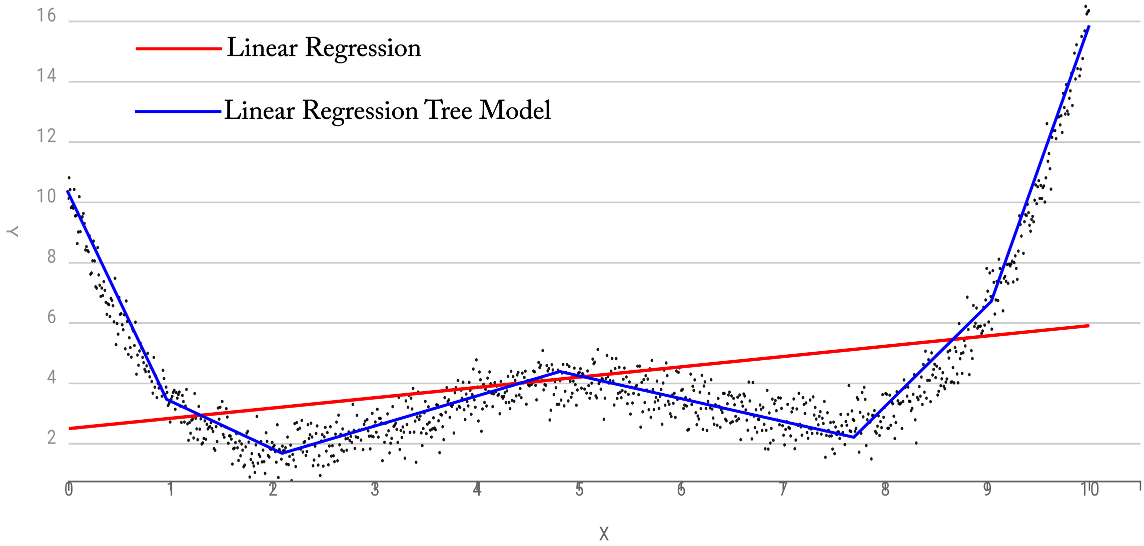


Figure 3.9: Mathematical modeling of a set of data with Gaussian noise using LR (red) and LRTM (blue).

RF was created by Breiman [8] in 2001, which has since then been widely applied to many regression problems. This method has been investigated in construction [47, 58], semi-conductor manufacturing [34], and a flow-shop manufacturing [21]. In these applications it has come out as one of the most accurate prediction methods. As many uncorrelated trees are made which lowers the variance, this method can handle noise in the data. One disadvantage of this method however is it cannot predict outcomes outside the range of the training data [21], meaning some results cannot be extrapolated from the model. Next to this, due to splitting the training data and training trees from this, a large amount of training data is desired to create an accurate prediction method. Lastly, as many trees are randomly created and the predictions of these trees is averaged, the method is not interpretable of what relationships exist in the data and how it came to its prediction.

Neural Networks

A last prediction method is using an artificial NN to estimate the remaining time of the project. A NN is a network of nodes with multiple layers, namely the input layer, hidden layers and the output layer. The input layers feed into the hidden layers, which associates weights to the connections between the nodes. With this weighted network, the input is multiplied throughout the network until at the end a prediction is made. This network of nodes is visualized in Figure 3.10. The weights between the layers are found during the training phase of the NN, where the weights are iteratively found through forward and backward propagation using the training set [43]. Through this iterative method and non-linearities in the layers, NN can model complex systems to create predictions on the project.

With the growth of data and the acquisition thereof, NN has grown in popularity to analyse large data sets. Research has been done with this method in project progress prediction in semi-conductor manufacturing [34], shipbuilding [22] and batch production processes [50]. From Raaymakers and Weijters [50] they found that the prediction accuracy of NN exceeded linear regression, while Lingitz et al. [34] found the prediction accuracy of a NN with a single layer to have a low prediction accuracy. This variation is dependent on how the prediction method is set up. Next to the set up, a NN requires a large training data set and after being trained, due to the weights in the hidden layers, the predictions are not easily interpretable.

3.3.3. Mathematical Modeling Method Comparison

In Table 3.4 all the modeling methods are listed with their characteristics described as well. From the methods, a low variance and low bias would be ideal, but as this is usually a trade off between the two, having flexibility within the variance and bias is beneficial. Additionally, the training data size in planning is relatively small in an ETO environment, where project progress is reported regularly. Furthermore,

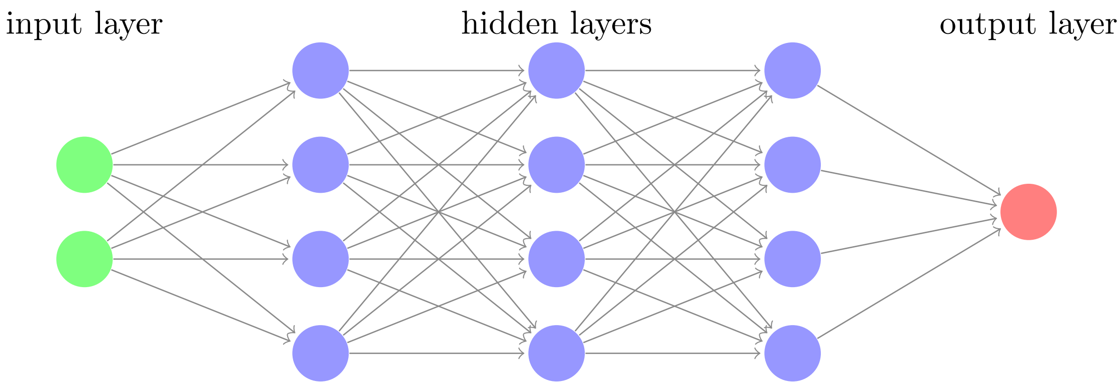


Figure 3.10: Diagram of a NN with three hidden layers, two inputs and one output [59].

every project is unique and can have their own complexities involved meaning that the training data is limited. Lastly, planning is continuous, therefor the predictions from these methods should be easily interpretable as they would be used often and require some insight on how such a prediction is made. For these reasons, looking at the methods available, SVR or LRTM are the most applicable for this investigation. From these two, SVR is more suitable than LRTM as it has a flexible variance bias trade off and the training data it requires is smaller. For that reason, SVR will be used for the method to be implemented.

Table 3.4: Overview of the mathematical modeling methods and their different characteristics described in section 3.3.1.

Method	**Variance**	**Bias**	**Training Data Size**	**Interpretability**
Linear Regression	Low	High	Small	High
Multiple Linear Regression	Low	High	Small	High
Support Vector Regression	Low[a]	Low[a]	Small	High
Linear Regression Tree	Med	Med	Medium	High
Random Forests	Med	Low	Large	Low
Neural Networks	Med	Low	Large	Low

[a]Can be adjusted by changing a parameter (C) which maximizes margin and minimizes mistakes. Changing parameter C does still maintain the Bias variance trade off, where lowering one will increase the other.

3.4. Error Quantification Review

As discussed in Section 3.2.3, the prediction method requires a way of quantifying the errors in its prediction. Quantification is done by propagating the error throughout the method into the output. The characteristics necessary for the prediction methods are defined which will be used to compare the error propagation methods. Followed by an overview of the available propagation. From a comparison the most suitable error propagation method will be selected for the progress tracking method.

3.4.1. Criteria for Methods

When looking at error propagation, there are only two characteristics which can influence the how well SSFP functions, namely:

- **Robustness:** The error propagation method should be able to handle different types of Probability Density Function (PDF), as to make to keep the robustness requirement for the method in consideration.
- **Ease of Use:** The method should be easy to use, where if a distribution of a variable changes it does not require the user to more than just change the probability distribution of the single variable.

3.4.2. Error Quantification Method Overview

In this section an overview of error propagation methods is given.

Analytical Solution

Error propagation can be done through an analytical method, where with known PDFs of variables the confidence limits can be calculated. With the known distributions, the uncertainty is calculated considering the original formula to give a confidence interval over which the solution can span. This method is not as robust, as once the distribution type changes, the calculation has to be redone considering the new distribution. This makes it harder to use as well, as the user needs to check that the distribution is similar to the assumed distribution used in this method, and if not the user needs to calculate the error further as well.

Monte Carlo Simulation

Monte Carlo simulations are used to propagate the error of variables in functions by running many simulations by randomly assigning the variables a value according to their PDFs. With more random simulations, the better the PDF of the samples converges to the actual solution [2]. With this simulation the PDF is input before the simulation. Once input, the simulation runs according to the defined PDFs meaning that the Monte Carlo simulation samples will still converge to the actual distribution regardless of the PDF, making it an easy to use error propagation method once implemented. The robustness of the method is higher than the analytical solution, as its easier to implement different types of distributions, but this method does assume that the given distributions of the input variables are correct.

Markov Chain Monte Carlo Simulation

Markov Chain Monte Carlo (MCMC) simulation uses Markov Chains in conjunction with Monte Carlo simulations to approximate the actual probability distribution of the solution, the posterior distribution. To get to the posterior distribution, MCMC is based on the idea that random samples are generated by a special sequential process, where the next random sample generation is based on the previously generated sample, like a chain [55]. The chain is MCMC built so that the next sample is dependent on the previous sample, it is not dependent on any samples before that one, giving it its 'Markov' property [55]. The generated values are also accepted or rejected at a probability based on a predicted distribution and a small sampled likelihood curve. This method is more complex than the Monte Carlo simulation making it harder to implement and harder to use. MCMC simulation is robust as the posterior distribution considers the information from a prior estimation and a likelihood distribution (a sampled distribution) in the accepting and rejecting step of this simulation.

3.4.3. Error Quantification Method Comparison

From the overview a comparison can be made of the available error propagation methods. In Table 3.5 an overview of the error propagation methods and their characteristics can be seen. Analytical error propagation method is the least suited method, as it scores lowest on both characteristics. The Monte Carlo simulation will be used as it may be less robust than the MCMC simulation method, it is much easier to use and implement. Additionally assumptions will have to be make on the variable PDFs as there are only a limited amount of projects to sample for a likelihood distribution required for a MCMC simulation. Therefor, for this investigation the Monte Carlo simulation method will be used as the error quantification and propagation method for this investigation.

Table 3.5: Overview of the error propagation methods and their different characteristics described in section 3.4.1.

Method	Robustness	Ease of Use
Analytical Solution	Low	Low
Monte Carlo Simulation	Medium	High
Markov Chain Monte Carlo Simulation	High	Low

3.5. Chapter Summary

Before being able to investigate progress tracking methods, models for the data are required. From multiple models it was discussed that the Loglet Lab model is the most suitable model for the S-curve. Using this curve on progress curves and the available mass curves it was found that the mass curves best represent the manufacturing design phase.

Predicting the current progress of a large project in an ETO environment with concurrent planning is challenging with many uncertainties. From literature, EVM, StS-Curve estimation, and geometric feature estimation were the available methods, all not meeting the requirements to be suitable for the intended application. Using features from StS-Curve estimation and geometric feature prediction can result in a new integrated method, SSFP, which could be suitable. SSFP would use the stochastic nature of the envelope with a the predicted S-curve features to provide an estimation of the progress of a project. This method would include two independent components which can work together, namely a mathematical modeling method for feature prediction and an error propagation method.

Potentially suitable mathematical modeling methods for SSFP were investigated and compared. Considering the accuracy (variance, bias), training data size, and ease of use, SVR is the most suitable mathematical modeling method. SVR is a regression algorithm which finds a relationship within data by enveloping the trend with upper and lower limits. To provide insights on the uncertainty in the progress prediction, multiple methods are available to quantify the error. Using Monte Carlo Simulations was the most suitable method due to its robustness and ease of use.

4

Development of Prediction Method

In this chapter the progress tracking method will be explained based on the conclusions presented in Section 3.5. The main assumptions of the method will be explored, as well as its advantages and limitations. A general overview of the method will be given first, followed by a more detailed explanation.

4.1. Method Overview

As discussed in Chapter 3, SSFP can be considered as the most suitable method for progress tracking of projects in an ETO environment. In the development of the method, only projects of a specific equipment type were considered to ensure data sets as homogeneous as possible. Within this selection completed projects were considered. Data from completed projects were used in order to identify the main features of these projects that the tracking method should account for. Partial data from the completed projects were considered as ongoing (i.e. in progress) projects in order to develop the prediction part of the method.

The data was further restricted to the Mechanical engineering documents, both because of their relevance for the project execution (see Chapter 2 for details) and because of the large amount of data available. The mass of each designed block of the system will be used to measure the progress on the mechanical design. In practice the amount of designed mass will be compared to the total amount of mass (in mt) to be eventually built.

As outlined in Figure 4.1, the method can be layed out through the following steps:

1. Analysis of historical data and S-Curve fit to extract the features of a number of completed projects (see Section 3.1).
2. SVR analysis of S-curves features, as retrieved from step 1, to retrieve project features of the current ongoing project (see Section 4.2).
3. Forecast the S-curve features for the ongoing project at hand, based on the SVR analysis (see Section 4.2).
4. Fit of current project mass curve using the least square method to determine corresponding S-curve.
5. Estimation of predicted S-curve features using a weighted average between the forecast and estimated S-curves (see Section 4.3).
6. Monte Carlo Simulation to estimate the error on the progress prediction (Section 4.4)

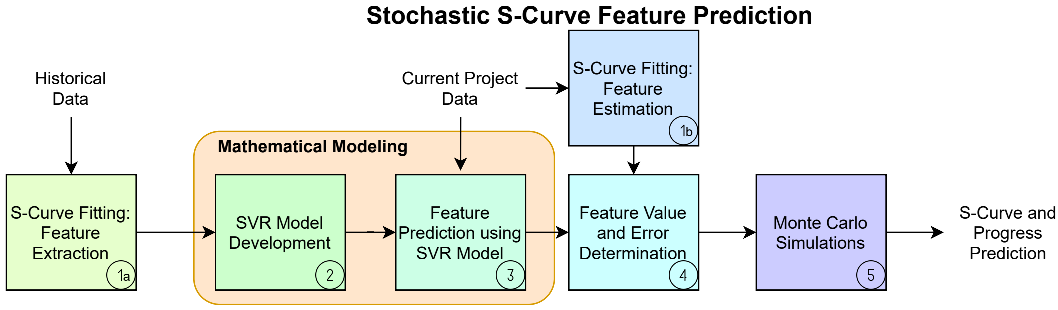


Figure 4.1: Block diagram of the proposed SSFP method to develop. Where block ⓐ and ⓑ is explained in Section 3.1, ② in Section 4.2, ③ & ④ in Section 4.3, and ⑤ in Section 4.4.

4.2. Feature Analysis

As mentioned in the method overview in section 4.1, historical data of completed projects were retrieved from the document repository (see Section 2.2.2 for details) in order to extract the corresponding S-curves and project features. The S-Curve for running projects will be then forecast based on the results from the SVR analysis conducted upon the features of the S-curves representative of completed projects. Within this process, each S-curve feature for the ongoing project is obtained through comparison with the estimated total mass of the equipment (mass corresponding to 100% progress) and an SVR analysis is run in order to find the relationship between the two.

The (estimated) total mass of the equipment or system was used as a metric to differentiate projects. It is related to its Safe Working Load (SWL), which identifies the maximum load that the equipment can safely handle and it is known from the start of the project. The SWL ultimately determines the overall size and complexity of the equipment and has therefore, a great impact on the design process and total weight of the equipment.

The mass is used as an independent variable in the analysis of the features of the progress curves at hand. These features are identified with duration to midpoint, i.e. how long it takes to reach the midpoint of the S-curve, maximum slope, i.e. progress at midpoint (slope of curve at midpoint), total released "mass", i.e. mass associated with all released shop drawings for a certain project. These features (visualized in Figure 4.2) are from equation 4.1 discussed in Chapter 3.

$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}} \tag{4.1}$$

where '$f(x)$' is the progress, 'L' is the total released "mass" of progress, 'k' is the progress at the midpoint, 'x' is time, and 'x_0' is the midpoint.

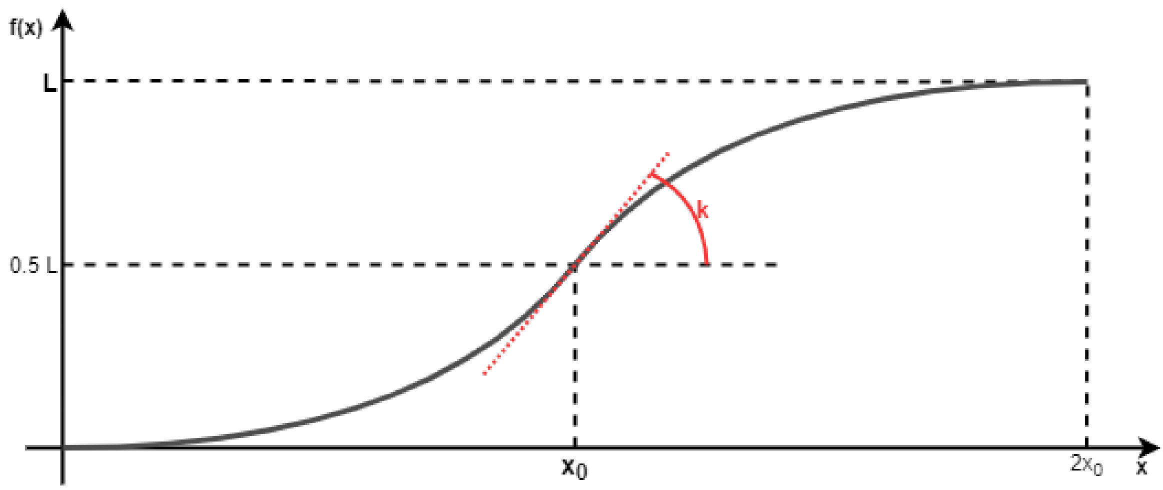


Figure 4.2: Diagram with the S-curve features labeled (L - total released "mass" or progress, k - progress at midpoint, x_0 - midpoint)

The relationship between mass curve features and the design mass of the equipment are presented in Figure 4.3. It is found that projects usually reach their progress midpoint in about 400 days, over the entire range of design mass (see Figure 4.3.A). The outlier to reach its midpoint in 1000 days is identified as such due to non-normal operation, in this case a hold on the project, delaying the project.

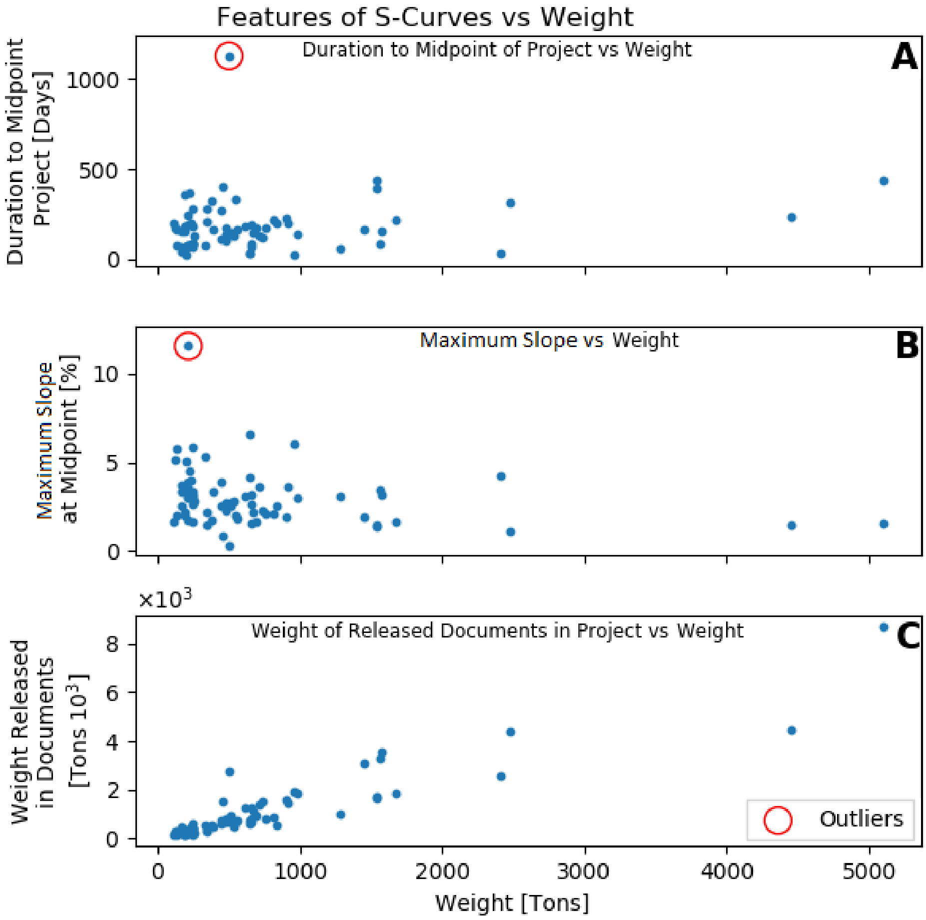


Figure 4.3: Scatter plots of the features of the mass curves compared to the overall weight of the equipment.

The slope is to be found within 5% (see Figure 4.3.B). An outlier was found linked with a project from more than a decade ago, i.e. 2010, characterized by a slope twice as high as the average of all other selected projects resulting from a different document administration. Finally, the amount of released documentation was found to linearly increase with the design (see Figure 4.3.C). With this data an SVR analysis can be done to find a trend within the dependent and independent variables.

For an SVR analysis to be conducted, the value of the parameters 'C' and 'ϵ', as well as the regression model need to be determined. The 'C' parameter represents the penalty value of points not in the data envelope, whereas the parameter 'ϵ' identifies the size of the dataset in the envelope. In order to determine the appropriate values for these two parameters, a SVR analysis is conducted multiple times. The 'C' and 'ϵ' values are sought for within a so-called "search grid". Such a grid includes all 'C' values located in the range 1×10^{-10} to 1×10^{10} in 21 steps in a logarithmic scale and 'ϵ' values in the range 0.02% to 50% of the maximum value set over 25 steps. The logarithmic scale was selected as to maintain a large range for parameter selection due to the large range of scales in the three features, while also reducing the calculation time. Similarly number of steps in the search grid was chosen to balance between the calculation time and density of the search grid. The regression model with respect to the SWL was assumed to be linear, as to reflect the increasing complexity of the design process, as well as the amount of released documentation.

To prevent over-fitting of the model, the training data set in the grid were separated from the validation data set. The latter set was used to assess the model fitted onto the training data in order to identify the best parameter sets to fit the data. Based on the results of the SVR analysis, a model for the S-curves features was created, as shown in the example of figure 4.4.

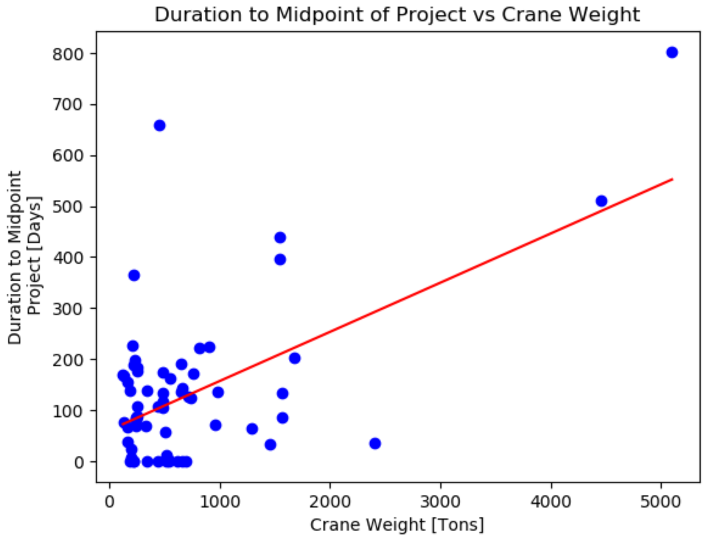


Figure 4.4: Midpoint of the S-curve based on SVR analysis - example.

4.3. S-Curve Prediction

As briefly shown in Section 4.1, the S-curves of ongoing projects were predicted based based on both curve fitting of the available data points and the data collected from the feature analysis conducted over completed projects.

This approach results into two S-curves, whereby the first one has the features forecast through SVR analysis, whereas the second one fits the available raw data of the ongoing project. As the design process continues the expected weight can deviate, which can be updated as necessary. The predicted S-curve will then be formed using the predicted features of the midpoint and slope. As the S-curve is measuring progress from 0 to 100%, the maximum value of the S-curve does not change. The expected weight of released documents will also be predicted, but this value will be used in further steps in predicting the progress.

The second S-curve was generated by fitting the available mass data from ongoing projects. Within this approach the progress can be tracked based on the mass associated with the shop drawings released throughout the course of the project. Each of such data point is the mass associated with each issued drawing normalized with respect to the total mass of the system. Using the least squares method as described in Section 3.1 the midpoint and slope of the S-curve are constrained to positive values. To prevent unphysical S-curves from being generated. Additionally, a 'phantom' point is added to the data set provided to the curve fit algorithm. The extra data point is placed one year prior to the first data point and sets a certain point where the project has not started yet, therefore giving an origin to the fitting algorithm. Adding this point ultimately, prevents the algorithm from predicting unrealistic project durations, e.g. thousands of days corresponding to approximately 50 months of project.

On the basis of the above S-curves a Monte Carlo simulation was conducted in order to predict the progress of the ongoing project. In order to run the Monte Carlo simulation, the uncertainty on the features of the two S-curves was first estimated. The estimate resulted as an average between the uncertainty distributions of both kinds of S-curves. To this purpose, the two models, i.e. SVR-based and fitted S-curves respectively, were treated as an ensemble. In particular, the Bishop [5] approach was used and a weighted average of the two models was calculated as follows:

$$\hat{y}_{ens}(x) = \sum_{i=1}^{N_M} w_i \hat{y}_i(x), \tag{4.2}$$

where $\hat{y}_{ens}(x)$ is the predicted value of the ensemble, w_i is the weight factor for the i_{th} model, $\hat{y}_i(x)$

is the predicted value of the ith model, and N_M is the total amount of models. For equation 4.2 it is assumed with the condition:

$$\sum_{i=1}^{N_M} w_i = 1. \tag{4.3}$$

The RMSE was selected as a suitable weight factor for the model, based on the approaches Acar and Rais-Rohani [1] and Goel et al. [20]. To this purpose the weight factor for the curve fit was calculated first, as:

$$w_{CurveFit} = 1 - RMSE - (0.5 \times max(\frac{-1}{d_{thresh}} \times d_c + 1, 0), \tag{4.4}$$

The weight factor for the forecast S-curves was then derived as:

$$w_{SVRPrediction} = 1 - w_{CurveFit}, \tag{4.5}$$

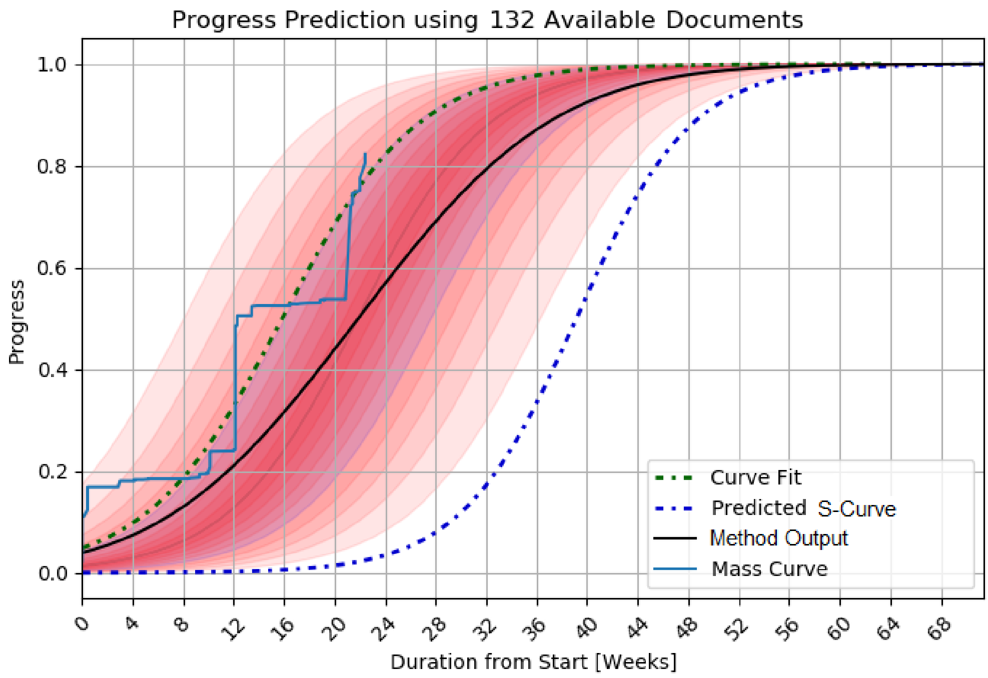
with d_c being the amount of available documents and d_{thresh} being the threshold amount of documents. The weight factor was scaled by the RMSE of the curve fit, as well as to the amount of available data. The dependency on the number of available documents was included in order to reflect that the accuracy of the progress estimate improves by increasing the available documents. Such an influence was defined as a linear function and was defined with the average amount of documents released per project within the project start and the S-curve midpoint. In the present case this number was found to be around 55 documents. Using the weight factor as calculated above, the average S-Curve features and their error distribution for the Monte Carlo simulation were determined.

4.4. Monte Carlo Simulation

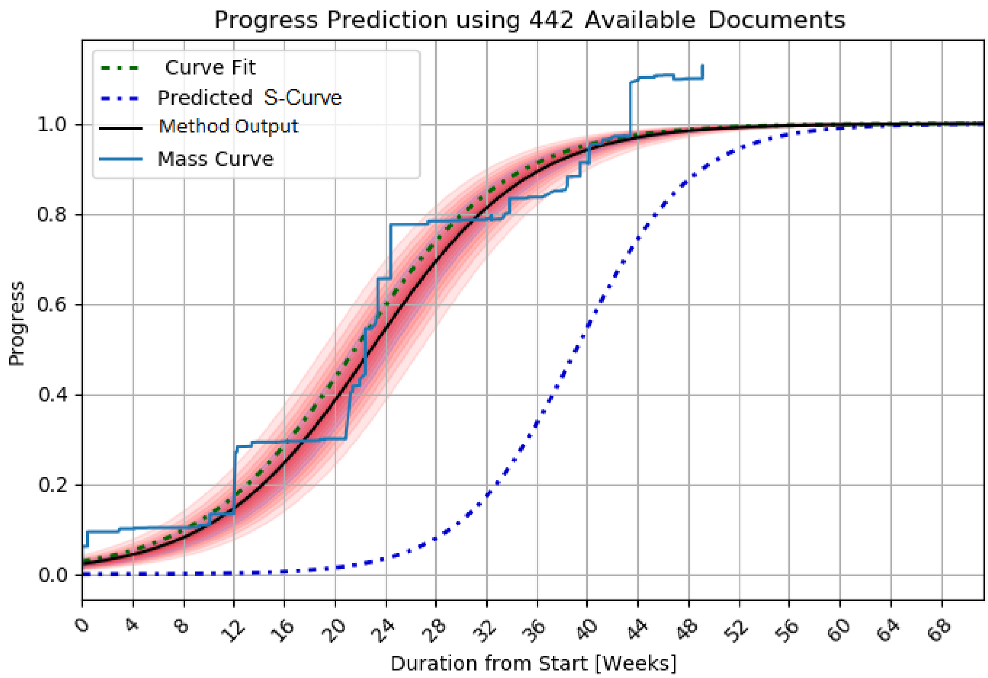
The probability density functions of the S-curves features as obtained from the two models, were extracted to ensure the success of the Monte Carlo simulation. A Gaussian distribution was assumed for the present case based on the work of Barraza et al. [4] and Vladimir and Dražen [56]. Prior to determine the probability distribution, the extracted S-Curve features of the two models was calculated using the weight factor.

The predicted S-curves features were randomly selected from the above PDF's. The predicted S-curve was obtained as to have these features and to reach between 1 and 99% of the progress within 20 steps. This procedure was reiterated over 10000 times to ensure high accuracy [32] while ensuring a computational time in the order of seconds. Based on the simulations a mode was determined in order to extract the data S-curve. Figure 4.5 shows the distributions of the prediction error of the simulations for different amounts of available documents.

With the distributions of the three features of the S-curves determined, a Monte Carlo simulation can be done to predict the S-curve. Random values are sampled from all three features based on the provided PDFs. With these three values, an S-curve is created where the expected duration to reach 1% to 99% progress of the project in 20 steps is calculated. This is then done for 10,000 simulations as this exceeds what is necessary to achieve a high accuracy of the expected output (assuming input variables are accurate) [32] and has a computational time in seconds. From all the simulations, the mode is then determined to provide the expected S-curve of the data. Next to the mode, a color gradient around the mode S-curve is created showing the density of the simulations portraying the error in the prediction. In Figure 4.5 an example can be seen of two different S-curve predictions, where one has a large error (Figure 4.5a) and the other a small error (Figure 4.5b).



(a) Predicted S-Curve with the mode line shown in black with a large distribution of the Monte Carlo simulations



(b) Predicted S-Curve with the mode line shown in black with a small distribution of the Monte Carlo simulations

Figure 4.5: Example of the output of the method of the same project with different amount of available documents.

4.5. Chapter Summary

In this chapter the SSFP integrated model was explained. It was shown that the progress S-curve of an ongoing project can be determined based on the SVR analysis of the S-curve features of completed projects along with the curve fitting of the mass data available for the ongoing project. A Monte Carlo simulation was carried out based on the S-curve estimated from the ensemble weighted average of the two S-curves models. It was shown that the amount of available documents can be used as a suitable weight factor to determine the accuracy of the prediction.

5 Performance Evaluation

The method developed in chapter 4 will be validated in the present chapter. In particular, a simulated data set will be used in the verification of the model, whereas the validation of the model will be conducted based on a case study.

5.1. Model Verification

The verification of the SSFP method will be illustrated hereafter. This procedure is carried out in order to asses the accuracy of the method in predicting S-curves of ongoing projects using a varying amount of data. Furthermore, the robustness of the method shall be assessed, i.e. it should be verified that the uncertainty on the available data does not affect the quality of the prediction. For this purpose, data sets will be used using different preconditions (see Section 5.1.2).

5.1.1. Verification Criteria

Within the present verification the performance criteria below will be considered:

- **Tracking Error:** The error on the estimated current progress compared to the actual progress. Both magnitude and sign of the error will be considered in order to evaluate whether the progress is over or under-estimated by the present method.
- **Prediction Error:** This is similar to the tracking error will instead measure the error on the forecast time needed to reach a certain predicted progress.

The influence of the individual S-curves upon the predicted progress can be represented as follows:

$$x = x_0 + \frac{\ln\left(\frac{f(x)}{L - f(x)}\right)}{k} \tag{5.1}$$

where 'x' is the predicted time to reach a certain progress, 'x_0' is the midpoint, '$f(x)$' is the 'certain' progress, 'L' is the total released "mass" of progress, and 'k' is the progress at the midpoint (see Chapter 4).

The predicted time to reach a certain progress from equation 5.1 ('x') is used as the prediction value in equation 5.2 to calculate the error of the values.

$$Error = \frac{Actual - Prediction}{Actual} \times 100 \tag{5.2}$$

Figure 5.1 shows how the error in the estimation of the S-curve feature affects the quality of the overall progress prediction. In particular, prediction error and midpoint error are found to be in a inverse linear relationship. Therefore the impact of the midpoint error is consistent as the error grows further. The other two features have an inverse logarithmic relationship, where the error has a significant a symmetric influence on the overall progress prediction. Considering the features independently will not provide meaningful insights into the accuracy, as the features may compensate the error of one for another. Similar relationships between the features and the tracking error can also be found considering the loglet model.

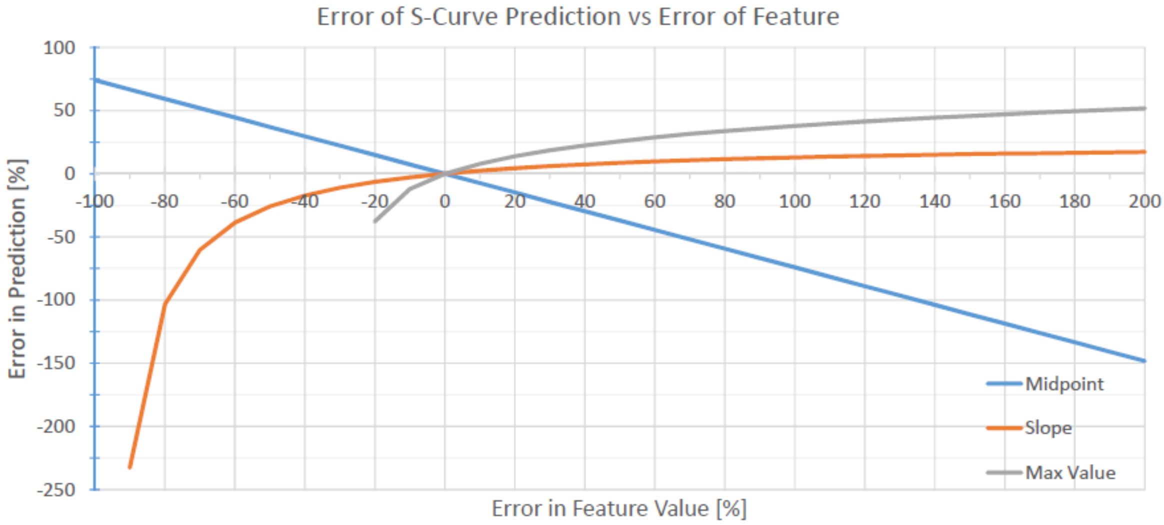


Figure 5.1: Relationship between error on predicted progress at 75% and error on estimated S-curve features.

5.1.2. Verification Tests

The verification tests conducted are explained in this section. 30 different curves were generated to be used as inputs for the S-curves features and the simulation data points, respectively. The curves were split into 3 sets of 10 curves each. Each set was obtained by changing the value of one of the three curve features. For this purpose, the three ranges below were considered:

- Midpoint: 100 to 1000 in steps of 100
- Slope: 0.011 to 0.1 in steps of 0.01
- Maximum value: 1000 to 10000 in steps of 10000.

For the ”unvaried” features, the following default values were considered:

- Default midpoint value: 300
- Default slope value: 0.051
- Default maximum value: 6000.

500 data points were considered within the verification tests to represent the typical amount of documents released during a project. The accuracy of the estimate was also assessed herein with respect to the to total amount of issued documents. Details on the different verification tests herein conducted is given below. An overview is given in 5.1.

1. **Noiseless Data with Error-less Predictions:** These tests were conducted to evaluate how the method is influenced by total amount of available documents under the assumptions that the predicted S-curve has no error compared to the simulated data. The tests were carried out assuming a total number of issued documents equal to 10,20,50,100,500, and 900 respectively.
2. **Noiseless Data with Error in Predictions:** For these tests no noise was added onto the simulation, whereas finite values of error were added onto the predicted curve.
3. **Noiseless Data with Unphysical Predictions:** These tests were carried out considering no noise on the simulated data and 'unphysical' features were introdued into the predicted curve.

4. **Gaussian Noise on Data with Errorless Predictions:** For these tests a gaussian distribution of noise was super-imposed onto the simulated data, the standard deviation being 100, 250, 500, 750, and 1000kg respectively.
5. **Gaussian Noise on Data with Error in Predictions:** These tests assumed both an error in the S-curve prediction and a gaussian distribution of noise super-imposed onto the simulated data with a 250kg standard deviation applied to it.
6. **Uniformly Distributed Data with Errorless Predictions:** These tests simulating data points from a uniform distribution between 0 and 100% completeion. This case is intended to consider the output of the model when no S-curve relationship exists in the simulated data.

Table 5.1: Tests (numbered) which will be performed to verify the method and its output. The numbers represent the subsection in which the verification will be discussed in section 5.1.

		Input Data		
		No Noise	With Noise	Random
Predicted S-Curve Features	No Error	1	4	6
	With Error	2	5	
	Impossible	3		

5.1.3. Verification Results

The results of the verification are discussed in this section. Figure 5.2 shows example curves obtained from the tests. It is found that the number of data points collected over the course of the project has direct impact onto the accuracy of the prediction. Similar results are found for other projects with similar features.

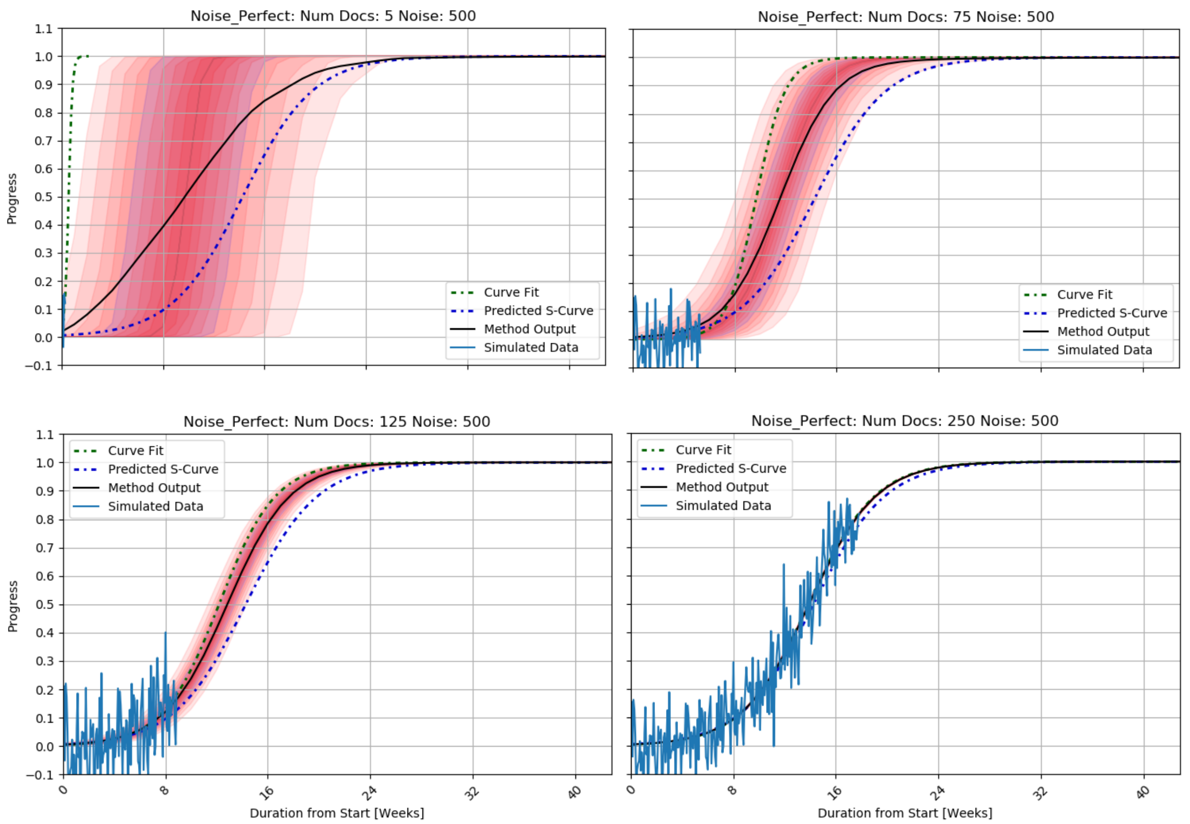


Figure 5.2: Test 4 - Gaussian Noise on data with *errorless* prediction: effect of increasing simulated points on prediction accuracy

Table 5.2 gives an overview of the mean and standard deviation of the tracking and prediction error relative to the actual progress. It can be seen that the tracking accuracy is high, but as noise and errors are introduced the standard deviation of the tracking accuracy increases. The best tracking accuracy of the method is when the predicted S-curve features had no error compared to the actual S-curve, but this error is influenced strongly by the magnitude of the error at the start of the project (with few documents available). This initial error at the start of the project is clear, as shown for example in Figure 5.3.

Table 5.2: Tracking and Prediction Accuracy Mean and standard deviation of the tests using controlled data explained and numbered further in table 5.1. All the tests in this example used 500 data points. The error is calculated by subtracting the output of the method from the actual progress or duration.

Test	**Tracking Accuracy**		**Prediction Accuracy**	
(Input Data - Predicted Features)	**Mean Error [%]**	**Error STD [%]**	**Mean Error [Weeks]**	**Error STD [Weeks]**
1. No Noise - No Error	-0.01	0.06	-0.5	6
2. No Noise - With Error	-0.02	0.2	2	15
4. With Noise - No Error	-0.5	0.8	-19	41
5. With Noise - With Error	-0.4	1	-16	45

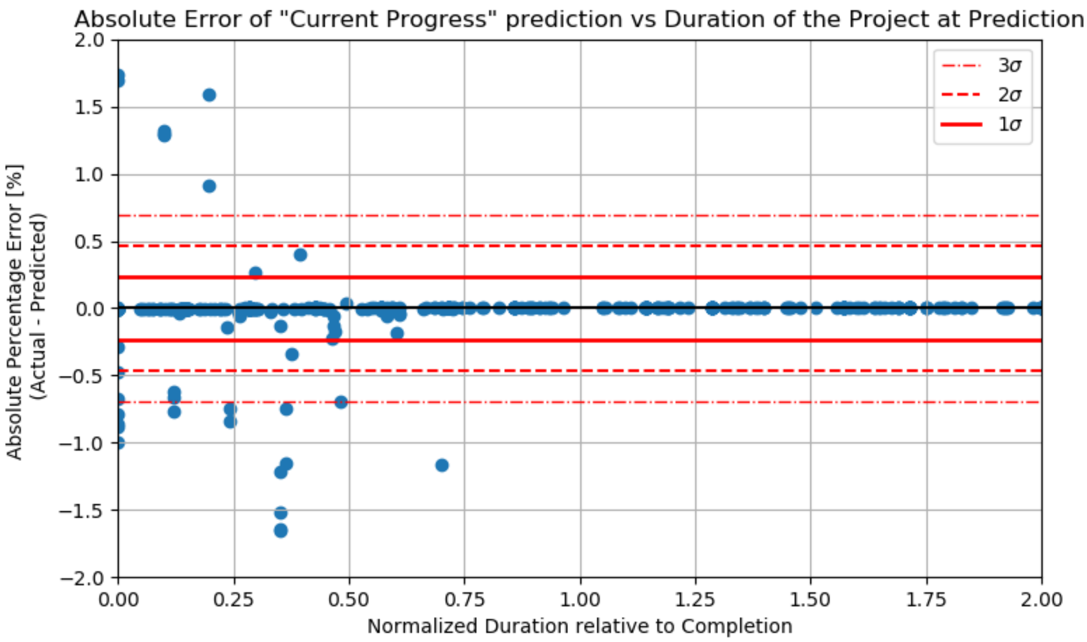


Figure 5.3: Test 2 - Noiseless Data with *Error* in Predictions: Error on estimated progress over time

1. **Noiseless Data with Errorless Predictions**

   Adding no noise to the simulated data and assuming no error in the uncertainrty of the prediction was found to converge quicker, i.e. for a lower amount of documents. In fact, the amount of issued documents was found to have a negligible effect on the tracking accuracy (see Table 5.3).

Table 5.3: Tracking and Prediction Accuracy using simulated data with different amount of total possible documents.

Test	**Tracking Accuracy**		**Prediction Accuracy**	
Number of Documents	**Mean Error [%]**	**Error STD [%]**	**Mean Error [Weeks]**	**Error STD [Weeks]**
10	0.1	1	-0.6	8
20	-0.01	0.1	-2	7
50	-0.01	0.1	-0.8	6
100	-0.01	0.3	-0.9	6
500	-0.01	0.06	-0.5	6
900	0.1	2	-0.5	7

2. **Noiseless Data with Error in Predictions**

   This test was found to give similar results as Test 1. The uncertainty of the predictions was found to remain larger and for a longer period of time and it was found to reduce over time.

3. **Noiseless Data with Unphysical Predictions**

   In this case no prediction was expected, as the values provided as a prediction were not feasible. No matter if the midpoint, slope or maximum value was changed to unphysical values, the method returned an methematical errors and did not provide a prediction. This was as expected and should trigger the user of the method to check the feasibility of the initial prediction.

4. **Gaussian Noise in Data with Errorless Predictions**

   The outcome of this verification test can be inferred from Figure 5.2, showing that a prediction can still be made even with large uncertainty, for a small amount of data points. When introducing noise into the data, the prediction was found to be more uncertain. However, the uncertainty was found to decrease with increasing data points, with the prediction converging towards the "actual" S-curve (Green dashed line in Figure 5.2). Additionally, the magnitude of the Gaussian noise in the simulated data was found to have a negligible effect on both the tracking and the prediction accuracy. It can be concluded that introducing noise into the data has only marginal/minor effect onto the tracking accuracy, whereas it tends to have a great impact on the prediction accuracy.

Table 5.4: Tracking and Prediction Accuracy using simulated data with different magnitudes noise.

Test	Tracking Accuracy		Prediction Accuracy	
Stdev of Gaussian Noise	Mean Error [%]	Error STD [%]	Mean Error [Weeks]	Error STD [Weeks]
100	-0.5	0.8	-17	39
250	-0.5	0.8	-19	41
500	-0.5	0.8	-17	40
750	-0.5	0.8	-15	36
1000	-0.5	0.9	-16	37

The prediction was found to be the most affected by data noise at the start of the project, where the progress grows the most rapidly and curve fitting is the most challenging. This is clear to see in Figure 5.4(a), as the data still shows low progress increases over time and as such it is hard to to correctly fit an S-curve. As progress starts picking up, in the case of the output in Figure 5.4(b), with an additional 50 data points, the prediction S-curve is much closer to the actual data than before. This increase in accuracy is mostly due to the clear upwards trend in the data.

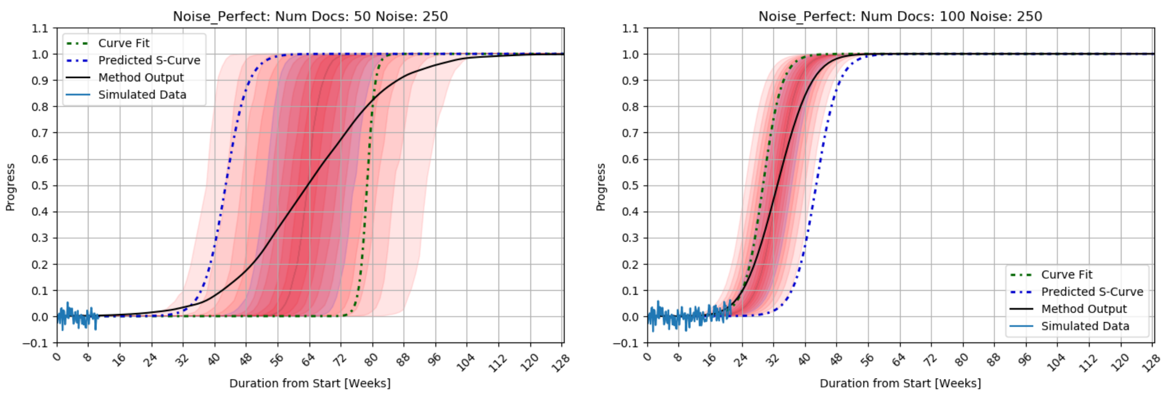


Figure 5.4: Predicted progress for noisy data: 50 data points (a) and 125 data points (b), and an errorless S-Curve prediction.

5. **Gaussian Noise in Data with Error in Predictions**

   This verification test best represents realistic situations, as it involves both error on the prediction and the simulated data. In comparison with test 1, the uncertainty of the prediction was found

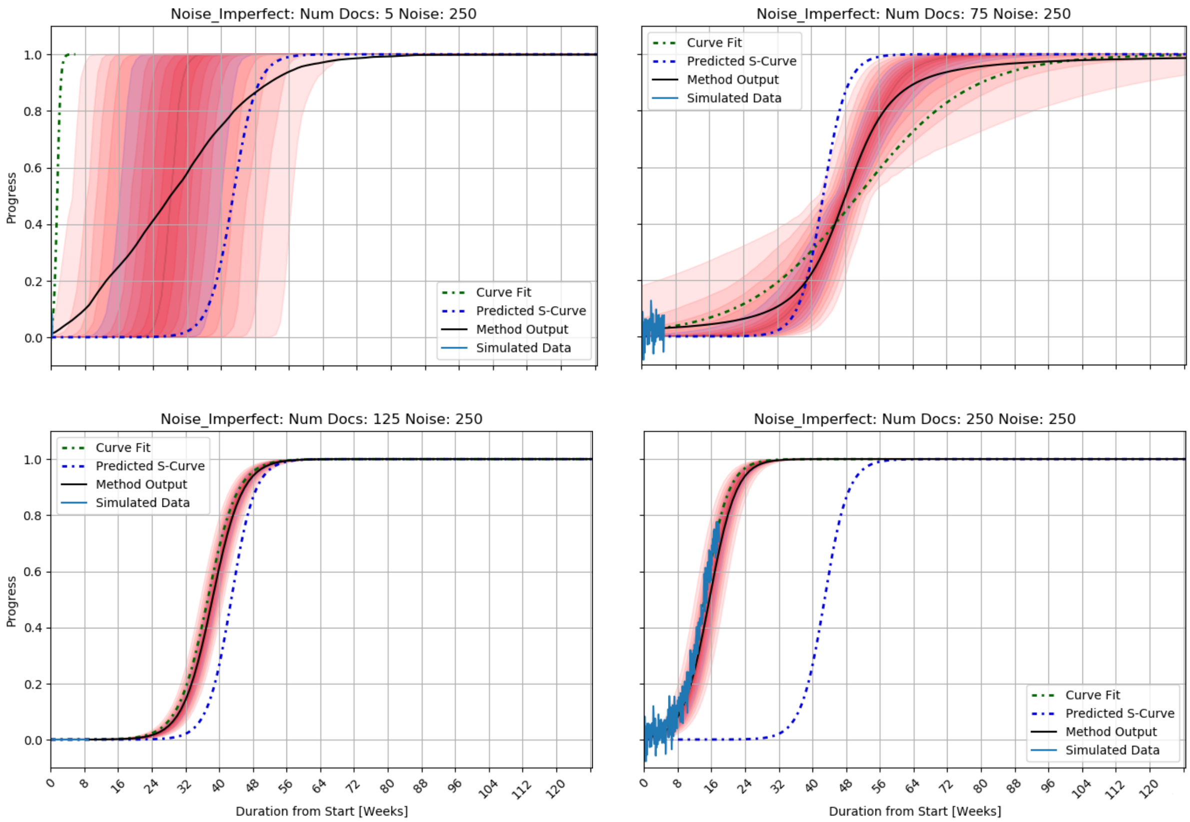


Figure 5.5: Plots of increasing amounts of simulated data points provided as the project progresses from the verification test: 'noise in data with an error in the prediction'.

to remain larger with increasing data points, which can be inferred by comparing Figure 5.5 to Figure 5.2.

6. **Uniformly Distributed Data with Errorless Predictions**

   Figure 5.6 shows the outcome of test 6. The uncertainty on the prediction was found to be large, despite the increasing number of data points. Additionally, the midpoint of the S-curve was found to shift rightwards as more data was provided. This can be considered expected as the 'average' of the uniform distribution is at 50%, and so the midpoint of the project trends towards the midpoint in the available data. It can additionally be noticed that this trend is slightly skewed due to the added phantom point (see Section 4.3 for details on the *phantom* point) in the curve fit.

These simulated tests indicate that the method developed and implemented is able to track the progress of projects. In test 1 it was shown that the number of available documents has negligible influence on the tracking accuracy. This flexibility in the amount of documents reflects the robustness of the method. Test 2,4 and 5 has also shown that Gaussian noise in the data and/or error in the predicted progress, an expected consequence of human influence, has an unsubstantial effect on the tracking capabilities of the method. Additionally the results visually (e.g. Figure 5.5) show that as more documents are available, the more accurate the tracking capabilities is (see Figure 5.3). These results verify that the method outputs a project's progress, even with errors in the input data.

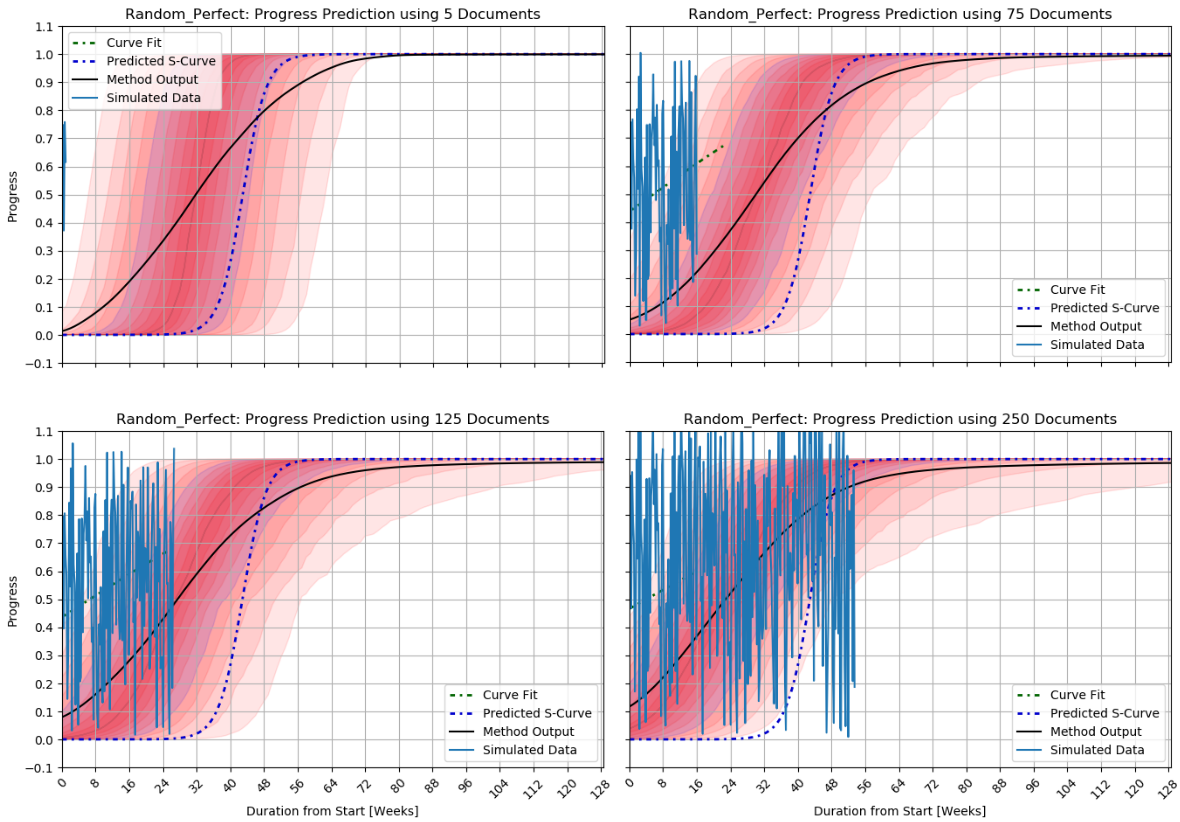


Figure 5.6: Plots of increasing amounts of simulated data points provided as the project progresses from the verification test: 'random data with an errorless prediction'.

5.2. Model Validation

After developing and verifying the SSFP method a validation was conducted using the mass curves retrieved from the data available at the case study ETO company. Mass curves were for all the projects to predict S-curve features (see Section 4.3 for details). For sake of the current model validation, 5 projects were extracted from the data set to be used as test data, whereas the remaining projects were used as training data. Using such data, a tracking error of $0.6 \pm 4\%$ and a prediction error of $7 \pm 23 weeks$ was found. The tracking accuracy obtained from the model verification is shown in Figure 5.7 and shows a larger spread in the data than what previously found in the verification tests discussed in Section 5.1.3 (see e.g., Figure 5.3). It should be noticed however, that in spite of the larger spread, the mean obtained from actual project data are comparable to the values obtained from the simulated data in Section 5.1.3. The RMSE of this case is higher, as the time-interval between each document release is in reality not uniform and therefore yields a larger range of predictions compared to the simulated data.

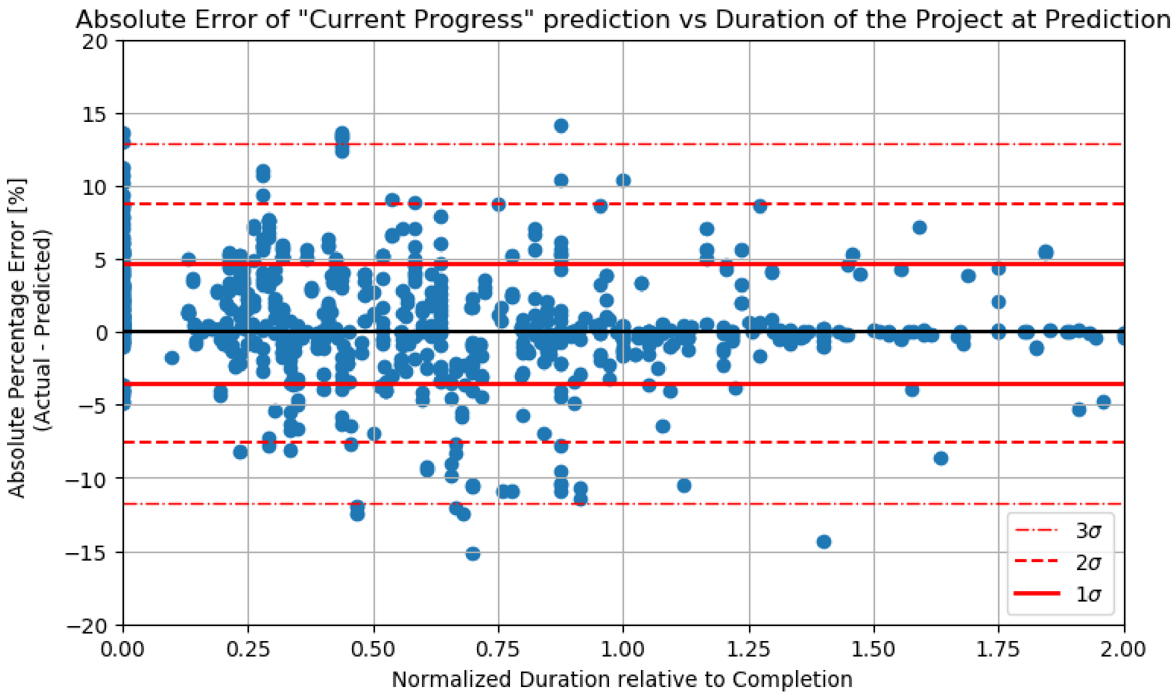


Figure 5.7: Error of the tracking accuracy versus the normalized time relative to project completion of the mass curves extracted from an ETO based company.

Considering the tracking accuracy, an error of 4% can also be translated to over or underestimated progress in relation to time. Adding and subtracting the tracking error to the output of an S-curve of the SSFP method also influences the time scale of the project. In Figure 5.8, it can be seen how the S-curve is translated up and down providing a range in time the 'tracked' progress may actually fall in. When this is averaged over the projects, it is shown that at one sigma (4%) the overestimation error can vary up until 4 weeks (see Figure 5.9). Only the overestimation of progress is considered, as this would result in a later delivery which can lead to extra costs. This does not consider the edge cases at the start, when progress is hard to measure (due to lack of data), and at the end, when only a few documents remain and consequently engineers can provide more accurate progress estimates. It is common practice for projects to have a planned 'float' time to compensate for delays, and sampled from a few projects this 'float' usually is between the one and two weeks. The potential over estimated time considered at 4% falls below the upper margin of this float until almost 80% completion.

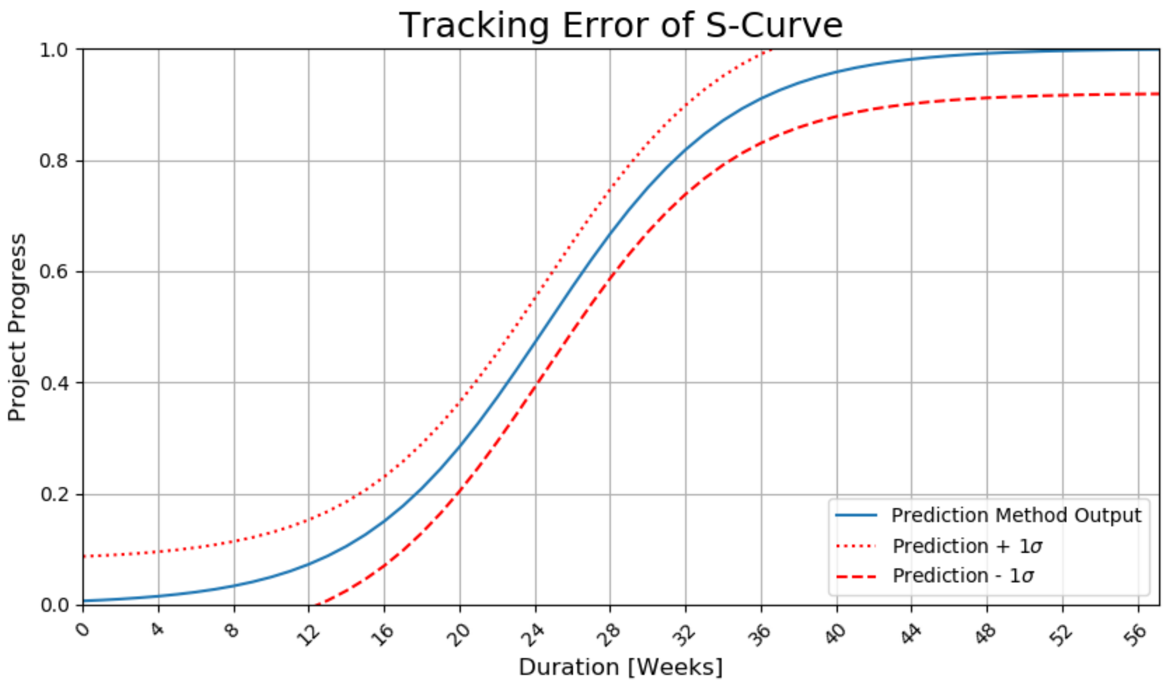


Figure 5.8: Found tracking error of 4% added (or subtracted) to an example S-curve from the SSFP method of case study project.

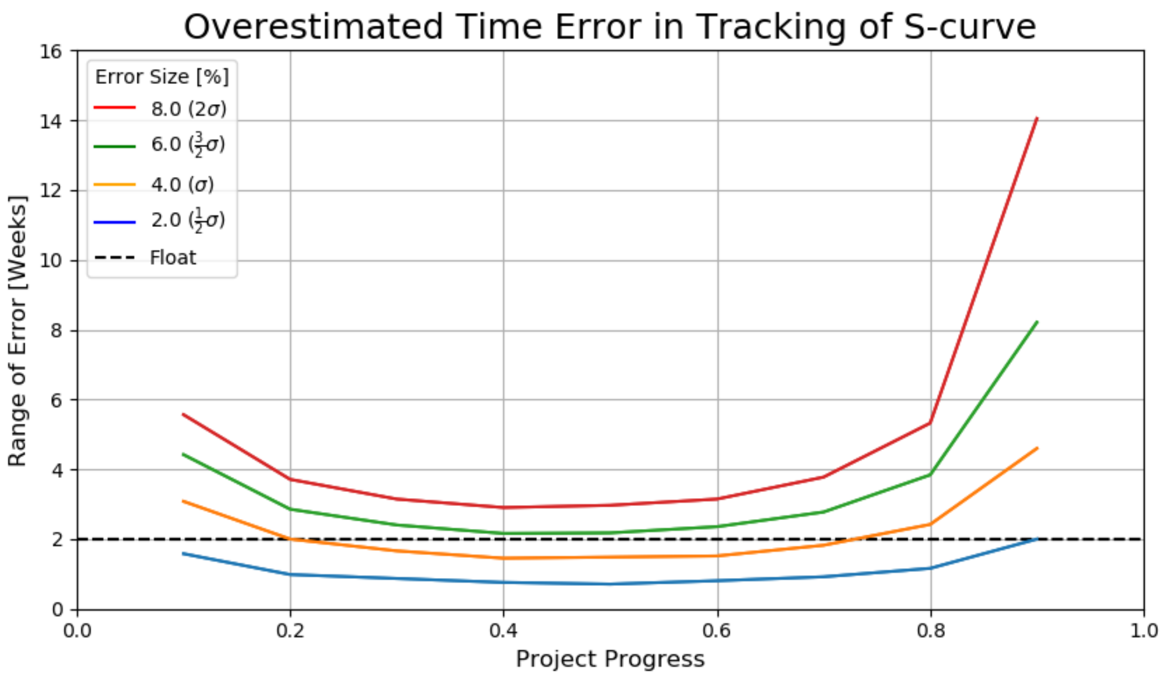


Figure 5.9: Average duration in time that overestimated progress tracking errors have on projects over the project progression.

From the model verification highlights that the prediction method tends to over-estimate the progress. The over-estimation might be attributed to the lack of data at the beginning of the project. This first portion of the project is found to have great impact onto the overall prediction accuracy, as can be seen in Figure 5.10. In fact, the error on the prediction, as expected, is shown to decrease with increasing released documents.

The prediction accuracy is optimistic in its prediction, expecting faster progress than what is achieved. The method is likely over estimating the rate of the projects progression. This 'optimism' can also be attributed to the fact that at the start of a project, when the final mass of the mass curve is hard to predict, every increase in the curve predicts a curve with a much steeper slope than reality, which results in optimistic predictions. This is, as can also be seen in Figure 5.11, a large contributor to the error, which over time is reduced as more documents are known. The prediction shown also has a high related error to it, which is not considered in the found error values.

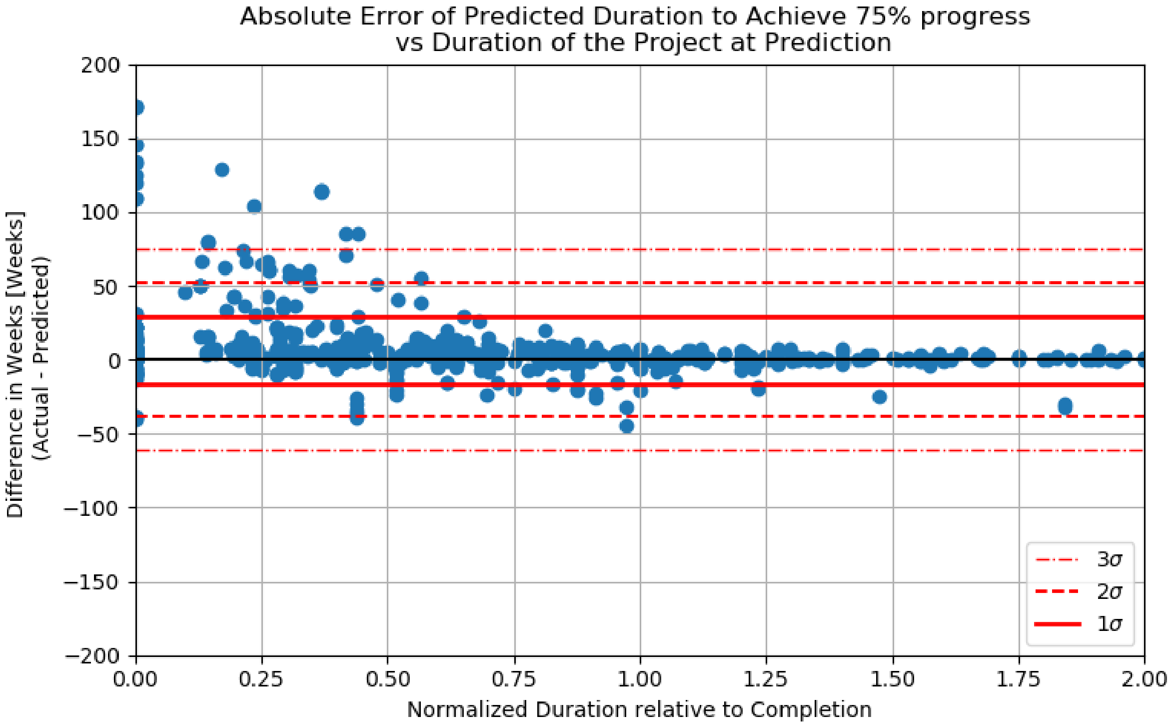


Figure 5.10: Error of the prediction accuracy versus the time relative to project completion of the mass curves from the case study.

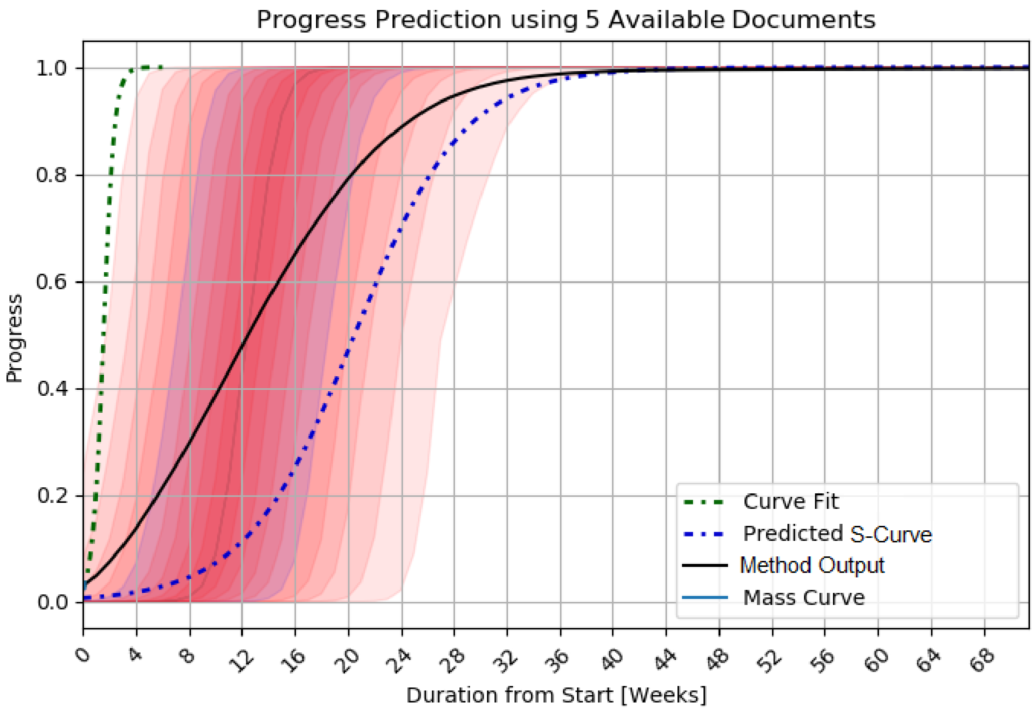


Figure 5.11: Output of the method in a case study test where only 5 documents are used to make a prediction.

5.3. Chapter Summary

The SSFP method was assessed in this chapter. Test 1 showed that the tracking and prediction accuracy of the method is only marginally affected by the total amount of released documents. By superimposing an error on to the predicted progress curve was found to increase both tracking and prediction error of the method. The increase was found to be within the standard deviation found for the test with ideal circumstances, however the spread in the error was found to be higher than in the latter case increased. Introducing Gaussian noise onto the simulated data was found to provide a negligible change in tracking accuracy, while dramatically increasing the prediction error. Furthermore, the magnitude of the noise also marginally influenced both tracking and prediction error, similarly to the total amount of released documents.

Besides the verification tests, a case study was conducted using the mass curves retrieved from the case study ETO company. Five projects were extracted from the available pool to and used as test data, whereas the rest of the data was used as training data. The tracking error resulting from these tests resulted to be $0.6 \pm 4\%$, whereas the prediction error was found to be $7 \pm 23 weeks$. Translating the tracking error to the time domain, it was found that there was a 68% chance that the method over estimates the progress no more than 2 weeks.

6 Conclusion and Discussion

A new progress tracking method was discussed and developed in the previous chapters. The main objective of the research was to develop a progress tracking method suitable for design activities in an ETO environment. It was shown in chapter 1 that effective planning of engineering projects requires good progress tracking. The tracking method was therefor also expected to be accurate and robust as to not limit its applicability.

Initially it was shown in chapter 2 that design activities greatly affect the course of an engineering project and in fact, drive its overall progress. A general overview of the state of the art of project planning in ETO environments was given in this chapter. The high degree of customization of ETO projects and the associated design iterations required were identified as challenges to the planning and monitoring of design activities. The present work was conducted in the context of a typical ETO company specialized in large scale equipment, facing similar challenges. It was found that the tracking of engineering progress is currently based mainly on the individual reports of progress percentages by engineering leads. The main biases associated with such an approach were discussed.

The current progress tracking method was developed based on data available from ongoing, as well as completed projects of the same type. The cumulative mass of released documents over time was found as a suitable objective source of data to track the progress of engineering (see also chapter 2). It was shown in chapter 3 that these mass curves are especially a good metric for the progress of the manufacturing design phase. With the assumption that the reported progress is unbiased, it was found that the mass curves underestimate the progress. This underestimation may also be due to overestimation of the reports by the engineers, which consequently can affect the accuracy on the progress of all other project activities following and/or linked with the design process. In this way with an additional objective metric, a second measurement can provide more insights on the progress of projects.

While, project planning in an ETO has been broadly treated and extensive literature exists on that, not much research was found about the use of robust techniques for accurate progress monitoring of engineering activities. From the available methods in the literature, no method individually met the requirements to be suitable for effective project tracking. In chapter 3 the methods were discussed and how an integration of multiple methods would be suitable. Stochastic S-Curve Feature prediction (SSFP) is the result of this integration, where the S-Curve features of the project are predicted using an SVR analysis on previous projects and a curve fit to the available data. This is then averaged using a a weight factor to find the final outcome using Monte Carlo Simulations. This method excels over other available methods as it provides progress tracking without the need for in depth knowledge of all the related activities. As engineering is flexible, iterative, and creative, tracking the progress without insights into the exact course of action is essential.

In chapter 4 the initialization of the method, with the parameters of the weight factor and SVR analysis described. Each element of SSFP can tuned for their application. The method was developed mainly for the objective tracking of mechanical engineering design tasks, as all functional designs from other disciplines, i.e. hydraulic engineering, electrical engineering, etc., typically revolve around those. For this application, the weight of the equipment was used as a way to differentiate the projects from each other in the SVR analysis. In this way, completed projects can be used as a basis for a prediction of project tracking, which can help in the initial stages of a project when little progress is made and limited data is available. This in combination with the weight factor increases the accuracy, and reduces extreme predictions, at the start of a project.

From the verification tests, discussed in chapter 5 it can be concluded that the method is capable of tracking the progress of a project. The output of the method provides an predicted S-curve of the estimated project progress with a related uncertainty. This uncertainty decreases as the curve fit of the data has a lower RMSE as well when more documents become available. Additionally from the verification tests it was shown that the method is not influenced by the amount of total documents available. When noise is added to the mass curves, the tracking accuracy is also not influenced irrespective of the amplitude of the noise. Both of these tests indicate that the method meets the robustness requirement as the method is not dependent on a minimum amount of documents or a noiseless source. This is essential as engineering activities can be creative and iterative which means it is hard to reduce noise in the released document mass (and revisions) or ensure a minimum amount of documents. This robustness is also shown as the method increases the error if the predicted S-curve from historical data has an error, but this increase is within the standard deviation of similar tests with no error in the prediction.

As no methods currently exist to estimate progress of engineering activities, the results of the progress estimation are validated through a case study from an ETO environment with no similar method as comparison (see chapter 5). In this case study the mass curves were used, where a tracking error of $0.6 \pm 4\%$ was found. The error translates to a maximum overestimation (resulting in delay in delivery) of around 2 weeks up until 80% completion, which falls within the upper bound of the sampled 'float' found in different project plannings. This points towards that this method can be used to track the progress of engineering activities. This in combination with the verification result that the amount of available documents marginally influences the accuracy indicates that this method may not be limited to progress tracking of only complete projects, but also individual construction blocks as well.

The mean tracking error under 1% can be considered an accurate estimation, as the reported progress of engineers do not consider a precision under 1%. The noise in the mass curves do cause a larger spread in the the tracking error, as this noise is due to the fact that there is human influence in the creation and release of the documents. This case study is limited to a single equipment type and the data from a single ETO company, but has shown that the method can provide robust and accurate estimations for this specific application. This limit to the case study can be further expanded on in future research to provide more insights on its effectiveness on other deliverables, disciplines, products, and companies.

The prediction accuracy of the method in the case study was also investigated in chapter 5. This was not an direct objective of this investigation, but as an S-curve is created for the whole project it was considered. With an error of 7 ± 23 weeks, this method lacks the accuracy for reliable predictions to be used within plannings spanning around a year. With a mean error of more than 13% of the duration of the project, this method is not suited for this application in this form. This prediction of how long it will take to reach a certain progress percentage has the added challenge that it requires to make assumptions about future progress rates. The relationships between total mass and S-curve features show that this is not a straight forward task and more investigation would be required to achieve this.

Table 6.1 shows an overview of the available progress tracking methods in the literature. It can be seen that the proposed method, SSFP, fills the gap in the literature by being able to track the progress of flexible projects without defining all the activities required to complete the project. This flexibility in combination with the fact that this method can consider metrics which can directly reflect the progress makes it a valuable contribution to the progress tracking literature.

Using mass curves as a progress metric for a case study, it was found that the method provides enough accuracy to give a strong indication of the progress. This method can be essential to move towards continuous progress tracking which would make frequent replanning, essential for effective planning, possible. This in combination with progress reports of the engineers could result in an planners having more insights in the progress of the design phase. In this way, with accurate and robust progress tracking, the proposed method effectively achieves what was sought after in the main research question on how to design a progress tracking method in an ETO environment.

Table 6.1: Overview of the capabilities of available methods

Method	**Track Progress**	**Forecast Progress**	**Objective Input Data**	**Direct Progress Measurement**	**Requires Predefined Project Activities**	**Flexible**
EVM	Yes[a]	No	No	No	No	Yes
StS-Curve Estimation	Yes	Yes	No	Yes	Yes	No
Geometrich Feature Prediction	No	Yes	No	Yes	No	No
SSFP	Yes	Yes	Yes	Yes	No	Yes

[a]By comparing it to subjective predetermined budgets

6.1. Discussion

With positive results of this investigation, some assumptions and opportunities arose which require further consideration or further investigation:

- **Objective metrics for progress measurement**: finding a representative and objective metric to measure the progress of engineering activities is essential for the provided method. If the metric does not represent the progress, the output will not either. Further investigation to potential metrics can be done, as well looking into how process changes or standardization can mean for better progress metrics
- **More discipline applications**: Currently this investigation looked at progress tracking of engineering, with the main focus on mechanical engineering. Further investigation in applying this method to other disciplines would be interesting to prove this method is applicable over the complete design phase of equipment in all discplines.
- **Smaller scale**: with the case study focusing on the last phase of design with most available documentation, validating this method with other design phases and/or deliverables (smaller scope) can lead to more applications for this method. Looking into available data for other phases will less documentation and more creative work could lead to a more accurate prediction of progress for the complete design phase.
- **Weight factor tuning**: In the proposed method a weight factor between the curve fit and the predicted S-curve was introduced. This weight factor was not optimized further for this application, therefor further research could be done into the weight factor considering other potential error metrics other than the RMSE and number of available documents.
- **Product/Equipment Variety**: This investigation focused on progress tracking of engineering activities within a single product type. Validating this method using other types of equipment, potentially using features independent of the type of product to forecast the progress, provides more insights into the applicability of this method.
- **S-Curve shaped data:** The proposed method and the validation and verification of these results make the assumption that the data can be described using an S-curve. To be able to make the method more robust, further investigation into other models to describe progress data of similar and different data sets can provide more insights into objective progress tracking. This can also provide more options to consider more objective metrics for progress measurements

With these considerations and opportunities the proposed method could be developed further to exceed its current capabilities and limitations.

Bibliography

[1] E. Acar and M. Rais-Rohani. Ensemble of metamodels with optimized weight factors. In *AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, volume 49, pages 279–294, Schaumburg, IL, 2008. American Institute ofAeronautics and Astronautics. doi: 10.1007/s00158-008-0230-y.

[2] Jorge S. Ballaben, Hector E. Goicoechea, and Marta B. Rosales. An alternative to Monte Carlo Simulation Method. *Mecánica Computacional*, XXXVI:631–640, 2018. doi: 10.2514/6.1967-210.

[3] Gabriel A. Barraza, W. Edward Back, and Fernando Mata. Probabilistic Monitoring of Project Performance Using SS-Curves. *Journal of Construction Engineering and Management*, 126(2): 142–148, 2000. doi: 10.1061/(ASCE)0733-9364(2000)126:2(142).

[4] Gabriel A. Barraza, W. Edward Back, and Fernando Mata. Probabilistic Forecasting of Project Performance Using Stochastic S Curves. *Journal of Construction Engineering and Management*, 130 (1):25–32, feb 2004. ISSN 0733-9364/2004/1- 25–32/. doi: 10.1061/(ASCE)0733-9364(2004)130:1(25).

[5] Christopher M. Bishop. *Neural Networks for Pattern Recognition*. Clarendon Press, Oxford, 1995. ISBN 9781536144307.

[6] Karl Blyth and Ammar Kaka. A novel multiple linear regression model for forecasting S-curves. *Engineering, Construction and Architectural Management*, 13(1):82–95, 2006. ISSN 09699988. doi: 10.1108/09699980610646511.

[7] Leo Breiman. Bagging predictors. *Machine Learning*, 24(2):123–140, 1996. ISSN 08856125. doi: 10.1007/bf00058655.

[8] Leo Breiman. Random forests. *Machine Learning*, 45(1):5–32, 2001. ISSN 08856125. doi: 10.1023/A:1010933404324.

[9] Roger Buehler, Dale Griffin, and Michael Ross. Exploring the "Planning Fallacy": Why People Underestimate Their Task Completion Times. *Journal of Personality and Social Psychology*, 67 (3):366–381, 1994. ISSN 00223514. doi: 10.1037/0022-3514.67.3.366.

[10] Roger Buehler, Deanna Messervey, and Dale Griffin. Collaborative planning and prediction: Does group discussion affect optimistic biases in time estimation? *Organizational Behavior and Human Decision Processes*, 97(1):47–63, 2005. ISSN 07495978. doi: 10.1016/j.obhdp.2005.02.004.

[11] Roger Buehler, Dale Griffin, and Johanna Peetz. *The Planning Fallacy. Cognitive, Motivational, and Social Origins*, volume 43. Elsevier Inc., 1 edition, 2010. doi: 10.1016/S0065-2601(10)43001-4.

[12] Chambers & Associates Pty Ltd. Earned Value Management. URL https://www.chambers.com.au/glossary/earned{_}value{_}management.php.

[13] Daniel W.M. Chan and Mohan M. Kumaraswamy. Forecasting construction durations for public housing projects: A Hong Kong perspective. *Building and Environment*, 34(5):633–646, 1999. ISSN 03601323. doi: 10.1016/S0360-1323(98)00040-7.

[14] Li Chung Chao and Hsien Tse Chen. Predicting project progress via estimation of S-curve's key geometric feature values. *Automation in Construction*, 57:33–41, 2015. ISSN 09265805. doi: 10.1016/j.autcon.2015.04.015.

[15] J. R.San Cristóbal. The S-curve envelope as a tool for monitoring and control of projects. In *Procedia Computer Science*, volume 121, pages 756–761. Elsevier B.V., nov 2017. doi: 10.1016/j.procs.2017.11.097.

[16] F.M. Dekking, C. Kraaikamp, H.P. Lopuhaa, and L.E. Meester. *A Modern Introduction to Probability and Statistics*. Springer Science & Business Media, London, 2005. ISBN 9781852338961. doi: 10.1198/tech.2007.s502.

[17] Harris Drucker, Chris J.C. Surges, Linda Kaufman, Alex Smola, and Vladimir Vapnik. Support vector regression machines. *Advances in Neural Information Processing Systems*, 1:155–161, 1997. ISSN 10495258.

[18] Jan Alarik Elfving. *Exploration of opportunities to reduce lead times for engineered -to -order products*. Doctoral, Helsinki University of Technology, 2003.

[19] Jan Emblemsvåg. Lean Project Planning: Using Lean Principles in Project Planning. *International Journal of Construction Project Management*, 6(2):185–207, 2014.

[20] Tushar Goel, Raphael T. Haftka, Wei Shyy, and Nestor V. Queipo. Ensemble of surrogates. *Structural and Multidisciplinary Optimization*, 33(3):199–216, 2007. ISSN 1615147X. doi: 10.1007/s00158-006-0051-9.

[21] David Gyulai, András Pfeiffer, Gabor Nick, Viola Gallina, Wilfried Sihn, and Laszlo Monostori. Lead time prediction in a flow-shop environment with analytical and machine learning approaches. *International Federation of Automatic Control*, pages 1048–1053, 2018. doi: 10.1016/j.ifacol.2018.08.472.

[22] Minhoe Hur, Seung kyung Lee, Bongseok Kim, Sungzoon Cho, Dongha Lee, and Daehyung Lee. A study on the man-hour prediction system for shipbuilding. *Journal of Intelligent Manufacturing*, 26(6):1267–1279, 2015. ISSN 15728145. doi: 10.1007/s10845-013-0858-3.

[23] Gabriele Hofinger Jünge, Erlend Alfnes, Kristina Kjersem, and Bjorn Andersen. Lean project planning and control: empirical investigation of ETO projects. *International Journal of Managing Projects in Business*, 12(4):1120–1145, 2019. ISSN 17538386. doi: 10.1108/IJMPB-08-2018-0170.

[24] A. P. Kaka. The development of a benchmark model that uses historical data for monitoring the progress of current construction projects. *Engineering, Construction and Architectural Management*, 6(3):256–266, 1999. ISSN 09699988. doi: 10.1108/eb021116.

[25] V. Kecman. *Support Vector Machines – An Introduction*, volume 47. Springer-Verlag, Berlin Heidelberg, 2005. doi: 10.1007/10984697_1.

[26] Russell Kenley and Owen D. Wilson. A construction project cash flow model - an idiographic approach. *Construction Management and Economics*, 4(3):213–232, 1986. ISSN 1466433X. doi: 10.1080/01446198600000017.

[27] Kristina Kjersem. *Contributing to Resolving a Project Planning Paradox in ETO: From plan to planning*. Doctoral, Molde University College, 2020.

[28] Kristina Kjersem and Jan Emblemsvåg. Literature review on planning design and engineering activities in shipbuilding. In *22nd Annual Conference of the International Group for Lean Construction: Understanding and Improving Project Based Production, IGLC 2014*, pages 677–688, Oslo, jun 2014.

[29] Kristina Kjersem, Lise Lillebrygfjeld Halse, Peter Kiekebos, and Jan Emblemsvåg. Implementing Lean in Engineer-to-Order Industry: A Case Study. *IFIP Advances in Information and Communication Technology*, 460:248–255, 2015. ISSN 18684238. doi: 10.1007/978-3-319-22759-7.

[30] Kristina Kjersem, Gabriele Hofinger Jünge, and Jan Emblemsvåg. Project Execution Strategy and Planning Challenges. In Lodding Hermann, Ralph Riedel, Klaus Dieter Thoben, Gregor von Cieminski, and Dimitris Kiritsis, editors, *Project Execution Strategy and Planning Challenges*, pages 243–250. Springer International Publishing, 2017. ISBN 9783319669250. doi: 10.1007/978-3-319-66926-7_28.

[31] Eetu Lehtimaki. *Concurrent project planning and Scheduling in a Project Business Company*. Master, Tampere University of Technology, 2017.

[32] Ian Lerche and Brett S. Mudford. How many Monte Carlo simulations does one need to do? *Energy Exploration and Exploitation*, 23(6):405–427, 2005. ISSN 01445987. doi: 10.1260/014459805776986876.

[33] A Liaw and M Wiener. Classification and Regression by randomForest. *R News*, 2(3):18–22, 2002.

[34] Lukas Lingitz, Viola Gallina, Fazel Ansari, David Gyulai, Andras Pfeiffer, Wilfired Sihn, and Laszlo Monostori. Lead time prediction using machine learning algorithms: A case study by a semiconductor manufacturer. In *51st CIRP Conference on Manufacturing Systems*, pages 1051–1056. Elsevier B.V., 2018. doi: 10.1016/j.procir.2018.03.148.

[35] David Little, Ralph Rollins, Matthew Peck, and J. Keith Porter. Integrated planning and scheduling in the engineer-to-order sector. *International Journal of Computer Integrated Manufacturing*, 13 (6):545–554, 2000. ISSN 13623052. doi: 10.1080/09511920050195977.

[36] Chen Yuan Liu and Jhen Cheng Wang. Forecasting the development of the biped robot walking technique in Japan through S-curve model analysis. *Scientometrics*, 82(1):21–36, 2010. ISSN 01389130. doi: 10.1007/s11192-009-0055-5.

[37] Wei Yin Loh. Classification and regression trees. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 1(1):14–23, 2011. ISSN 19424795. doi: 10.1002/widm.8.

[38] Wie-Yin Loh. Classification and Regression Tree Methods. *Wiley StatsRef: Statistics Reference Online*, pages 1–11, 2014. doi: https://doi.org/10.1002/9781118445112.stat03886.

[39] Cuauhtemoc Lopez-Martin, Shadi Banitaan, Andres Garcia-Floriano, and Cornelio Yanez-Marquez. Support vector regression for predicting the enhancement duration of software projects. *Proceedings - 16th IEEE International Conference on Machine Learning and Applications, ICMLA 2017*, 2018-Janua:562–567, 2018. doi: 10.1109/ICMLA.2017.0-101.

[40] Mario Henrique Mello, Jonathan Gosling, Mohamed M. Naim, Jan Ola Strandhagen, and Per Olaf Brett. Improving coordination in an engineer-to-order supply chain using a soft systems approach. *Production Planning and Control*, 28(2):89–107, 2017. ISSN 13665871. doi: 10.1080/09537287.2016.1233471.

[41] Arash Mohsenijam, Ming Fung Francis Siu, and Ming Lu. Modified Stepwise Regression Approach to Streamlining Predictive Analytics for Construction Engineering Applications. *Journal of Computing in Civil Engineering*, 31(3):1–16, 2017. ISSN 08873801. doi: 10.1061/(ASCE)CP.1943-5487.0000636.

[42] Peter W G Morris and Jeffrey K Pinto. How Projects Differ, and What to do About it. In *The Wiley Guide to Managing Projects*, chapter 50, pages 1266–1286. John Wiley & Sons, Inc., Hoboken, NJ USA, 1 edition, 2004. ISBN 0471233021.

[43] Derrick H. Nguyen and Bernard Widrow. Neural Networks for Self-Learning Control Systems. *IEEE Control Systems Magazine*, 10(3):18–23, 1990. doi: 10.1109/37.55119.

[44] Josef Oehmen. *The Guide to Lean Enablers for Managing Engineering Programs*. Joint MIT-PMI-INCOSE Community of Practice on Lean in Program Management Edited, Cambridge, MA, 2012. ISBN 9788578110796. doi: 10.1017/CBO9781107415324.004.

[45] Aarti Pandit and Yimin Zhu. An ontology-based approach to support decision-making for the design of ETO (Engineer-To-Order) products. *Automation in Construction*, 16(6):759–770, 2007. ISSN 09265805. doi: 10.1016/j.autcon.2007.02.003.

[46] Silvana Petruseva, Valentina Zileska-pancovska, Ž Vahida, and Aida Brkan Vejzović. Construction costs forecasting: comparison of the accuracy of linear regression and support vector machine models. *Tehnicki vjesnik - Technical Gazette*, 24(5), 2017. ISSN 13303651. doi: 10.17559/tv-20150116001543.

[47] András Pfeiffer, Dávid Gyulai, Botond Kádár, and László Monostori. Manufacturing Lead Time Estimation with the Combination of Simulation and Statistical Learning Methods. *Procedia CIRP*, 41:75–80, 2016. ISSN 22128271. doi: 10.1016/j.procir.2015.12.018.

[48] Project Management Institute. *A guide to the Project Management Body of Knowledge (PMBOK guide)*. Project Management Institute, Newton Square, PA, 6 edition, 2017. ISBN 9781628251845.

[49] J. Ross Quinlan. *C4.5 Programs for Machine Learning*. Morgan Kaufmann Publishers, San Mateo, California, 1993. ISBN 1-55860-238-0.

[50] W. H.M. Raaymakers and A. J.M.M. Weijters. Makespan estimation in batch process industries: A comparison between regression analysis and neural networks. *European Journal of Operational Research*, 145(1):14–30, 2003. ISSN 03772217. doi: 10.1016/S0377-2217(02)00173-X.

[51] Shai Shalev-Shwartz and Shai Ben-David. *Understanding machine learning: From theory to algorithms*, volume 9781107057. Cambridge University Press, New York, 1 edition, 2014. ISBN 978-1-107-05713-5. doi: 10.1017/CBO9781107298019.

[52] TheP6Pro. Assigning Notepad Labels to Primavera P6 Gantt Chart Bars, apr 2015. URL https://tensix.com/2015/04/assigning-notepad-labels-to-primavera-p6-gantt-chart-bars/.

[53] Hajnalka Vaagen, Michal Kaut, and Stein W. Wallace. The impact of design uncertainty in engineer-to-order project planning. *European Journal of Operational Research*, 261(3):1098–1109, 2017. ISSN 03772217. doi: 10.1016/j.ejor.2017.03.005.

[54] L.A. van der Plas. *Predicting Manufacturing Times Using Building Information Models*. Master thesis, Delft Univeristy of Technology, 2019.

[55] Don van Ravenzwaaij, Pete Cassey, and Scott D. Brown. A simple introduction to Markov Chain Monte–Carlo sampling. *Psychonomic Bulletin and Review*, 25(1):143–154, 2018. ISSN 15315320. doi: 10.3758/s13423-016-1015-8.

[56] Križaić Vladimir and Hranj Dražen. Project Planning by Modified Gauss S-Curve. In *Creative Construction e-Conference 2020*, pages 65–70, Online, 2020. Budapest University of Technology. doi: 10.3311/ccc2020-047.

[57] Mathieu Wauters and Mario Vanhoucke. Support Vector Machine Regression for project control forecasting. *Automation in Construction*, 47:92–106, 2014. ISSN 09265805. doi: 10.1016/j.autcon.2014.07.014.

[58] Mathieu Wauters and Mario Vanhoucke. A comparative study of Artificial Intelligence methods for project duration forecasting. *Expert Systems with Applications*, 46:249–261, 2016. ISSN 09574174. doi: 10.1016/j.eswa.2015.10.008.

[59] Xanadu. Quantum Neural Network, 2019. URL https://strawberryfields.readthedocs.io/en/stable/algorithms/quantum{_}neural{_}network.html.

[60] Qingmeng Yan. Study on prediction model of construction period of power transmission and transformation project based on support vector machine. *IOP Conference Series: Earth and Environmental Science*, 446(4), 2020. ISSN 17551315. doi: 10.1088/1755-1315/446/4/042049.

A

Academic Paper

Intermediate Project Progress: Tracking and Prediction

T.M.M.P. van Engelshoven, dr. V. Gentile, ing. L.J.P. Verhoef, dr. ir. X. Jiang, prof. dr. R.R. Negenborn

***Abstract*—With the increasing focus on project planning in engineer-to-order(ETO) companies, tracking the progress of the design phase of a project is essential for effective planning. Such progress tracking currently is done through the regular feedback of discipline leads, which are intrinsically subjective. The information thus collected is then plotted in the form of so-called S-curves, to represent the progress over the course of the project. The present method tracks progress of the manufacturing engineering phase based on how much mass is designed with respect to the design weight of the equipment. This so-called mass curves are used and fitted to an S-curve and represent the tracked progress. It is shown that the fitted mass curves represent the progress of the engineering phase with a systematic average error of 25 days. Additionally, mass data retrieved from completed projects are used to predict the S-curves shape of the ongoing project. The weighted average of tracked and Predicted S-curves is then used in a Monte Carlo simulation in order to estimate the progress of the ongoing project. The method was found to have a tracking accuracy of $0.6 \pm 4\%$, which translates into an uncertainty on the project duration and therefore on the equipment delivery date, by 2 weeks. This uncertainty is found to be the upper bound of typical grace periods agreed with most clients. The present results might offer a new outlook on progress tracking on the progress tracking of manufacturing engineering activities. Further research shall be conducted to address the progress of earlier engineering phases equally.**

***Index Terms*—Planning, Control, Progress, Tracking, Prediction, ETO Projects, Engineering.**

I. Introduction

TRACKING the progress of the design phase is key to a successful and timely execution of the so-called Engineering to order (ETO) projects. The increasing competition in the sector of customized large-scale equipment demands reduction of project lead times. As a result, the design phase becomes heavily intertwined with the other disciplines. Furthermore the design changes often requested by clients result into the engineering phase to span over at least half of the entire project duration [1]–[3]. Within this context, efficient and accurate project planning gains utmost importance [4], [5].

A good progress measurement tool was already identified as one of the main requirements of a so-called lean project planning [6]. While different methods exist to monitor the progress of tasks such as procurement and production; engineering activities are inherently more difficult to monitor in Engineer To Order (ETO)'s environments due to their complexity and often creative and iterative nature [4], [5], [7], [8].

This investigation is done in cooperation with an ETO based company producing large scale equipment. It is assumed that a typical company adopting an ETO project based approach is similar to the collaborating company. So-called deliverables are the basis on which the projects within ETO companies are planned. These are physical blocks of the system which are to be eventually built. For each of such blocks, design activities are planned along with the procurement of the necessary materials and components, as well as with the production and testing activities. The current sub-division into so-called ”construction blocks” can be mainly referred to the mechanical engineering activities and later on to the fabrication and assembly of the different parts. Within this sub-division however, emphasis is given to the physical parts of the system and therefore, to their mechanical design. Less space is given on the other hand, to the design tasks of the other engineering disciplines, i.e. electrical, hydraulical and controls systems, which focus on the functionalities of the system.

Currently to ensure timely delivery, a typical ETO company relies on planning on multiple levels. In particular, discipline planning is extensively used in order to schedule engineering as well as production activities. The project schedule is structured such to reflect the sub-division of blocks and sections defined in the system design. For effective planning and replanning, regular planning meetings with the project team are needed to discuss the current and expected progress. This progress is reported to the planners directly from the discipline leads verbally or in an overview document. As a result, the information provided by the schedules is highly dependent on the quality of the received input. This can be especially true for progress, which when reported is susceptible to the planning fallacy. Based on the input, planners make progress reports using the so-called S-curves.

The main goal of the present investigation is to overcome this challenge, namely to develop a non-subjective method for progress tracking and prediction to support project planning in ETO environments. Focus is given to the design activities, as they are unanimously considered to drive progress and execution of ETO projects [1]–[4].

II. Available Data

A set of requirements was identified for the current progress tracking tool, namely:

- Accuracy,
- Error propagation within the method,
- Ease of implementation,
- Robust prediction,
- Limited amount of data required .

In order to develop the current method, data from ongoing and completed projects were used. The data set was restricted to the case of mechanical engineering due to the great amount of available documentation. Within the present approach, mass was used as a metrics for progress. In particular, the mass information linked with each released design (i.e. drawing) is herein compared to the total amount of mass to be designed, that corresponds to the design weight of the equipment. In this way, so-called mass curves can be obtained, which display the amount of mass designed over time (see Fig. 1).

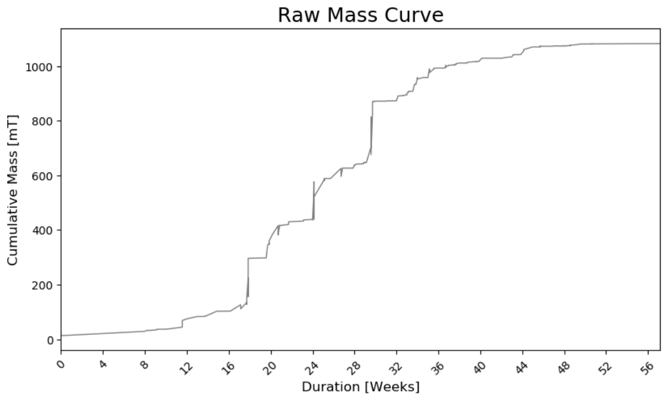


Fig. 1: Mass curve of a completed project

To ensure uniform progress pattern among different projects, the data set was restricted to the case a specific type of equipment. Furthermore, copy projects and projects with missing data were excluded. More specifically, an average document count was identified over the different projects for the mechanical engineering activities and projects with at least 25% of this average document count were considered in the study.

To represent the reported progress and mass curves, the loglet lab model [9] was used (equation 1):

$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}}, \tag{1}$$

where 'L','k', 'x_0', and 'x' represent the maximum value, growth rate, inflection point, and independent variable (duration in this investigation) respectively. This model was chosen as it models an S-curve shape, has variables that directly represent a characteristic of the curve, and represents reported progress and mass curves with an Root-Mean-Square Error (RMSE) of 0.0450%. This RMSE is similar to the more complex Pearl, and Gompertz model.

The validity of the progress as retrieved from the mass curves was assessed in comparison with the progress curves, S-curves of completed projects, which were based on the progress input provided by the engineering discipline leads. At 50% and 90% progress the duration was compared by subtracting the mass curve value from the reported progress curves. The results of this comparison can be seen in Fig. 2 and Fig. 3. It can be seen that the mass curves best represent the progress of the manufacturing design phase, with the least spread in the results and an average error of 25 days. This result reflects the complexity in tracking the progress of the earlier engineering phases, i.e. basic and detailed design, due to the complexity of the design process in comparison with the release of shop drawings based on the assessed designs.

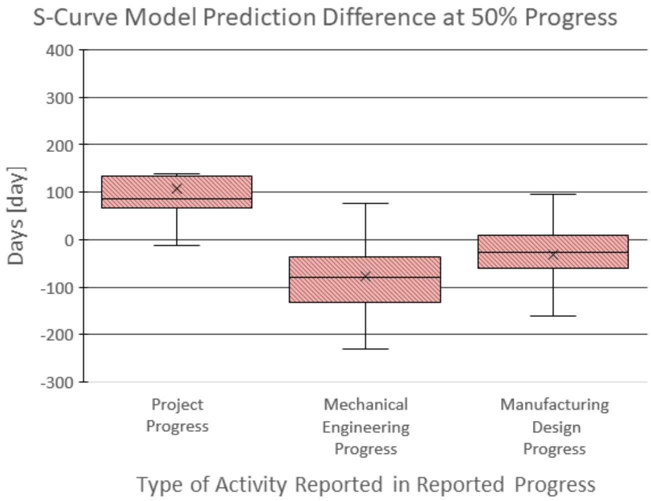


Fig. 2: Comparison between progress from S-curves and mass curves: duration at 50% progress.

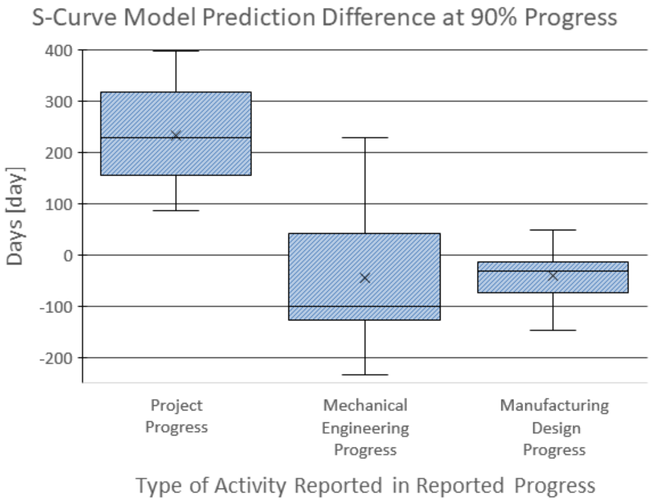


Fig. 3: Comparison between progress from S-curves and mass curves: duration at 90% progress.

III. Literature Review

Prior to proceeding with the development of the current progress tracking tool an overview of the existing progress tracking approaches is given.

A. Progress Tracking Methods

Predicting and tracking progress within a ETO environment, where concurrent project planning is typically implemented presents several challenges. Those were broadly discussed by Kjersem and Emblemsvåg [4]. Nonetheless, limited amount of studies is found with respect to systematic ways of planning and controlling the progress of engineering activities in ETO environments [4].

A most common progress tracking method is known as Earned Value Management (EVM), where the earned value

(EV) is calculated as the product of the progress percentage and the hours spent on the project. Within this method the earned value is tracked over time and compared to the expenses over the course of the project. Comparing the EV to the budgeted expenses makes this method flexible, as its implementable in any kind of project that has a budget. The strength of this method is in its flexibility and the results are easy to interpret. However, EVM is based on the cost and earned value of the project which do not directly represent the actual progress.

Based on the EVM, the Stochastic S-curve method, or StS-curve method, predicts progress by creating an envelope of S-curves mapping the variability of costs and durations of all the activities involved in the project. The envelope around the existing project S-curve is obtained through Monte Carlo simulations and based on the variability of activities in the S-curve [10], [11]. A major challenge in adopting the StS-curve method lies in defining the range of project costs and durations, which can be extremely hard to predict for creative processes such as involved in design.

Lastly, the Geometric Feature Prediction method uses key features of the project to predict the geometric features of its S-curve [12]. A Neural Network (NN) model is used in this method to predict slope and inflection point of the project S-curve and the S-curves matching these values is generated. This provides an estimate, which can be used for early planning and forecasting [12]. This method requires data from completed projects, including the corresponding S-curves. This method is therefor not intended for progress tracking, but rather for progress forecasting in the early stages of the project.

While the aforementioned methods might not be individually suitable for progress tracking of design tasks StS-curve and Geometric Feature Prediction are herein combined in a Stochastic S-Curve Feature Prediction (SSFP) method. More specifically, the SSFP method uses the stochastic nature of the StS-curve method along with the S-curve features predicted from the Geometric Feature Prediction method to estimate the progress of a project and involves a mathematical modeling method for feature prediction and an error propagation method.

B. Mathematical Modeling Methods

Three categories of mathematical methods are herein considered, namely:

1) Regression Algorithms,
2) Regression Tree Algorithms,
3) Neural Networks.

Regression algorithms, also called machine-learning algorithms, are used to automatically detect meaningful patterns in data [13]. Linear Regression (LR) andMultiple Linear Regression (MLR) are widely applied among others. The LR algorithm seeks for linear functions to describe the data with the minimum sum of mean square error [14]. The MLR algorithm also accounts for the relationship between multiple variables [15]. Both methods have limited accuracy due to the linearization of the relationship [14], [16], [17], but they exceed the capabilities of some analytical methods [16].

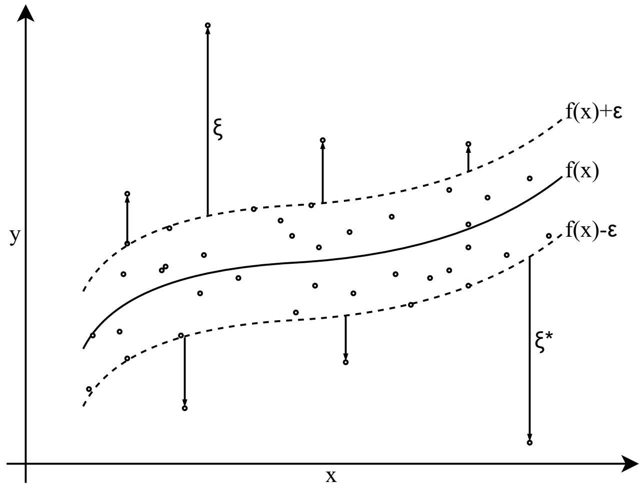


Fig. 4: Graphical representation of the SVR method on a data set

Support Vector Regression (SVR) is another regression algorithm which finds a relationship within data by enveloping the trend with upper and lower limits [18] (see Fig. 4). This method can simplify regression problems [19], and proved to provide accurate forecasts even with small training data sets [20], [21].

Regression Tree Model (RTM) algorithms provide prediction by dividing the input data into smaller groups and applying the LR method to these sub-divisions [22]. Resulting in a so-called a Linear Regression Tree Model (LRTM). This method splits the non-linear model into piece-wise linear estimation [22], [23] and is commonly used for complex regression problems to provide visual information about trends [22].

Another example of a RTM method is the Random Forest (RF) method. This method is based on the basic decision tree and the "Bagging" ('**B**ootstrap **Agg**regat**ing**') method [24]–[26]. In this approach multiple trees are generated from the same training data through re-sampling using the Boot Strapping method. Afterwards these trees are combined and averaged in order to give a prediction [24], [25]. This method is considered very accurate but it requires a large training data set spanning over the desired range, as it cannot extrapolate outside of the training data set [16].

NN algorithms are considered. A NN is a mesh or network consisting of an input layer, hidden layers and an output layer. Within this network the input layers feed data to the hidden layers, linking different weights to the connections between the nodes. Within this weighted network, the input is multiplied throughout the network and results into a prediction onto the output layer. The accuracy of this method depends on the implementation, as Raaymakers and Weijters [27] and Lingitz et al. [14] found contrasting accuracy results.

Looking at accuracy (variance, bias), size of training data , and ease of use, SVR appears to be the most suitable method. In fact, Table I shows that SVR scores best in all criteria scoring high with respects to the variance and bias when in comes to reduce over- and under-fitting.

TABLE I: Overview of the mathematical modeling methods according to the design requirements

Method	Variance	Bias	Training Data Size	Ease of Use
LR	Low	High	Small	High
MLR	Low	High	Small	High
SVR	Low[a]	Low[a]	Small	High
LRTM	Med	Med	Medium	High
RF	Med	Low	Large	Low
NN	Med	Low	Large	Low

[a]CCan be tuned by changing the parameter C, thus maximizing the margin and minimizing the error.The Bias variance trade off remains constant.

C. Error Propagation

Insights on the uncertainty in progress prediction can be gained by propagating the error of the model. This can be achieved through multiple methods. Analytically the error can be propagated, by knowing the probability density function (PDF) of the data the uncertainty can be calculated using eq. 1. Alternatively, Monte Carlo simulations can be also conducted. In particular, random values can be assigned to the PDF of each data set and Monte Carlo simulations can be then run multiple times. Finally, Markov Chain Monte Carlo (MCMC) simulations can be also considered. Within this approach each new random sample is generated on the last one that was previously generated, but not on the previous ones, similarly to a chain [28].

From the available error propagation methods Monte Carlo Simulations is the most suitable. Analytical error propagation method is the least suited method, as it is hard to use and sensitive to the accuracy of the model. The Monte Carlo simulation will be used as it is more robust and it is much easier to use and implement. MCMC simulation will not be implemented due to its low ease of use and necessity for a larger sample for it to function as desired.

IV. Implementation

As outlined in Fig. 5, SSFP can be layed out through the following steps:

1) Extract S-Curve features from completed projects,
2) Perform an SVR analysis on the extracted features,
3) Forecast the S-Curve for the current project from the SVR analysis,
4) Curve fit the available data of running project using least square error method,
5) Find weighted average of forecast and curve fit,
6) Run Monte Carlo Simulation determine the error in progress estimate.

A. Feature Analysis

Using the data from completed projects in a SVR analysis, the S-Curve features for the current project can be forecast. The overall final weight of the equipment was determined to be the independent variable in the SVR analysis, as this is estimated at the start of every project and scales with the

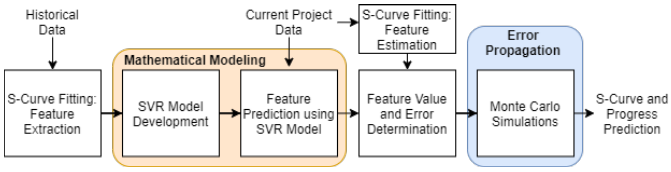


Fig. 5: Block diagram of the proposed SSFP method.

required loads or additional features. The relationship between features and the independent variable was assumed to be linear to reflect the increasing complexity of the design process as the weight increases, as well as the amount of released documentation.

For the SVR analysis, key parameters need to be determined. Namely the 'C' value and the ϵ value as seen in figure 4. These values represent the penalty value of points not in the 'tube' and the size of the tube respectively. A so called 'search grid' was created to determine the values of the key parameters; with the 'C' value logarithmic ally ranging from 1×10^{-10} to 1×10^{10} in 21 steps and the 'ϵ' value ranging from 0.02% to 50% of the maximum value in the data set in 25 steps. The chosen regression model and 'search grid' for the key parameters are the basis of the SVR analysis which models the individual S-curve features (see Fig. 6).

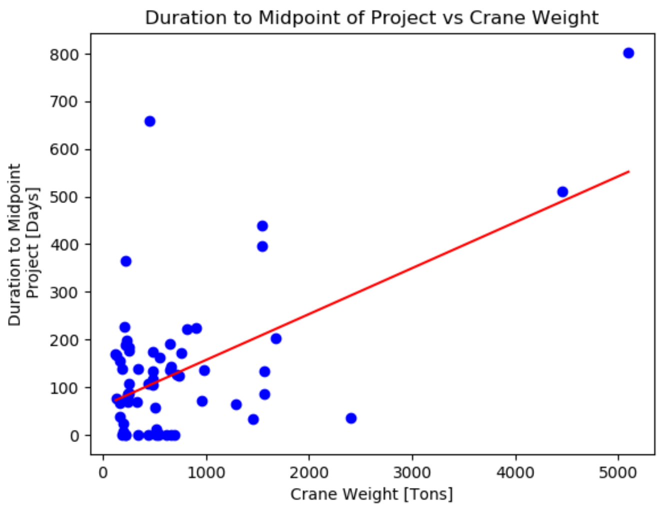


Fig. 6: Example output of the SVR analysis of the S-curve feature of the midpoint of the curve.

B. S-Curve Prediction

From the SVR analysis, a forecast can be made about the S-curve of the current project. Curve fitting the available data using the least squares method provides another estimate of the S-curve. This curve fit S-curve is bounded to positive values for all the S-curve features, as to prevent a physically impossible estimations. Additionally, a 'phantom' point is placed one year prior to the first data point, giving an origin to the fitting. Adding this point ultimately prevents the algorithm from fitting unrealistic progress S-curves.

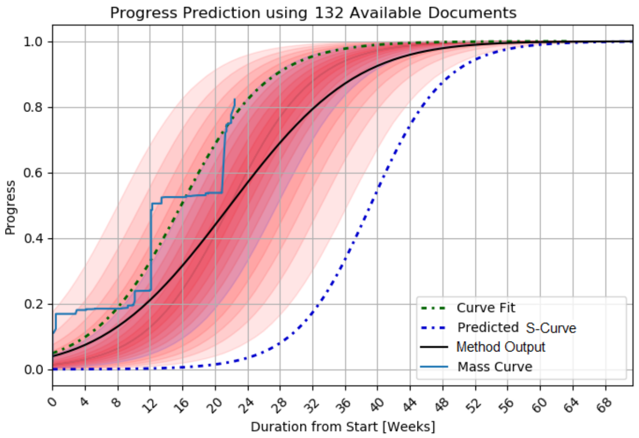


Fig. 7: Predicted S-Curve with the mode line shown in black with a error distribution of the Monte Carlo simulations in red

On the basis of the above S-curves a Monte Carlo simulation was conducted in order to predict the progress of the ongoing project. The forecast and curve fit S-Curves were treated as an ensemble. In particular, the Bishop [29] approach was used, using a weighted average. This was based on the RMSE [30], [31] and number of available documents. The weight factor of the curve fit was calculated first using (equation 2):

$$w_{CurveFit} = 1 - RMSE - (0.5 \times max(\frac{-1}{d_{thresh}} \times d_c + 1, 0), \quad (2)$$

where w is the weight factor, d_{thresh} is the threshold amount of documents, and d_c is the amount of available documents. The weight factor for the forecast S-curve was then derived as:

$$w_{SVR\_Prediction} = 1 - w_{CurveFit}, \quad (3)$$

The dependency on the number of available documents was included in order to reflect that the accuracy of the progress estimate improves by increasing the available documents. Such an influence was defined as a linear function and was defined with the average amount of documents released per project within the project start and the S-curve midpoint. In the present case this number was found to be around 55 documents.

C. Monte Carlo Simulations

The probability density functions of the S-curves features, as obtained from the two models, were extracted to ensure the success of the Monte Carlo simulation. A Gaussian distribution was assumed for the present case based on the work of Barraza et al. [11] and Vladimir and Dražen [32]. Prior to determine the probability distribution, the extracted S-Curve features of the two models was calculated using the weight factor. From these simulations, the SSFP output (mode of Monte Carlo Simulations) and distribution of the results can be visualized to provide a progress estimate (see Fig. 7).

V. Results

The verification and validation of the method will be measured using two performance indicators:

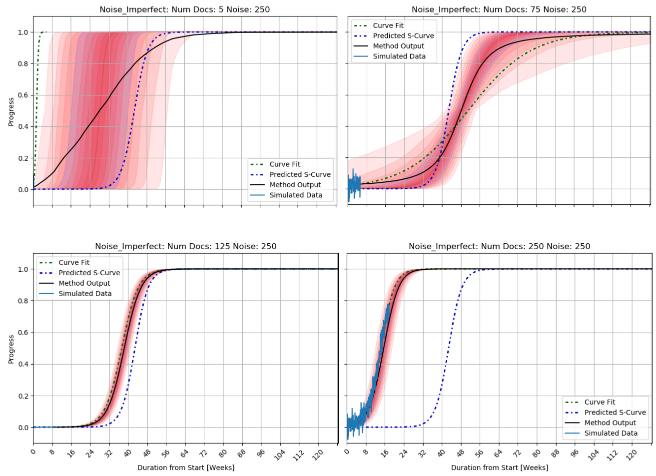


Fig. 8: Plots of increasing amounts of simulated data points provided as the project progresses from the verification test: 'Gaussian noise in data with an error in the prediction'. (Plot elements similar to Fig. 7)

- **Tracking Error:** The error on the estimated current progress compared to the actual progress. Both magnitude and sign of the error will be considered.
- **Prediction Error:** This is similar to the tracking error will instead measure the error on the forecast time needed to reach a certain predicted progress.

A. Verification

To verify the output of SSFP, multiple tests were conducted to examine what influences the tracking and prediction error. These tests were conducted using simulates data sets of predetermined S-curves. The data sets were altered by varying: the error between the forecast and actual S-curve, the amount of available data points, and the magnitude of Gaussian noise added to the data. A representative output of a single test with Gaussian noise added to the data can be seen in Fig. 8. Table II gives an overview of the mean and standard deviation of the tracking and prediction error relative to the actual progress. It can be seen that the tracking accuracy is marginally influenced by all the alterations in the tests. The prediction error however, was significantly increased by noise in the data set, irrespective of the magnitude of the Gaussian noise. Additionally, superimposing an error in the forecast S-curve also negatively influenced the prediction accuracy, but to a lesser extent.

B. Validation

Besides the verification tests, a case study was conducted using the mass curves retrieved from the case study ETO company. Five projects were extracted from the available pool to and used as test data, whereas the rest of the data was used as training data. The tracking error resulting from these tests resulted to be $0.6 \pm 4\%$ (see Fig. 9), whereas the prediction error was found to be $7 \pm 23 weeks$. The prediction error was found to gradually decrease as more data was available, but a larger error was maintained. It can also be seen that the

TABLE II: Tracking and Prediction Accuracy Mean and standard deviation of the verification tests.

Test	**Tracking Accuracy**		**Prediction Accuracy**	
(Simulated Data - Forecast S-Curve)	**Mean Error [%]**	**Error STD [%]**	**Mean Error [Weeks]**	**Error STD [Weeks]**
No Noise - No Error	-0.01	0.06	-0.5	6
No Noise - With Error	-0.02	0.2	2	15
Gaussian Noise - No Error	-0.5	0.8	-19	41
Gaussian Noise - With Error	-0.4	1	-16	45

tracking error has a consistent spread throughout the project duration, with no visual systematic preference for over- or under-estimating the progress. Translating the tracking error to the time domain, it was found that SSFP overestimates the progress no more than 2 weeks until 80% progress(see Fig. 10). It is common practice for projects to have a planned 'float' time to compensate for delays. From three representative projects the 'float' was found to vary between 1 and 2 weeks, the largest overestimation error of SSFP falls within this range.

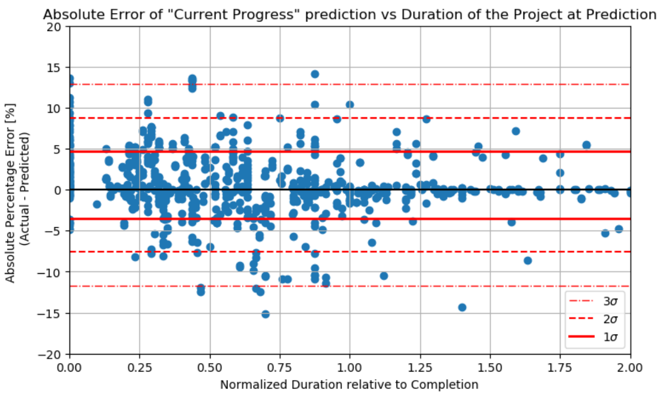


Fig. 9: Error of the tracking accuracy versus the normalized time relative to project completion of the mass curves extracted from an ETO based company.

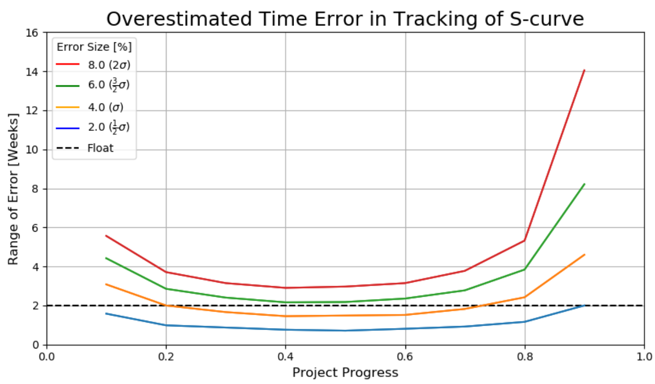


Fig. 10: Average duration in time that overestimated progress tracking errors have on projects over the project progression.

VI. Conclusion

A progress tracking method has been proposed in this paper for intermediate, objective progress estimations during the design phase of a project. With the SSFP method using mass curves based off of the mass of released documents, a progress tracking accuracy has been achieved of $0.6 \pm 4\%$ and a prediction accuracy of $7 \pm 23 weeks$. The large error and spread in the prediction accuracy does not make SSFP suitable for forecasting project durations. However, the tracking accuracy was found not be affected by the amount of available documents, demonstrating the possibility for SSFP to track the progress of a single deliverable or a complete project. Additionally, no prerequisite information about required activities to complete a project contributes to the robustness and ease of implementation of proposed method.

The proposed method requires a higher accuracy and further investigation to be used as a reliable progress tracking method, but does provide insights on the progress and how to further approach the problem. Exploring alternative progress tracking metrics can lead to more representative progress data for other engineering phases and disciplines, as this paper was limited to mechanical engineering in the manufacturing design phase. Additionally, a wider assortment of metrics for the independent variable of the SVR analysis (eg. novelty scale, number of unique features in equipment, workforce size, etc.) to distinguish the projects can bring more insights and accuracy to the forecast S-curve features. Lastly, this investigation assumed that the case study company represents a typical company adopting an ETO approach. Verifying this assumption by analyzing a broader amount of companies in similar and other industries can further strengthen the feasibility of this method as an effective progress tracking tool for ETO environments.

References

[1] D. Little, R. Rollins, M. Peck, and J. K. Porter, "Integrated planning and scheduling in the engineer-to-order sector," *International Journal of Computer Integrated Manufacturing*, vol. 13, no. 6, pp. 545–554, 2000.

[2] A. Pandit and Y. Zhu, "An ontology-based approach to support decision-making for the design of ETO (Engineer-To-Order) products," *Automation in Construction*, vol. 16, no. 6, pp. 759–770, 2007.

[3] J. A. Elfving, *Exploration of opportunities to reduce lead times for engineered -to -order products*. Doctoral, Helsinki University of Technology, 2003.

[4] K. Kjersem and J. Emblemsvåg, "Literature review on planning design and engineering activities in shipbuilding," in *22nd Annual Conference of the International Group for Lean Construction: Understanding and Improving Project Based Production, IGLC 2014*, (Oslo), pp. 677–688, jun 2014.

[5] K. Kjersem, *Contributing to Resolving a Project Planning Paradox in ETO: From plan to planning*. Doctoral, Molde University College, 2020.

[6] K. Kjersem, G. H. Jünge, and J. Emblemsvåg, "Project Execution Strategy and Planning Challenges," in *Project Execution Strategy and Planning Challenges* (L. Hermann, R. Riedel, K. D. Thoben, G. von Cieminski, and D. Kiritsis, eds.), pp. 243–250, Springer International Publishing, 2017.

[7] J. Oehmen, *The Guide to Lean Enablers for Managing Engineering Programs*. Cambridge, MA: Joint MIT-PMI-INCOSE Community of Practice on Lean in Program Management Edited, 2012.

[8] P. W. G. Morris and J. K. Pinto, "How Projects Differ, and What to do About it," in *The Wiley Guide to Managing Projects*, ch. 50, pp. 1266–1286, Hoboken, NJ USA: John Wiley & Sons, Inc., 1 ed., 2004.

[9] C. Y. Liu and J. C. Wang, "Forecasting the development of the biped robot walking technique in Japan through S-curve model analysis," *Scientometrics*, vol. 82, no. 1, pp. 21–36, 2010.

[10] G. A. Barraza, W. E. Back, and F. Mata, "Probabilistic Monitoring of Project Performance Using SS-Curves," *Journal of Construction Engineering and Management*, vol. 126, no. 2, pp. 142–148, 2000.
[11] G. A. Barraza, W. E. Back, and F. Mata, "Probabilistic Forecasting of Project Performance Using Stochastic S Curves," *Journal of Construction Engineering and Management*, vol. 130, pp. 25–32, feb 2004.
[12] L. C. Chao and H. T. Chen, "Predicting project progress via estimation of S-curve's key geometric feature values," *Automation in Construction*, vol. 57, pp. 33–41, 2015.
[13] S. Shalev-Shwartz and S. Ben-David, *Understanding machine learning: From theory to algorithms*, vol. 9781107057. New York: Cambridge University Press, 1 ed., 2014.
[14] L. Lingitz, V. Gallina, F. Ansari, D. Gyulai, A. Pfeiffer, W. Sihn, and L. Monostori, "Lead time prediction using machine learning algorithms: A case study by a semiconductor manufacturer," in *51st CIRP Conference on Manufacturing Systems*, pp. 1051–1056, Elsevier B.V., 2018.
[15] F. Dekking, C. Kraaikamp, H. Lopuhaa, and L. Meester, *A Modern Introduction to Probability and Statistics*. London: Springer Science & Business Media, 2005.
[16] D. Gyulai, A. Pfeiffer, G. Nick, V. Gallina, W. Sihn, and L. Monostori, "Lead time prediction in a flow-shop environment with analytical and machine learning approaches," *International Federation of Automatic Control*, pp. 1048–1053, 2018.
[17] A. Pfeiffer, D. Gyulai, B. Kádár, and L. Monostori, "Manufacturing Lead Time Estimation with the Combination of Simulation and Statistical Learning Methods," *Procedia CIRP*, vol. 41, pp. 75–80, 2016.
[18] H. Drucker, C. J. Surges, L. Kaufman, A. Smola, and V. Vapnik, "Support vector regression machines," *Advances in Neural Information Processing Systems*, vol. 1, pp. 155–161, 1997.
[19] Q. Yan, "Study on prediction model of construction period of power transmission and transformation project based on support vector machine," *IOP Conference Series: Earth and Environmental Science*, vol. 446, no. 4, 2020.
[20] S. Petruseva, V. Zileska-pancovska, Ž. Vahida, and A. B. Vejzović, "Construction costs forecasting: comparison of the accuracy of linear regression and support vector machine models," *Tehnicki vjesnik - Technical Gazette*, vol. 24, no. 5, 2017.
[21] V. Kecman, *Support Vector Machines – An Introduction*, vol. 47. Berlin Heidelberg: Springer-Verlag, 2005.
[22] W. Y. Loh, "Classification and regression trees," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 1, no. 1, pp. 14–23, 2011.
[23] J. R. Quinlan, *C4.5 Programs for Machine Learning*. San Mateo, California: Morgan Kaufmann Publishers, 1993.
[24] A. Liaw and M. Wiener, "Classification and Regression by randomForest," *R News*, vol. 2, no. 3, pp. 18–22, 2002.
[25] L. Breiman, "Bagging predictors," *Machine Learning*, vol. 24, no. 2, pp. 123–140, 1996.
[26] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
[27] W. H. Raaymakers and A. J. Weijters, "Makespan estimation in batch process industries: A comparison between regression analysis and neural networks," *European Journal of Operational Research*, vol. 145, no. 1, pp. 14–30, 2003.
[28] D. van Ravenzwaaij, P. Cassey, and S. D. Brown, "A simple introduction to Markov Chain Monte–Carlo sampling," *Psychonomic Bulletin and Review*, vol. 25, no. 1, pp. 143–154, 2018.
[29] C. M. Bishop, *Neural Networks for Pattern Recognition*. Oxford: Clarendon Press, 1995.
[30] E. Acar and M. Rais-Rohani, "Ensemble of metamodels with optimized weight factors," in *AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, vol. 49, (Schaumburg, IL), pp. 279–294, American Institute ofAeronautics and Astronautics, 2008.
[31] T. Goel, R. T. Haftka, W. Shyy, and N. V. Queipo, "Ensemble of surrogates," *Structural and Multidisciplinary Optimization*, vol. 33, no. 3, pp. 199–216, 2007.
[32] K. Vladimir and H. Dražen, "Project Planning by Modified Gauss S-Curve," in *Creative Construction e-Conference 2020*, (Online), pp. 65–70, Budapest University of Technology, 2020.