Disturbance Maintenance Labor Hour Modelling

Traas, M.P. (Max, Student B-IEM)

Supervisors University of Twente
Dr. E. Topan
Dr. I. Seyran Topan

Supervisor ASML
E. Schmellekamp

Management Summary

In this thesis presents an assignment offered by ASML, specifically the Customer Support department. Customer Support has the responsibility to organize the engineer teams that maintain ASML machines on customer production sites. The engineer teams are filled with a certain amount of service engineers, depending how many labor hours it costs to maintain a machine a year. In a few years ASML plans on releasing a brand new machine to the market, the EXE:5000. For this machine Customer Support wants to estimate the total amount of Labor hours required to maintain it for a year, to be able to determine how many engineers they need to train to maintain a single EXE:5000 on a customer site.

In the past Customer Support has used a top-down approach when determining the total maintenance labor hours. This approach uses the design of the machine as a basis of its estimation. The issue with this approach is that Customer Support does not know what type of activities the total amount of labor hours consists of. Within ASML 3 different types of labor hours are identified, namely A-time, B-time, and C-time. A-times are defined as 'Optimal Execution Time'. This is the normative time that is required for a service action under normal conditions, without any delay and disturbance. C-times capture the time that the engineer is not directly working on the service action, but nothing has gone wrong. This includes all hours spent preparing for a service action.

In this assignment the focus is only on the B-time, namely the labor hours surrounding disturbances. B-times are defined as Unplanned Delay in Execution Time. B-times are the sum of the unplanned disturbances during a service action between start and finish. The goal of this assignment is to create a bottom-up estimation of the B-time Labor hours required to maintain the EXE:5000 over time. A bottom-up approach means that the estimation will primarily be based on data collected from the field.

There are 2 main aspects that are relevant within this assignment. The first is that ASML finds that the further a certain machine is in its product lifespan, the less disturbances occur and the less maintenance it requires. This effect is modelled as "learning" within the B-time labor hour model. The second aspect is that currently B-times, are not being measured in the field. The B-time labor hour model must introduce a way of modelling B-times based on scarce data, as well as introduce a way to model B-times in labor hours. The B-time labor hour model uses the ASML Issue Resolution database to determine how many and how long the disturbances are in the field. However this database has its limitations, as the ASML Issue Resolution database is not designed to represent the B-times in labor hours experienced in the field. The fact that ASML has no means to predict B-times from bottom-up field data, means that the model has to rely on concepts to calculate the B-times in labor hours. The concepts and strategies used in the model are not based on engineering experience over concrete field data, this leads to validity and accuracy limitations in the final estimation. The validity and accuracy limitations will be addressed through a data quality assessment on the input data and a linear regression model.

Within ASML the B-time disturbances consist of 9 different categories, based on the root cause of the disturbance. Estimating the values of all the individual B-categories in Labor hours, will provide a bottom-up total of the B-time Labor Hour estimation. The output of the model shows that namely B8-Design, B7-Work Preparation, and B2-Part Quality have the largest impact on B-time labor hours. The labor hours are determined on a yearly basis for a single machine. Therefore B8-Design caused disturbances are the largest source of B-time labor hours for a machine each year. The model also indicates that the impact of B8-design disturbances on the total labor hours, reduces significantly over time. While the impact of B7-Work Preparation disturbances stay constant over time. In this model the impact on the total B-time in labor hours each year caused from the other B-categories are very low, specifically B5-Customer Facilities and B9-Customer Processes are 0. The model is able to generate these values based on an analysis done on historic data.

The ASML Issue Resolution (AIR) reports from NXE operating in the field, indicate how many hours the a machine was down due to a disturbance, this value is referred to as the coverage value. The analysis done on these reports also create new insights on the quality of AIR report data base as well as the B-time hours found in the field. Such as the coverage duration is in hours and not in labor hours, to compensate for this a labor hour concept is integrated into the model. Based on engineer experience and rough estimations, the B-time model transforms duration of disturbance into B-time labor hours. Through this process the B-time labor hour model loses accuracy and validity. The accuracy and validity of the model is also linked to how well the input data set represent reality. To measure the data quality an assessment is done.

There is no single test one can perform to assess the quality of data. There are many different dimensions of data quality that need to be considered. There are both subjective data quality assessments and objective data quality assessments. Subjective data quality assessments include the needs and experience of relevant stakeholders. With objective data quality assessments, certain data quality dimensions are quantified and are calculated. From both types of quality assessments, the AIR-report data set scores poorly. The subjective assessments indicates that the AIR-reports are often incomplete to be utilized, the objective assessment supports this claim. The AIR-report data set is filled with 83% duplicated values, and only 20% of the reports hold a desirable coverage value in multiply data quality dimensions. Low scores in the data quality assessment indicates that the B-time labor hour model will have a low accuracy and validity. To explore how the B-time labor hour model can improve a linear regression is done to identify important field data information.

The service actions required to maintain the EXE:5000 are already defined, through Linear Regression features of a service action that link strongly with coverage are identified. Assessing what characteristics of a service action lead to coverage, can provide Customer Support insight to what data to collect from the field. A dataset is created from the Availability Matrix (AvM), and through backward selection the characteristics that correlate with coverage are identified. 5-fold cross-validation is used to measure the predictive performance of the created model. The R^2 is almost 0.5 and the Mean Absolute Error (MAE) is high, indicating that the linear model is not a strong predictor. However the backward selection indicates that data on the duration of service actions and the type of service action (unscheduled or scheduled machine down), have a statistically significant relation with coverage. Customer Support could implement systems to collect and link information such as the duration of service actions and the type of service action to the B-time duration and failure, this would improve models such as the B-time labor hour model.

From the results of the different findings of the research, recommendations and insights can be made. The outputs of the B-time labor hour model for the EXE:5000 shows the trend of the labor hours required to maintain the EXE:5000. These trends or graphs portray the estimated B-time in labor hours in the form of a learning curve. For each of the 9 B-time categories the amount of B-time labor hours is established. Using this model ASML is able to identify what type of disturbances impact the B-times the most. ASML can then invest resources in addressing the B-times that have the largest impact on B-times, such as preventing the disturbances from occurring initially or implement processes that prevent the same disturbance from recurring. The results of the data quality assessment it show that ASML can optimize the way they keep track of field disturbances. The issues found are primarily inconsistent disturbance reports and the inability to cross reference a single disturbance between databases. If ASML is able to accurately collect field data, through the use of smart devices timing the duration of individual processes, and this information is properly organized, then ASML can gain tremendous benefit of predictive and analytical models. The datasets used will then be extremely accurate and provide a great amount of information on the instance of disturbance. From the linear regression model, characteristics of service actions have been identified which correlate with disturbance related labor hours. From this linear model, Customer Support can design a database which presents information specifically related to them. Information such as the type of service action or the planned duration (in labor hours) of the service action are all relevant for Customer Support according to the linear model.

The changes made in recording and organizing information is currently an area which is improving quickly. On the release of the EXE:5000 ASML expects to have equipment in place that automatically records all service actions from start to finish. A Customer Support database that holds accurate and relevant information will be feasible. Using a database such as this opens a wide range possibilities to create analytical and predictive models. The B-time labor hour model (with some adjustments) will also increase its effectiveness. Implementing these recommendations could lead to exciting new possibilities and insights for Customer Support in the future.

Confidentiality acknowledgement

This thesis is written on an assignment provided by ASML. ASML is a front runner in microchip producing machinery, partially due to their great investments in research and development of their technology. To help protect their competitive advantages this thesis has been provided confidentiality from the University of Twente. ASML raised certain confidentiality concerns and for this certain information has been anonymized to address these concerns. Specifically the data displayed in chapter 4, is both a combination of generated data as well as fragments of real data. This is done to be able to present how the model makes its calculations and present outputs that are similar to the outputs calculated using actual data. In the chapter 6 the data set in which the model is trained and validated on is a normalization of the actual data set from ASML. This was done under the supervision of both ASML and university supervisors. Resulting in a dataset of which the individual entries hold no meaning, however the (possible) relationships between the different variables remain intact. Keeping the relationships between variables intact enables the possibility to create a linear regression model. The focus of the thesis lies on finding managerial and conceptual insights, as mathematical insights would be difficult to validate due to these confidentiality concerns.

Abbreviations

ASML uses different terms that are specific to ASML operations. These terms are used throughout the thesis. The first time a word is used, the full word will be written out and the abbreviation mentioned. The abbreviation will then be primarily used. The list of ASML specific abbreviations is given here.

AIR ASML Issue Resolution

AvM Availability Matrix

CS Customer Support

D&E Design and Engineering

EUV Extreme Ultraviolet

SD Scheduled Down

SO Service Order

USD Unscheduled Down

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1 Introduction

In this chapter, we discuss ASML and the role that the Customer Support department plays within it. The description of the initial assignment is given combined with a problem statement. In the following section the methodology and a solution is proposed. Lastly later sections, relevant research questions are defined as well as the scope of the assignment.

1.1 About ASML

ASML is the front runner in chip-machine manufacturing technology. With facilities across the global and a large amount of employees from all over the earth, ASML is one of the largest chip-manufacturing companies in the world. ASML started off as a collaboration between the companies Advanced Semiconductor Materials International (ASMI) and Philips in the 1980's. The combined company was named ASM Lithography. Focusing on research and development ASM Lithography grew fast and introduced the PAS 2500 stepper in 1986, to the world. Following that success they partnered with a German lens manufacturer Carl Zeiss, this partnership still holds today. ASML's success fluctuated until in 2001 the TWINSCAN system was developed, which revolutionized the market. Newer and newer iterations of the TWINSCAN paved way for the legacy of ASML. In 2010 the first Extreme Ultraviolet (EUV) lithography tool was introduced to the market. The EUV lithography technology enabled ASML to manufacturer machines that could create smaller, faster and more powerful chips. This machine line was named the NXE, starting with the NXE:3100 in 2010 and developing up to the NXE:3400. For 2020 ASML has further improved their chip-machine manufacturing and are preparing to design the first EXE machine, in 2023. This machines utilizes a next-generation EUV platform to create significantly faster production speeds.

1.2 About Customer Support

The assignment proposed by ASML is one that falls under the responsibility of the Customer Support Department (CS). CS is responsible for the training and the organization of service engineers. Service engineers are the engineers that perform maintenance activities on the machine. They are the ones that conduct the periodic maintenances to prevent the machine from breaking. Service engineers are also the "first line of defense", they are the first ones at the machine when the machine breaks. It is their responsibility to diagnose what the issue is and fix it if possible. The last main task that a service engineer needs to be trained for is monitoring. By closely monitoring the machine they are able to minimize the amount of time the machine is turned off for maintenance, and thereby increase the machines availability.

ASML has plans to install a new line of machines, namely the EXE:5000. A new machine line like this requires specially trained service engineers that are able to perform the previously mentioned tasks to maintain the machine. The machines ASML has made are complicated and expensive, therefore training an engineer to be ready for the field can take between 12 to 15 months. This essentially means that up to 2 years prior to the first machine being in the field, CS needs to start training service engineers. The complexity of the machine also requires engineers to be specialized in certain parts of the machine. A simple example of this are the lenses, working with lenses on a machine requires a service engineer with a specific competency (competency refers to a skillset that an engineer has specialized in). The CS department not only needs to determine the correct amount of engineers to train per machine to provide 24/7 support, but they also need to determine the number of engineers need a certain competency. The amount of engineers needed per machine is referred to as team size. To determine the proper team size and what competency to train in those teams, the CS department needs to know the total amount of labor hours required to maintain a machine. Currently CS determines the amount of labor hours necessary to maintain a new line of machine based on the design labor hours. Design labor hours are simply the minimum amount of hours service engineers need to complete all service actions that the service engineers are scheduled to do in a year. Within ASML, different types of labor hours are identified, these labor hours indicate what kind of activities the service engineer are doing. CS does not have an overview of these different types of labor hours (the different types of labor hours will be covered in the following sections). The current method of predicting labor hours, revolves around multiplying the design labor hours by an agreed upon value, such as 2,4. This means that besides the value of the design labor hours, the CS department is unaware of the impact of other types of labor hours. The creation of the B-time labor hour model is a first step into addressing the issues surrounding CS's inability to estimate labor hours from a bottom-up perspective.

1.3 Problem Introduction

One of the roles of the Customer Support department is to predict how many service engineer labor hours a certain design of a machine requires. This prediction is calculated is by the Design and Engineering department (D&E). The Design and Engineering department will create an Availability Matrix (AvM), which holds certain information of all possible service actions for a machine. Information such as the required amount of engineers, the duration/Meant Time To Repair (MTTR) of the action, and if the action requires tools or not and more. The AvM is mainly based on the design of the machine, this means that the duration of the service action given in the AvM is the expected duration of the action under optimal circumstances (without mistakes and with an engineer with perfect knowledge of the procedure). Customer Support use the AvM as well as historical data, and their own departmental experience to determine the total amount of labor hours required to maintain the machine. With this prediction they can also determine the quantity of engineers needed to maintain a single machine. The prediction of the total amount of labor hours is primarily based on the design of the machine rather than on field data. The CS department make their estimation primarily on experience and history. They do not distinguish between different types of labor hours.

ASML identifies 3 different types of 'time'; A-time, B-time, and C-time. They are used to structure and categorize the many different activities that service engineers spend their time on. A-time is the duration of executing a task under optimal conditions or the time it takes to perform a procedure. C-time is all the time around that action, the time it takes to travel to the facility or the time it takes to prepare for the task. B-time is the duration of all the things that go wrong during A-time. For example, a missing tool during A-time, ASML only determines the A-times and roughly estimates the B-times. (A more elaborate description on the different times will be given later). There is no data on C-times nor is there particularly useful data on the B-times. It is here where the assignment comes into play. CS wants to determine the C-times and B-times and create a model that estimates the total labor hours associated with the EXE5:000. This paper will primarily focus on B-times.

Distinguishing the different types of labor hours is crucial to the labor hour estimation model. As each type requires its own assumptions and approaches to model. They are also useful for identifying what information CS does have and what information they do not have. A-times are directly taken from the Availability Matrix provided from the Design & Engineering department. C-times are not taken into consideration at all within ASML, these times are neither clearly defined nor collected from the field. The model will be one of the first to take C-times into consideration in the calculation of the total labor hours. B-times are abstract and complex times, and are also poorly documented. Once a disturbance occurs, the priority is to get the machine running again and then the local service team will internally reflect if they can prevent the issue from occurring again. The duration of the disturbance and the labor hours spent on resolving the disturbance, is not accurately measured within ASML.

ASML does not have an overview of B-times and disturbances, which makes it difficult to create a bottom-up labor hours model. B-times are documented through AIR-reports. AIR stands for "ASML Issue Resolution". If during a service action on the machine an issue arises that can be identified as a source of B-time, then an AIR-report can be written. The AIR-report identifies the B-number as well as the coverage, and other information. Such as the date, location, machine ID, and more. The coverage is the amount of time lost due to a B-issue per machine per year, in hours. This means that a coverage of 10 means that a certain disturbance causes a machine to lose 10 hours of machine uptime each year. Coverage represents the amount of downtime created by a disturbance or failure per year. The model uses these AIR-reports as input to represent the B-times experienced in the field. However the quality of the AIR-reports needs to be pulled into question, as the value for coverage is not a measured value. Coverage is estimated by the service engineer, this amongst other factors indicate that the quality of AIR-reports should be assessed.

Another aspect regarding modelling B-times is the fact that the amount of mistakes decrease over time. In this assignment the effect of learning efficiencies is assumed to be present in the B-time data. Which means that for the B-time in labor hours learning needs to be determined to represent the reduction in mistakes over time, as the engineers learn from their mistakes. This can be achieved by identifying the learning rate of B-times to model B-times as a learning curve. Determining the effect of learning as well as determining accurate B-times for the EXE:5000 will give a representation of the B-time labor hours for the engineers and how it changes as time passes.

The inability of the Customer Support department to accurately determine the amount of engineers needed to maintain a machine, has remained under ASML's radar in the past. Whenever introducing a new machine to the field it is ASML's highest priority to increase the availability of the machine as much as possible. This is because ASML is contractually obliged to meet a certain availability. Not meeting this availability will lead to great monetary and reputation costs for ASML. Therefore to prevent unscheduled downs from lasting too long, ASML offers 24/7 Customer Support. This makes it so that as soon as the machine shuts down unexpectedly an engineer can immediately be on site to diagnose the issue. The cost of offering this service, is only a fraction of the costs of having a machine fall under the agreed availability. ASML also uses the term 'intro-dip' which refers to a low machine uptime or runtime for the initial period that the machine is in the field, because the machine has recently been installed and unforeseen issues occur. This 'intro-dip' is also present in the labor hours required to maintain a machine. The first year of a machines introduction will cost significantly more labor hours than 5 years after its introduction. After an issue occurs ASML attempts to prevent the issue occurring again, this reduction in the frequency of issues over time as well as the simple fact that engineers become better at their job over time leads to less labor hours needed to maintain a machine, are causes for learning. This means that the amount of engineers required to maintain a machine slowly decreases over time. The engineer team size required to maintain the EXE:5000 changes as the machine matures, less engineers are necessary the further the machine is in its lifetime. The costs of assigning too many engineers to a machine, will build up over time. As mentioned before the cost of offering 24/7 support is only a fraction of the cost of a machine not running for long periods of time. However paying for extra engineers becomes costly for ASML on the long term. It is for this reason that in recent years Customer Support is pushing to optimize the way they calculate and determine labor hours. The B-time Labor Hour estimation model is a step towards making a full Labor Hour overview model.

1.4 Problem Definition and assignment goal

The assignment lies within the Customer Support department and it is here that an organizational gap in the role division of Customer Support is identified. There is no role that is responsible for gathering and assessing field data to keep track of the labor hours of maintaining a machine. This leads to the assignment ASML has provided; 'there is no bottom-up assessment model for the total Labor hours required to maintain a machine'. This paper explores the underlying problems that form this issue and will also propose possible solutions that could assist ASML in addressing these issues.

At face value the assignment can be seen as one of a predictive nature, however that is not the goal of the assignment. The inability to estimate the total amount of labor hours needed to maintain a machine, is caused by a larger underlying issue. Namely an organizational gap within the Customer Support department as well as a disconnect in the information flow between management and engineers in the field. It is the goal of the assignment to create a model that roughly estimates the components of the total amount of labor hours required to maintain the EXE:5000. Which in turn can be used to address the issue of not having an overview of all the different types of labor hours and to be used as a tool to push for a restructure in the way Customer Support tracks information from the field and predicts labor hours. ASML does not create an accurate estimation of the amount of all the labor hours required to maintain a machine. Both an overview of how the B-time Labor hours can be modelled and how to improve information flow from the field to management are the main objectives of this assignment.

A bottom-up B-time model that estimates the total B-times in labor hours for maintaining an EXE:5000 for a year will provide ASML with an estimation of the total amount of labor hours required to maintain a machine. Providing the CS department with more depth in their calculations when determining the amount of engineers to train per machine. Customer Support is the department that is responsible for the service engineers in the field. However currently there are no systems in place that track data on the service engineers. The only system in place that keeps track of disturbances, are AIR-reports. However AIR-reports are written to inform Design Engineers of common disturbances, so that they can be prevented. They are not designed to represent the B-times in Labor Hours, however in this thesis they are used as the main source of B-time data. The quality of the AIR-report dataset used for the model, is assessed through a data quality assessment. An indication of the accuracy and validity of the prediction can be related to the quality of the input data of the model.

The accuracy of the B-time Labor Hour model is limited by the information that is currently is available, there is not enough data on the B-time labor hours to make an accurate estimation on the labor hours made on maintaining the EXE:5000. Therefore this paper proposes options for Customer Support on how field data can accurately be calculated and used for the B-time labor hour model. Specifically what values are important to track from the field and how to track and combine them into a single database, specialized to the needs of Customer Support. This is done by using linear regression to find correlation between certain service action characteristics and the associated coverage value.

The problem statement for this paper is defined as:

> "*ASML is unable to determine the B-time Labor hours required to maintain the EXE:5000 over time using a bottom-up approach."*

Which leads to the goal of this thesis:

> *"Create both a bottom-up model that estimates the B-time Labor hours required to maintain EXE:5000 overtime."*

The B-time estimation model will be used for two things. One as a tool to be used by Customer Support to determine the amount of engineers they need to train for their machine per year from a bottom-up perspective. The second purpose of this paper, is to present the lack of high quality data and identify the reasons for it. To then propose a solution that can improve the quality of data collected from the field and in turn improve the estimation of the model.

1.5 Core problem

Within this assignment the recurring issue is the lack of data on labor hours. This is simply caused because the information that is needed to estimate the labor hours required to maintain a machine, is not being tracked by ASML. ASML creates high cost machines that produce high quality products that are essential for their customers. Due to the costs of an ASML machine, customers are inclined to use them intensely to maximize their investment. It is common that these factories produce in high volume and customers run the machine up to 80% utilization. The other machines in the customer's factory are linked to match this pace, specifically the flow of wafers. Therefore when the machine goes down a buildup of wafers is formed. Therefore these machines must also be halted, and the machines that provide the supplies for the wafer machine as well. Most factories also have a production schedule, but the production stops when the machine goes down and a delay is formed. The factory needs to work away this delay to catch up to their schedule. The issue here is that the ASML machine was already running at 80% utilization, running it higher also increases the risk of machine failure. It is therefore very difficult for factories to make up for lost time when ASML machines go down, so every machine down can lead to considerable losses for the customer. It is for this reason that ASML is so focused on machine availability. This is also why ASML offers 24/7 customer support, so that in the case that a machine goes down unexpectedly a first line engineer is immediately on site.

By making sure an engineer is available 24/7, ASML does not need to know many labor hours are put into maintaining the machine. ASML is not interested in how many labor hours are required to maintain the machine, they are much more interested in machine availability. This is because extra costs in labor hours is only a fraction of the losses that customers deal with if the machine is unnecessarily down. To keep the availability of a machine as high as possible they keep track of machine 'down' data. Information such as MTTR (how long was the machine down) and what are the reasons for the machine down. ASML has an organized system to keep track of unscheduled 'downs' and issues that occur during maintenance to prevent them from repeating or causing too much delay. ASML also makes use of quick and efficient monitoring systems in place that enable them to optimize the timing of the periodic maintenance, in turn reducing the amount of times the machine goes down per year.

It is primarily the Customer Support department that suffers from not accurately measuring the labor hours. Without knowing the amount of labor hours required to maintain a machine each year, the CS department has to make estimations and assess risks. For it is this department's responsibility that the engineers are trained in time and in the proper quantities. The CS department determines the amount of engineers they need in a year based on the estimation of the expected amount of labor hours. Inaccurate estimations can lead to a shortage of engineers and over-utilization of engineers or ASML can hire too many engineers, which leads to unnecessary costs. It is difficult for CS to accurately determine the proper range of engineers needed, because they have very little high quality data from the field.

1.6 Methodology

The methodology applied to systematically address problems is the Managerial Problem-Solving Method (MPSM). (Heerkens & Winden, 2017) The assignment had many different aspects and problems the MPSM method creates structure to solve these problems. The MPSM method is a cycle, and problems are systematically solved by constantly rotating through the different steps. The MPSM has 7 different steps (Heerkens & Winden, 2017):

1. Defining the problem
2. Formulating the problem approach
3. Analyzing the problem
4. Formulating solutions
5. Choosing a solution
6. Implementing a solution
7. Evaluating the solution

This method supports systematic problem solving. Research in the B-time labor hour model, Customer Support and ASML as whole, leads to a wide range of problems that need to be addressed. The MPSM enables systematic progress in solving these problems, while granting the ability to simply cycle through the steps to solve a wide range of different problems.

1.7 Research Scope

By forming research questions, the main problem can be addressed. The research questions also help structure the research process. In the following section they are defined, and in throughout the paper they will be answered.

1.7.1 Research Questions

There are many different issues in this thesis. Defining research questions is crucial in addressing these issues. The research questions are categorized by the different topics this thesis covers.

1.7.2 B-time labor hour model

The process of creating the B-time estimation model is just as important as the B-time estimation itself. The following research questions are defined to show the process in which the B-time estimation model was formed. The following research questions are thereby formed:

- What are B-times?
- How to model B-times in Labor hours?
- How to model learning within B-times?
- What is the B-time related data gathering process?

1.7.3 Data quality

A large part of creating a predictive model is determining its validity. Through a data quality assessment, the input of the B-time labor hour model is assessed and used to estimate the validity of the output of the model. The following research questions are thereby formed:

- What is the quality of the B-time-related data?
- What dimensions of quality are especially relevant in the B-time related data?
- How valid is the B-time estimation model, based on the used data?

1.7.4 Linear regression

In this research many insights are made. Linear regression is used to support recommendations made based on insights found while creating the B-time labor hour model and the performing a data quality assessment. The following research questions are thereby formed:

- What features are important for predicting B-time?
- What evaluation metrics can be used to measure the performance of the linear regression model?
- What methods can be used to validate the linear model?
- What methods can be used to measure the predictive performance of the linear model?

1.7.5 Research Scope

The research scope of this assignment regards to estimating the B-times in labor hours. The method in which the B-times are calculated will be partially determined by the scope of stakeholder. The scope namely being B-times in labor hours specifically made by service engineers. Once the B-time estimation calculation method is determined, data will needed to be added to the model. The B-times are difficult to measure and collect high quality data on. In this paper the quality of the data used in the model is also researched. The different problems within the data are analyzed. This paper will also suggest solutions that address the causes for low quality data, which in turn could create a higher quality set of data.

In the grand scheme of things, the goal is to estimate the different types of labor hours required to maintain an EXE:5000 change per year. This paper will focus strictly on the B-time element of the labor hours. A-times and C-times fall out of scope as these are handled by others within ASML.

In this research the B-time required to maintain a machine is estimated per year. This is because the more a machine matures the less B-time it faces. This is simply due to the fact that both engineers and the design of the machine improve as time passes. Engineers make less mistakes and the design of the machine is modified to fail less. A look into learning curve theory is necessary to understand the different concepts related to learning. For this paper, it is not its primary scope. Learning will be implemented in the model with a theoretical perspective.

2 ASML context analysis

In this chapter the definitions of the many different ASML specific terminology are stated. Followed by an example of the entire service engineer maintenance process.

2.1 Different types of Labor Hours

Within ASML a lot of terminology and abbreviations are used that are exclusive to ASML. To break down the core issues within this assignment, divisions have been made within the labor hours. The basic divisions are the ABC-times, with each letter defining what labor time is being spent on. These are concepts that translate universal theories as well but are defined here as A-, B-, and C-times.

2.2 A-Times

A-times are more commonly known as 'Optimal Execution Time'. This is the normative time that is required for a service action under normal conditions, without any delay and disturbance. This is the duration of the service action when performed under perfect circumstances. This is the time when all needed personnel are available, normal working speed, all tools and materials are available. These Labor hours are also seen as the Design Labor hours. The D&E department spends a lot of resources in determining accurate and valid A-times.

2.3 B-Times

B-times or Unplanned Delay in Execution Time. Is the sum of the unplanned disturbances during a service action between start and finish. If a service action has an A-time of 3 hours and the engineers complete the service action in 4 hours, the extra hours are seen as B-times. There are many different root causes of disturbances, within ASML the B-time disturbances are separated in 9 categories. The definition of each type of disturbance is defined in Table 1. They are defined as B1 through B9, this is so that when documented it is clear what type of failure caused a delay. The purpose of the B-categories is to isolate failures based on their root cause. This allows ASML to distinguish what type of failures occur the most and have the largest impact, which in turn informs ASML on what specific areas to improve on. Due to the many different types of B-times and its nature, it is the most complex and important category of the labor hour model.

Table 1. B-time Categories

B1	Spare part availability disturbance
B2	Spare part quality disturbance
B3	CS Engineer induced disturbance
B4	Tooling induced disturbance
B5	Customer Facility induced disturbance
B6	Supporting software tooling disturbance
B7	Work preparation disturbance
B8	Design induced disturbance
B9	Customer process induced disturbance

2.4 C-Times

C-times are the hours surrounding the A-times and B-times. The definition used is, operation efficiency loss in the Engineering Time state. C-times capture the time that the engineer is not directly working on the service action, but nothing has gone wrong. This includes all of the preparation before a scheduled service action, as well as all the finalization and calibration with the customer after the service action. C-times also include the time it takes to swap shifts, lunch breaks and the time it takes to travel to the machine. The C-time Labor Hour model calculates A- and C-time, and is combined with the B-time model to calculate the total Labor hours.

2.5 Unscheduled Down and Scheduled Down

Engineers perform maintenance during either a scheduled down or an unscheduled down. In both cases the machine is 'down', not running. Scheduled and unscheduled simply refers to either planned maintenance or unplanned maintenance respectfully. With a scheduled down, the machine is planned to be turned off for a period of time. While during an unscheduled down the machine is turned off due to a system failure. It is during this maintenance or 'troubleshooting' processes (in the case of an unscheduled down) that the engineers make the labor hours that B-times can occur. In the Total Labor Hour Model, the labor hours engineers make before and after the machine being down, such as preparation and clean-up, are included as C-time.

2.6 Learning Curve Theory

The simple definition of a learning curve is "A representation of the correlation between a learner's performance on a task on the number of attempts or time required to complete the task". ASML has identified that the labor hours required to maintain a machine decrease over the course of the maturity of the product. This is both due to the fact that with each iteration of the machine, the machine improves and the occurrence of failure reduces. As well as after every mistake made by the engineer teams, they improve and learn. After repeating the same task over and over the time to tasks completion naturally reduces as the individual becomes more proficient at the task. With engineers performing routine service actions means that this theory is properly applicable to the model. It is expected that the learning curve will be most apparent in the B-time division of labor. Per definition there cannot be any learning during A-times. As this is specifically the time allocated to performing the task. Any delays during the task automatically fall under B-time, and let the engineer learn and improve. Learning also occurs on C-time activities, which consists mainly of preparation and finalization of the service action. In the preparation phase of performing a service action, it has been observed that engineer teams become more proficient after preparing for the same task several times. For this paper the focus is on B-times, learning regarding C-time activities is not discussed.

2.7 Service Orders

Every time an action or task is executed onto a machine, a Service Order (or SO for short) is drafted. Service Order's hold a lot of information, such as what type of task is being executed, dates & timestamps, as well as what machine on which site. However during a task on the machine, engineers can run into different issues that they then need to address. For this issues separate SO's need to be written. Service Orders are important in this model as they indicate whether or not the service action was performed during a scheduled down or an unscheduled down.

2.8 AIR-report

AIR-reports or "ASML Issue Resolution", is a request to solve a B-time issue in the field. AIR-reports are originate from Service Orders. If during a task on the machine an issue arises that can be identified as a source of B-time, then an AIR-report can be drafted. The AIR-report identifies the B-number as well as the coverage, and other information. Such as the date, location, machine ID, and more. AIR-reports are tracked to identify common root causes in the field and enable Design and Engineering with information to address these root causes. Through the AIR-report system D&E can create solutions for root causes in the field and by implementing them to all relevant machines, they can prevent issues from occurring again. AIR-reports are used in the B-time Labor Hour model as the main source of estimating the B-times that occur in the field. The AIR-reports should indicate how long a disturbance was and what B-category the disturbance falls under. However, AIR-reports are not obligatory to draft after a disturbance and are only written if the local engineer team feel the need to do so.

2.9 Coverage

Coverage is determined by a service engineer whenever they encounter a B-related issue. Coverage is the amount of time lost due to a B-issue per machine per year, in hours. This means that a coverage of 10 means that this issue costs ASML 10 hours of machine availability per year. AIR-report need to be approved before they are resolved or acted upon. Within ASML a certain board looks into the AIR-reports and uses the coverage estimation to determine how much time they will be saving, and perform a cost analysis to determine how expensive is creating a solution and implementing it. This is simply because not all issues are worth solving, sometimes implementing solutions are too expensive compared to their costs.

2.10 Engineer maintenance example

This section will further explain the process in which information is put into the database. Defining the process is important to identify weaknesses and to be able to model the labor hours as accurately as possible.

A *service order* is always created for every action or task on a machine. *SO's* are written as soon as the engineer knows what action will be performed on the machine. The moment in time differs between a *scheduled down* (Figure 1) and an *unscheduled down* (Figure 2). A *scheduled dow*n is planned as soon as certain operations or parts within the machine are failing to meet expected performance, this is determined through monitoring efforts. Monitoring is done both by engineers themselves and the machine itself. Due to accurate monitoring maintenance can be scheduled beforehand. Once a *scheduled down* is planned, the local engineer team is also aware of what tasks needed to be performed. They will then draft an SO regarding the tasks they need to perform.

ASML machines have built in failsafe systems. This means that if something goes wrong the machine can detect it itself and shut itself down. This is to prevent the machine from further damage to itself. Once the machine stops itself, the local team is immediately notified of the unscheduled down. In an *unscheduled down* situation, the engineer will arrive at the machine as soon as possible. The engineer will then diagnose the machine to find the issue. In the cases that the engineer is able to diagnose the issue they will immediately also create an *SO*. In this diagnose process the engineers determine what service action needs to be performed to solve the issue. This service action is listed within the *AvM* and has an associated A-time to it. When performing the service action the engineer does not meet the expected A-time, the extra time is considered to be B-time. Only once the service action is complete and the machine is running again, will an *AIR*-report be drafted. *AIR*-reports are made to explain why the service engineers did not meet the defined A-time. Here a B-category is determined and the amount of time lost to is noted. The engineers that enter *AIR*-reports into the data base are not always the engineers that executed the service action. This means that the one inputting the data into the system, based off of the *SO* and other information need to determine the B-number and the coverage.

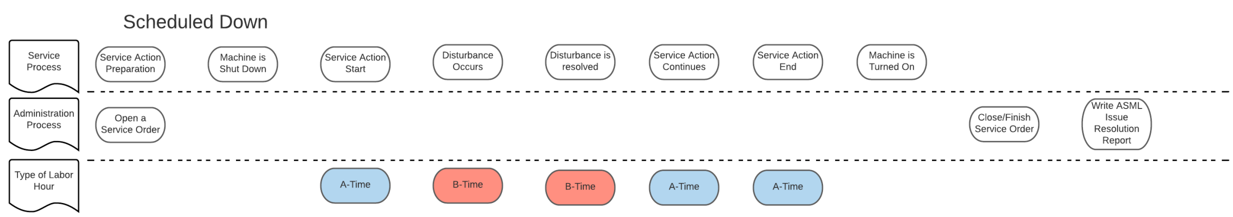


Figure 1. Scheduled Down Disturbance

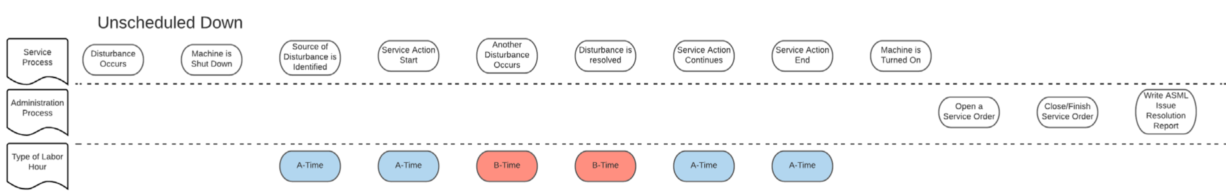


Figure 2. Unscheduled Down Disturbance

3 Literature Review

A literature review is provided in this chapter. There are three main theoretical elements in this thesis, namely the learning curve, data quality assessment, and the linear regression modelling. The literature will cover these topics to describe methods and identify established research. First theory and applicability of the learning curves will be discussed, followed by identifying proper methods to apply a data quality assessment. Finally relevant linear regression modelling literature will be presented and followed by a summary in the last section.

3.1 Learning Curve Theory

Initially knowledge on the learning curve effect was rather limited. ASML is able to identify the effect of learning due to data patterns on customer maintenance time. However the learning effect more commonly seen in other departments, as these have elaborate data schemes for analysis. The learning curve effect was considerable and but ASML primarily modelled learning from a top-down perspective. This perspective looks at labor hours as a whole and applying a certain learning rate. There is little existing data and research related to learning regarding B-time in labor hours.

An important aspect within this assignment is how team sizes and compositions influence the learning rate. Anzanello & Fogliatto (2007) and Peltokorpi & Jaber 2020 give insight to the effects of group learning. Tasks with a higher difficulty should be given to teams with faster learning. (Anzanello & Fogliatto, 2007) Traditionally ASML only trained high proficiency in each and every one of their engineers. With proficiency we refer to their level of understanding of the machine in their respective skill area, such as optics which covers the light systems and lenses. During disturbances, these engineers have the capabilities to diagnose and resolve the issue on their own. It could be said that service engineers have a high learning potential. For the B-time labor hour model, the moment of learning needs to be identified. Learning can be defined as a representation of the correlation between a learner's performance on a task on the number of attempts or time required to complete the task. The service engineer can be seen as the learner and the instance of maintenance can be seen as a task. Ideally the duration of the maintenance would be plotted over repetitions, to graph the learning of the service engineer. However as the engineer does a wide range of different types of maintenance, and encounters different types of disturbances, and without field data on maintenance in labor hours, learning cannot be modelled in such a way for the B-time labor hour model. Using the data on hand, learning is instead modelled on a yearly basis on a per machine basis.

The most widely agreed upon and accepted form of the learning curve is the Wright's learning curve. (Jaber & Guiffrida, 2004) (Jaber et al., 2008) This learning curve form is also utilized and applied in different departments within ASML. According to these papers there are two interesting parts of the Wright's learning curve, that also directly relate to the assignment. First the importance of the curvature of the learning curve, also known as the "Learning Rate". The learning rate represents how much an individual improves form one instance to the next. This is valuable for ASML to know as this will lead to an estimation of the distribution of the labor hours over time. It is common to set up an experiment to measure the learning rate and model a learning curve. Works such as Mackrous & Simoneau, (2011), Kasahara & Saito, (2015) and Jaber et al, (2021) all form learning curves through experiments. As mentioned before, reasons to create a learning curve model for an individual service engineer is not possible. Instead the model determines the learning rate, through analyzing the time spent on disturbance maintenance each year. The model assumes that the moment of learning occurs after a year of maintaining a machine.

The second important aspect of the Wright learning curve is the ‘learning plateau’. This refers to the part of the learning curve model in which improvement of the learner’s performance happens very little or not at all. This is simply because at a certain point a task cannot be performed any faster. Disturbances are always present within ASML machines, due to the high complexity of the machines. The learning curve modelling the B-times needs to establish what level of disturbances will always be present. The goal of the assignment however is to model the fluctuation of B-times in the first 4 years. Therefore identifying the impact of long term disturbances falls is not included in the research scope.

3.2 Data quality assessment

An important aspect in establishing the accuracy and validity of the B-time labor hour model is to establish the quality of the data used. The quality of data on which a recommendation is based, has important impact on the quality of the recommendation. (Heinrich et al., 2019) There is no single test one can perform to assess the quality of data. There are many different dimensions of data quality that need to be considered. Both subjective data quality assessments and objective data quality assessments are possible to assess data. (Nagle et al., 2020) Subjective data quality assessments include the needs and experience of relevant stakeholders. The stakeholders can determine, from experience, the quality of the data. There are two forms of objective data quality assessments. One form can be applied to any data set and is considered to be task-independent. The other form integrates business rules, constraints and is created for specific applications. The data used as input of the model is assessed both through different objective data quality assessments methods. The quality of the data is determined by measuring what portion of the data is ‘correct’, under the different dimensions, shown in Table 2. (Günther et al., 2019) and a subjective data quality assessment is derived from conversations with relevant stake holders.

Table 2. Data Dimensions Definitions

Dimensions	**Definitions**
Accessibility	to what degree is the data available, or easily and quickly retrievable
Believability	to what degree is the data regarded as true and credible
Consistency	to what degree is the data unique as non repetitive
Completeness	to what degree is is data not missing
Free-of-Error	to what degree is the data correct and reliable

3.3 Linear Regression

The B-time labor hour model will base its estimations on historic data collected from machines in the field. The issue with this is that this estimation will not hold any of the characteristics of the EXE:5000 into account. A linear regression model is formed to explore the possibility of creating a predictive model off of EXE:5000 data that currently is available. The service actions required to maintain the EXE:5000 are already defined, through linear regression features of a service action that link strongly with coverage can be identified. Assessing what characteristics of a service action lead to coverage, can provide Customer Support insight to what data to collect from the field.

There are many different types of machine learning, linear regression is the simplest type of regression model. There are two different types of variable predictions: quantitative variables and categorical variables. Regression analysis methods, such as linear regression, are used to predict continuous target variables. While classification analysis methods, such as decision trees, are used to predict categorical variables. The variable that is trying to be predicted is the coverage value, which is a representation of the duration that the machine was not running due to an issue. This is a continuous variable, and a linear regression model is appropriate to utilize. Linear regression is a supervised learning method. Supervised learning refers to historic data is used to train the model to predict the output variable. (Hastie et al., 2009) Linear regression is a simple supervised learning method that predicts the value of a continuous outlet variable, assuming the relation between output variable and the input variable is linear. Weights are assigned to the input variables to form a linear calculation to calculate the output variable. The linear regression model optimizes the weights, so that the error between the prediction and the actual value is minimized. This is done through the least squares method. The least squares method uses the residual sum of squares. The residual sum of squares is the total value that the predicted value is off from the actual value. By minimizing this value, the difference between the prediction and reality is smallest. Through the least squares method the best fit for the input variables is determined. Linear regression models are linear by nature, they perform best under the assumption that the input variables have a linear relationship with the output variables. Linear models perform poorly when this is not the case.

There are many different features available to use as input variables for the linear regression model. The predictive performance of the linear model is determined on the features selected. The three main methods used for feature selections are: wrapper methods, filter methods, and embedded methods. Wrapper methods consists of methods that add and remove features to eventually determine the features that form the 'best' model. Two common wrapper methods used are forward and backward feature selection. Forward selection simply starts with an empty model, and adds features that improve the models prediction performance. A stopping feature can be added to prevent forward feature from simply including all features. Backward selection is the opposite of this process. All features are initially added to the model and the feature that has the worst performance measure, is removed. Again a stopping feature can be added, to halt the feature selection to a certain size or to a certain performance measure threshold. (Jayalaxmi et al., 2021) Through backward selection, the features for the linear regression model will be determined. This approach will indicate what features from the input variables are linked to coverage. This in itself would provide insight for ASML.

Once the features have been selected the performance of the linear regression modelled is measured. Using k-fold cross-validation, the data set is randomly divided into k-folds. The k - 1 folds are used to train the data and the remaining fold is used to test the performance of the created model. This process is repeated k times, with every repetition until every fold has been used as a test fold once. Then the average performance of the formed models is taken. (Hastie et al., 2009) The performance metrics in which the result is measured are; R^2, RMSE, and MAE. It is through these performance metrics that the predictive performances of the linear regression model can be measured.

R^2 (equation (1)) represents what portion of the variation can be explained through the input variables. R^2 is scored between 0 and 1. With an R^2 of 1 representing perfect explanation of the variance of the output, using the input variables. An R^2 of 0 indicates that none of the output variance can be explained through the input variables. (Hastie et al., 2009)

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2} \tag{1}$$

The MAE (equation 2()) or "Mean Absolute Error" is a simple metric to measure predictive accuracy. The MAE is determined by calculating the mean of the absolute difference between the actual output and the predicted output. The unit of the MAE is the exact same as the predicted output, which would be in hours in this model. However as all values in the dataset used as input for modelling are normalized, it is still unclear what a preferred MAE is. In all cases a MAE close to 0, acts as an indicator of an accurate model. MAE is used in works such as Wen et al., (2019), to compare predictive models with each other.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\mathrm{yi} - \bar{\mathrm{y}}| \tag{2}$$

The Mean Square Error (MSE) (equation (3)) is similar to the MAE as it represents the difference between the predicted output and the actual output. It is calculated by taking the mean of the squared difference between the predicted output and the actual output. Similar to the MAE the unit of this metric is the unit as the predicted output, which is hours. The MSE takes the square of the difference, this leads to large outliers being penalized harshly. To compensate for this the RMSE (equation (4)) value is used. The RMSE is simply the Root Mean Square Error. Similar to the MAE, the preferred value of this metric is close to 0.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

3.4 Conclusion

In this chapter, the different areas of relevant literature were touched upon. Relevant methods and theories were described. These will be used to support the work in the following chapters. The learning curve model most appropriate to model service engineer disturbances on is the Wright learning curve (Jaber & Guiffrida, 2004) (Jaber et al., 2008) ASML has existing research and data on these types of learning curves, however modelling B-time labor hours on the Wright learning curve is a new application. Concepts such as the learning rate and the learning plateau are important in modelling learning. In the B-time model the learning rate is determined from historic data over a yearly basis. The model assumes that learning occurs between years of maintaining a machine. The learning plateau is an interesting aspect of the curve as well. There is a certain point in the long term in which the time it takes to complete a task is optimized. B-times represent disturbance hours, ASML machines are highly complex and constantly updating. The complexity and implementation of upgrades leads to an ever present source of disturbances. The exact level of the plateau however, is outside of the scope of the B-time labor hour model. As it is in the first 4 years, estimating B-times is the most crucial.

The B-time labor hour model, has a predictive element to it. The model makes an estimation of the B-times in labor hours for the EXE:5000 based on historic data from other machines in the field. The validity and accuracy of the estimation is closely tied to how well the historic data set represents reality. A data set with low quality suggests that the resulting estimation is also of poor quality. (Heinrich et al., 2019) Through both an objective data quality assessment as well as a subjective data quality assessment, the different dimensions of quality can be determined.

Lastly, this chapter discusses the relevant literature surrounding linear regression. Linear regression is the simplest type of machine learning. Linear regression is a simple supervised learning method that predicts the value of a continuous outlet variable, assuming the relation between output variable and the input variable is linear. Historic data is used to train the model. (Hastie et al., 2009) The first step is to select the features used to create the linear model. (Jayalaxmi et al., 2021) Backward selection is an appropriate method to determine what features correlate the strongest with coverage. This assessment could be a valuable insight for ASML in itself. Through the k-fold cross-validation method the model can be trained and tested. The performance metrics: MAE, RMSE and R^2 are used to determine the results of the created model. (Hastie et al., 2009)

4 Model development

In this section the created B-time labor hour estimation model explained. First relevant definitions and aspects of the assignment will be defined. Then the exact method of estimating the B-times in labor hours, as well as the inputs used to make the estimation are covered, Figure 3. The model not only aims to estimate the amount of B-time labor hours that are made by the local engineer team for maintaining the EXE:5000, but to provide an overview of where the labor hours comes from and how they change over the lifetime of a machine. Note that all the values used in the calculations and graphs of the B-time model are not the final values of the model, but are used as examples to indicate how the model works. The values originate from AIR-reports of a comparable scope of machines.

4.1 Model explanation

4.1.1 Labor hours

The labor hours that the model aims to estimate are the labor hours made by the local engineer team. The engineer team consists of first line and second line engineers. The first line engineers are the ones that interact and work on the machine, the second line engineers are in place to support them. Second line engineers have different tasks compared to first line engineers, however only the labor hours made when performing maintenance related work is calculated in the model.

4.1.2 B-times

B-times or Unplanned Delay in Execution Time is the sum of the unplanned disturbances during a service action between start and finish. ASML categorizes the root cause of these disturbances and defines 9 different categories of disturbances, as shown in Table 1. These 9 categories each have their own frequency of occurrence and average failure duration. Therefore estimating these values individually and taking the total sum of all the B-time categories will provide the total B-time Labor hours estimation. By using the existing data from the AIR database, an overview of the impact and frequency of the B-categories is estimated.

Table 1. B-time Categories

B1	Spare part availability disturbance
B2	Spare part quality disturbance
B3	CS Engineer induced disturbance
B4	Tooling induced disturbance
B5	Customer Facility induced disturbance
B6	Supporting software tooling disturbance
B7	Work preparation disturbance
B8	Design induced disturbance
B9	Customer process induced disturbance

4.1.3 Unscheduled Downs and Scheduled Downs

Service engineers work on service actions during either a scheduled down or an unscheduled down. With a scheduled down, the machine is planned to be turned off for a period of time. While during an unscheduled down the machine is turned off due to a system failure. In scheduled down scenarios engineers have time to prepare in advance, this could lead to a difference in the B-times that occur during a scheduled down compared to an unscheduled down. During preparation the engineers study the procedure and check their tools and parts, so that during the execution of the service actions the engineers know exactly what to do and have everything they need available to them. During scheduled downs, engineers are primarily susceptible for unforeseen failures, such as a part or tool breaking during the service action. During unscheduled downs the engineer does not know what service action is required to fix the machine and needs to determine that themselves. It is entirely possible that a part of the machine needs to be replaced while that part is not available for the engineer. This means that every B-category has a different estimated impact based on service action being performed during a scheduled down or an unscheduled down. Both are bound to occur therefore the B-categories are modelled twice, using scheduled down estimations and unscheduled down estimations.

4.1.4 Learning

ASML is able to identify the presence of learning due to data patterns seen on customer maintenance time. The learning curve effect was considerable, and a possible cause of inefficiencies. An integral part to the B-time estimation model is how it incorporates learning and estimates the B-time Labor hours over time. Providing an overview of the initial amount of labor hours required to maintain the EXE:5000 in the first years compared to 10 years after the model's introduction, will allow Customer Support to minimize the amount of excess engineers per machine while offering 24/7 customer support. The B-time Labor hours estimation model uses historic field data to determine the expected amount of B-time in labor hours. Defining a proper learning model will provide Customer Support with an estimation on the fluctuation of the B-time in Labor hours over time.

According to literature the most widely used learning cure is the Wright model, as seen in section 4.1. To model a learning curve a first year estimation of the B-times in labor hours and a learning rate needs to be determined. An estimation of the amount of B-time in Labor Hours in the first year can be made from historic data. To determine the learning rate, the moment of 'learning' needs to be identified. The definition of learning used is: "A representation of the correlation between a learner's performance on a task on the number of attempts or time required to complete the task". The 'learner' and the 'task' can be the service engineer solving a B-category disturbance. For example; during an unscheduled down the solution has been identified and a service action has been selected to solve the disturbance. However the service action requires a tool, this is a typical B1-Part Availability disturbance. The duration of the B-time is simply the time it takes to obtain the tool and continue working on the service action.

It is difficult to define where in this process learning has taking place, if at all. The engineer will not bring the specific tool the next time, as the engineer does not know whether or not the tool is needed therefore if this exact disturbance were to happen again the B-time will be the same. However in the case that the engineer simply makes an execution error during the service action, such as breaking off a piece of the machine, and causes a B3-Execution disturbance, learning does take place. Simply because if the exact same service action would be executed by the same engineer the engineer will not make the same mistake again. Every B-category has different failures, depending on the failure there is room for learning or not. Therefore for each B-category the respective learning rate must be determined. Identifying the exact moment of learning, and determining the learning rate is difficult. In the B-time Labor Hour model, the number of AIR-reports written for a B-category in a year is used to determine the learning rates of the individual B-categories.

4.2 Model Description

The key goals of the assignment was to create a B-time model that provides an overview of the different sources of B-time in labor hours. As well as to model the B-times overtime, as ASML notices a strong presence of B-times in the first years of introducing a new machine line but they decline over time. As mentioned above the main elements of the model are the B-categories, USD vs SD, and the learning rate. For this reason the model individually models learning curves for the USD and SD parts of all B-categories. This essentially means that the B-time Labor Hour estimation graph will be the sum of 18 individual graphs. Namely 2 graphs, a SD and USD graph, for each of the 9 B-categories.

The learning curve formula that is used to model all of the B-time graphs is the Wright Learning Curve. $Formula: Y(t) = at^b$

t = Machine Lifetime = The accumulative amount of years that have passed maintaining the EXE:5000
a = The amount of B-time in Labor hours required to maintain the EXE:5000 in the first year.
b = Representation of the Learning Rate (b = log 2/ log Learning Rate).
Y(t) = Average amount of B-time in Labor hours required to maintain the EXE:5000 for Machine Lifetime 't'.

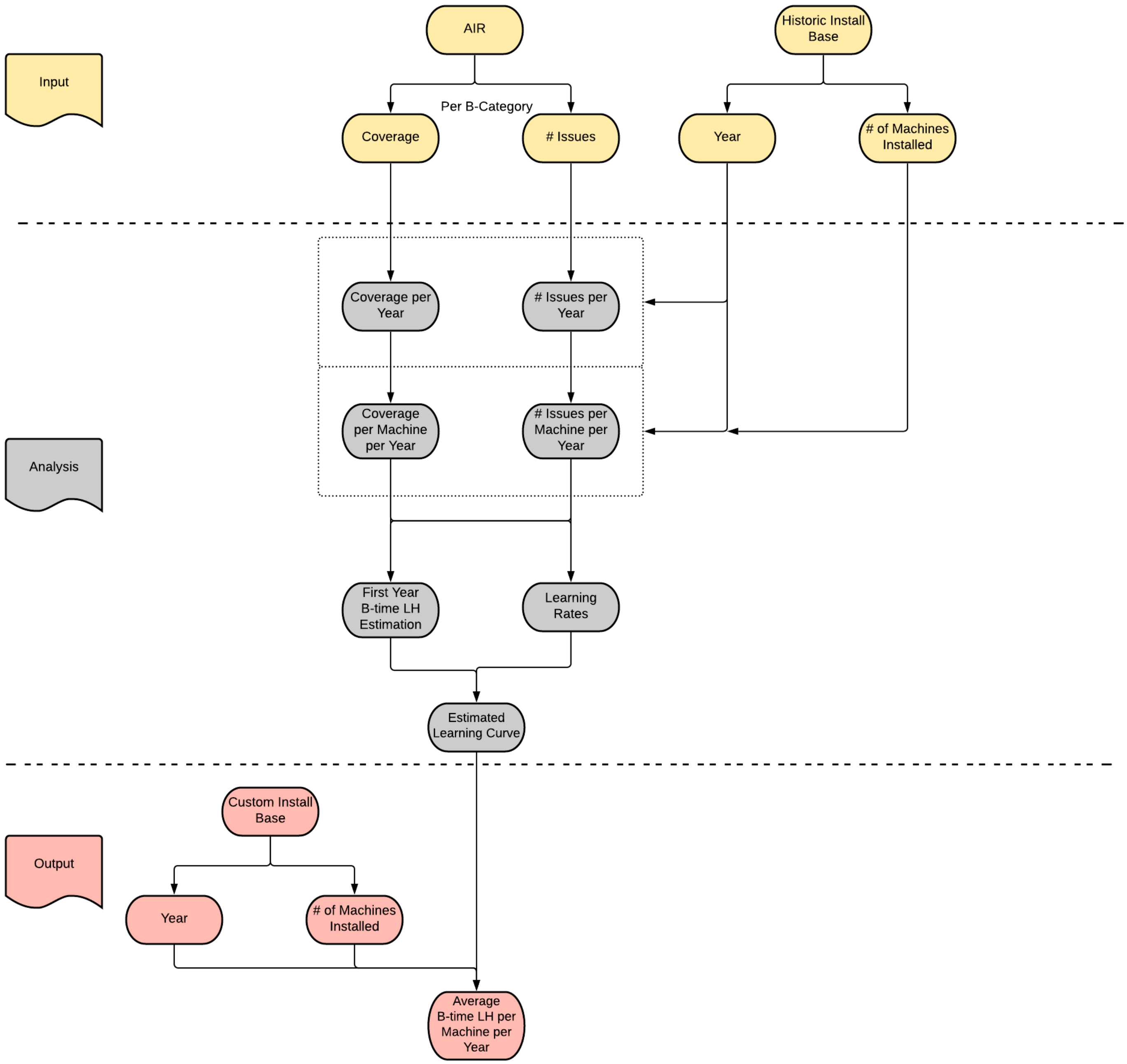


Figure 3. B-time Model Method

4.2.1 Model Inputs

This model requires an estimation on the B-time in Labor hours required to maintain an EXE:5000 machine in the first year. In the figure above the steps of the model are portrayed. There are 2 main inputs of the model. The model uses historic data to create its initial estimations on the B-times for the EXE:5000, and uses a concept to turn these B-time coverage hours into labor hours. This refers to AIR-reports and the Install Base of historic machines. For the estimation the estimation is based off of the machine line the NXE's. The scope of the Install Base and the selected AIR-reports are on all the NXE machines ,besides the NXE:3100, from 2014 to 2020. As 2014 was the first year an NXE machine reported an AIR-report, besides the NXE:3100. The NXE:3100 was omitted due to it being very poorly represented in the AIR-reports. Information within most of the reports was incorrect and the number of AIR-reports was very low. From this AIR-report dataset, duplicate reports were filtered out. As well as reports with coverage values that were greater than 20000 or less than 0, as these were considered outliers or errors. From the AIR-reports the coverage value can be taken, as well as the B-time category of disturbance that has occurred. The AIR-reports combined with the Install Base of all NXE machines, which is the information on what year what machine was installed in the field, the B-time Model can create its learning models for the B-categories.

4.2.2 Model Calculations

To create the Wright Learning Curve for the B-categories 2 variables need to be determined. The 'a' value, which represents the expected amount of B-time in labor hours for EXE:5000 in the first year. The other value is 'b', which is a representation of the learning rate. The model determines the 'a' and 'b' value for all B-categories, from the inputs.

The first step in calculating the learning curve is to determine the 'a' value of the Wright Formula. This value represents the expected coverage or # Issues in the first year, for the very first machine. To make an estimation on this first year value of B-time for a B-category, the first year B-time value of NXE machines was taken from the AIR-reports.

The next step is to determine the Learning Rate for each B-category. Learning is an abstract concept and it is difficult to define at what point in time learning occurs. The B-time Labor Hour model makes the assumption that learning is not related by the amount of time that has passed, but also how many machines are running in the field. One would expect that maintaining 2 EXE:5000's for a year will lead to more experience and knowledge on the machine compared to maintaining only a single EXE:5000. To keep track of how long EXE:5000 machines have been running the term Machine Lifetime is used. This value indicates how many years the EXE:5000 machine line has been running. It is calculated by taking the amount of machines running in a year and adding the Machine Lifetime of the previous year to it, shown in Figure 3. This is the X-axis on which the Learning Curves are plotted. The process of calculating the learning rate for the # Issues and for the coverage for each B-category is the identical. The learning rate of coverage as well as the # Issues per year is determined by first plotting the accumulative amount of issues over the Machine Lifetime, instead of plotting the # Issues per year for each year (e.g. 2014,2015, etc.,).

This will result in a rising curve that represents the total amount of issues that occur, shown in Figure 4. Dividing the total amount of Issues by the respective Machine Lifetime, will lead to a graph that shows the Average amount of Issues per Machine Lifetime, shown in Figure 5. Now the Average amount of Issues per Machine Lifetime, for certain Machine Lifetime points are known. A Wright Curve ($Y = aX^b$) can be determined from the points, and the given 'b' value can be used to calculate the learning rate of the B-category.

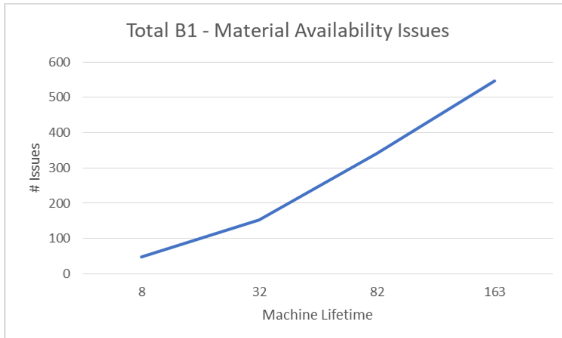


Figure 4. B1-Material Availability Total Issues

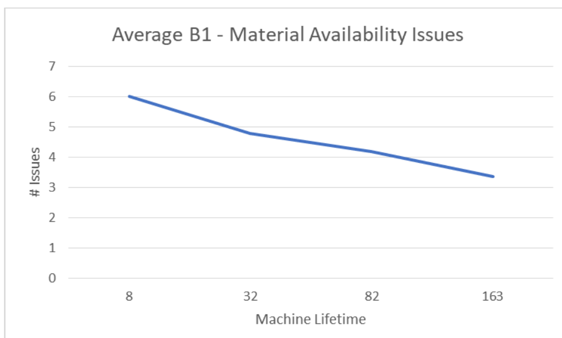


Figure 5. B1-Material Availability Issues per Machine

Using the found 'a' and 'b' values for each of the B-categories, learning curves for them can be plotted. However the coverage and the # of Issues learning curves still do not represent the B-times in labor hours. Therefore this B-time Labor Hour model transforms the coverage and # Issues values into Labor hours. This is a concept designed based off of the experience of experienced service engineers. Each time a B-time occurs, there are different Labor hours spent by the engineers. In this model 3 Labor Hour elements are identified. They are Labor hours lost to Failure, Labor hours spent to Solve, and Labor hours spent to Prevent. During the disturbance itself, an engineer can either be working on solving the disturbance, the amount of engineers solving the issue multiplied by the duration of the disturbance, represent the Labor hours spent to Solve. It is also possible that due to the issue, an engineer cannot continue the service action and cannot assist in solving the issue. The engineer is then idle for the duration of the issue, these are Labor hours lost to Failure. Lastly, once machine is running again, service engineers come together every time there is an issue and they discuss it to see if they can prevent the issue from occurring again.

The duration of this process multiplied by the amount of engineers participating is the Labor hours spent to Prevent. The sum of the 3 Labor Hour elements is the B-time in Labor hours. It is through this process that the total B-time in labor hour is estimated, shown in Figure 6. The three Labor Hour elements concept, to determine the labor hours based off of coverage and the number of Issues in a year, only creates a very rough estimation. However ASML has no data on the B-times that is in labor hours. The constants that make up the labor hour elements, such as the number of engineers idle, are values that are not measured in the field. They are roughly estimated based on engineer experience. The validity and accuracy of the estimation is limited due to this concept of 3 different labor hour elements.

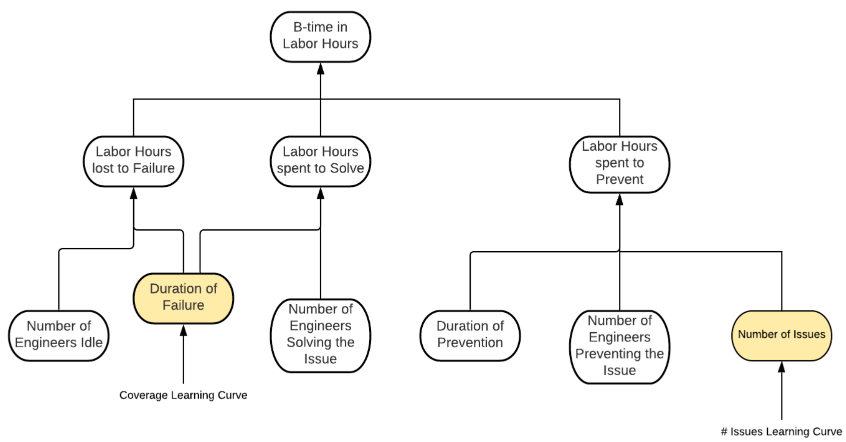


Figure 6. Three Labor Hour Element Concept Tree

4.2.3 Model Output

The curve that is formed by combining the 3 labor hour elements is in Figure 7 and Table 3. Note that the values are calculated off of placeholder values. The curve consists out of the 3 labor hour elements. The Labor Hours lost to failure and the Labor Hours spent to Solve, are formed from the coverage learning curve. The Labor Hours spent to prevent are formed from the number of issues learning curve. The curve indicates the average amount of B-time labor hours per Machine Lifetime, however by itself it is not very practical in determining the estimated amount of B-time in labor hours required to maintain a machine per year. This is because the Machine Lifetime, the X-axis, does not specify how many years have passed or how many machines are in the field. To be able to utilize the graph more effectively a tool has been added. The user input the install base for the EXE:5000. This is the “Total Machines Installed” line in Figure 9, also shown in the Output area of Figure 3. The install base indicates for every year the amount of machines installed. With this added information the average B-time in Labor hours per machine can be determined for each year.

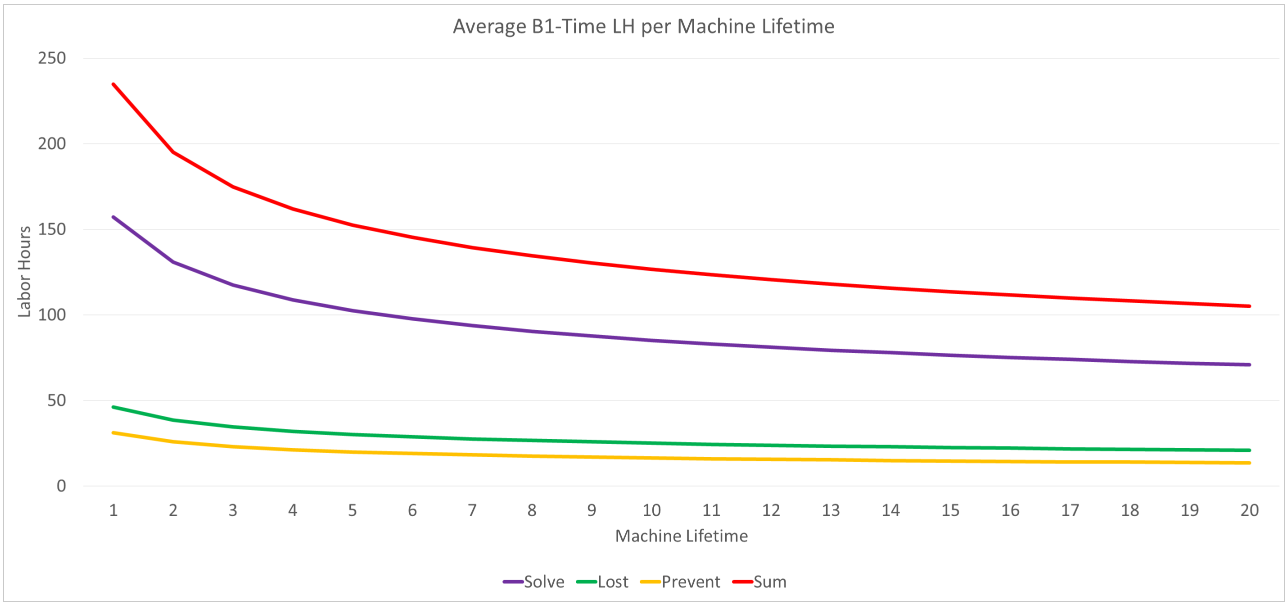


Figure 7. Average B1-Material Availability in Labor Hours per Machine Lifetime

Table 3. Labor Hour Element Curves Values

Labor hour Element	a (LH)	b
Labor hours spent to Solve Learning Curve	157.25	-0.2664
Labor hours lost to Failure Learning Curve	46.25	-0.2664
Labor hours spent to Prevent Learning Curve	6.25	-0.2793

Table 4. Machine Lifetime calculation

Install Base Machines in the field per Year				
Year	1	2	3	4
Total Machines Installed	1	2	3	4
Machine Lifetime	1	3	6	10

The Learning Curves of the B-categories are shown in the Figure 8. Depending on the selected Install Base, such as in Figure 9 where the Total Machines Installed each year is an input that can simply be changed. The Total Machines Installed combined with the Year, calculates the Machine Lifetime. This Machine Lifetime is used to determine the Average B-time in labor hours per machine each year, shown in Figure 9.

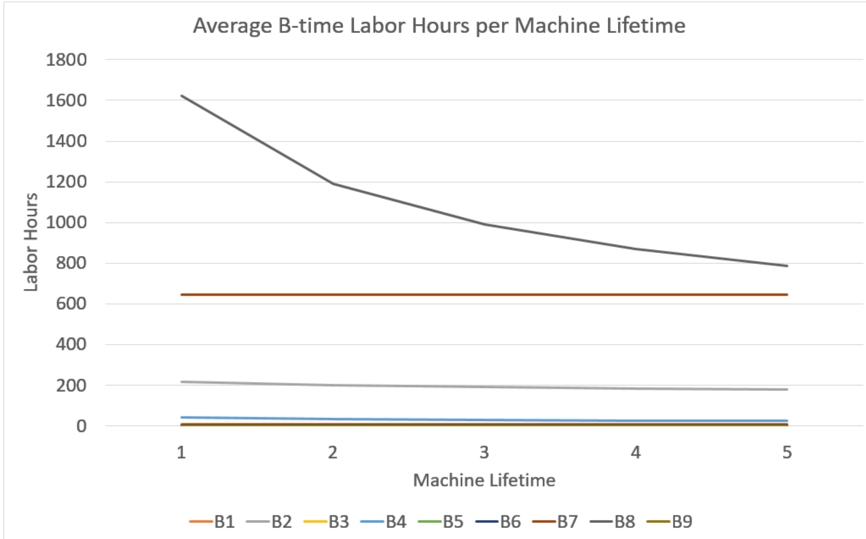


Figure 8. Average B-time Labor Hours Curve per B-category overview

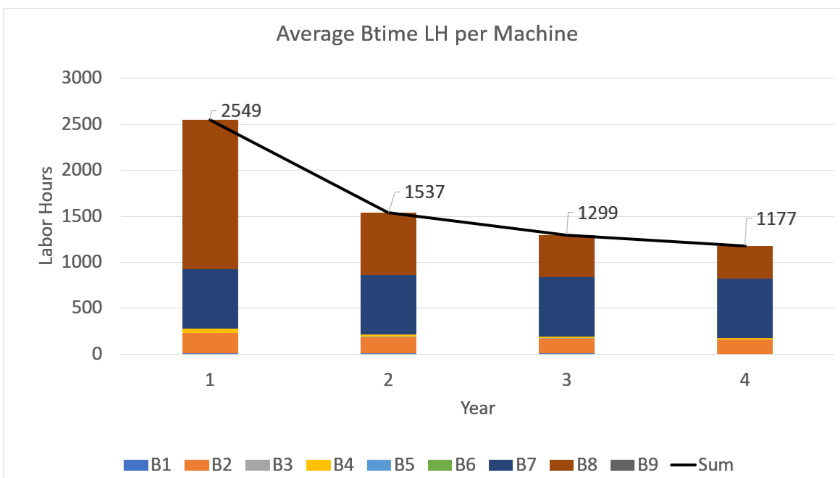


Figure 9. Average B-time in Labor Hours per Machine per Year

The following analysis on the output, is based on the actual AIR-reports used in the final model. A representation of the output is shown in Figure 9. From this output the B-categories with the largest impact can be determined. This namely B8-Design, B7-Work Preparation, and B2-Part Quality. What is notable is that the B-category that decreases the most with experience, is B8-Design. This is likely due to the fact that B8-Design disturbances are represented the most in AIR-reports, the ASML Issue Review system was initially created to solve design based issues. The category B7-Work Preparation experiences no learning, indicating that no learning takes place in this disturbance category. In this model the other B-categories are very low, specifically B5-Customer Facilities and B9-Customer Processes are 0. More outputs of the model are presented in appendix A.

4.3 Conclusion

B-times or Unplanned Delay in Execution Time. Is the sum of the unplanned disturbances during a service action between start and finish. There are many different root causes of disturbances, within ASML the B-time disturbances are separated in 9 categories. The model not only aims to estimate the amount of B-time labor hours that are made by the local service engineers for maintaining the EXE:5000, but to provide an overview of each of the B-categories and how they change over the lifetime of a machine. To achieve this the B-times will be modelled using the Wright Learning Curve formula ($Formula: Y(t) = at^b$). With 'Y(t)' representing the average amount of B-time labor hours in for Machine Lifetime 't'. The variables 'a' and 'b' need to individually determined for each B-category.

The 'a' and 'b' are determined by using data on a previous machine line, namely the NXE's, as input. The AIR-reports and the Install Base combined, create an overview of the average amount of issues and coverage per machine per year. From this input the 'a' and 'b' for both the amount of issues and coverage for each B-category, can be found. The 'a' value represents the expected coverage or # Issues in the first year, for the very first machine. It is determined by taking the amount of issues divided by the coverage per machine of the very first year in which NXE machines started reporting AIR-reports. The 'b' value is taken from plotting the accumulative values of issues divided by the coverage over the Machine Lifetime.

Once the 'a' and 'b' values are determined for both the amount of Issues and coverage, for every B-category, the model then uses the 3 B-time labor hour elements to determine the B-time in Labor Hours (Figure 3). The 3 labor hour elements are Labor hours lost to Failure, Labor hours spent to Solve, and Labor hours spent to Prevent. The learning curves created for both the amount of issues and the amount of coverage per Machine Lifetime are used to calculate the 3 B-time labor hour elements. The sum of the 3 labor hour elements represent the total B-times in labor hours, as shown in figure 6. Due to the 3 B-time labor hours elements only being a concept that is created with the model, the accuracy and validity of the estimation is limited. The limitations of the accuracy and validity are further explored in the Data Quality Assessment (chapter 5) and alternative methods to improve the method are seen in the Linear Regression section (chapter 6). The learning curves created however, are plotted over the Machine Lifetime. Using an interactive Install Base, where the user can input how many machines are installed in what year, the model can calculate the average B-time in labor hour per machine for each year.

The output of the model provides on overview of the impacts of all the B-categories. The B-categories B8-Design, B7-Work Preparation and B2-Part Quality have the largest impact, with B8-Design being the largest of all. This is primarily caused by the fact that in the introduction year of a machine unforeseen design issues are encountered. However B8-Design reduces rapidly as the machine matures, while B7-Work Preparation and B2-Part Quality remain constant. If ASML is able to reduce the initial impact of B8-Design, the B-time labor hours of the first year will reduce significantly. However it is difficult to reduce the amount of unforeseen B8-Design issues in the very first year. As ASML will always encountered unforeseen issues in the machine design and through the AIR-reports they identify and prevent them for occurring in the next installation of the machine. This is why B8-Design disturbances reduce rapidly. An area with more possibilities to reduce B-times is B7-Work Preparation and B2-Part Quality. B7-Work Preparation and B2-Part Quality show very little learning over time, for B2-Part Quality this is understandable. As B2-Part Quality are issues that are created repair parts being too low quality to be used in the machine. Besides improving the quality of all repair parts, the chance for parts breaking during the maintenance process will also be present. However improving the Learning Rate of B7-Work Preparation is feasible. By improving feedback loops, service engineer teams can also learn from each other. By universalizing learning and improving the way engineers prepare for a service action, both the initial B7-Work Preparation impact and the B7-Work Preparation impact over time can reduce. Local teams make different improvements to the work preparation, this local learning is extracted and globalized then all the local teams help each other improve.

Disturbance categories such as B5-Facilities and B9-Process are areas in which very little labor hours are lost. The expected amount of B-time labor is 0 for both of these B-categories. This suggests that there is very little to gain in this area. Instead, possibilities to integrate with other B-categories or to remove them entirely can be explored. This would reduce the amount of categories and complexity of the B-category system. By reducing the amount of resources spent on estimating, analyzing, and organizing these B-categories, the ASML Issue Review process could become more efficient.

5 Data Quality

In this section the different inputs of the B-time Labor Hour Estimation Model are analyzed. The quality and validity of the estimation are reliant on the quality of the input. The inputs are individually identified with their associated issues or limitations. After, the inputs are assessed utilizing existing data quality literature. By assessing the quality of the model's input, the validity of the output is also addressed.

5.1 Problems with the current process

In this section some of the issues regarding the information flow from field to management are mentioned. These issues provide explanation and context to why Customer Support is unable to estimate B-time labor hours and why Customer Support has not already addressed these issues.

The information flow from field to management through the use of AIR-reports and Service Orders, as described in the previous section, has its short comings. The current process is designed to keep track of the different actions performed and information regarding why the action was performed. Information that the AIR-reports provide do not align with the information that the Customer Support needs to make calculations regarding B-time Labor hours. AIR-reports are designed to keep an administrative log for ASML of what the engineers are doing to the machine and when. The issue is that it is not possible to simply request service engineers to keep track of extra variables (for example; number of engineers working on the machine during the action), because the time of service engineers is very valuable and increasing the length of the administration process is unfavorable. It is the role of management to support the service engineers and for service engineers that work in a high pressure environment, filling in reports and other administrative tasks can turn into a burden. Increasing the amount of information that an engineer has to input into the system will be met with resistance from the field engineers.

Another reason why Customer Support cannot simply request more information from the field, the quality of data that is received from the field first should be estimated. Requesting more data from the field, could simply result in more data of which the quality is too low to make valid calculations and conclusions. The goal of AIR-reports is to describe the failure in enough detail for engineers involved with the design of the machine, so that they can analyze common failures and solve them within the design of the machine. The field data that is being put into the system is dependent on the individual engineer. Engineers may work with different definitions and different descriptions than other engineers or management. This also occurs between ASML departments because B-numbers are differently defined over departments and regions. This means that one engineer will input a failure as a B3 failure, while another engineer will input the exact same failure as a B6 failure, while the manager reading the database believes that those failures are part of B1. This distorts sizes of the B-time numbers. The reason the B-time numbers were defined initially, was to categorize, analyze, and manage the different types of issues that can occur in the field. Some B-times are quite abstractly defined and it is up to the reader to determine what type of issues do fall under it. This essentially causes the B-numbers to lose their value. The data on B5 issues is questionable if, for example, half the issues of B5 are actually B7 and B3 issues in reality. The B-time Labor Hour Estimation Model relies heavily on the proper identification and reporting of the different B-categories. This area is especially sensitive as the amount of issues per B-category is used to determine the learning rate, which is used to curve all learning curves.

Another limitation that looking at the AIR-reports is that these reports are naturally skewed. AIR-reports are designed to explain why a certain service action took longer than expected, however an AIR-report is not always drafted. If the duration is very short or the second line engineer individually determines that the report is not useful, for example the issue was a B3 Execution failure and the engineer already knows that management will not address the issue, then it will also not enter the system. This means that the reports that are represented in the AIR-report database are skewed. Primarily B8 Design issues will be reported as these issues are can only be prevented by changing the design of the machine, which the engineers review board can do. While issues such as B7 and B3 can be reviewed by the local team internally and will not be reported as an AIR-report, however they still might have a considerable impact on B-time Labor hours.

Lastly, it is quite common that engineers do not input the duration of the failure, this can be for a wide range of reasons such as the duration of the failure was actually 0 or that the engineer simply forgot to input the actual duration or does not remember it. Another possibility is that the failure did not cause an increase in MTTR, therefore the engineer did not report it.

5.2 Data Quality Assessment

The B-time Labor Hour Model relies on the AIR-reports, as it uses AIR-reports of the NXE:3400 machine line to determine the Learning Curves of the B-categories. The reasons for why the AIR-reports have quality issues are mentioned above, in this section the extent of the quality issues are measured. There is no single test one can perform to assess the quality of data. There are many different dimensions of data quality that need to be considered, the ones used in this assessment are shown in Table 2. There are both subjective data quality assessments and objective data quality assessments. Subjective data quality assessments include the needs and experience of relevant stakeholders. The stakeholders can determine, from experience, the quality of the data. There are two forms of objective data quality assessments. One form can be applied to any data set and is considered to be task-independent. The other form integrates business rules, constraints and is created for specific applications. In this section the data used as input of the model is assessed both through different objective data quality assessments methods and a subjective data quality assessment is derived from conversations with relevant stake holders.

Table 2. Data Dimensions Definitions

Dimensions	Definitions
Accessibility	to what degree is the data available, or easily and quickly retrievable
Believability	to what degree is the data regarded as true and credible
Consistency	to what degree is the data unique as non repetitive
Completeness	to what degree is is data not missing
Free-of-Error	to what degree is the data correct and reliable

5.3 Subjective data quality assessment

Subjective data quality assessment is primarily based on the opinions of stakeholders that are involved with the data. There is no universal metric or scale on which these opinions can be placed, in this assignment the subjective assessment is simply; that a portion of the data is poor. Especially the AIR-report data set, the individuals whom use the program for its original use; to identify common root problems and to implement solutions for all respective machines, assessed that a large portion of the reports were lacking too much information to be useful. It is not possible to express on a scale how poor the stakeholders found the data, however with talking to experts involved with the data, they general consensus was that a portion of the data was not fully useable. Experts regarding the individual B-categories also mentioned that AIR-reports do not fully represent the B-times in the field. B-categories such as B7 are misrepresented. This supports the claim that the estimated B-times in labor hours should not be based solely on the current way AIR-reports are written. For the purposes of the subjective data quality assessment this result is satisfactory.

5.4 Objective data quality assessment

With objective assessments a set of values need to be determined that match the specific needs of the data consumer. In this case the data consumer will not be the original data consumer that the data is for, but the needs will be oriented to how effective the data is in representing the B-times. The functional form that is used to assess the quality of the data is the Simple Ratio. The Simple Ratio represent the amount of desired outcomes over the total outcomes, or the amount of undesirable outcomes over the total amount of outcomes minus 1. The value represents the amount of data that is desirable, indicating the quality of the data in a specific dimension with 0 being the least desirable and 1 the most. It is the aforementioned dimensions that are namely the hardest to define, these dimensions combined with the Simple Ratio will provide the objective data quality assessment. In AIR-reports model the most relevant values to determine the B-times are: B-time, coverage, Created date, Machine Type. These columns in the data set were used to represent the quality of data for determining the B-time. The result of the analysis is shown in Figure 10, and the definitions of the dimensions used are described below.

Free of error: This dimension indicates the amount of data that is 'correct'. This correctness is determined by checking if the value is plausible. For example the B-category needs to be a B-value between 1 and 9. Values such as B11 or A6 are deemed incorrect. In situations where the B-category is B3 and therefore plausible, the report can be deemed an error if the coverage is 0 or blank. For each of the 4 columns (B-time, coverage, Created date, and Machine Type) the Simple Ratio will be calculated for each dimension. This will give an indication of the quality of the individual columns, the Simple Ratio of the entire data entry will indicate the quality of the overall reports. Basically indicating how many reports are completely 'correct', without missing either the coverage of B-time category.

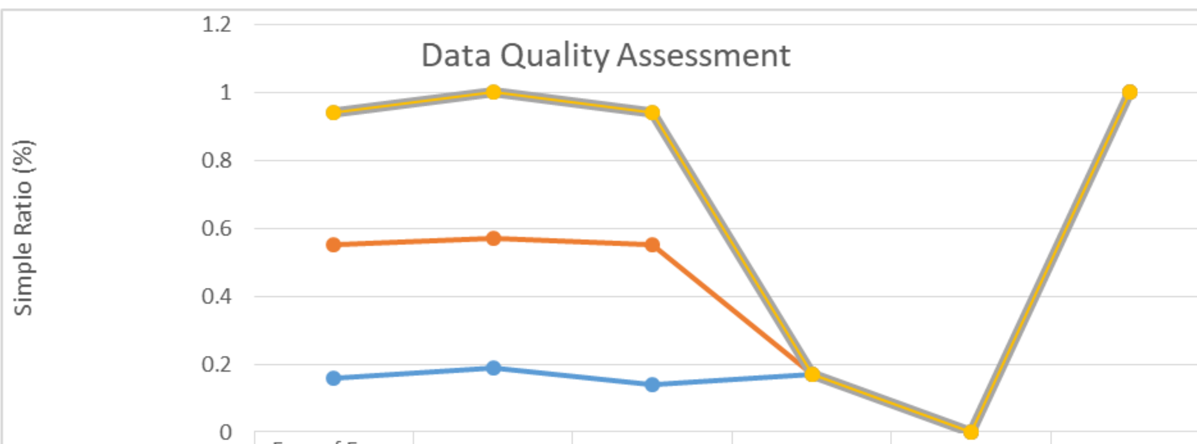
Completeness: This dimension will indicate how many reports are filled in. Regardless of error.

Consistency: This dimension will simply look to the overall database and identify the amount of unique reports. Each Issue has a unique Issue Number, the AIR-reports used in estimating the B-time Learning Curves only 17% of the reports have a unique Issue Number. This means that the same report appears twice in the database. This is likely caused by the fact that AIR-reports remain open if they are still under consideration or work. An engineer can change the coverage value of the open AIR-report, this causes the report to appear twice in the database, once without coverage value and once with. However this is not always the case, and many reports are duplicated without change.

Believability: This dimension determines how believable the data is. This is done by determining ranges in which the data is deemed believable. For example, coverage is an indication of how long a machine was kept down due to a failure. Technically a coverage value of 0 should indicate that no failure transpired. The range in which coverage is deemed "believable" is larger than 0 and less than 1000 hours. Negative coverages and coverage values entering the millions of hours, are not believable.

Timeliness: Indicates how long the data will hold its value. For example data that can predict the weather tomorrow is not useful the day after, as then the weather has already occurred. The Timeliness dimension of this data-set is high. Problems that happened in the past are always relevant when estimating the future B-times. The model uses historic data to estimate B-time therefore the report will never lose its value in the sense that the report indicates a moment of B-time. The moment of B-time can be used to represent frequency or impact of that B-time in a year. Therefore the Timeliness dimension of the data is 1.

Accessibility: This dimension focusses on what point in time does the data become available. In the case of AIR-reports and SO's, they can only be fully written once the engineer is finishing execution their tasks. The purpose of the B-time Labor Hour Model is to model Labor hours of the EXE:5000 over time. Currently the estimation approached assumes that the NXE:3400 will have comparable B-time Curves as the EXE:5000, this is not necessarily the case. The best data to predict the B-times of the EXE:5000 is to analyze the B-times of the EXE:5000, at which point the B-times have already occurred and the engineer team size has been determined. Therefore the Accessibility dimension of the AIR-reports is 0.



	Free of Error Value	Completeness	Believability	Consistency	Timeliness	Accessibility
Coverage	0.16	0.19	0.14	0.17	0	1
B-time	0.55	0.57	0.55	0.17	0	1
Created Date	0.94	1	0.94	0.17	0	1
Machine Name	0.94	1	0.94	0.17	0	1

Figure 10. Objective Data Assessment

5.5 Conclusion

From the Data quality assessment, it can be identified that the current AIR-report data set that is used to determine the Learning Curves and predict the B-time Labor hours for the EXE:5000, is limited. The result from the subjective data quality assessment is that the AIR-reports do not properly represent the total B-times experienced in the field. This will cause that the estimation generated from the B-time Model will also only represent a portion of the B-times. A way to compensate for this is to determine exactly what portion of the total B-times in the field is actually captured in AIR-reports and then to multiply the output of the B-time labor hour model to represent the total B-times.

From the Objective data quality assessment, it is apparent that the coverage column, the column in which the value for coverage is given in the AIR-report, performs poorly in all data quality dimensions. In all dimensions besides Accessibility, the coverage column scores less than 20% using the Simple Ratio. In each of these dimensions less than 20% of the coverage column held desirable and quality values. Indicating that coverage is a poor value to use to calculate the B-times with, as the data on it is of such a low quality. The column B-time, the column in which the B-time category is stated, scored better than the coverage column in the objective data quality assessment. In the Free of Error, Believability and the Completeness dimension, the B-time column scored around 55%. This still means that almost half of the reports hold undesirable B-time values in these dimensions. Similar to coverage, these scores are quite low. Indicating that the B-time in AIR-reports is not accurately depicting reality.

Lastly looking at the reports as a whole in the database, only 17% of all reports are unique. The AIR-report database is filled with duplicated reports, 83% of the reports are duplicated and need to be filtered out. The data quality assessment has shown that the AIR-report database is an inefficient database to accurately base B-times in labor hours off of. Both the qualitative as the subjective assessment have strongly indicated that the current B-time Labor Hour estimation that the model puts out is not accurately representing the oncoming reality, as the database used as input is of low quality.

6 Linear Regression

In chapter 5 the accuracy and validity of the B-time labor hour model estimation have been stated. Both the accuracy and the validity of the estimation leave a lot to be desired. In this section, ways to improve the validity and accuracy are explored. The service actions required to maintain the EXE:5000 are already defined, through Linear Regression features of a service action that link strongly with coverage are identified. Assessing what characteristics of a service action lead to coverage, can provide Customer Support insight to what data to collect from the field. In chapter 7 methods to collect data from the field effectively are explored.

6.1 Data collection

The Service Action list in the AvM, represents all the A-time related information for any service action that can be executed on a machine. For every service action a description is given, the required competencies, the MTTR (mean time to repair), the labor hours, and all related costs. The SA list is created before the machine is on the field, ASML invests a lot of resources in making sure that the values such as the MTTR are very accurate. The TopX is a representation of the service actions with the highest availability impact, these service actions hold a coverage value. The TopX is filled with service actions that were performed in the field and had a large impact on machine uptime and is frequently updated. This is because failures in the field can occur that need to be solved with a service action that does not yet exist in the AvM because D&E, the ones responsible for the AvM, did not foresee this failure. Once the failure has been resolved the service action is then added to the SA data set. The TopX also updates, if certain service actions prove to have large coverage values due to certain failures occurring. The TopX is therefore a representation of the service actions that currently have the largest impact on the machine uptime. A key difference between the TopX and the list of service actions, is that the TopX is formed only after the machine is used in the field and data is collected. While the list of service actions is created before the machine enters the field. Using the Availability Matrix of the NXE:3400 machine line, the TopX and the list of service actions can be combined into a single data set. This data set then holds for all TopX service actions, the service action information from list of service actions and the coverage value from the TopX, shown Figure 11. It is this database that is used for Linear Regression purposes in the following sections.

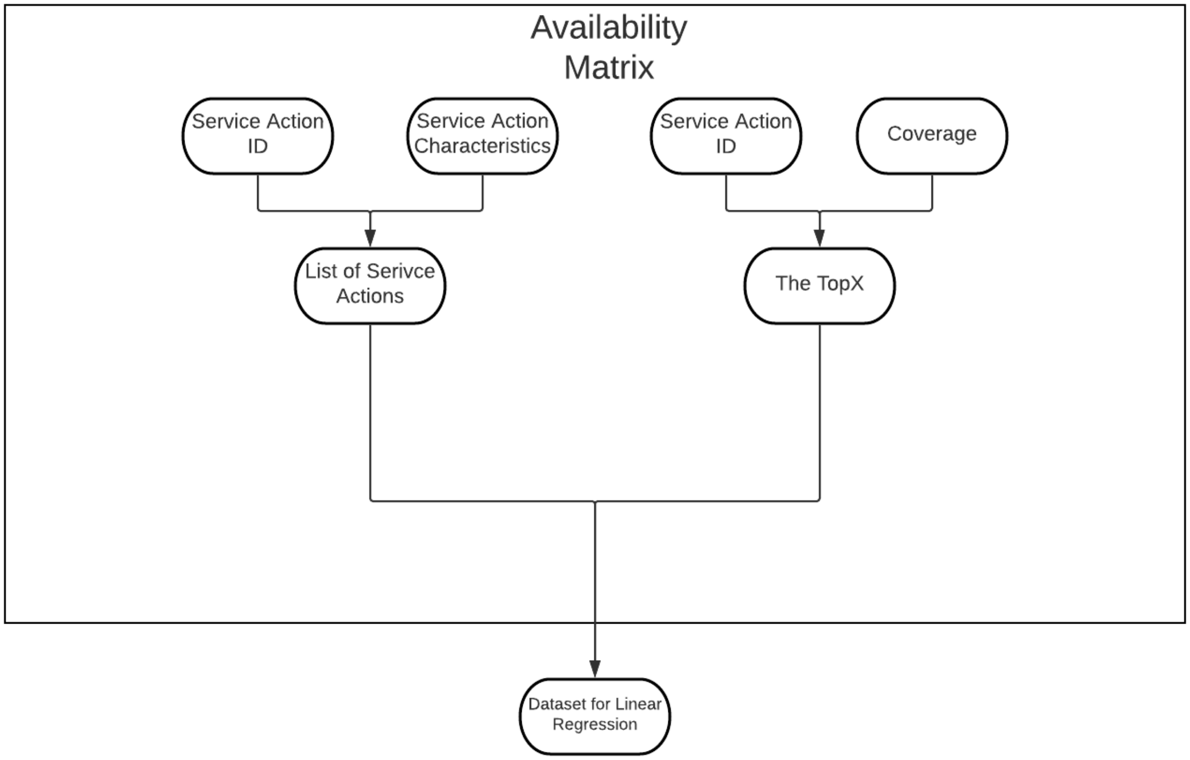


Figure 11. Data set creation

6.2 Linear Regression Approach

The linear regression is done using the created dataset shown in Figure 11 which is from the Availability Matrix of the NXE:3400. Using the created dataset, linear regression strategies can be applied to identify if a relationship exists between service action characteristics and the coverage value. All linear regression work is used within the statistical computing software R.

6.3 Feature Filter

The dataset created from the TopX and list of service actions, holds all of the information from the list of service actions and only the coverage value is taken from the TopX. This is because all of the service actions in the TopX are also listed in the SA list. The combined dataset, the one in Figure 11, holds only the service actions that are present in the TopX and shows the SA data set information on it, with the addition of the coverage value from the TopX. There are many columns that are not utilizable for linear regression. All column that held dates or unique written descriptions were removed. This is because the date in which the service action was performed or written is not a direct characteristic of a service action. Written descriptions and notes are also difficult to make use of in a linear regression. As they are long unique strings of text, which can't be effectively used in a linear regression model. Also columns that contain an ID of sort are removed. There are many columns that hold an ID, this is so that the service action can be found in other data bases. Lastly costs are also removed, because these values are primarily the estimated labor hours multiplied by a fixed number. The costs are simply a time value multiplied by a constant. After preparing the data there are 17 features, excluding the coverage, that describe 379 service actions.

Table 5. Total Features

ID	Activity ID
X1	Service Action Type
X2	frequency
X3	MTTR
X4	nr_persons
X5	SD
X6	USD
X7	XLD
X8	Part usage
X9	Total labor hours
X10	Diagnostic labor hours
X11	Diagnostic nr engineers
X12	Access labor hours
X13	Access nr engineers
X14	Replace labor hours
X15	Replace nr engineers
X16	Recovery labor horus
X17	Recovery nr engineers
Y	Coverage

The 17 features shown in Table 5, are the features used in this linear regression. Important to note is that all the features are quantifiable features besides Service Action Type, SD, USD, XLD, and Part usage. These 5 variables are qualitative features. SD, USD, XLD, and Part usage are either 0 or 1. With 1 representing that the service action is a Scheduled Down, Unscheduled Down, Extremely Long Down, and that parts are used during the service action. Extremely Long Down represents service actions which have experienced over 8 hours of delay, or B-time. Service Action Type is either a value between 1 and 5. Each value represents a different type of Service Action, such as Unscheduled Down No Parts, or Scheduled Down Maintenance. Service Action Type basically represents the different combinations of service action from SD, USD, and Part usage in one feature. However it also can indicate if a Scheduled Down is maintenance or not. The definitions of the following quantifiable features are shown below:

- Frequency: Represent how often a service action is performed on a single machine each year.
- MTTR: Stands for “Mean Time To Repair”, indicates in hours how long the machine is down for.
- Nr_persons: Represents the average amount of engineers required to perform the service action.
- Total labor hours: Represents the amount of labor hours spent to perform the service action. Note that this value only represents the labor hours spent when the machine is down.
- X10 – X17: ASML identifies 4 phases when performing a service action. The order goes as follows; Diagnostics, Access, Replace, and Recovery. The labor hours and the amount of engineers linked to each phase is given with these features.
- Coverage: Represents the amount of time lost due to a B-issue per machine per year, in hours.

6.4 Data preparation

The Z-score is used to detect outliers. Working under the assumption that the data is a normal distribution, values that exceed 3 times the standard deviations from the mean are removed. The data can also not be normally distributed, therefore the outliers are first identified with this method and then based on further analysis of the features the cut-off value is determined.

Not all service actions in the AvM, are completely filled out. To indicate a temporary assumption value an "easy way" is put down. For example the labor hours column might be blank, but the "easy way labor hours" will instead have a value. The easy way value represents an estimation and is not validated. In the used dataset all service actions that are not completely filled out, the easy way value is used to fill in blank columns.

If for a line of data more than 8 quantifiable features are 0, the line of data is removed. For features that have a value they can't have, such as a negative value for coverage (coverage is an indication of the duration of a task), an analysis is done. In most cases the report is removed however in few cases a value can be determined to replace the incorrect value. There are a few cases in which the coverage value is negative, most of these reports were -999 hours. These service actions are removed. After preparing the data, the total amount of service actions used for linear regression is reduced from 379 to 346.

6.5 Feature Selection

Backward selection was used to find the most statistically significant features. To perform Backward selection initially add all the features to the model and remove the feature which has the largest p-value. Once the feature has been removed fit the model and again remove the feature which has the largest p-value. This strategy removes the least statistically significant feature one at a time. Similar to forward selection the process stops once a stopping rule is met. A possible stopping rule could be the inverse stopping rule, backward selection is halted once all the features have a p-value below a certain threshold.

Table 6. Feature Selection Result

X1	Service Action Type
X2	frequency
X3	MTTR
X8	Part usage
X9	Total labor hours

The remaining features after performing backward selection are shown in Table 6. Removing features increases the total p-value. After defining the best set of features through backward selection, interactions within the features are added. Interactions are simply when the features are multiplied with each other to create a new feature. The features become connected and are able to more accurately correlate with coverage. It is these features and the interactions with each other that are used in the 5-fold cross validation.

6.6 Performance results

Before the linear model is validated, the selected features can be ranked on training errors. In Table 7 the features are listed. Note that the service action type feature has 5 different categories, the averages have been taken in this table. The standard error, is a simple performance measure, it is an estimation of the expected error when calculating the difference between the actual value and the predicted value. The larger the standard error, the larger the expected error between the prediction and the actual values. The p-value is a simple indication of how likely the null hypothesis can be rejected. The smaller the p-value the more likely there is an actual relationship within the data. Note that in Table 7 the total labor hours feature has a very high p-value, this is caused by the fact that the linear model also includes interractions between its features. Therefore a combination variable of the total labor hours and the frequency can take away the statistical significance of the total labor hours variable on its own. Removing the interacctions between features will then again place the statistical significance back on to the total labor hours variable on its own again, and the the p-value will drop significantly. Graphs on other basic performance measures of the linear regression model are in appendix B.

	Standard Error	p-value
Service Action Type*	0.003109053	0.002895
frequency	0.004470508	0.004971
MTTR	1.553	0.00019
Part usage	0.002757202	7.78E-05
Total labor hours	0.369148148	0.700723

Table 7. Feature results

The performance of the linear regression is determined through the 5-fold cross-validation method. With the 5-fold cross-validation method the data set is split in five folds, four folds are used to train the model and the last fold is used to test the performance of the model. This is repeated so that each fold is used as testing fold once. There are many different folds that can be made and depending on the folds selected the resulting model will perform better or worse. This is way the results of the 5-fold cross-validation is repeated 5 times and the average of the results are taken. The performance metrics in which the result is measured are; R^2, RMSE, and MAE, as explained in section 4.3.

Table 8. Linear Model performance result

RMSE	R^2	MAE
3.505	0.504	0.488

The performance of the models are shown in Table 8. Note that the 5-fold cross-validation process was repeated five times and the average of the results were taken. The results of the predictive model are rather poor. R^2 is a value that preferable should fall between 0.7-1, the 0.504 value of this model indicates that the variance is not sufficiently explained by the input variables. Both the MAE and RMSE values are rather high. As the data is normalized these values are also effected by the change. The MAE of 0.488 doesn't indicate that the average error of the model is 0.488 hours, in reality the model is on average ~50 hours off of the actual output. This means that the data used and the model created is not accurate and valid enough to be taken as a predictive model.

6.7 Conclusion

The accuracy and validity of the estimation of the B-time labor hour model leaves a lot to be desired. Improving field data collection systems could be a strategy to improve the B-time labor hour model in its estimations. Identifying what characteristics commonly link with coverage, will give insight on what service action characteristics should be tracked. To determine what characteristics of service actions lead to coverage, a linear regression is performed on the AvM. A combination of the list of service actions held in the AvM and the TopX is formed. This dataset links the information listed in the AvM on service action with the coverage values listed in the TopX. The TopX shows the service actions which have the largest impact on the machine up time each year. For these service actions a coverage value is listed, if a coverage value is present. The dataset is formed as shown in Figure 11. Through the backward selection method, the features which have the largest correlation with coverage are identified, shown in Table 6. These features indicate the critical characteristics of service actions in relation to coverage.

The two common themes that become apparent from the remaining features, is the duration of the service action and the type of service action. It is these characteristics that are for Customer Support interesting to collect and integrate in their data systems. The predictive performance of these features is also measured through the 5-fold cross-validation. The average scores are shown in Table 8 these results still leave a lot to be desired. With a low R^2 and high RSME and MAE, the predictive performance of the created model is poor. A direct explanation for the poor prediction performances, could be that the relationships between the input variables and the output, is not linear. Linear regression performs best under the assumption that the input variables have a linear relationship to the output variables. The low scores could also be attributed to the fact that in the dataset used coverage is not always present, almost half of the service actions are noted without coverage. The model will identify when coverage is present over predicting the exact value of coverage. Combing more AvM's and increasing the amount of data entries could address this issue. Instead of aiming to predict coverage as a continuous value, the problem could also be changed to a classification model. Utilizing other predictive models as well, a model could be formed that could predict what characteristics are likely to encounter coverage of any kind.

7 Conclusion

In this chapter the results and the findings of chapters 4,5 and 6 are discussed and connected. The final result of the thesis is then drawn upon the conclusions from chapters 4,5 and 6. This chapter also discusses progress and results of the assignment provided by ASML. Areas in which work can continue are also mentioned. Lastly this chapter summarizes both the practical and theoretical contributions of the work.

7.1 Conclusion

One of the roles of the Customer Support department is to predict how many service engineer labor hours a certain design of a machine will require. Once the total amount of labor hours required to maintain a machine for a year have been determined, CS can calculate the appropriate team size. The prediction of the total amount of labor hours is primarily based on the design of the machine over field data. The CS department make their estimation primarily on experience and history. They do not distinguish between different types of labor hours. ASML identifies 3 different types of 'time'; A-time, B-time, and C-time. Within the assignment the A-time and C-time are modelled separately by a colleague. The summation of A-time, B-time, and C-time will provide ASML with a bottom-up assessment of the total labor hours required to maintain the EXE:5000.

In this assignment a B-time Labor Hour model is created, with historic data of older machines an estimation of B-times are made. From the overview of the different impacts of the B-categories, conclusions can be drawn. Assuming that the AIR-reports represent the B-times actually experienced in the field, the B-times can be classified on their impact. The B-categories B8-Design, B7-Work Preparation and B2-Part Quality have the largest impact, with B8-Design being the largest of all. This is primarily caused by the fact that in the introduction year of a machine unforeseen design issues are encountered. However B8-Design reduces rapidly as the machine matures, while B7-Work Preparation and B2-Part Quality remain constant. If ASML is able to reduce the initial impact of B8-Design, the B-time labor hours of the first year will reduce significantly. However it is difficult to reduce the amount of unforeseen B8-Design issues in the very first year. An area with more possibilities to reduce B-times is B7-Work Preparation and B2-Part Quality. B7-Work Preparation and B2-Part Quality show very little learning over time, for B2-Part Quality this is understandable. As B2-Part Quality are issues that are created repair parts being too low quality to be used in the machine. Besides improving the quality of all repair parts, the chance for parts breaking during the maintenance process will also be present. However improving the Learning Rate of B7-Work Preparation is feasible. By improving feedback loops, service engineer teams can also learn from each other. By universalizing learning and improving the way engineers prepare for a service action, both the initial B7-Work Preparation impact and the B7-Work Preparation impact over time can reduce.

On the other hand B5-Facilities and B9-Process are areas in which very little labor hours are lost. The expected amount of B-time labor is 0 for both of these B-categories. This suggests that there is very little to gain in this area. Instead, possibilities to integrate with other B-categories or to remove them entirely can be explored. This would reduce the amount of categories and complexity of the B-category system. By reducing the amount of resources spent on estimating, analyzing, and organizing these B-categories, the ASML Issue Review process can become more efficient.

The output of the model however does have its limitations, namely the fact that its estimation is roughly based on AIR-reports. ASML Issue Review or AIR, is designed to reduce the amount of recurring issues of a machine. Local engineers team can write an AIR and describe the issue to Central Support, who can then change the design of the machine to resolve the issue. There are two main issues with this, namely the accuracy and validity of the estimation created by the B-time labor hour model is linked to the accuracy and validity of the AIR-report used as input. If they do not accurately represent reality, then the B-time estimation will not be accurate. The second issue is that AIR-reports do not report the B-time in labor hours, instead they report in coverage. Coverage represents the disturbance in regular hours. To compensate for this the model estimates how much labor hours are linked to a single hour of coverage. This depends on the amount of engineers working on the disturbance. ASML has no data on this, therefore a concept of different labor hour elements is formed based on engineer experience and rough estimations. These are the two issues which limit the accuracy and validity.

From the Data quality assessment, it can be identified that the current AIR-report data set that is used to determine the Learning Curves and predict the B-time Labor hours for the EXE:5000, is limited. The result from the subjective data quality assessment is that the AIR-reports do not properly represent the total B-times experienced in the field. This will cause that the estimation generated from the B-time Model will also only represent a portion of the B-times. From the Objective data quality assessment, it is apparent that the coverage column, the column in which the value for coverage is given in the AIR-report, performs poorly in all data quality dimensions. In each of the given dimensions less than 20% of the coverage column held desirable and quality values. The column B-time, the column in which the B-time category is stated, scored better than the coverage column in the objective data quality assessment. The B-time column scored consistently around 55% in the respective dimensions. This still means that almost half of the reports hold undesirable B-time values in these dimensions. Similar to coverage, these scores are quite low. Indicating that the B-time in AIR-reports is not accurately depicting reality. Lastly looking at the reports as a whole in the database, only 17% of all reports are unique. The AIR-report database is filled with duplicated reports. The data quality assessment has shown that the AIR-report database is an inefficient database to accurately model B-times in labor hours off of. Both the qualitative as the subjective assessment have strongly indicated that the current B-time Labor Hour estimation that the model puts out is not accurately representing the oncoming reality, as the database used as input is of low quality.

The accuracy and validity of the estimation of the B-time labor hour model leaves a lot to be desired. Improving field data collection systems could be a strategy to improve the B-time labor hour model in its estimations. Identifying what characteristics commonly link with coverage, will give insight on what service action characteristics should be tracked. To determine what characteristics of service actions lead to coverage, a linear regression is performed on the AvM. Through the backward selection method, the features which have the largest correlation with coverage are identified in Table 6. Namely the duration of the service action and the type of service action, are strongly correlated with coverage. A 5-fold cross-validation is done to measure the predictive performance of the model and the results still leave a lot to be desired. With a low R^2 and high RSME and MAE, the predictive performance of the created model is poor.

The goal of the model, however, not to predict the coverage of the EXE:5000 through the AvM and machine learning. As this would not provide Customer Support the bottom-up overview they require. The goal is to identify what characteristics are relevant for Customer Support to measure from the field. Based off of the linear regression model these are; Service Action Type, frequency, MTTR, Part usage, and Total labor hours. If these are accurately tracked and used as input for the B-time labor hour model, the accuracy and validity of the labor hour model would increase. By putting the service action sequence on a smart device that simultaneously tracks the duration of the individual steps, that is also functional during failures, it becomes possible to track accurate field data without interfering with the service engineers. From this research, creating database that holds labor hour information of service engineers is, that is constantly updated by the incoming data from the field is recommended. Linking a database that is shows failures in real time with the B-time Labor Hour model will increase its accuracy and validity. The database could also open further possibilities for ASML to create analytical and predictive models, that function on a bottom-up perspective.

This assignment as a whole is one that will continue to run. Estimating the B-times in labor hours for the EXE:5000 is a first step. Through this assignment different problems have been identified. Primarily the lack of data on labor hours that is measured in the field. As well as the data quality of not only the AIR-database but other systems as well. Information on a disturbance instance can be poorly connected across datasets, making the information on disturbances quite limited. The MPSM-cycle method made navigating these issues possible, by creating separate solutions for different problems. The data quality assessment and the creation of the linear regression model where solutions to address the limited accuracy and validity of the model.

7.2 Discussion

The purpose of this assignment was to address the hole that the Customer Support has regarding labor hours data from the field. This was the first phase of an assignment that will last much longer. In this initial thesis many different aspects of the assignment were touched upon, within each of these topics further research could be added. The B-time labor hour model is not fully complete. It is a model that has room to expand and improve. For example, the nine B-categories consists out of disturbances that occur during either an unscheduled down or a scheduled down. The B-categories could each consists out of 2 individual curves, with each their own 'a' and 'b' values. The reason this current was not possible is due to AIR-reports not indicating if the disturbance was on an unscheduled down or a scheduled down, however in the future this could change. With the introduction of the EXE:5000 ASML plans on integrating the recommended changes mentioned in Chapter 9 Recommendations. Once Customer Support is able to create a database that gives a real time overview of the disturbances occurring in the field in labor hours. A database such as this could be used to explore other avenues of bottom-up B-times that are currently not conceivable. The automated data collection systems ASML plans on implementing could provide detailed information of every step the service engineers make. This could mean that both A- and B-time could accurately be measured, and an analysis could be done on the relationship between A- and B-times. Lastly large and accurate databases would allow for more complex deep learning predictive models to be developed. These models could then predict B-times for future machine lines. This assignment is a first step into improving bottom-up estimations, by shedding light onto the information flow between the field and management. There are many directions in which this project can further develop, either more focus on the nature of B-times and how they fluctuate or learn over time, or a larger focus on improving data collection systems and using machine learning for accurate estimations.

7.3 Contributions

7.3.1 Contributions to practice

There are many insights this research provides ASML. As this was the first stage of a longer assignment, many discoveries and possibilities regarding the topic have been established. An assessment of exactly what, relevant, information from the field exists within ASML has been determined. As well as the limitations of using these datasets are both established and addressed. The initial investigation of the AIR-report database also provides insight to both the quality of the AIR-report database as well as insight on the impacts of the different B-categories on machine uptime. Through this assignment ASML has a better understanding of the possibilities of creating a bottom-up labor hour estimation model, as shown in chapter 7.2. This research also provides ASML recommendations on what actions to take next that will benefit the current labor hour model. These recommendations are clarified in chapters 7 and 8.

7.3.2 Contributions to theory

This research was primarily ASML specific, therefore the contributions to wider theory is quite limited. This thesis however does touch upon a few different literature fields. The research applies literature from the topics of machine learning, learning curves, and data quality assessments, onto the ASML specific case. The way the theory is administered as well as the results of this research can provide insights and guidance to future works.

8 Model Recommendations

The primary issue with estimating B-times labor hours, is that there is no standardized flow of information from the field tracking B-time labor hours. ASML uses the AIR-report data base to track issues in the field identify common root causes and create solutions for them. In the AvM all information on all service actions is listed, including their impact on availability. The service actions with the highest impact on machine availability are listed in the TopX. In this section the benefits of combining these datasets for the purposes of Customer Support are explored. The results of the Linear Regression are taken to help indicate what variables are key for Customer Support to track, to help estimate the expected labor hours. In this section strategies and issues are discussed regarding how to measure these features.

8.1 Recommendations

There are two main areas in which the Total B-time Labor hours required to maintain the EXE:5000 estimate can improve. The first area is simply the quality of data that is taken from the field can improve. Engineers in the field work under high pressure and stress. It is not to their direct interest to spend long periods of time inputting the data of their work into the database. This is also seen in their behavior, if they write logs and request help from ASML's Central Support and don't receive it, they will stop writing the respective logs. Requesting the service engineers to log more data on things such as B-times in Labor hours and more, without the service engineers seeing the direct benefit of the process will lead to engineers not logging the information. Or even if the requested data would be to log the risk exists that due to the existing issues, as previously mentioned(data being left out, improperly put in, engineer using different definitions, etc.,), the extra asked data will still not be enough to estimate the labor hours with. The more time service engineers will need to spend on logging, the more benefit they need to receive to compensate for their time.

Implementing a system that can supply the CS department with high quality field data will require to reduce the 'human error' element (inaccuracies from the engineers) while not increasing the amount of time spent on inputting information into the databases. A type of autonomous system that uploads relevant data without interfering with the engineers, fits this criteria. The specific data that CS is interested in is labor hours and the labor hours spent on different tasks. Especially, the labor hours during and around a service action.

By adapting the service action sequences into a digital check list and using smart devices such as phones or tablets, to check off the completed tasks, the individual steps of a service action can be recorded. The smart device can simply track the time it takes to move from one task to the next. In the service action sequence the amount of engineers to perform a certain task is already known (and could even be reported to the smart device during the service action), this way all involved service engineer and the entire service action can be accurately logged and the labor hours are known. This system can work especially well in scheduled down situations when the service action is known and the procedure for it is available. In the cases where the engineers come across an issue, the possibility to report delay can also be implemented. The engineer can report a delay during one of the steps in the procedure and smart devices can keep track of the duration of the delay. The smart devices enable engineers to accurately keep track of the duration of individual steps, which in turn can later be identified as A-time, B-time, or C-time. This system could enable Customer Support to collect high quality data without interfering with the engineers. Using smart technology ASML can track all the actions the engineers are making, giving Customer Support information on everything the engineer is doing.

ASML can not only improve how they measure field data, but also what they measure. The second area in which the B-time labor hour estimation model could improve is by offering it more B-time Labor Hour specific data, through the creation of a database specific to the needs of Customer Support. ASML uses many different databases and systems to keep track of specific aspects of field performance, however there is not one regarding the labor hours of the engineer teams. The B-time Labor Hour estimation model as well as the linear regression analysis on the TopX indicate what features are important to estimate the B-time labor hours. The B-time Labor Hour estimation model uses AIR reports as input to make its estimation. However it uses different variables to convert coverage into Labor hours. In Figure 12 the variables that the B-time Labor Hour estimation uses to make its estimation. The model calculates every B-category from the bottom-up, therefore for every B-category it requires variables to determine the Learning Curve.

LABOR HOURS SPENT TO SOLVE Number of engineers needed to solve (# Engineers)	
B-Category	**Average**
B1	1.7
B2	1.2
B3	2
B4	1
B5	0
B6	1
B7	1.8
B8	1.5
B9	1

LABOR HOURS LOST TO FAILURE Number of engineers lost to Failure (# Idle Engineers)	
B-Category	**Average**
B1	0.5
B2	0.8
B3	1
B4	0.2
B5	0
B6	2
B7	1.4
B8	1.8
B9	0.9

LABOR HOURS SPENT TO PREVENT Number of engineers spent to Prevent (# Engineers)	
B-Category	**Average**
B1	1.5
B2	1.6
B3	2
B4	1
B5	0
B6	0
B7	1.8
B8	1.5
B9	0

LABOR HOURS SPENT TO PREVENT Time spent to prevent (Hours)	
B-Category	**Average**
B1	0.5
B2	0.7
B3	0.8
B4	1
B5	0
B6	0
B7	1.3
B8	1.8
B9	0

Figure 12. Labor Hour Element constants

If Labor hours are directly measured from the field, the need to convert coverage into Labor Hour is removed. This reduces the amount of variables and estimations involved, and both simplifies and increases the validity of the model. In this database features are added that would give the B-time Labor Hour model even more avenues to do analysis on. Such as the FC column, this indicates what part of the machine the issue was on. It will allow the B-time Labor Hour model to create an overview of the impacts of different parts of the machine. It will also help indicate what type of engineers are needed most, for if the lenses of the machine break frequently an engineer with that competency will be needed often.

With small adjustments the B-time labor hour model can use a database such as in Table 9, to have a much more accurate estimation of the B-times in Labor hours for future scenarios. A database like this could offer much more room for analysis on labor hours, as more data is being tracked. Also this data set can support machine learning algorithms that can be used to estimate B-times.

Table 9. Database Example

Failure ID
B-time
Idle Labor Hours
Solving Labor Hours
Prevention Process Labor Hours
Total B-time Labor Hours
Funcitonal Cluster
Machine Type
Machine Number
Data of Issue Occuring
MTTR
Service Action Type
Scheduled Down
Unscheduled Down

8.1.1 Recommendation limitations

There are some shortcomings and challenges that remain with utilizing smart devices and creating a Customer Support specific database. The main issue with using a system that creates a digital checklist for service engineers to use during maintenance, is that there are many different situations that can occur as soon as the machine goes down. The software should be able to identify all of the different permutations while remaining simple to navigate for the engineer. This is currently already being worked on by ASML. They too believe that they should centralize the data they try to collect and make it easier for engineers to log their work. For the EXE:5000 ASML will create a central database, in which all field data will be uploaded to. As well as a system to organize this database and make it simple for different departments to find what they need.

Another issue that remains unaddressed is the difficulties surrounding categorizing failures in the correct B-category. The engineers in the field are highly skilled and well trained in all aspects of their work, however errors are human. Due to abstract definitions and ambiguous failures that can occur, misplacement of a failure in the wrong B-category can occur. If these misplacements are too frequent then the value of the B-categories must be pulled into question. Dividing failures into categories, opens up many different analytical possibilities and grants managerial benefits as well. By isolating different types of failures and making individuals responsible for a certain B-number, failures can systematically be addressed and their impact reduced. However, if the average accuracy of field engineers placing failure in the 'correct' category is lower than ~60%, all following analysis loses value. If a large portion of the failures are misplaced, it will cause that the overview of the B-categories will not be representative of what is truly happening in the field and any analysis performed on that data will decrease in validity. For the B-category system to be effective failures need to be categorized accurately. There currently is not a defined KPI that indicates B-category placement accuracy, the only indications that engineers sometimes struggle to place failures is the occurrence of B0 or 'blank' within the AIR-report. ASML could launch a research to determine how accurate are the failure placed, this could simply be done creating a failure placement test. Using real world AIR-reports, scripted failures can be prepared and described to a group of service engineers. A comparison can be made with the service engineer's failure placement with the actual 'correct' placement to determine their accuracy. A research such as this could support the validity of all analysis's on B-categories.

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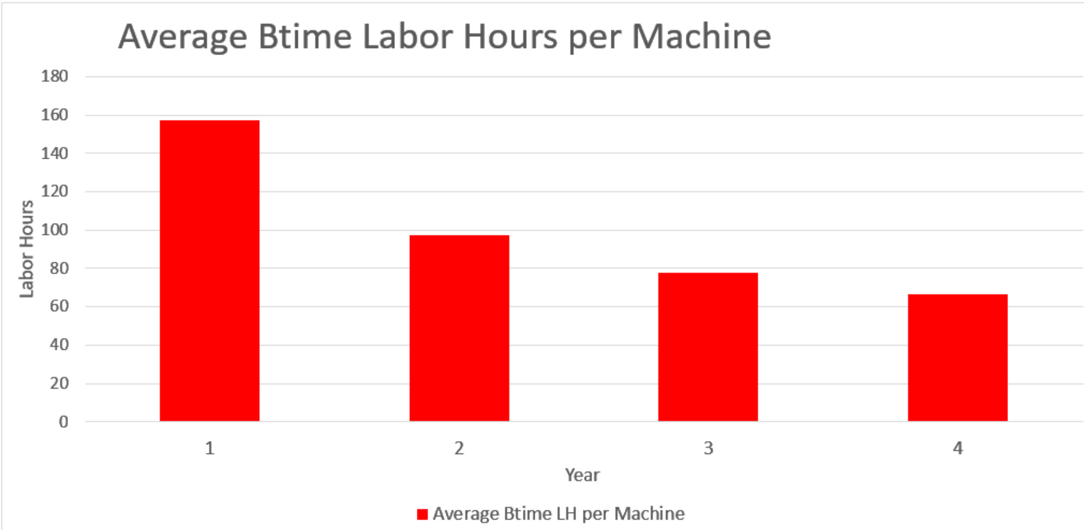
Appendices

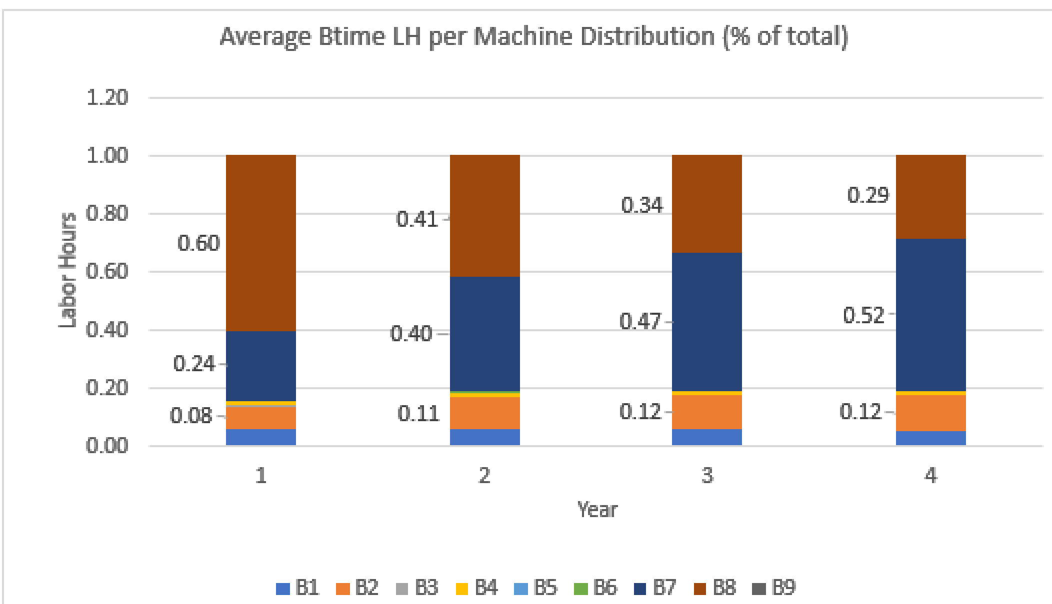
Appendix A



Average B1-time in labor hours per machine, for a certain install base.

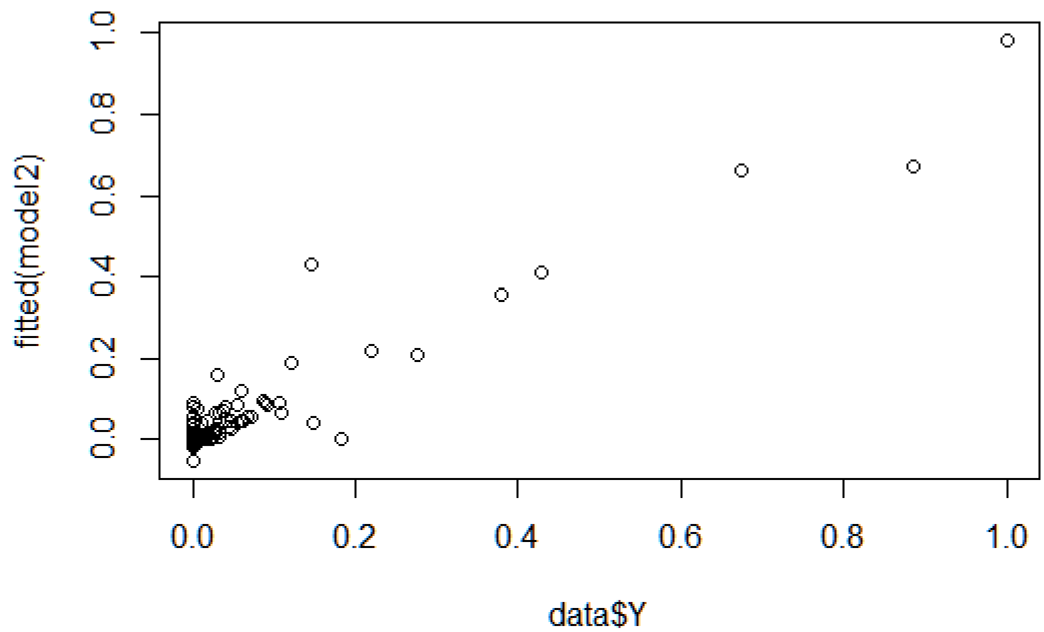
VARIABLES		Btime Estimation Settings
SD%		0.4
USD%		0.6
COVERAGE Learning Rate Issue per Machine (variable)		-0.266354378
Estimated Coverage in a year (hours)	min	32.41975309
	ave	56.61743827
	max	92.5
	first year	92.5
Estimated Issues in a year (Nr of issues)	min	2.098765432
	ave	3.674691358
	max	6.25
	first year	6.25
Nr Engineers needed to solve		1.7
Nr Engineers Lost to Failure		0.5
Nr Engineers needed to prevent		1.5
Average time needed to prevent (HOURS)		0.5
Issues learning rate		-0.279302857
Issues First year value		6

B1-time Estimation model constants and variables.

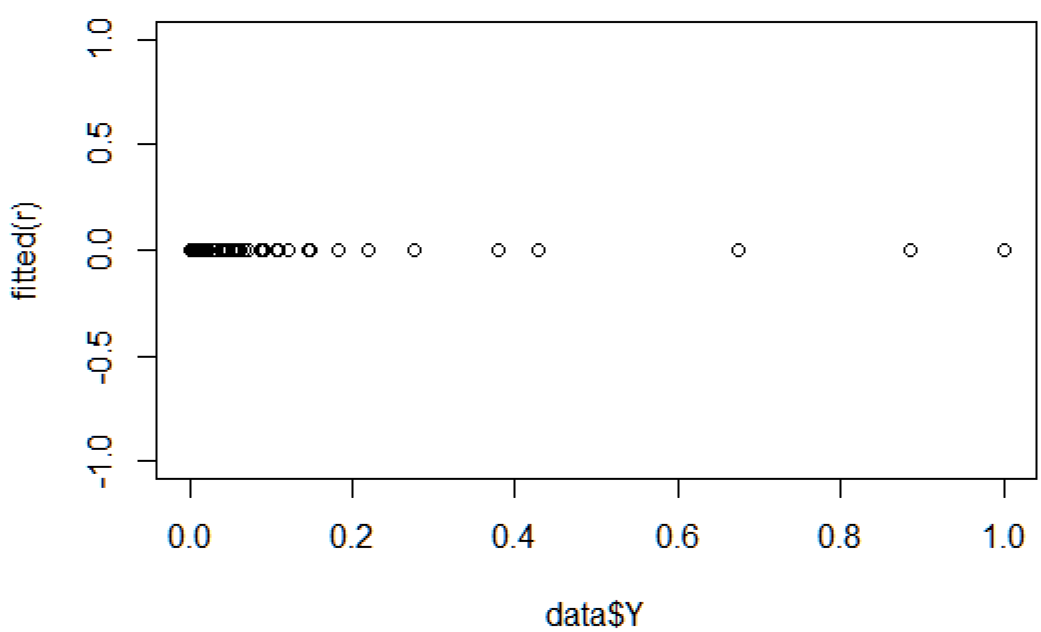


Average B-time in labor hours per machine percentage distribution.

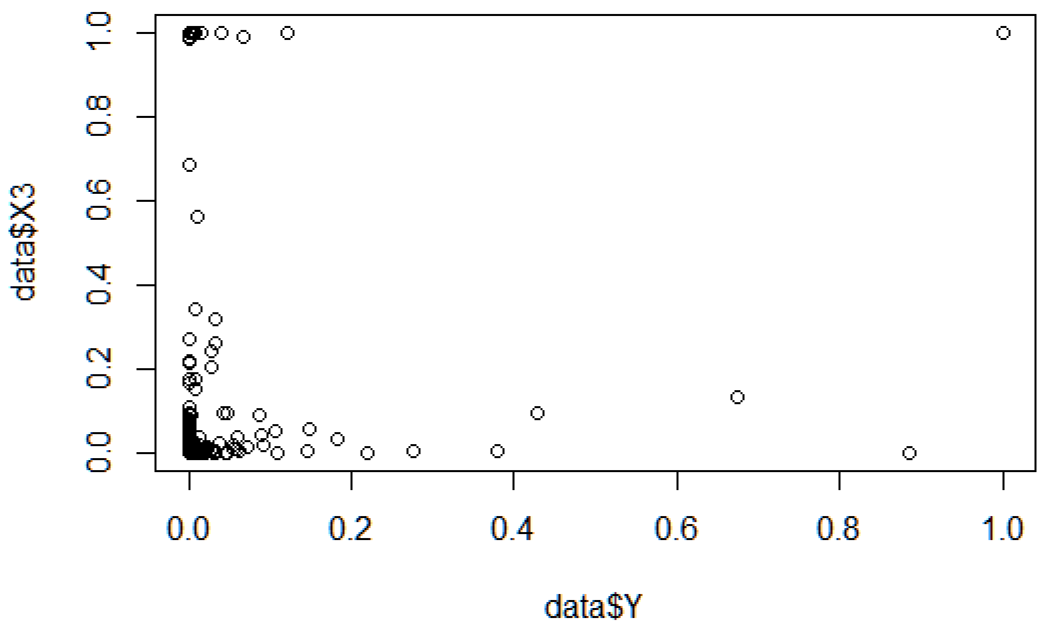
Appendix B



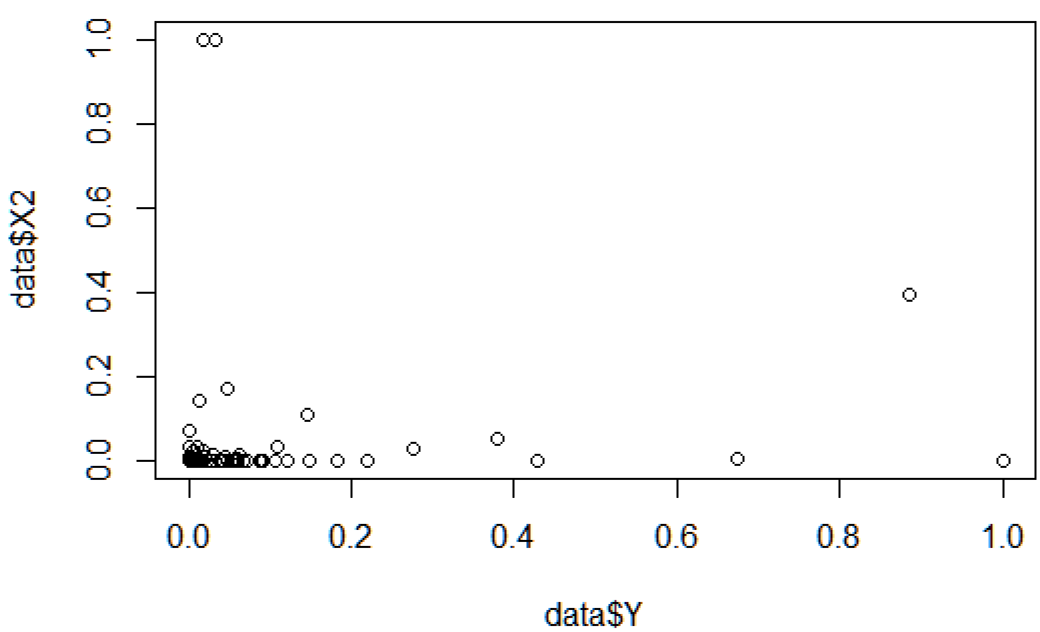
Scatterplot of the linear models’ predicted value of coverage (Y) against the actual value of coverage.



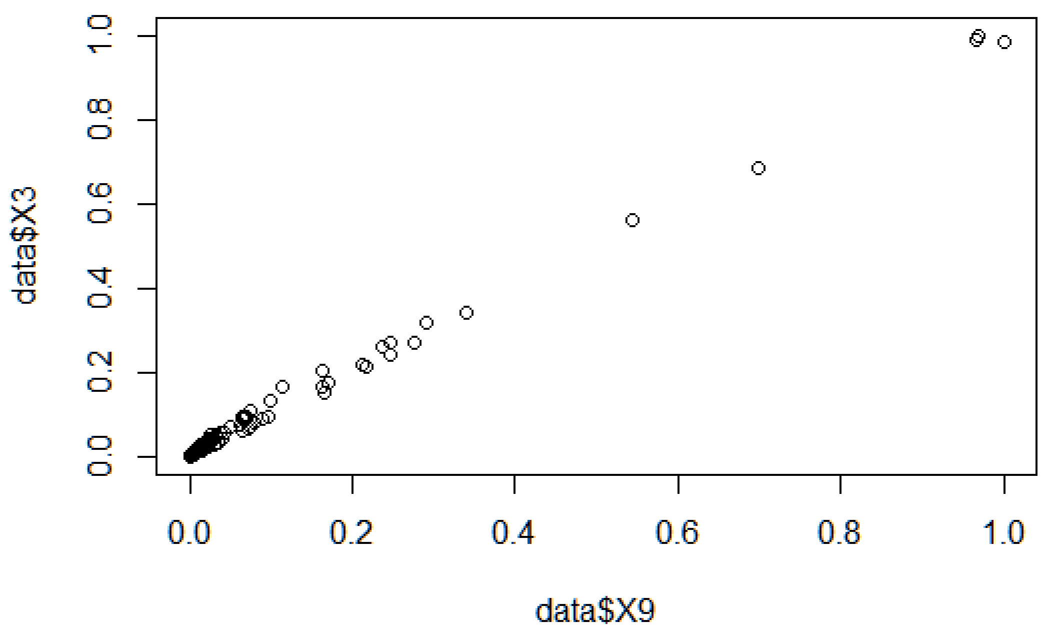
Scatterplot of a 0 prediction value of coverage against the actual value of coverage.



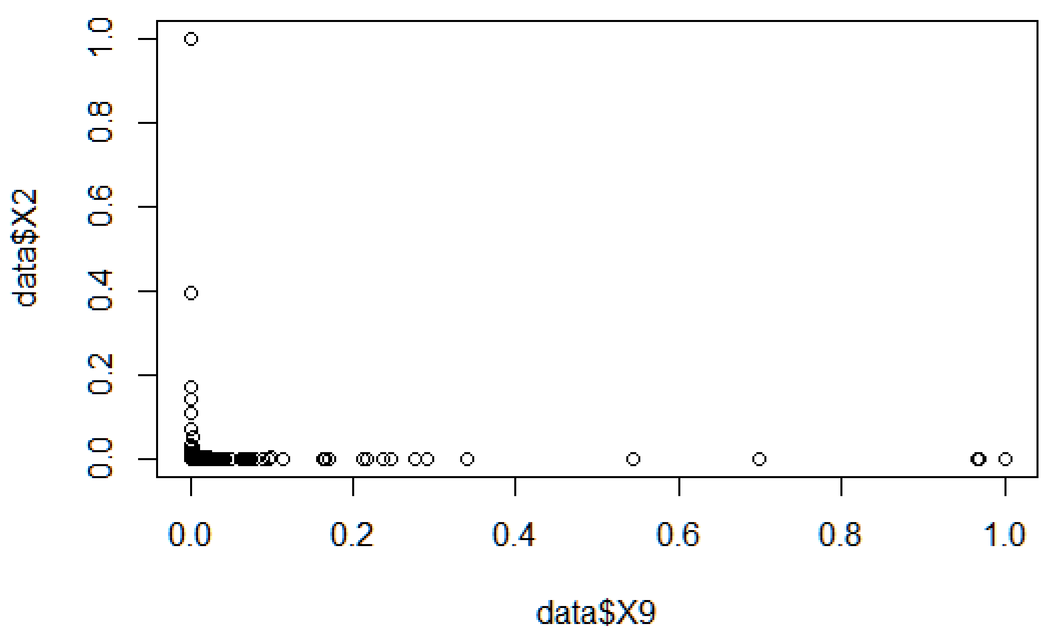
Scatterplot of MTTR against coverage.



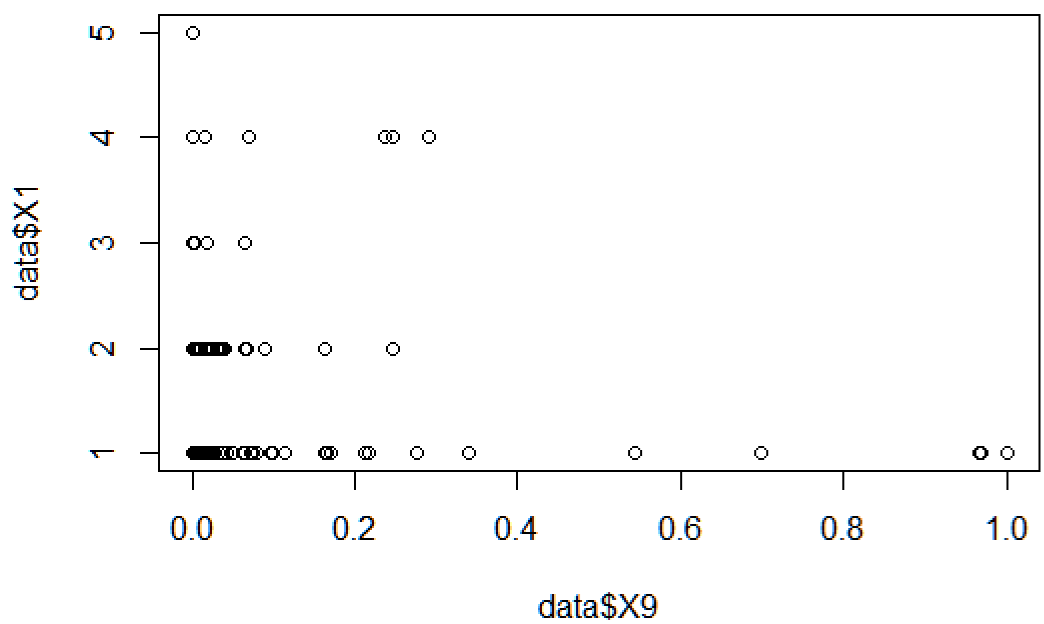
Scatterplot of frequency against coverage.



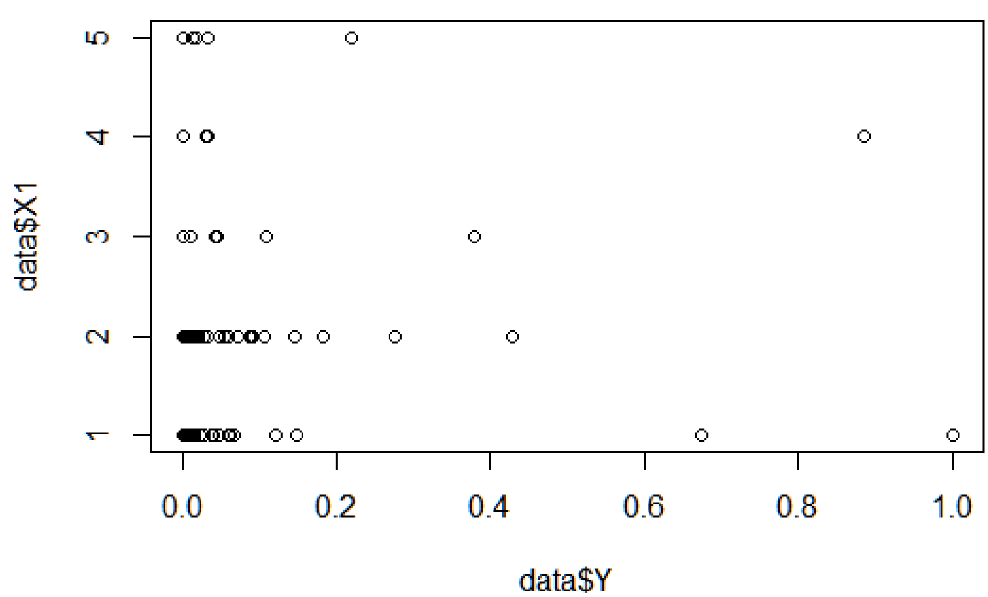
Scatterplot of MTTR against total labor hours.



Scatterplot of the frequency against the total labor hours



Scatterplot of type of service action against the total labor hours.



Scatterplot of the frequency against the coverage.